Essays on the Economics of the Gulf Cooperation Council

Islamic Banking and Financial Contagion

A thesis presented

by

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Declaration

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This Thesis is Dedicated to

Στον αδελφό μου Γιώργο
Στην κοπέλα μου Αθανασία
Στους γονείς μου Αλέκο και Νένα

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Thesis Abstract

Islamic banks have performed remarkably well despite the limitations of their ethical parameters have developed significantly during their relatively short existence. The Western world's attention was particularly drawn to Islamic finance during the 2007 financial crisis when Islamic banks outperformed conventional banks in terms of profitability, asset growth, liquidity and solvency. The comparative performance between Islamic and conventional banks in the face of the financial crisis deserves special attention for two main reasons. It is the first time that an investment universe, restricted by the Islamic Law, has outperformed the conventional system. Secondly, the predominance within the Gulf states of the Islamic banking sector, has made the GCC region more resilient to the recent financial crisis. The 2007 financial crisis has been the first time that the region maintains a positive economic growth amidst falling oil prices. Economic policy measures such as the revenue diversification programme and the subsequent development of a strong financial sector have paid off. The Islamic banking sector and its contributions to the GCC's economic endurance through the recent crisis warrants interest. The thesis starts by investigating two specific topics; the technical efficiency and failure risk of Islamic banks. Building from a somewhat rudimentary basic of a few years ago, in terms of know-how, restrictions, managerial competencies, Islamic banks have managed to close the gap with conventional banks. Their significant rise in techni-

cal efficiency is attributable to higher revenue and profit efficiency scores, achieved by improvements in human resources, compared to conventional banks. To the best of our knowledge this research is distinct in that it encompasses bootstrap tests for the equality of means testing in the context of financial ratio analysis and a meta-frontier decomposition of the DEA efficiency scores into; a managerial component and to the *modus operandi* of the bank.

The efficiency of the Islamic banking system together with its investment restrictions not only shows in lower failure risk but also in the composition of a unique financial product whose characteristics are radically different to products of conventional banking. In particular, different sensitivities exist between the two banking systems in regard to failure risk. In addition, Islamic banks are less likely to be affected by contagion effects found with conventional banking. The study offers the first application of survival analysis in comparing the failure risk of Islamic and conventional banks.

From comparisons between the financial sector (stock markets) of the GCC against developed and developing countries, we show that the GCC were among the last countries to be affected by the 2007 financial crisis. Furthermore, they recovered much faster than financial systems of many other countries. The predominance of Islamic banking in the region with its principles on risk-sharing, investments in real assets and the shunning of conventional debt instruments, has helped the GCC to weather the crisis. The chapter contributes to the literature in a number of ways.

First it allows for every country an endogenous way of detecting the timing of the crisis. Other studies have taken the route of exogenously imposing a crisis date. Secondly it introduces measures of crisis duration and intensity of the crisis on every country while it distinguishes between global and regional contagion effects.

Contents

Chapter 1
Introduction

Following the two oil crises in the 70s and 80s, the Gulf Cooperation Council (GCC) states embarked upon large-scale investment projects to reduce their dependence on highly volatile hydrocarbon income. As a result, many industrial and service sectors were promoted among which financial services sector received the greatest attention. Of special interest, Islamic finance evolved to become hugely important in the GCC.

That the 2007 financial crisis spurred Islamic finance to faster growth can be attributed to the fact that Islamic banks were relatively less affected. This can be explained by the business model that they follow granting them better capitalization and liquidity indicators, the concept of risk sharing and the disinclination to become involved in high-risk products (derivatives, securitization and short sale). Even so, Islamic and conventional banks have many similarities. For example they are both vulnerable to credit risk. In addition they operate in the same environment, facing the same macroeconomic shocks and the same regulatory requirements. Recent developments in the Arab world which have led to the overthrow of long-standing regimes, might be expected to boost Islamic banking even further as newly established governments establish new priorities. For instance, Egypt has been looking into the possibility of launching an Islamic sovereign bond.

1.1 Motivation

Islamic finance is an interesting field for research for three main reasons. First, although Malaysia remains the market leader in Islamic finance products, the GCC offers a much broader client base with even higher Islamic bank penetration (Hasan and Dridi 2010). Secondly, the income diversification attempts of GCC countries together with the stronger presence of Islamic banks has helped the GCC sustain economic growth even after oil prices plummeted during the 2007 crisis (IMF 2010). It was the prevalence of Islamic banks that insulated the financial sector from the worst repercussions of the financial crisis. Thirdly, as Islamic banks weathered the financial crisis better than their conventional counterparts, the Western world's attention was attracted (Čihák and Hesse 2010). Conventional investors have become interested in empirical comparative research between the two bank types. This remains neglected as the literature on Islamic finance primarily focuses on theoretical aspects. By our current contribution, we add to the existing empirical literature with three studies that compare the Islamic *vis-à-vis* the conventional banking system from two aspects; that of technical efficiency and that of failure risk. Furthermore, we investigate the benefits that the presence of Islamic banks brings to the financial sectors of the GCC and we draw comparisons with developing and developed countries in the period of the 2007 financial crisis.

1.2 Structure of Thesis

The thesis is organized in five chapters of which this, the introduction is the first. The second chapter compares the relative efficiency of conventional and Islamic banks. Cost, profit, revenue and technical efficiency are examined using Financial Ratio Analysis (FRA) and Data Envelopment Analysis (DEA). Methods used include a bootstrap test for equality of means testing in the context of FRA and a meta-frontier decomposition of DEA efficiency scores into managerial efficiency and efficiency due to *modus operandi*. Results show that cost efficiency is higher in conventional banks but Islamic banks are closing the gap. The closing gap is due to the importance of human resource development in the recent years and the higher spending associated with it. Although the restrictions of the Islamic banking system inhibit efficiency, superior managerial quality offsets this disadvantage.

The third chapter investigates the failure risk of conventional and Islamic banks using survival analysis models. Survival analysis has a long history in the fields of health economics and engineering. Its application in bank failure studies remains limited. Our study is the first application of survival analysis in a comparative study of Islamic and conventional banks. The chapter provides an extensive investigation of the relevance of idiosyncratic and systemic factors upon failure risk. We find that Islamic banks exhibit lower failure risk and, being less interconnected, there is a reduced likelihood of co-failure.

The fourth chapter focuses on the "synchronization" of the 2007 financial crisis and investigates the contagion effects in developing and developed economies. The GCC is compared with other groups of developing (*i.e.* Eastern Europe, BRICS) and developed (*i.e.* Core EU) economies to identify their different levels of dependence to the impact of the exposure to the financial crisis. The Markov-Switching framework is used to identify the specific crisis transition dates and the crisis intensity for every country.

We find that the GCC was the last group of countries to be affected and that the impact of the crisis on the region was minimal. Bahrain, the financial hub of the GCC, contrary to other major financial centres like Malaysia or Hong Kong as, is affected with a significant delay and at lower intensity. In short, the prominence of the Islamic banking sector has contributed to the region's weathering of the crisis. A fifth chapter provides an overall summary of the conclusions of the thesis.

1.3 GCC Background Information

The Gulf Cooperation Council (GCC) is a political and economic union of the Arab states that was founded on May 1981 among the six states: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the UAE. The superior economic performance of the GCC relative to other developing economies as well as the increased integration they have achieved compared to other Middle Eastern countries is remarkable (UNDP 2002). The GCC states show significant homogeneity among them on various geopolitical, macroeconomic and institutional aspects (IMF 2005). At first the six countries[1] share the same language and history. In terms of monetary convergence, all GCC states have generally low inflation rates compared to other developing countries (IMF 2005). In addition, they all maintain long-standing fixed exchange rates to the US dollar with Kuwait being the only exception after switching to an undisclosed basket of currencies in May 2007. The remarkable exchange rate stabil-

1 Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the UAE

ity given the liberalized financial sector has led to co-movements in the interest rates and similar sovereign creditworthiness (ECB 2005).

Economic activity in the GCC benefited from rising oil prices in the period 2003-2008. Oil prices then rose at a mean annual rate of 14%. Over the same period real GDP growth averaged 6.6% per year, which was roughly three percentage points higher than during the period 1997-2002 (IMF 2011b). The strong positive correlation between oil prices and real GDP growth is a key characteristic of the GCC economy.

[Table 1 here]

There have been two similar cases in the past where rising oil prices led to significant revenues for the GCC countries yet these could not be manifested into sustainable growth after the oil prices reverted to normal levels due to the dominant size of the hydrocarbon sector. Relying on a non-renewable and highly volatile source of income, such as oil and gas, can be an impediment to the growth prospects of any country. Saudi Arabia and Qatar have the largest endowments of oil and gas respectively in the region. By contrast, Bahrain's energy resources are depleted. All these necessitate the need for careful investment planning that would diversify the income of these countries away from energy towards sources that are non-exhaustible and less susceptible to price fluctuations.

To a degree, the GCC appears to have seized the opportunity better. Fiscal balances show increasing surpluses. International reserves soared to a record high level of 515 USD billion in 2008, up from 75 USD billion in 2002 (IMF 2011b). Having cut their external debt obligations from 66% to 12% of GDP, national governments now have the capacity to invest in projects designed to sustain economic growth (IMF 2011b). Investments in infrastructure and technology at the GCC level increased from 300 USD billion in 2004 to 2.5 USD trillion by the end of 2008 (IMF 2011a).

[Figure 1 here]

Some countries have taken significant steps towards income diversification with Bahrain, which has established itself as a financial hub in the region offering exquisite products such as Islamic finance. Tourism and transportation are also promoted. The UAE have diversified into tourism, manufacturing and financial services (IMF 2012d). Although Kuwait recently has engaged with financial services, its dependence on oil remains high. Saudi Arabia, by far the largest economy in the region (469.4 USD billion - 44.3% of GCC total), has the huge revenues from energy related products (89.3% of total revenue in 2008); construction and manufacturing are increasingly important as revenue sources (IMF 2011a). As a result of this diversification process, non-oil sectors in the GCC have been expanding at 7.3% yearly, while the non-oil GDP represented 65% of total GDP in 2008, up from about 56-58% in the early 90's. Economic growth is no longer entirely energy related.

[Figure 2 here]

1.3.1 Financial Sector

During the period 2003-2008 bank credit to the private sector has averaged a mean annual growth rate of 23% (IMF 2010). Credit expansion was stronger in the UAE and Bahrain than other GCC states, peaking at 122% of non-oil GDP in 2008. The availability of credit coupled together with low inflation and rapid economic growth prospects gave rise to high demand for real estate and equities. The UAE, Dubai in particular, were in the frontline of the real estate boom. Stock markets in the GCC region gained 22-60% in 2007 (IMF 2012d).

The financial sector in the GCC is bank-based, in line with the fact that in most developing economies banks have a dominant role in channeling funds. Yet the size of the banking sector varies considerably from state to state. Bank assets are highest in Bahrain (1200% of GDP in 2008) and lowest in Oman (40% of GDP in 2008) (IMF 2010). In 2008 absolute values, the UAE and Saudi Arabia are leading by 380 and 345 USD billion respectively, while Oman is at the bottom of the ranking scale with 10 USD billion. During the boom years, banks with access to international financial markets have been borrowing to saturate the need for credit.

The state's influence in the banking sector and infrastructure investment is significant. State ownership is highest in the UAE and Saudi Arabia, accounting for 52% and 35% of bank assets respectively while in Bahrain and Kuwait it is much lower at 20% and 13% respectively (IMF 2012a). Infrastructure investments in the GCC region are made through alternative (to banks) investment structures like sovereign wealth funds, mutual funds and central banks. The Bahraini wholesale banks are amongst the few in the region that specialize in project financing, mostly in Saudi Arabia, and pursue aggressive retail strategies in the broader MENA/South Asia region due to their less restricted operational framework. However, as the energy sector is entirely under state control, the state's influence on the non-oil sector, inclusive of banks, is significant particularly when it comes to equity injections needed to avoid financial distress as was the case during the Dubai crisis in 2009.

Stock market capitalization in the GCC has grown to 650 USD billion in 2009 from 117 USD billion in 2003 (IMF 2010). Although there have been examples of GCC states issuing debt in the past, debt markets never really took off mainly due to the ample state liquidity together with the state's role in investments. Recent developments in the stock markets of the region include negotiations with Western stock exchanges which could help in further development (*e.g.* know-how, innovation) and integration of GCC region stock markets with global financial markets.

1.3.2 Islamic Banking

Islamic banking industry was worth 1.3 USD trillion assets in 2011, representing a 150% increase over 5 years while countries like Australia, Nigeria and Russia have expressed their interest to promote Islamic banking operations (IMF 2010). Still Islamic banking is considered a niche market as Islamic assets represent only 1% of the global market. Islamic bond issuance reached 82 USD billion globally with Malaysia, the largest market in Islamic finance, accounting for two thirds.

[Figure 4 here]

Islamic banking industry is particularly strong in the GCC where the presence of Islamic banks ranges between 12% and 35% of total banking assets (IMF 2010). Islamic bond issuance (Sukuk) has grown substantially from around 5 billion USD in 2004 to 32 billion USD in 2007. Islamic bonds represent about one-third of sovereign and about a quarter of corporate debt obligations.

[Table 2 here]

Financial products utilized by Islamic banks remain tailor made to client needs. This lack of standardization could be an impediment to subsequent development as it makes Islamic financing options more expensive than those of conventional finance. In addition legal compliance and regulatory issues receive increasing attention as for most of these products there is no precedent to highlight potential issues in case of dissolution or liquidation. In addition, the Shariah compliance of some financial products and the unstandardized Shariah scholar opinion rulings enhance uncertainty.

Islamic banking is fundamentally different than conventional banking as it has evolved on the basis of Islamic Law which prohibits any transaction involving interest. Certain business types are not investable with respect to their sector (*i.e.* conventional finance, pork, alcohol, pornography) and their financial characteristics (*i.e.* debt to market capitalization $< 30\%$). Islamic banks are not allowed to utilize complex derivatives (*i.e.* hedging instruments, credit default swaps, options and short-selling) due to their uncertainty. At the same time financial products on the supply and demand side of credit are built upon the notion of equity participation and that all transactions need to involve a tangible asset. Risk sharing happens with depositors and investors neither of those having capital protection; hence allowing risk to pass through an Islamic bank granting it procyclical protection.

Mudarabah and Musharakah are some contracts that are based on the profit-and-loss sharing technique (PLS). In Mudarabah an investor (usually an Islamic bank) and an entrepreneur (individual or institutional) enter a joint venture where the investor provides the necessary funds and the entrepreneur provides the knowhow. The investor cannot interfere with the running of the business which is left entirely to the entrepreneur. Both parties agree *ex ante* on a ratio according to which they will split the profits which are unknown at the time of the agreement (*e.g.* 70/30 bank and investor accordingly). In case of losses each party loses what he had contributed to the venture unless negligence of a party can be proven. Musharakah basically differs in the number of participants in the venture and the contributions each one is allowed to make.

In practice, equity contracts are overshadowed by fee-based contracts where the bank charges a fee on top of the cost of a provided service. Fee-based contracts include the widely used Ijarah and Murabahah. Murabahah is in essence a cost-plus-profit sale. The bank arranges to sell a good to a customer and it charges a fee on the price which incorporates risks, costs and a profit margin. Ijarah on the other hand is a lease contract where the bank leases an asset to an investor (or consumer) and the latter pays fees for being allowed to use the asset. The preference of fee-based contracts is mainly due to the complexity and increased risks and costs in the tailor-made equity contracts.

Islamic banks face additional kinds of risk than conventional banks. For example, Shariah compliance risk is specific to Islamic banks and it entails potential losses arising from the Shariah Supervisory Board ruling a contract as illegitimate. The mission of a Shariah Supervisory Board (SSB) is to ensure that the products offered by an Islamic bank are in accordance with the Islamic Law. Every product needs the approval of the SSB; however as SSBs are unregulated and Scholars may not always agree a Shariah compliance risk is applicable for Islamic banks. In addition, other risk types such as operational and liquidity risk acquire a different perspective. Operational risk is inherent in Islamic finance as it is largely based on bespoke contractual agreements such as the tailor-made equity contracts. Moreover the fact that Islamic banks are relatively young, small and typically domestically owned may result in cost inefficiencies as there is evidence that cost efficiency requires a critical mass (Miller and Noulas 1996). Liquidity risk is crucial for Islamic banks given their restricted access to interbank market and the lack of central bank lender of last resort facilities. These facilities are based on conventional principles which makes an Islamic bank less eager to utilize them. At the same time the asset-backed nature of Shariah compliant contracts (*i.e.* collateralized by commodities or real estate) and the fact that conventional hedging instruments are banned, makes liquidity management vulnerable to market conditions, particularly inflation.

1.4 Appendix

Table 1. Average Annual Real GDP Growth

	Oil Real GDP		Non-Oil Real GDP		Real GDP	
	1997-2002	**2003-2008**	**1997-2002**	**2003-2008**	**1997-2002**	**2003-2008**
Bahrain	6.7	-3.1	4.0	9.3	4.7	6.9
Kuwait	9.1	7.3	6.8	9.8	7.2	8.7
Oman	15.0	1.0	6.5	9.2	9.3	5.8
Qatar	16.1	10.8	5.5	15.6	10.6	13.0
Saudi Arabia	-1.7	5.8	3.5	4.6	1.7	4.9
UAE	-0.1	3.9	7.3	9.9	4.7	8.3
GCC	**1.7**	**5.6**	**4.8**	**7.3**	**3.7**	**6.6**

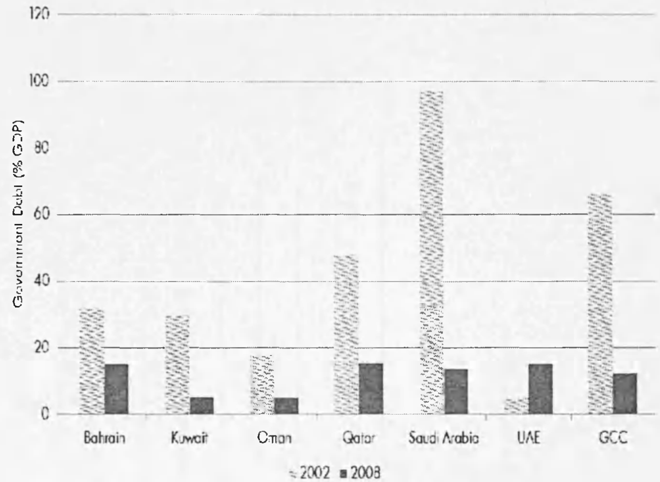
Source: Country Authorities

Table 2. Debt Market in GCC, 2009

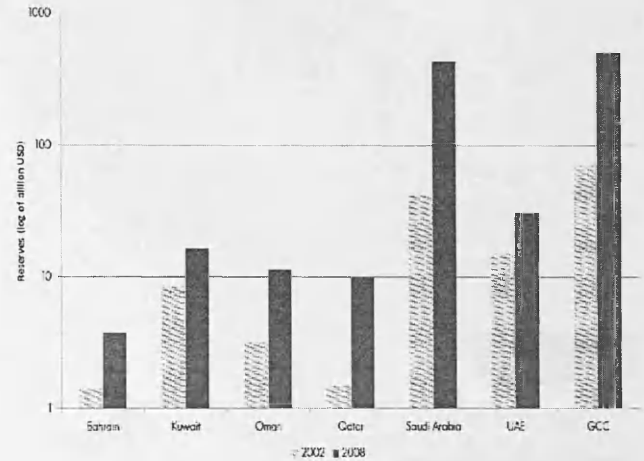
	Sovereign	**Financial**	**Non-Financial**	**Total**
Islamic Bonds (Sukuk)	1.9	5.5	6.4	13.8
Conventional Bonds	3.4	19.3	19.3	42.0
Total	5.3	24.8	25.7	55.8

Note: Numbers represent outstanding debt in billions of USD. Source: IMF

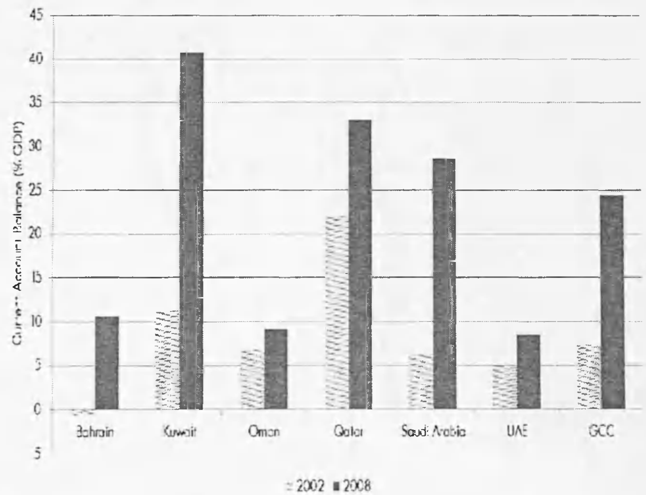
Figure 1. Monetary Economics



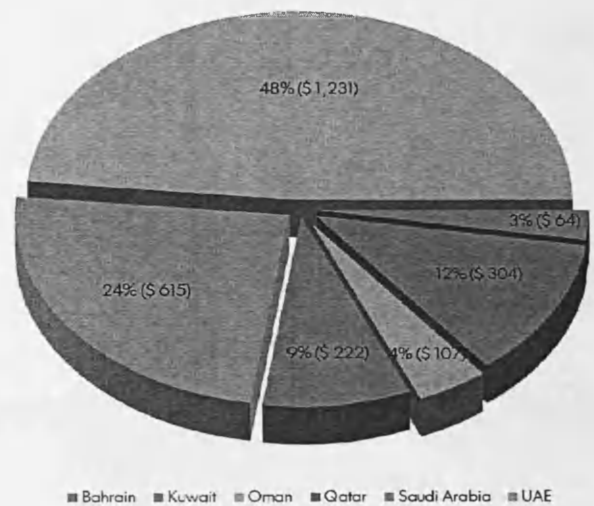
a) Government Debt (% of GDP)



b) Reserves (logs of billions of USD)



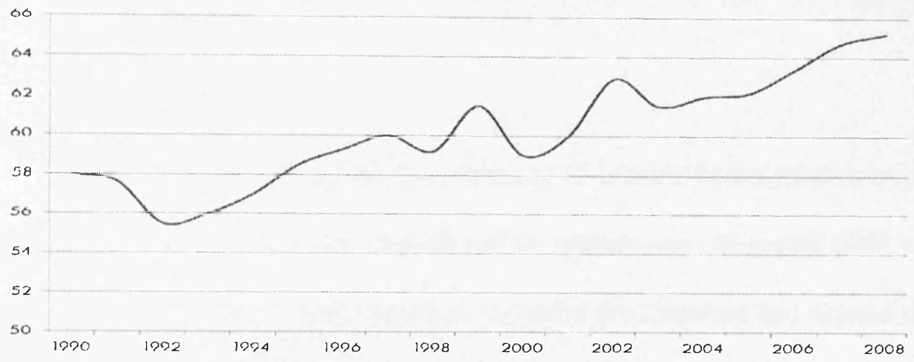
c) Current Account Balance (% of GDP)



d) Investment Projects per Country

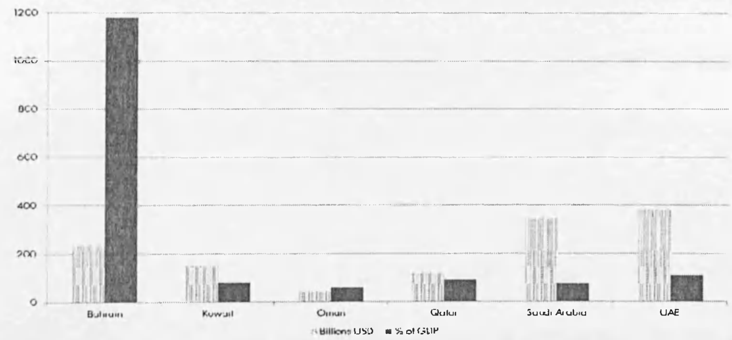
Note: Numbers in brackets are billions USD Source: IMF

Figure 2. Revenue Diversification



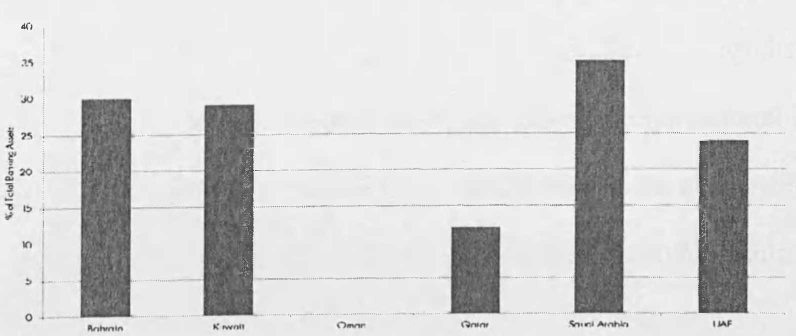
Source: Country Authorities, IMF

Figure 3. Total Bank Assets, 2008



Source: IMF

Figure 4. Market Share of Islamic Banks, 2008



Notes: Oman does not have any Islamic Banks. Source: IMF

Chapter 2
Efficiency comparison between Islamic and conventional banks in the GCC region

Abstract

In this chapter we examine the efficiency of Islamic banks relative to conventional banks in the Gulf Cooperation Council (GCC) region over the period 2004 to 2007. We employ two of the most widely used approaches in the literature and expand them further. Financial ratio analysis and DEA have been used over the same dataset so that results are directly comparable. Evidence from the financial ratio analysis are that Islamic banks are more revenue and profit efficient than their conventional counterparts but fall behind in terms of cost efficiency although the gap is closing in the last years of the sample. Bootstrapping techniques ensure avoidance of small sample bias. DEA efficiency (from now on "gross efficiency") is decomposed into "net efficiency" (reflecting managerial inadequacies) and "type efficiency" (reflecting bank type specific inadequacies). In this way the advantages of Stochastic Frontier Analysis are incorporated in the DEA approach since Islamic banks are not required to have the same goals as the conventional ones. Conventional banks are more efficient, attributable mainly to their higher "type efficiency" rather than having more capable personnel. Malmquist total factor productivity results show that productivity has risen for Islamic banks while it has fallen for conventional banks. Islamic banks had a massive expansion in technology, attributable to the new technologies implemented by some of the largest banks of the sector. Finally, correlation results between financial ra-

tios and DEA efficiency scores show that these methods should be viewed as complements rather than substitutes.

2.1 Introduction

The 2007 financial crisis had a significant impact upon the conventional banking sector across the globe in terms of resilience, profitability and growth. By contrast, Islamic banks were largely insulated from the crisis (Willison 2009; Yilmaz 2009). The highly regulated operating environment which is in accordance with the Shariah principles, prohibits investments in financial instruments that were largely blamed for aggravating the crisis (Hasan and Dridi 2010). Islamic banks are prohibited from investing in complex derivatives (hedging instruments, credit default swaps), engaging in short-sales, receiving and charging interest as well as investing in certain prohibited lines of business like conventional finance, pork and alcohol.

Conventional banks earn profits through the implementation of interest on both the asset side, where they offer a low interest rate on deposits, and the liability side, where they charge a high interest rate. The difference, or the spread, between the two rates constitutes the revenue of the bank. Additionally conventional banks earn fee-based revenues for some of their services. Islamic banks are essentially partners with entrepreneurs and borrowers through the equity-type profit and loss sharing (PLS) contracts[2]. In addition, Islamic banks

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[2] Mudarabah and Musharakah are two contracts that are based on the profit and loss sharing (PLS) technique. In Mudarabah and investor (usually an Islamic bank) and an entrepreneur (individual or institutional) enter a joint venture where the investor provides the necessary funds and the entrepreneur provides knowhow. The investor cannot interfere with the running of the business which is left entirely to the entrepreneur. Both parties agree *ex ante* on a ratio according to which they will split the profits - which are unknown at the time of the agreement (*e.g.* bank 70% and individual 30%). In case of losses each party loses what he had

offer fee-based services[3]. Conforming to Shariah principles means that Islamic banks need to obtain the approval of each financial product from the Shariah Supervisory Board (SSB). Islamic banks have taken significant steps towards standardizing their products and practises, aided by organizations such as the Accounting and Auditing Organization for Islamic Financial Institutions (AAOIFI). Yet many contracts, particularly of the equity-type remain unstandardized meaning that they need to be tailored to each specific client or project and subsequently approved by the SSB. As Islamic banks are smaller in size relatively to conventional banks they are unable to reap any benefits of economies of scale. In addition, most Islamic banks are domestically owned and therefore have less opportunities to benefit from outside innovations and efficient practises. For these reasons the success of Islamic relative to conventional banks at the macroeconomic level is in contrast to expectations of performance at the microeconomic level. The characteristics that make Islamic banking macroeconomically successful are the ones likely to make it less technically efficient.

The first Islamic bank, the Dubai Islamic Bank, was founded in 1975 at which point only fundamental contracts (*e.g.* safekeeping accounts, PLS contracts) were available. Islamic bonds were launched in 1978 followed by Islamic equity funds and Islamic insurance during the 1990s. More recently Islamic equity indices have been introduced such as the Dow Jones Islamic Markets (DJIM) and the Financial Times Stock Exchange (FTSE) Shariah. The first Islamic products were largely developed to cater for government and cor-

contributed to the venture unless negligence of a party can be proven. Musharakah differs in the number of participants in the venture and the contributions each one is allowed to make.

3 Murabahah and Ijarah are two widely used fee-based contracts. Murabahah is in essence a mark-up sale. The bank arranges to sell a good to a customer and it charges a fee on the price which incorporates risks, costs and a profit margin. Ijarah is a lease contract where the bank leases an asset to an investor (or consumer) and the latter pays fees for being allowed to use the asset.

porate funding requirements. But the growth in size and wealth of the Muslim population fed the appetite for financial products that would be Shariah-compliant. Response at the government level included the introduction of a dedicated Islamic banking system in Iran, Sudan and Pakistan. Today only Iran maintains this system while the rest of the countries operate a dual-banking system where conventional and Islamic banks operate alongside. At the corporate level the challenge has been to introduce financial products in accordance with Shariah that would cover the same needs as the conventional ones while at the same time offering similar rates of return. Through the subsequent evolutionary process Islamic credit cards and mortgages have been available to the mainstream investors in the recent years. Pressure on Islamic banks to continue to innovate is provided by the increasing appeal of the traditional values of Islamic finance to Western investors who are disillusioned with the banking practises of conventional banks in the wake of the 2007 financial crisis (Arthur D Little 2009). Appetite for Islamic banks is further enhanced as Islamic banks are found to exhibit less failure risk than conventional banks (Čihák and Hesse 2010). As a consequence, Islamic financial institutions, more than 300 in around 70 countries, are no longer confined to the Muslim world. Indeed, there are 5 Islamic banks in the UK and 19 Islamic financial institutions in the USA.

A study of the Islamic banking sector and how it compares to the conventional sector in efficiency terms receives renewed interest not only because of the traditional linkages between bank efficiency and economic development and stability but also for the increased interest from the conventional point of view. Yet problems may arise from a comparison of the two bank types as they do not necessarily share the same goals. While profit maximization is the goal of a conventional bank, Islamic banks may be willing to operate at a lower profitability level in order to remain Shariah-compliant. In addition the accounting statements of Islamic banks are not readily comparable to those of conventional banks; hence some standardization needs to take place before any analysis.

The paper contributes to the empirical research related to bank efficiency in four ways. Firstly by combining two widely used methodologies; bootstrapped Financial Ratio Analysis (b-FRA) and a Meta-Frontier variance of the Data Envelopment Analysis (DEA) (Charnes, Cooper and Rhodes 1978; Banker, Charnes and Cooper 1984). The use of two estimation approaches allows us to assess whether results and conclusions related to efficiency vary by the type of analysis; hence draw conclusions on whether the two methods can substitute one another. Advantages of the FRA approach are their ease of interpretation and the simple econometric analysis involved. As disadvantages the lack of an underlying theory as well as the inability to capture the comlexity of a bank in a few ratios. Another point of concern in FRA is the limited sample size that usually accompanies such studies. In our case small sample size is not an immediate concern, however we propose a bootstrapped version of the FRA which corrects for any small sample bias and provides more reliable estimates as well as an approach which could be used elsewhere. DEA on the other hand does not impose any restrictions on the distribution of efficiency scores (like Stochastic Frontier Analysis). By contrast, it allows for more complicated models that capture better than the FRA a bank's model of business. Secondly, in contrast to classical financial ratio analysis which can be affected by small sample bias, we implement a bootstrap technique - the first time utilized in banking context to correct for any small sample bias.

Thirdly, the Meta-Frontier Data Envelopment Analysis (MF-DEA) method decomposes efficiency into two components; one due to the *modus operandi* and one due to managerial competence at converting inputs to outputs (O'Donnell, Prasada-Rao and Battesse 2008). To our knowledge this is the first application of this technique in a comparative analysis of Islamic and conventional banks. Contrary to original DEA applications, MF-DEA does not impose the restriction that both bank types have the same goals. Fourthly, we use a large and consistent sample size of 69 banks over the 2004-2007 period in the Gulf-Cooperation Council (GCC). The particular strengths of our sample is the inclusion of 19 Islamic banks, much larger than similar studies and the inclusion of the whole GCC. Many studies in the field that compare these two bank types either use small samples, particularly of Islamic banks due to data limitations or, in an effort to boost sample size, they pool observations across a number of disparate countries which can lead to unreliable results. In addition, there have been efficiency studies focusing on the banking sector of specific GCC economies, like Darat *et al.* (2007) for Kuwait or Al-Jarrah and Molyneux (2005) for Saudi Arabia and Bahrain. Finally, we complement our study with a productivity analysis and its components under our study period to uncover reasons for the discrepancies in the efficiency scores. Policy implications from this chapter comprise the combined use of distance frontier methodologies with financial ratio analysis as well as the decomposition of efficiency score into a managerial component (this has been the focus of most studies in the past) and a component related to the modus operandi of the banks (Islamic versus conventional). We verify that the Islamic banking system is inherently less efficient due to its restrictions. By constrast the managers employed in Islamic banks are more efficient in dealing with these restrictions. Any policy attempts to further enhance efficiency in Islamic banks should target the restrictions of the system first and then the managers.

The paper is organized in six sections of which this is the first one. A literature review is presented in section 2 while section 3 describes the methodological approaches utilized. Data are presented in section 4 while section 5 presents the results. A sixth section concludes.

2.2 Literature Review

Performance evaluation within the banking industry at the macro level is essential to assess governmental policies related to deregulation, mergers and acquisitions and economic growth. At the micro level measuring efficiency is essential to promote good practises and discourage bad practises which would boost managerial performance and subsequently improve the bank's efficiency in converting inputs to outputs.

Since the true level of efficiency is unknown there is not consensus in the literature about the best approach. The common ground among all approaches is the notion of "benchmarking" the performance of selected Decision Making Units (DMUs) against themselves or some standards. The notion of relative comparison is very intuitive and easily understood by non-technical oriented industry managers. The benefit of combining statistical analysis with relative "benchmarking" is the quantification of the inefficiencies (Berger and Humphrey 1997).

2.2.1 Financial Ratio Analysis

Studying banking efficiency[4] can be done in two ways: by the use of financial ratio analysis (FRA) or by the more statistically intense frontier analysis methods (DEA). Financial ratios are popular for a number of reasons. First they are easy to calculate and interpret making them ideal for non-experts. Secondly the allow comparisons to be made to other banks or relative to a "benchmark", which is usually the average of the industry sector, or against time (Hassan and Bashir 2005; Halkos and Salamouris 2004). Despite the wide usage of financial ratios they are not without drawbacks. First of all financial ratio analysis does not have any underlying theory meaning that a firm can calculate its own ratios in such a way that conceals problems. Secondly, most financial ratios cannot capture the complete picture of performance of a complex organization over the breadth of its activities. In addition to that there is no criterion for selecting a ratio that is appropriate for all interested parties (Ho and Zhu 2004). In the context of Islamic banking there is the additional concern whether financial ratios can distinguish between the two bank types. Olson and Zoubi (2008) tackle this question by using nonlinear classification techniques such as neural networks and find that financial ratio analysis is indeed meaningful within such a comparative context. Yet the underlying assumption is that banks pursue such goals (*i.e.* profit maximization) which makes their financial ratios look better than the other banks. That could be a potential drawback of their application in the context of Islamic banks where these might not be the most pressing objectives (Abdul-Majid *et al.* 2010).

[4] A Decision Making Unit (DMU) in this case is a bank. The same approach can be used with firms or public organisations.

Financial ratio analysis can suffer from small sample bias especially in this comparative framework where data for Islamic banks are limited. Still as FRA boils down to some sort of statistical significance test of the difference in means any small sample bias would be eliminated if a bootstrapping methodology is applied. One of the first applications of conducting a bootstrapping version for a mean hypothesis test is found in Allen (1997). More recent applications include the Desagné *et al.* (1998)and the Peretti and Siani (2006) in a medical-economics context. The former is a non-parametric version while the second compares a parametric and a non-parametric approach. The parametric approach imposes a certain distribution on the financial ratios before drawing the bootstrap sample. The non-parametric is less restrictive as it is manifested by repeatedly drawing a random sample with replacement and each time calculating the test statistic.

2.2.2 Frontier Analysis Methods

The frontier analysis methods are based upon production theory and allow for multiple inputs and multiple outputs. The estimation of the production possibility frontier, which is tantamount to the efficiency frontier, has been done by at least five different approaches that can be broadly grouped into parametric and non-parametric. The differences in these methods relate to: i) whether a functional form is imposed for the production frontier; ii) the distribution assumption underlying the stochastic error, provided that the latter has been specified; iii) the distribution assumption for the efficiency scores.

Parametric approaches impose a functional form for the production function and allow for the presence of stochastic errors to affect the efficiency scores of all units. The most common parametric approach is the Stochastic Frontier Approach (SFA) while others include the Distribution-Free Approach (DFA) and the Thick Frontier Approach (TFA). The functional form that SFA posits is usually the half-normal, as efficiency scores cannot be negative while stochastic errors follow the normal distribution. Other distributions have been proposed (*i.e.* truncated normal, gamma) as more appropriate to deal with the issue of firm clustering around full-efficiency levels which occurs under the half-normal (Greene 1990; Berger and DeYoung 1996; Yuengert 1993). DFA relaxes the assumptions on efficiency scores and random error of the SFA by assuming that firm efficiency is constant across time. Any inefficiencies are then attributed to firm-specific characteristics in a way similar to a fixed effects model (Lang and Welzel 1996). Contrary to SFA and DFA, TFA only provides estimates of a general level of efficiency in the examined sector rather than individual efficiency scores.

Data Envelopment Analysis (DEA) is the most commonly used non-parametric approach. The method, which imposes no underlying assumptions on the production function, provides a piece-wise linear frontier that envelops the observed production points (*i.e.* the firms). The firms that constitute the frontier, the efficient ones, are those that make the optimal utilization of inputs to produce outputs. In other words no other firm can create more outputs, given inputs or utilize less inputs, given outputs. Moreover, by enveloping the observed production points, the DEA frontier allows each bank to have different objectives as it will only be compared with banks of similar input and output mix. In the present context this means that Islamic banks whose main objectives are likely to differ from those of conventional bank, will not be penalized (in terms of efficiency measurement) relative to their conventional counterparts.

There is a considerable literature on the efficiency of banking institutions of specific countries or broader regions. See for example Drake and Simper (2002) for the UK, Berg *et al.* (1993) for Norway, Halkos and Salamouris (2004) for Greece, Berger and Mester (2003) for the USA, Altunbas *et al.* (2001) for Europe, Staikouras *et al.* (2008) for Central and Eastern Europe, Al-Jarrah and Molyneux (2005) for Middle East and Allen and Rai (1996)for an international study. Reviews of studies on efficiency analysis can be found in Berger and Humphrey (1997); Berger and Mester (1997); Casu *et al.* (2001) and Brown and Skully (2002). The literature that addresses the issue of banking efficiency specifically in Islamic banks is less broad. There are studies focusing on individual countries, predominantly Malaysia (Kamaruddin *et al.* 2008; Sufian 2006, 2007) and Sudan (Hassan and Hussein 2003; Saaid 2005; Saaid *et al.* 2003). Others have a regional (El Moussawi and Obeid 2010, 2011; Mostafa 2007, 2011) for the GCC, or international focus (Hassan 2005,2006; Sufian, 2009; Yudistira 2004; Viverita *et al.* 2007, Brown, 2003). Nevertheless of special interest are the studies that compare Islamic and conventional banks. The remainder of this section will focus predominantly on studies which compare Islamic and conventional banks.

Islamic banks might be expected to have lower efficiency than conventional banks for a number of reasons. First, the strict application of Shariah rules means that many of the Islamic banking products are unstandardized thereby increasing operational costs relative to those of conventional banks. Second, Islamic banks tend to be small, in terms of accounting profile, compared to conventional banks, and there is consistent evidence that technical efficiency increases with the size of the bank (Miller and Noulas 1996 (USA); Bhattacharyya *et al.* 1997 (India); Jackson and Fethi 2000 (Turkey); Isik and Hassan 2002 (Turkey); Drake and Hall 2003 (Japan); Sathye (2003) (India); Abdul-Majid *et al.* 2005 (Malaysia); Chen *et al.* 2005(China); Drake *et al.* 2006 (Hong Kong)). Third, Islamic banks are often domestically owned and the majority of the evidence suggests that foreign-owned banks are more technically efficient than their domestically-owned counterparts (Isik and Hassan 2002 (Turkey); Jemric and Vujcic 2002 (Croatia); Hasan and Marton 2003 (Hungary); Weill 2003 (Europe); Sturm and Williams 2004 (Australia); Kasman and Yildirim 2006 (Central & Eastern Europe); Matthews and Ismail 2006 (Malaysia); Mokhtar *et al.* 2008(Malaysia)). Yet there are studies suggesting that the opposite is true (Rizvi 2001 (Pakistan); Sathye 2001 (Australia); Sensarma 2006 (India); Sufian 2006 (Malaysia)).

Three relevant studies adopting FRA methodology have generally found, contrary to our *ex ante* hypothesis, that Islamic banks are more efficient than conventional banks. Hassan and Bashir (2005) find that Islamic banks are more efficient than conventional banks in terms of resource use profitability, asset quality, capital adequacy and liquidity. Yet Islamic banks have higher cost inefficiencies which can be attributed to the higher importance of human resource development process taking place. Ahmad *et al.* (1998) finds that managerial staff in Islamic banks are worse qualified to than that of conventional banks but the gap is closing in recent years (Pellegrina 2008). A similar study of Bader *et al.* (2007) finds that Islamic banks perform similarly to conventional banks in terms of cost, profit and revenue efficiency. A third study, although not strictly related to efficiency, that of Hasan and

Dridi (2010)finds that Islamic banks have higher capitalization, profitability and liquidity ratios than the conventional counterparts.

The results from studies which use frontier estimation methods are not so clear-cut. Three studies (one of which is in the GCC) support our *ex ante* hypothesis by finding that Islamic banks are significantly less efficient than conventional ones (Mokhtar *et al.* 2007, 2008 (Malaysia); Srairi 2010 (Middle-East)). The vast majority of frontier studies find no significant difference between the two bank types (El-Gamal and Inanoglou 2005 (Turkey); Grigorian and Manole 2005 (Middle East); Mokhtar *et al.* 2006 (Malaysia); Bader 2008 (Middle East); Hassan *et al.* 2009 (Middle East)), while in other studies the significance of the difference between the two bank types is not tested (Hussein 2004 (Bahrain); Al-Jarrah and Molyneux 2005 (Middle East); Said 2012(International)). The small sample size primarily of Islamic banks might underpin the findings of some of these studies. Where sample sizes are large, the data have often been pooled over a variety of countries with very different economic backgrounds making it difficult to isolate the effect on efficiency on Islamic banks. Few previous studies have investigated the reasons why Islamic banks differ from conventional banks in terms of efficiency. There are four noteworthy exceptions which due to their decomposition of efficiency into "gross" and "net" (Abdul-Majid *et al.* 2008, 2010, 2011a, 2011b). The efficiency attributed to both managerial incompetence and the modus operandi is termed "Gross efficiency" while the managerial component can be isolated as "Net efficiency". Evidence from Malaysia suggest that "Gross efficiency" is significantly higher for conventional banks than Islamic banks. However, differences in "Net efficiency" are minimal and suggest that managerial competence does not differ between the two bank types (Abdul-Majid *et al.* 2008, 2011a, 2011b). A generalized version of the study for 10 countries reaches the same conclusion providing more evidence that any inefficiencies are mainly due to the constraints under which Islamic banks operate rather than managerial inadequacies (Abdul-Majid *et al.* 2010). The studies use SFA to achieve the decomposition of efficiency into "Gross" and "Net". Gross efficiency is in essence a SFA which makes no allowance for bank-specific characteristics while "Net efficiency" is a SFA conditional on bank-specific information.

Finally, various studies have examined productivity (Worthington 1999; Barros *et al.* 2009) but the empirical research comparing the productivity of the two bank types is very limited. Productivity, as defined by the Malmquist productivity index, has increased over the period 1996 - 2002 in the banking sector of Malaysia. However this change is a consequence of technology innovations rather than improvements in technical efficiency. There is no significant difference in the productivity between the two bank types (Abdul-Majid *et al.* 2008). In the GCC there are two studies with opposite findings. The study of Ramanathan (2007) documents an increase in the productivity of the banking sector in the period 2000 - 2004 while that of Ariss *et al.* (2007) evidences a decrease in, roughly, the same period. Yet neither study approaches the issue with a comparative perspective between conventional and Islamic banks. Table 1 summarizes the literature that focuses on Islamic banks either individually or in a comparative framework.

[Table 1 here]

2.3 Methodology

2.3.1 Financial Ratios Analysis and Bootstrapping

We adopt six standard financial ratios which assess cost, revenue and profit efficiency. Our choice of financial ratios is motivated by the study of Bader *et al.* (2007), which we restrict in the GCC, and also by data availability. Table 2 presents the financial ratios used and their definitions.

[Table 2 here]

In every year we report the mean and median ratios for Islamic, conventional and all banks. The t-test for equality of means is applied to test for significant differences in the means of Islamic and conventional banks. We also perform the Mann-Whitney and Kolmogorov-Smirnov non-parametric tests which capture differences in the medians and in higher moments of the distributions of the financial ratios.

To enhance the FRA analysis we adopt the bootstrap approach of Desagné *et al.* (1998) on our dataset of conventional and Islamic banks in the GCC region. Specifically we perform the bootstrap procedure for each of the 4 years in our sample and again for the pooled dataset. We expect the bootstrapped p-values to be much different to the original ones in the 4 individual years than in the pooled sample since the small sample bias will be more evident there. The bootstrap approach is briefly described below.

The original data sets for the conventional and the Islamic banks are defined respectively as:

$$X^i_{1,\tau}, X^i_{2,\tau}, ..., X^i_{m,\tau} \tag{2.1}$$

$$Y^i_{1,\tau}, Y^i_{2,\tau}, ..., Y^i_{n,\tau} \tag{2.2}$$

where sample sizes are $m = 50$ and $n = 19$ for conventional and Islamic banks respectively. The superscript i, which is not a power, takes values from 1 to 6 and is used to indicate one of the six financial ratios in the sample[5]. The subscript τ denotes the specific year analyzed and takes values $\tau = 2004, ..., 2007$[6]. The hypothesis test of the equality of means is outlined below.

$$H_0 \; : \; \mu_{m,\tau} = \mu_{n,\tau} \tag{2.3}$$

$$H_1 \; : \; \mu_{m,\tau} \neq \mu_{n,\tau} \tag{2.4}$$

We utilize the t-statistic for two unequal samples with unequal variances to do the hypothesis test of equality of means for the two groups[7].

$$t^i_\tau = \frac{(\overline{X}^i_\tau - \overline{Y}^i_\tau)}{\sqrt{\frac{s^2_{i,\tau}}{m} + \frac{s^2_{i,\tau}}{n}}} \tag{2.5}$$

The numerator is composed of the means values for the two original samples of conventional and Islamic banks for each of the i financial ratios at each of the τ years. The denominator is composed of their respective variances divided by the sample sizes. The

[5] 1=Cost to Income; 2=Non-interest expenses to average assets; 3= Return on average assets (RoA); 4=Return on average equity (RoE); 5=Net Interest Margin; 6=Other operating income to average assets

[6] We also run the bootstrap for the pooled sample in which case the t subscript can be dropped.

[7] The assumption of equal variances cannot be accepted as the Levene's test for equality of variances is rejected at least at the 95% significance level.

next step is to calculate the initial value of the t statistic ($t^i_{obs,\tau}$) directly from the sample. In our case there are 24 different values (6 for every year) presented in the table 3.

[Table 3 here]

The next step is to formulate the samples from where we will bootstrap. A prerequisite for bootstrapping is that we need respect the null hypothesis of equality of means (or bootstrap under the null); some transformation is necessary. This is done by changing one of the initial samples, in our case the sample of Islamic banks (Y). In each observation we add the mean of the conventional banks and subtract the mean of the Islamic banks. Again this is done over the 4 years of the analysis. Mathematically:

$$Y^i_{1,\tau} + \overline{X}^i_{1,\tau} - \overline{Y}^i_{1,\tau}, ..., Y^i_{n,\tau} + \overline{X}^i_{n,\tau} - \overline{Y}^i_{n,\tau} \tag{2.6}$$

Next we can apply the bootstrap which will create two new samples of the same size by selecting randomly and with substitution from the initial sample of conventional banks and the modified sample of Islamic banks. The new bootstrapped samples will be:

$$X^{i*}_{1,\tau}, X^{i*}_{2,\tau}, ..., X^{i*}_{m,\tau} \tag{2.7}$$

$$Y^{i*}_{1,\tau}, Y^{i*}_{2,\tau}, ..., Y^{i*}_{n,\tau} \tag{2.8}$$

From the bootstrapped samples we calculate again the t-statistic:

$$t^{i*}_\tau = \frac{(\overline{X}^{i*}_\tau - \overline{Y}^{i*}_\tau)}{\sqrt{\frac{s^2_{i*,\tau}}{m} + \frac{s^2_{i*,\tau}}{n}}} \tag{2.9}$$

We repeat the two final (drawing sample and calculating the t-statistic) steps b times and get b different values for the t-statistic. The final step is to calculate the new p-values based on the formula:

$$\widehat{p^i_\tau} = \# \frac{\left[|t^{i*}| \geq \left|t^i_{obs,\tau}\right|\right]}{b} \tag{2.10}$$

$$i \in [1,2,3,4,5,6] \tag{2.11}$$

$$\tau \in [2004,2005,2006,2007] \tag{2.13}$$

To give an example[8] in case of $b = 9999$, we have 359 t values greater than $\left|t^1_{obs,2004}\right|$ and 68 values smaller than $\left|t^1_{obs,2004}\right|$. So according to the formula the p-value will be:

$$\widehat{p^1_{2004}} = \frac{359+68}{9999} = 0.043 \tag{2.14}$$

2.3.2 Data Envelopment Analysis

The DEA technique was first used by Charnes, Cooper and Rhodes (1978) [CCR model] and developed further by Banker, Charnes and Cooper (1984) [BCC model]. It assumes that a decision making unit (DMU[9]) uses similar inputs to produce alike outputs using similar technology. The difference between the two models is that the CCR assumes constant returns to scale while the BCC allows for increasing or decreasing returns to scale. In other words the BCC model allows for conditioning the DMU's efficiency on its size.

8 The example is based on the Cost to income ratio of 2004

9 The DMUs can be banks, hospitals, educational institutes, supermarket branches, government bodies and so on.

One important step in the DEA analysis is the choice of input and output variables. Unfortunately data are not always available particularly for developing countries. Moreover when the DMU is a bank there is the long-standing debate on what constitutes a bank's output that must be tackled; for instance there is not unanimity on whether deposits should be considered as an input or an output variable (Heffernan 2005). Which measure of bank services is better; the number of transactions or their value? To deal with this problem there are two choices one can follow: the production approach or the intermediation approach. In the production approach the bank is treated as a firm that produces services by taking capital and labour inputs. Usually the number of deposit accounts is taken as output and the number of employees as input. In the intermediation approach banks act as intermediaries between savers and borrowers. Usually total loans, total deposits are outputs and operating costs are inputs. The intermediation approach is commonly used in banking context (Berger and Humphrey 1991).

The production technology of the DMUs is $P(x)$ and stands for all input vectors $x \in R^m_+$ that aid the DMU in producing all output vectors $y \in R^s_+$

This can be written as:

$$P(x) = \{y \in R^s_+ : x \text{ can produce } y\} \tag{2.15}$$

The output distance function which is non-decreasing in y and increasing in x, linearly homogeneous in y, if $y \in P(x)$ then $D_O(x, y) \leq 1$ and $D_O(x, y) = 1$ only if y belongs to the frontier of the output set (i.e. lies on the production possibility curve), is defined on the output set $P(x)$ as (Shepherd 1970; Coelli *et al.* 2005):

$$D_O(x,y) = \min_\theta\{\theta : (y|\theta) \in P(x)\} \tag{2.16}$$

DEA is a non-parametric estimator of the technical efficiency score of a DMU through the estimation of the output distance function. The DEA technique calculates an efficiency ratio as the weighted sum of s outputs over the weighted sum of m inputs for every of the k DMUs.

$$TE_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \tag{2.17}$$

Where y_{rk} and x_{ik} are respectively the r output and i input of the k DMU. Each DMU therefore uses the set of weights which gives it maximum efficiency (subject to the constraint that weights must be universal). Productive efficiency can be split in technical efficiency (TE) and allocative efficiency (AE)[10]. Technical efficiency is a measure of the firm's ability to maximize outputs given a set of inputs. Allocative efficiency measures the firm's ability to minimize the cost of inputs while maintaining the same level of output. Moreover a Variable Returns to Scale (VRS) model can be used which will allow the decomposition of technical efficiency (TE) into pure technical efficiency (PTE) and scale efficiency (SE). The VRS model allows DMUs to be working at different than optimal level (*e.g.* in some countries state owned banks might be working with more than required personnel for political reasons). Scale efficiency is the "penalty" that the DMU is paying for not working at the optimal level.

10 We do not calculate allocative efficiency due to data limitations

DEA creates a frontier, or an envelopment surface, from the efficient DMUs. These DMUs are the efficient ones in the sample as they produce the most output from a given set of input. These units are assigned an efficiency score of 1 while the rest, least efficient units, are assigned scores less than one[11].

The following primal linear programming equation set must be solved to get the optimal weights and consequently the efficiency scores. However we normally compute the dual since the fewer constraints, $s + m$ instead of $n + 1$, make computations easier. Table 4 lists the linear programming equations required to solve a DEA problem.

[Table 4 here]

The above model is the CCR or constant return to scales (CRS) model; however variable returns to scale can be easily incorporated, so that scale efficiency measures can be calculated if this additional constraint is included:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2.18}$$

Once the VRS model has been estimated, scale efficiency can be estimated by dividing the CRS efficiency score by the VRS efficiency score. DEA is very appealing to our context as it allows different banks to have different goals and priorities. Thus there are two efficient frontiers; one for the conventional and one for the Islamic banks. Of course there is a third, global frontier that envelops every bank. In figure 1 the dots represent Islamic banks and the X represent conventional banks. For the sake of simplicity there is only one input, fixed assets, and one output, loans. The frontier GHI is the Islamic frontier

[11] This is the output maximising approach. There is also the option of keeping the output fixed and then the most efficient unit will be the one that uses the fewest inputs.

and the BCD is the conventional frontier. These were created by running the DEA analysis twice; including only Islamic banks and including only conventional banks. Finally there is a general frontier, GCD that treats every bank as having the same management priorities. In figure 1 assume for instance bank Y. This bank lies inside the general frontier so it is inefficient. We will call this efficiency *"Gross efficiency"*. Bank Y has a gross efficiency score of 0y/0y" which is obviously less than 1 since 0y">0y and represents the proportion of output (loans) achieved by bank Y relative to the best possible output in the sample using bank's Y input as reference[12]. Relative to frontier GHI (Islamic frontier), bank Y is also inefficient. We call this inefficiency called *"Net efficiency"* and is represented by the distance 0y/0y' on the graph. Net efficiency shows how well a bank performs relative to its type. In this case for instance bank Y is an Islamic bank which is 0y/0y' inefficient compared to Islamic banks and 0y/0y" inefficient compared to all banks. If we divide "gross efficiency" by *"Net efficiency"* we get a ratio of 0y'/0y" which is the *"Type efficiency"* score giving an indication of the impact of conducting business in a Shariah compliant way can have on efficiency.

[Figure 1 here]

The construction of metafrontiers on DEA estimates comes with the assumption of convexity. Convexity is particularly important as the enveloping surface of DEA connects via straight lines the efficient banks while all the inefficient are located below the enveloping surface (Beltran-Esteve *et al.* 2013). However the straight lines imposes a restriction

12 This is the maximising output approach. One could use the minimising input approach where output would be used as reference and the DMU achieving that output with the least input would be the most efficient.

that the inputs and outputs are not always divisable. For example, if the input is the number of buildings then a bank may have one, two or three buildings but cannot have two and a half buildings. If this assumption is considered restricting then other techniques may be prefered like Free Disposal Hull (FDH) which works in the same way as DEA besides that it does not impose convexity (De Witte and Marques 2009). However when inputs and outputs are in monetary units and when the sample size is large, then the convexity assumption would not be as restricting since the frontier of DEA would tend to be smoother and approximate that of the FDH. Hence we employ DEA to maintain the comparability of our results to the majority of the studies which have used DEA approach as opposed to the very limited amount of research that has utilised FDH (Tiedemann *et al.* 2011).

2.3.3 Malmquist productivity

The Malmquist productivity index, another instrument within the DEA framework, is made up of the change in technical efficiency and the change in technology (Malmquist 1953). This shows if an inefficient DMU is moving closer to the efficiency frontier (catching up) and how much the efficiency frontier is shifting due to technological change.

For the Malmquist productivity index to be calculated a balanced panel of data is needed so that cross-sectional data over a period of time are available. Assuming $t, t+1, ..., T$ as superscripts to denote different time periods we have $D_O^t(x^t, y^t)$ and $D_O^{t+1}(x^{t+1}, y^{t+1})$ representing the output distance functions for periods t and $t+1$ respectively. The Malmquist productivity change index is defined as (Coelli *et al.* 2005):

$$M_O(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^t(x^t, y^t)}\right) * \left(\frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^t, y^t)}\right)\right]^{1/2} \tag{2.19}$$

where:

$$D_O^t(x^{t+1}, y^{t+1}) = \min\{\theta : x^{t+1}, y^{t+1}/\theta) \in P^t\} \tag{2.20}$$

and

$$D_O^{t+1}(x^t, y^t) = \min\{\theta : x^t, y^t/\theta) \in P^{t+1}\} \tag{2.21}$$

Which can be decomposed further into (Coelli *et al.* 2005):

$$M_O(x^{t+1}, y^{t+1}, x^t, y^t) = E.T = \tag{2.22}$$

$$= \left(\frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^t(x^t, y^t)}\right) * \left[\left(\frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^{t+1}, y^{t+1})}\right) * \left(\frac{D_O^t(x^t, y^t)}{D_O^{t+1}(x^t, y^t)}\right)\right]^{1/2} \tag{2.23}$$

The first component (E) shows an increase in technical efficiency if it is greater than 1 or a decrease in technical efficiency if less than 1. It provides evidence on whether DMUs become more efficient over time meaning that resources are being used more productively. The second term (T) shows an increase (if greater than 1) or decrease (if less than 1) in technology. This is explained by shifts, inwards or outwards, in the benchmark efficient frontier.

The Malmquist productivity index has certain drawbacks which are elaborated in (Aparicio et al. 2013). Here we mention briefly that the main drawbacks are the slacks that are left from the previous stage of the DEA analysis and these constitute a non-radial form of inefficiency which is not taken into account. This may be corrected using two approaches; i) first the slacks may be incorporated into the analysis as in Grifell-Tatje et al. (1998)and Chen (2003)or ii) the use of radial measures in the DEA efficiency stage which avoids the existence of slacks as in Dharmapala (2010). We adopt the second and more recent approach in our analysis which is found to perform better (Aparicio et al. 2013).

2.4 Sample Data

A consistent sample of all the GCC banks that have a full set of values for the variables required for the FRA and DEA over the entire period under study (2004-2007) is required. Bankscope is the data provider. Since most banks report their accounting statements in their home currency their values were converted to United States Dollars (USD) using exchange rates provided by the Financial Times website[13]. These countries maintain fixed exchange rates to the USD so the choice of the date would not change the results. In addition, all variables were converted to 2007 prices using the GDP deflator which is calculated by dividing the nominal GDP by the real GDP for each country[14]. The number and type of banks included in the sample and population is shown in table 5 below:

[Table 5 here]

To implement DEA we select the intermediation approach as more appropriate for our kind of study (Pasiouras 2008). The choice of input and output variables is motivated

13 1$ = 0.37686BHR(Bahrain) = 0.27283KWD (Kuwait) = 0.38495OMR (Oman) = 3.63871QAR (Qatar) = 3.74736SAR (SaudiArabia) = 3.67249AED (UAE).

14 Necessary data were collected from the World Economic Outlook 2009

by previous literature (Abdul-Majid *et al.* 2008; Casu and Girardone 2004; Casu *et al.* 2004)and subject to data limitations. The output variables are:

- Total Loans
- Other Earning Assets

The inputs which comprise the funds from depositors as well as capital and labour employed by the banks are defined as:

- Deposits and Short term funding
- Fixed Assets
- General and Administration expenses (Overheads)
- Equity

General and administration expenses are used as a proxy for labour input. Better proxies exist in the literature to capture labour costs (*e.g.* number of employees or wage expenditure) yet they are not as easily available. In addition, it has been argued that a large share of general and administrative expenses is comprised by personnel expenses (Drake and Hall 2003).

Equity is included as an input to capture risk-taking in the banking sector. Charnes *et al.* (1990) first identified the necessity of a risk proxy to be incorporated in banking efficiency models. They identified loan-loss provisions as a valid proxy. However data limitations prohibit us from utilizing loan-loss provisions as the sample, particularly that of

Islamic banks, is reduced heavily. Therefore we include equity as a proxy for risk which has also been used in relevant studies (Abdul-Majid *et al.* 2008; Alam 2001; Mostafa 2007). Given the different financial products and practises of Islamic banks, one would expect a difference in risk behavior between Islamic and conventional banks. Hence the inclusion of a risk variable in the model could make a difference to results. Indeed, Sufian (2006) finds that Islamic banks rank considerably higher in the efficiency scores when a risk proxy (loan-loss provisions in this case) is incorporated in the model.

Descriptive statistics for the DEA variables are presented in Table 6.

[Table 6 here]

The upward trend in banking business is clear for both types of banks. *Total loans*, for example, have grown by around 90% (in real terms) over the 4-year period. For conventional banks the growth is a little above 90% while for Islamic banks it is a little below. Similarly *Deposits and short term funding* as well as *Equity* have increased, on average, by 62% and 81% respectively. The table also indicates that the average size of an Islamic bank (at least in terms of *Total loans*) is around half the size of a conventional bank. However, Islamic banks have higher fixed assets, on average, than conventional banks a finding plausibly attributed to the asset-backed securities that they utilize.

2.5 Results

2.5.1 Financial Ratios

The evolution of cost, revenue and profit efficiency of conventional and Islamic banks can be seen in Figure 2 and Table 7.

[Figure 2 here]

[Table 7 here]

The *Cost to Income* and *Non Interest Expenses to Average Assets* ratios are generally higher for Islamic compared to conventional banks. The difference is statistically significant in the case of *Non Interest Expenses to Average Assets.* Yet the gap between the ratios for the two bank types is closing towards the latter years.

The higher expenses of Islamic banks could be associated to the different costs they face. An example would be the Shariah compliancy costs that include high salaries for the maintenance of a Shariah Supervisory Board, higher legal costs due to the *de facto* higher complexity of Islamic finance contracts as well as the legal ramifications for compliance of Islamic products with foreign laws. Furthermore the development Islamic financial products is a process which has not yet been standardized; hence many contracts need to be tailored made to the specific needs of every project or investor (Willison 2009). Islamic banks have been investing significantly in human resource development (Pellegrina 2008). The supply of Islamic information technology solutions is more scarce than for conventional banks which, besides the impact on operational risk, forces Islamic banks to maintain in-house technology developers. Moreover, cost efficiency requires a critical size of a bank necessary for economies of scale and scope to emerge. Islamic banks are smaller than conventional ones in terms of assets or almost all accounting measures as well as the variety of financial products they offer. Evidence from these two ratios show that conventional banks are more cost efficient than Islamic banks. However the gap is closing partly because Islamic banks learn the way of doing business and partly because of increases increase in size which allow gains in terms of cost efficiency as time goes by.

The Return on Average Assets (ROA) ratio is higher for Islamic than conventional banks. As Return on Assets is defined as Net Income/Assets where the assets are made up of debt and equity. In that sense, ROA is a measure of profitability used to show the level of bank efficiency in generating profits. Higher profit efficiency, verified by higher ROA is attributed to better managerial skills or more profitable projects that the Islamic banks are implementing and more efficient use of their resources[15]. The better quality of resources for Islamic banks is verified in Hasan and Dridi (2010) as they find Islamic banks to be superior to conventionals in terms of liquidity and assets quality. Reasons for the higher profitability of Islamic banks, which has been verified elsewhere, may be related to the fact that their investments are focused in the productive sector rather than in debt contracts (*e.g.* Certificates of Deposit, Bonds) (Hasan and Dridi 2010). A closer relationship between the banking sector and the real economy is evidenced here which could make Islamic banks resistant to financial crises as they have less exposure to speculative debt instruments. As a consequence, financial products based on the Shariah could lead to risk decrease and better portfolio diversification.

As Islamic banks are prohibited from debt transactions, that is they cannot expand their operations by issuing bonds like conventional banks, their Return on Equity ratios,

15 At this stage FRA cannot decompose the efficiency to a part attributed to managers and another attributed to practises. DEA analysis in the subsequent section will provide more insightful results.

defined as Net Income/Equity is expected to be lower than that of their conventional counterparts. This is plausible given the higher leverage that CBs can achieve which would lead to higher earnings for their shareholders[16]. Yet, ROE is statistically the same for the two bank types. Islamic banks are smaller than conventional banks in terms of equity however their net income is proportionally smaller which ensures the validity of this result. This is indeed an important result highlighting that the stockholder is not significantly disadvantaged by investing in a Shariah compliant way. Islamic banks have managed to be equally profit efficient to conventional banks despite their restrictions.

Revenue ratios indicate that Islamic banks are more efficient than conventional banks. The *Net Interest Margin* (NIM) is higher for Islamic banks although the difference between the two bank types is not statistically significant. Net Interest Margin shows the profit margin of a bank's traditional activity, borrowing at a low interest rate and lending at a higher one. For Islamic banks, the same concept applies but with reference to the profit-loss share ratio instead. Conventional banks working mainly in the retail sector face strong competition and meaning that they cannot afford to maintain a NIM higher than the (conventional) competition. The primary source of NIM for IBs are large infrastructure and real estate projects via equity-type contracts on which they charge a premium. IBs are known to rely on connections with large and often family-owned conglomerates and name lending practises are widespread (IMF 2011b). Typical IB clientele are governments that pay more attention to the ethics aspect of the investment rather than its higher cost compared to a

16 Consider an IB and a CB of the same asset size and the same income but different capital structure. The first operating at 0% leverage (zero debt, only equity) and the second at 50% leverage (50% debt; 50% equity). The IB would have ROE=20% while the CB would have ROE=40%.

conventional alternative; this is termed "Islamicity premium" in the literature (Khalil *et al.* 2002).

Figure 3 shows that the GCC countries are developing very fast with an average real GDP growth of 8.1% for the study period and 6.9% for the first decade of the 21^{st} century. The economic boom in the Gulf region over the examined period can explain the higher returns on investments mainly in real assets which through PLS contracts manifest themselves into higher Net interest margins. In a period of economic boom PLS operates as a form of equity for the investor (the bank) without capping its potential revenues. Similarly the economic boom can explain the "Islamicity premium" as if funds were limited then the cheapest option might have been favoured over the more ethical one.

[Figure 3 here]

The *Other Operating Income to average assets* (OOI) ratio is higher for Islamic banks throughout the examined period with the difference being statistically significant for the pooled data and for 2006 and 2007. This is indicating that the decomposition of revenues into interest (or share ratio) and fee sources favors more the fee-based revenues (which are represented by OOI) in the case of Islamic banks. The reason for this is that the majority of IBs favor the use of fee-based contracts rather than those of the equity type due to their lower administration costs and complexities, shorter duration and lower risk (Khalil *et al.* 2002).

Bootstrapping

The application of bootstrapping can avoid problems that arise from small samples and distort hypothesis testing. In our case we have benefited from more accurate p-values that help us understand better the magnitude of inefficiencies that exist in the banking sector of the GCC markets. We run the bootstrapping tests for b=999, b=9999 and for b=99999 repetitions. Table 8 presents the original p-values as well as the three bootstrapped ones for each equality of means test. T-test p-values calculated using the non-parametric bootstrap approach are different to the original ones indicating a small sample bias in the yearly samples. Pooled p-values are not much different as the yearly ones.

[Table 8 here]

After correcting for the small sample bias, we find that differences in cost efficiency between conventional and Islamic banks are not as pronounced as the original p-values imply. Thus the "gap" in cost efficiency is adjusted downwards.

Rejecting the null hypothesis of equality of the means at the 99%, 95% and 90% significance levels based on bootstrapped[17] p-values occurs only 1-time, 2-times and 2-times respectively[18]. Using the original p-values we were rejecting the null hypothesis 2-times, 3-times and 0-times at the aforementioned significance levels. Furthermore all bootstrapped p-values are higher (less significant) than the original ones. This indicates that cost inefficiency of Islamic banks was overstated due to a small sample bias. Therefore, in

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17 b=9999

18 The null hypothesis of equality of means is rejected at the 99% significance level for Non-interest expenses in 2005. The null hypothesis of equality of means is rejected at the 95% significance level for Cost to income in 2004 and Non-interest expenses in 2006. The null hypothesis of equality of means is rejected at the 90% significance level for Non-interest expenses in 2004 and 2007.

spite of the Islamic banks still being less cost efficient when compared to their conventional counterparts, we argue that the difference is not as pronounced. Secondly Islamic banks are closing the gap as it can be observed from the significance level of rejecting the null that is being reduced as we move from 2005 to 2007 in the *Non Interest Expenses* ratio and the rising p-values in the *Cost to Income* ratio[19].

In profit efficiency there are also important differences between the significance levels of the bootstrap procedure and the original ones. Although results are not significant in the conventional significance levels, we get a less biased picture of the evolution of profit efficiency across time which was previously less clear. Most important differences are found in the *Return on Assets* ratio in 2005 and 2006 where the original p-values were 0.185 and 0.099[20], the bootstrapped ones being 0.379 and 0.276 correspondingly suggesting that profit efficiency was overestimated. The p-value of ROA in 2007 is very close to being significant at the 90% significance level both for the original and the bootstrapped ones providing clear evidence that IBs develop their processes across time and become more efficient. The bootstrapped p-values of *Return on Equity* ratio retain their insignificance.

Revenue efficiency ratios also have different p-values with the bootstrap approach. The bootstrapped p-values of the NIM ratio suggest that there is no statistical difference between the two bank types. Clearly the spike of NIM in 2005 was affected by the financial crisis in Saudi Arabia which is the largest financial market in the region. The p-values of

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19 This fall of significance across time represented by the rising p-values is observed much more clearly using the bootstrapped p-values.

20 Marginally significant at the 90% significance level.

the OOI ratio have changed slightly without any major change in the significance of the results[21].

The bootstrapped equality of means tests do not change the main story. It mainly corrects the results for small sample bias. Islamic banks are still less cost efficient though the gap is much smaller. In the context of profit efficiency the reliance of Islamic banks on favorable macroeconomic environment is highlighted. Profit efficiency based on ROA may be overestimated when periods of boom are part of the analysis. Revenue efficiency has improved significantly during the last two years of the analysis with robust results in favour of Islamic banks.

2.5.2 DEA

The results of the DEA are derived using CRS and VRS models respectively. A measure of the overall technical efficiency is given by the CRS model while a measure of the pure technical efficiency is provided by the VRS model. The VRS model factors out any scale inefficiencies; the latter can be calculated as the ratio of CRS to VRS efficiency. The DEA analysis has been performed for every year as production conditions, political instability in the region and expanding markets are factors likely to affect efficiency scores. However we include an analysis for the pooled dataset, this one assuming that environmental conditions remain unchanged, basically for comparison purposes.

[21] P-values of Other operating income were 0.021 and 0.027 for 2006 and 2007 respectively and the bootstrapped p-values are 0.034 and 0.043. Although a bit higher they still reject the null hypothesis of equal means at the 95% significance level.

Table 9 presents the descriptive statistics of the DEA analysis efficiency scores of the gross, net and type measures of efficiency. Table 10 presents neatly the percentage difference in the efficiency score between the two bank types. Figure 4 presents a graphical representation of the evolution of the efficiency scores across time.

[Tables 9 and 10 here]
[Figure 4 here]

The mean *Gross* efficiency (CRS and VRS) for the whole period are a little lower than estimates over the 5-year period 2000 to 2004 according to the study of Ramanathan (2007). Looking at the pooled efficiencies, *Gross* (CRS) efficiency is significantly higher, on average, for conventional banks compared to Islamic banks by around 5 percentage points. An examination of the VRS and scale efficiency scores suggests that this difference is caused by size differences (pure technical efficiency) where conventional banks outperform the Islamic ones by about 4 percentage points.

Net efficiency scores reveal smaller differences between the two bank types. This is in line with literature that utilized SFA (Abdul-Majid *et al.* 2010)[22]. The decomposition into *type* efficiency shows that the *modus operandi* of Islamic banks is less efficient to that of conventional banks. Thus the significant differences in *Gross* efficiency are mainly a consequence of the rules under Islamic banks operate rather than managerial inadequacies. A similar conclusion was reached for the Malaysia case (Abdul-Majid *et al.* 2008).

When we run the DEA without the equity[23] we find that conventional banks have (6.1% and 4.1% for CRS and VRS respectively) higher *Gross* efficiency than Islamic ones

22 We realise that we compare two different methodologies (DEA and SFA) however the fact that the same qualitative result is verified by both is reassuring.

23 These results can be found in table A1 in the Appendix

with results being statistically significant at the 10% significance level. Scale efficiency is 4.5% higher for conventional banks, a result statistically significant at the 10% significance level. Results without the equity tend to make the differences between the two bank types bigger, which is in line with Sufian (2006). In *Net* efficiency terms, conventional banks are still more efficient (6.7% and 0.8% CRS and VRS respectively) with CRS results being significant at the 5% significance level. Additionally conventional banks are 8% more scale efficient verified at the 99% significance level. Type efficiency shows that Islamic banks are 0.2% more efficient when CRS is used but when VRS is used conventional banks are 3.3% more efficient which is verified at the 99% significance level. Two differences in the efficiency scores of the two models (*i.e.* with and without the equity) are the higher efficiency scores when equity is included. Secondly, if equity is not included in the model then *Gross* efficiency differences are attributed both to the modus operandi of Islamic banks and to managerial insufficiencies. The inclination towards risk-taking activity in banking lies with managers and so it is no surprise that the model which does not capture risk-taking attributes a greater proportion of inefficiency to managerial shortcoming than the model which incorporates risk-taking activity.

Focusing on the evolution of efficiency scores across time, we observe that the general picture of all three types of efficiency is a decrease in the first three years of the study followed by a small rise in the last year. A reason for this pattern, which was also identified in the financial ratios part, could be the political instability in the region during the first years of the study. The increase at the end of the period is a signal that efficiency will increase as the region enjoys greater political and economic stability. An additional year could be the positive economic climate that existed in most countries around the world till about mid-2007 when the global financial crisis hit. However, the GCC countries were relatively unaffected by the first stage of the crisis due to their significant growth rates. The GCC were among the last developing economies to become affected by the financial crisis in mid-2008. Whilst the differences between Islamic and conventional banks that exist in the pooled dataset are also showing in the individual years, yet the differences are rarely statistically significant.

Table 11 presents mean DEA scores and financial ratios for each country.

[Table 11 here]

Gross efficiency is highest in UAE, Qatar and Bahrain. Evidence shows that Qatar and Bahrain, two of the most efficient and profitable countries according to the DEA and Financial Ratio results, operate in a concentrated markets (Qatar shows high concentration in some years). The comparatively low average efficiency for Saudi Arabia might seem surprising given the relatively large level of GDP and population in the country, as well as the competitive environment of its banking sector (see table 12).

[Table 12 here]

Concentration has been found to be positively linked to efficiency as efficient banks can afford to compete for greater market power (Demsetz 1973). Furthermore investments of a significant size are necessary to boost and maintain high economic growth require large banking institutions to mobilize the funds the presence of which can increase market concentration. This is in-line with our results for Bahrain and Qatar. However, the banking sector of Saudi Arabia is an exception to this rule as there are similar studies that also find the country's banking sector to be less efficient compared to the other GCC states (Ramanathan 2007; Al-Muharrami 2008). Banks in the UAE are highly efficient yet they operate under a competitive market structure. We believe that UAE is a special case however due to its diversified economy into tourism and financial services which make, particularly the Dubai emirate, a financial haven in the area with many international conventional banks having established a foothold there (UAE has more than double compared to any other country in the sample). Foreign owned international banks are more efficient than domestically owned ones see among others Isik and Hassan (2002).

This section concludes with a note on the comparison between the results of the FRA and DEA analyses. Table 13 presents the Spearman's rank correlation for the pooled sample and year by year.

[Table 13 here]

The main result is that bank rankings according to Gross efficiency scores show a significant positive correlation to bank rankings derived only from the two cost ratios (CTI, NIE). Other correlation pairs, in terms of Net or Type efficiency and other Financial ratios, do not exhibit any significant relationship. Arguments exist that inefficient banks, according to the DEA, could be more profitable than efficient ones (Taylor *et al.* 1997). The Spearman correlation's negative sign between DEA efficiency scores and profit and revenue efficiency financial ratios (ROA, ROE, NIM, OOI) supports this contention. It can be therefore suggested that FRA (particularly the profit and revenue efficiency ratios) and DEA should be considered as complementary techniques; hence used together to evaluate banking performance.

Malmquist Productivity Analysis

Table 14 presents the Malmquist productivity index[24] and its decomposition into the efficiency (E) and the technology change index (T). The indices are reported for the four year interval 2004-2007 under the CRS and VRS efficiency measures. The Equivalent Annual Average Productivity Index (EAAPI) is also reported.

[Table 14 here]

Productivity over the four year period (2004 - 2007) has increased by about 1% for all banks, which translates to about 0.3% EAAPI. Similar studies of productivity covering the period 2000 - 2004 have found no change or even a decrease in productivity (Ramanathan 2007; Ariss *et al.* 2007). The decomposition of the documented rise in productivity however reveals important findings. Technical efficiency has decreased by about 7% (1.9% EAAPI) whereas technology has increased by 9.4% (2.3% EAAPI). Broadly the same conclusion is reached through the VRS efficiency measures. Our results are contradicting the two previous studies for the GCC, namely those of Ramanathan (2007)and Ariss *et al.* (2007) which document a positive technical efficiency change and negative change in the technology. Yet our results show more similarities to the studies covering Malaysia over the period 1996 - 2002 and the USA over the period 1990 - 1993 (Abdul-Majid *et al.* 2008; Devaney and Weber 2000).

The considerable economic growth of the GCC has lead to growth of the banking sector as well, evidenced by the expansion in the banks' accounting statements (see table 6). This has been accompanied by a relatively large increase in technology, where technology

24 The Malmquist productivity index is calculated based on the gross efficiency measures.

reflects financial products and infrastructure developments. Technology developments have shifted out the production possibility frontier and at the same time a detrimental effect on technical efficiency (how close the banks are to the production possibility frontier). This is plausibly explained by the slow diffusion of the best-practise operations by all banks. Especially when best-practises are imported, via international banks, more time is needed so that know-how gains are transmitted to the whole banking sector. The fact that substantial growth in a sector contributes positively on technology but negatively on technical efficiency is not unique to the banking sector; it has been verified for studies in the higher educational sector as well (Johnes 2008).

The apparent large improvement in technology over the period can be attributed to some of the drivers for innovation in a financial context, which according to Willison (2009) are:

- Product innovation
- Customer service
- Operational efficiency
- Risk management and control
- Regulation

The study period is one which has seen considerable product innovation and operational improvements. Historically, the Islamic banking sector has had poor record of R&D and innovations because the banks are small with unstandardized products and systems (Khan and Bhatti 2008). Indeed, a study of productivity change in Malaysia over the 1996-2002 period identifies that Islamic banks have the lowest degree of productivity and technology change (Abdul-Majid *et al.* 2008). Recent increases in size and market coverage has provided strong motivation for change. Customer relationship management and reputation are high priorities for Islamic banks as identified by their increased spending on human resources compared to conventional banking practises (Pellegrina 2008). Education and know-how has been rapidly increasing during the recent years, particularly during the period of study, leading to Islamic banking being promoted to the general public using, for example, marketing campaigns[25]. Increasing customer numbers has put pressure on the development of more Shariah-compliant products and the increase of operational efficiency in Islamic banks. The pressure is likely to increase in the coming years as the global financial crisis has forced conventional customers to look alternative investments with Islamic finance being a high priority (Willison 2009).

It is no surprise, therefore, that Islamic banks have seen an increase in productivity of about 8% over the whole study period while conventional banks have documented a decrease of about 1%. A negative technical efficiency and a positive technology change are evidenced in both bank types. Yet the differences in magnitude are considerable. Islamic banks have witnessed a drop in technical efficiency of nearly 10% over the full period (2.6% EAAPI) and a surge of nearly 18% (4.2% EAAPI) in technology change. Greater growth and change have a detrimental effect on technical efficiency and a large positive effect on technology. This latter result is a consequence of the product and operational innovations

25 For example, Bank Syariah Mandiri in Indonesia sponsors documentaries on Islamic finance while Emirates Bank in the UAE waives loan payments during the Ramadan as part of marketing campaigns (Bloomberg).

in the Islamic banking sector which have been more prominent than in the conventional banking sector.

2.6 Conclusion

In this chapter we provide an in-depth analysis using Financial Ratio Analysis with Bootstrap tests and Meta-Frontier Data Envelopment Analysis (MF-DEA) of the comparative efficiency of Islamic and conventional banks. We use a consistent sample of banks in the GCC region over the period 2004 - 2007. The chapter contributes to the literature by introducing a meta-frontier method for decomposing the DEA efficiency scores into two separate components; one due to managerial inadequacies and one due to differences in the business models of the two bank types. Secondly we apply boostrap equality of means test in a financial ratio analysis to correct for small sample bias. Thirdly, we investigate productivity growth in the Islamic and conventional banking sectors finding significant differences.

The FRA suggests that Islamic banks are less cost efficient and more revenue and profit efficient than conventional banks. Four of the six ratios indicate that the differences are significant at the 5% significance level using a combination of parametric and non-parametric tests. The boostrapping confirms the significances and highlights the convergence of Islamic banks to the efficiency levels of conventional banks.

The MF-DEA results provide evidence that gross efficiency is significantly higher, on average, for conventional banks. The difference between the two bank types is significant even when bank size is taken into account. Net efficiency is generally not statistically different between Islamic and conventional banks. This gives a clear signal that the managerial staff in Islamic banks is not of inferior quality contrasting previous evidence. Clearly the investment in human resources from Islamic banks have paid off. However, any difference in efficiency levels needs to be traced to the *modus operandi* of the bank types. The rules under which Islamic banks operate are an important barrier to efficiency. The Islamic banking sector might have to address these rules if it is to improve its efficiency. The rules underlying Islamic banking are, however, not uniform globally (The Economist 2009). Banks need to go through various processes to obtain approval for financial products the Islamicity of which varies according to the geographical location. Malaysia for instance has traditionally been more progressive by allowing Islamic products that in the GCC are forbidden. Within the GCC region, the rules for Islamic banks are more uniform compared to other countries. Yet further harmonisation could be enforced under the auspices of a Financial Services Authority operating at GCC level. Certification of products by such an Authority should be recognized in each of the countries under the umbrella of this regulatory body.

The correlations between the measures of efficiency using FRA and MF-DEA are significantly positive only in the case of the cost ratios. While significant, however, the correlations are not particularly high. The conclusion from this part of the analysis is that MF-DEA and FRA offer different information; therefore the methods should be viewed as complements. Parties interested in assessing bank efficiency would have more reliable results if using both approaches.

Productivity change in the GCC has grown slightly over the examined period. However the components of productivity reveal that technical efficiency change has been negative while the change in technology positive. It should be noted that the examined period has been one of high economic growth in the region. Increased oil prices meant that oil revenues have been fuelling a large rise of GDP. Population growth and political stability also contributed to the economic growth of the countries which in turn fueled the growth of the banking sectors and particularly, Islamic banking. Product innovation, improved operational efficiency and higher priorities of customer satisfaction led to higher technology change and higher productivity. The stimulus for innovation in the Islamic banking sector is likely to continue given the attention the industry has attracted during the 2007 global financial crisis.

2.7 Table Appendix

Table 1. Islamic banking efficiency studies.

Studies	Method	Context
		No Significant Difference between IB/CB
Hassan *et al.* 2009	DEA	Bahrain, Egypt, Jordan, Kuwait, Lebanon, Qatar, Saudi Arabia, Tunisia, Turkey, UAE, Yemen
Mokhtar *et al.* 2006	SFA	Malaysia
El-Gamal and Inanoglou 2005	SFA	Turkey
Bader 2008	DEA	Algeria, Bahrain, Bangladesh, Brunei, Egypt, Gambia, Indonesia Iran, Jordan, Kuwait, Lebanon, Malaysia, Pakistan, Qatar, Saudi Arabia, Senegal, Sudan, Tunisia, Turkey, Yemen, UAE
Bader *et al.* 2007	FRA	Algeria, Bahrain, Bangladesh, Brunei, Egypt, Gambia, Indonesia Iran, Jordan, Kuwait, Lebanon, Malaysia, Pakistan, Qatar, Saudi Arabia, Senegal, Sudan, Tunisia, Turkey, Yemen, UAE
		IB significantly more efficient than CB
Al-Muharrami 2008	DEA	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE
		IB significantly less efficient than CB
Srairi 2010	SFA	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE
Mokhtar *et al.* 2007, 2008	DEA	Malaysia
Hassan and Bashir 2005	FRA	Algeria, Bahrain, Bangladesh, Brunei, Egypt, Gambia, Indonesia Iran, Jordan, Kuwait, Lebanon, Malaysia, Mauritania, Qatar Saudi Arabia, Sudan, Tunisia, UAE, Yemen
IB lower efficiency than CB attributed to modus operandi rather than managerial inefficiencies		
Abdul-Majid *et al.* 2010	SFA	Bahrain, Bangladesh, Indonesia, Iran, Jordan, Lebanon Malaysia, Sudan, Tunisia, Yemen
Johnes *et al.* 2009	DEA	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE
Abdul-Majid *et al.* 2008, 2011a/b	SFA	Malaysia
		No statistical comparison of efficiency between IB/CB
Said 2012	DEA	CB in the USA & International sample of IB
Al-Jarrah and Molyneux 2005	SFA	Bahrain, Egypt, Jordan, Saudi Arabia
Hussein 2004	SFA	Bahrain
		Studies of IB only
Hassan *et al.* 2005, Hassan 2006	DEA SFA	Algeria, Bahamas, Bahrain, Bangladesh, Brunei, Egypt, Gambia Indonesia, Iran, Jordan, Kuwait, Lebanon, Malaysia, Mauritania Qatar, Saudi Arabia, Sudan, Tunisia, UAE, UK, Yemen
Sufian 2009	DEA	Bahrain, Bangladesh, Egypt, Gambia, Indonesia, Iran, Kuwait Malaysia, Pakistan, Saudi Arabia, Turkey, UAE, Qatar, South Africa, Sudan, Yemen
Yudistira 2004	DEA	Algeria, Bahrain, Egypt, Gambia, Indonesia, Jordan, Kuwait Malaysia, Qatar, Sudan, UAE, Yemen
Viverita *et al.* 2007	DEA	Algeria, Bahrain, Bangladesh, Brunei, Egypt, Indonesia, Jordan Kuwait, Malaysia, Qatar, Sudan, UAE, Yemen
Brown 2003	DEA	Algeria, Bahamas, Bahrain, Bangladesh, Brunei, Egypt, Jordan Kuwait, Malaysia, Qatar, Saudi Arabia, Sudan, UAE, Yemen
El-Moussawi and Obeid 2010,2011	DEA	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE
Mostafa 2007,2011	DEA	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE
Kamarudin *et al.* 2008	DEA	Malaysia
Sufian 2006,2007	DEA	Malaysia
Hassan and Hussein 2003	SFA	Sudan
Saaid 2005, Saaid *et al.* 2003	SFA	Sudan
Saleh *et al.* 2007	FRA	Jordan

Table 2. Financial Ratios Definitions.

Cost Efficiency Ratios

Cost to Income	CTI	$= \left[\frac{\text{Overheads}}{\text{Net Interest Revenue + Other income}}\right] * 100$
Non Interest Expenses to Average Assets	NIE	$= \left[\frac{\text{Overheads + Loan Loss Provisions}}{\text{Average Total assets}}\right] * 100$

Profit Efficiency Ratios

Return on Average Assets	ROA	$= \left[\frac{\text{Net Income}}{\text{Average Total Assets}}\right] * 100$
Return on Average Equity	ROE	$= \left[\frac{\text{Net Income}}{\text{Average Equity}}\right] * 100$

Revenue Efficiency Ratios

Net Interest Margin	NIM	$= \left[\frac{\text{Net Interest Revenue}}{\text{Average Total Earning Assets}}\right] * 100$
Other Operating Income to Average Assets	OOI	$= \left[\frac{\text{Other Operating Income}}{\text{Average Total Assets}}\right] * 100$

Source: Bankscope

Table 3. Observed t-statistics from the original sample.

	CTI	**NIE**	**ROA**	**ROE**	**NIM**	**OOI**
$t_{obs,2004}$	−2.308	−2.158	−0.334	0.848	−1.386	−1.267
$t_{obs,2005}$	−1.325	−3.038	−1.369	−0.738	−1.214	−0.976
$t_{obs,2006}$	−1.214	−2.709	−1.692	−0.631	−0.524	−2.267
$t_{obs,2007}$	0.376	−2.108	−1.695	−0.441	−0.307	−2.291

Notes: These are the t-statistics from the original mean comparison test. CTI=Cost/Income NIE=Net Interest Expenses/Average Assets; ROA=Return on Average Assets; ROE=Return on Average Equity; NIM=Net Interest Margin; OOI=Other Operating Income/Average Assets.

Table 4. Linear Programming Equation Sets.

Primal	**Dual**
Minimize $\sum_{i=1}^{m} v_i x_{ik}$	Maximize ϕ_k
Subject to	Subject to
$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \quad j = 1, ..., n$	$\phi_k y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} \leq 0 \quad r = 1, ..., s$
$\sum_{r=1}^{s} u_r y_{rk} = 1$	$x_{ik} - \sum_{j=1}^{n} \lambda_j xij \geq 0 \quad i = 1, ..., m$
$u_r, v_i > 0 \quad \forall r = 1, ..., s; i = 1, ..., m$	$\lambda_j \geq 0 \quad \forall j = 1, ..., n$

Figure 1. DEA Efficiency/Gross,Net and Type Measures.

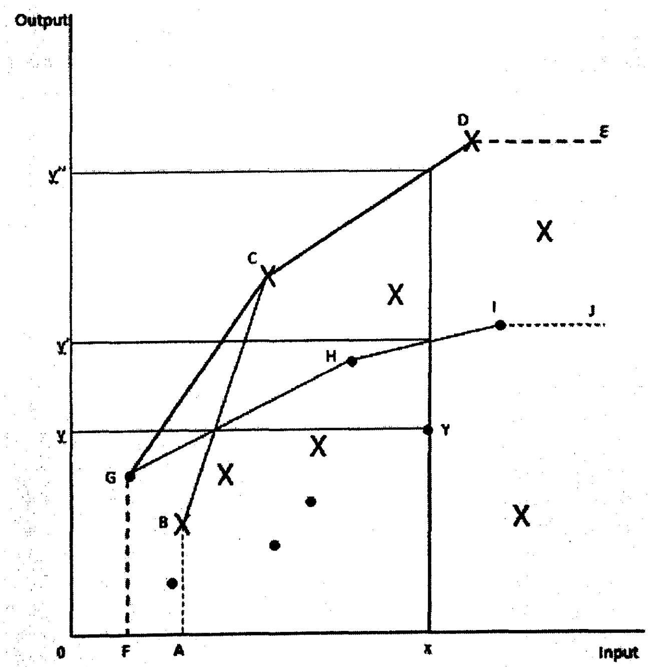


Table 5. Banks in the sample and population by country and type.

Country	**Sample**			**Population (2007)**		
	Islamic	Conventional	**Sum**	Islamic	Conventional	**Sum**
Bahrain	6	8	14	17	13	30
Kuwait	4	6	10	6	7	13
Oman	0	5	5	0	6	6
Qatar	2	6	8	5	6	11
Saudi Arabia	1	9	10	3	9	12
UAE	6	16	22	7	15	22
Sum	19	50	69	38	56	94

Source: Bankscope

Table 6. Descriptive Statistics for the DEA input and output variables.

	Conventional			Islamic			All		
2004	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
Total loans	4254	2789	4146	2454	741	4440	3758	2049	4273
Other earning assets	3489	1995	4063	912	364	1289	2780	1265	3699
Deposits and short term	6747	3830	7067	3083	934	4819	5738	3335	6697
Fixed assets	73	45	85	59	15	93	69	37	87
Overheads	106	70	113	69	34	112	95	61	113
Equity	1005	753	909	527	283	680	873	507	874
2005									
Total loans	5447	3447	5375	3208	1016	5590	4830	2261	5486
Other earning assets	3883	2683	4122	1241	928	1527	3155	1530	3778
Deposits and short term	7842	5039	7779	3831	1243	5817	6737	3573	7470
Fixed assets	82	54	91	84	21	127	82	47	101
Overheads	129	83	130	96	49	139	120	75	132
Equity	1346	930	1213	745	545	947	1180	714	1171
2006									
Total loans	6586	4721	6201	3721	1131	6205	5797	2595	6290
Other earning assets	4351	2679	4615	1727	874	2261	3629	2002	4254
Deposits and short term	9349	6351	8861	4500	1364	6670	8013	3945	8551
Fixed assets	93	68	99	167	37	340	113	57	197
Overheads	152	106	146	122	45	173	143	87	153
Equity	1472	1052	1325	1057	535	1362	1358	904	1338
2007									
Total loans	8236	5914	7606	4633	1696	7254	7244	3209	7632
Other earning assets	5258	2740	5989	2016	975	2592	4365	2079	5454
Deposits and short term	11840	8138	11410	5549	2241	7831	10108	4364	10866
Fixed assets	111	81	112	172	43	340	128	76	201
Overheads	202	134	217	140	60	183	185	116	209
Equity	1700	1242	1567	1302	557	1638	1591	1093	1585
All Years									
Total loans	6131	3815	6101	3504	1074	5894	5407	2574	6148
Other earning assets	4245	2481	4771	1474	838	1995	3482	1612	4370
Deposits and short term	8944	5712	9069	4241	1412	6318	7649	3646	8651
Fixed assets	90	61	98	120	23	253	98	50	157
Overheads	147	91	160	107	45	154	136	76	159
Equity	1381	946	1291	908	506	1226	1251	716	1289

Note: All variables are reported in US $ millions at 2007 prices. The number of observations in each year is 50 conventional and 19 Islamic banks

Figure 2. Evolution of Financial Ratios/Mean and Median Values.

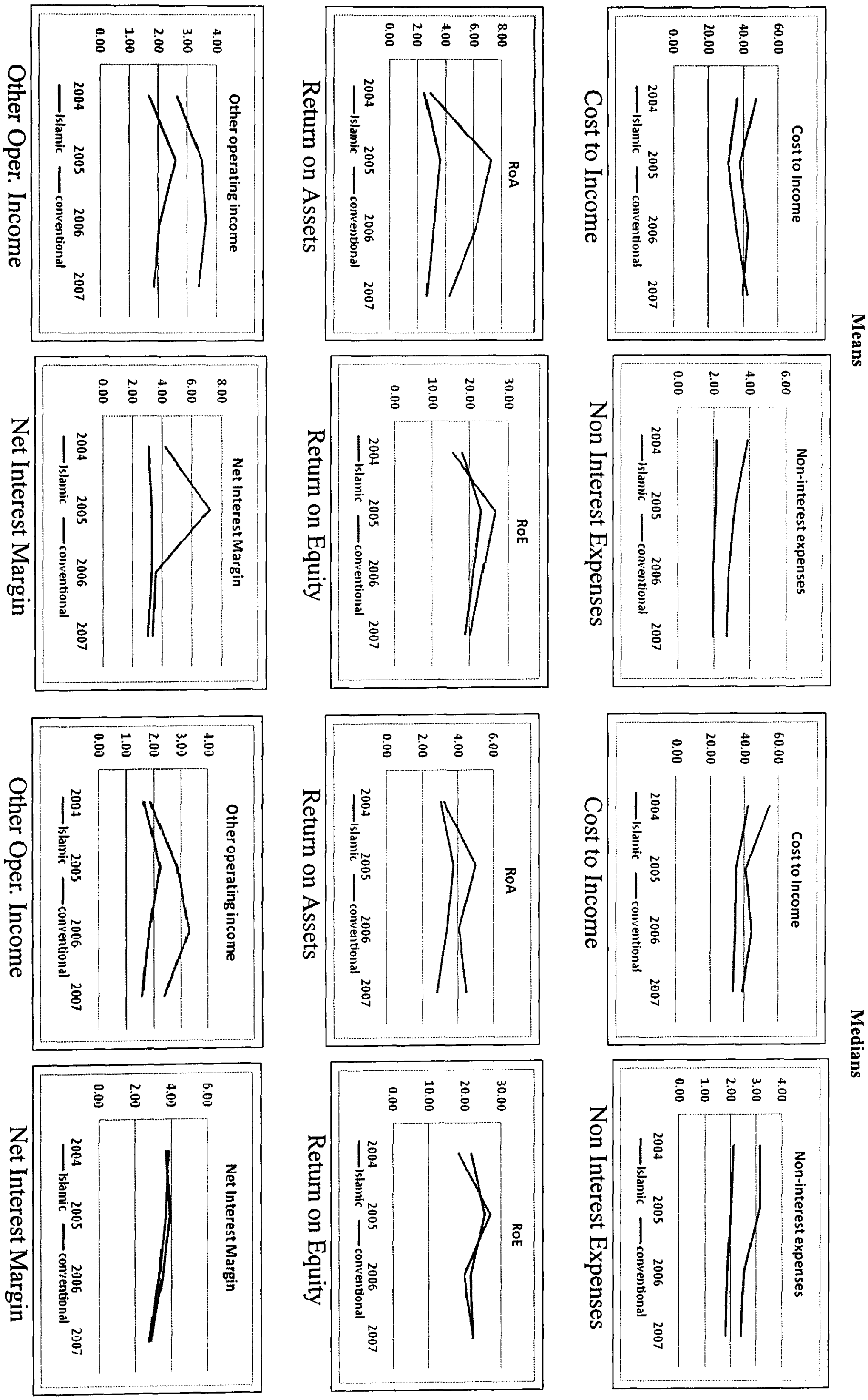
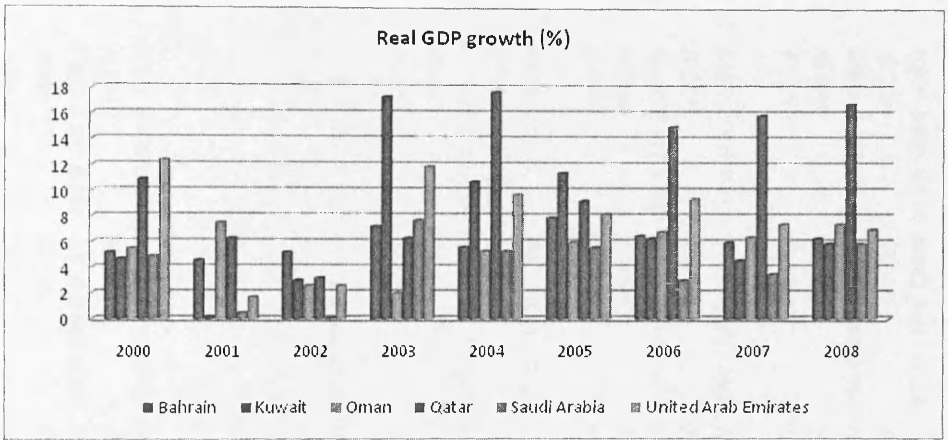


Table 7. Results of the Financial Ratio Analysis/Mean and median values and statistical tests.

	CTI			NIE			ROA			ROE			NIM			OOI		
	CB	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**
2004																		
Mean	36.40	47.70	39.30	2.16	3.90	2.64	2.54	2.93	2.65	18.04	15.48	17.33	3.08	4.23	3.39	1.69	2.67	1.95
T-test	*(0.024)***			*(0.040)***			*(0.716)*			*(0.379)*			*(0.169)*			*(0.191)*		
Median	42.30	54.78	44.01	2.12	3.14	2.21	3.07	3.21	3.08	21.88	18.22	21.46	3.71	3.88	3.75	1.66	1.88	1.66
M-W	*(0.047)***			*(0.007)****			*(0.554)*			*(0.493)*			*(0.274)*			*(0.641)*		
K-S	*(0.021)***			*(0.091)**			*(0.180)*			*(0.133)*			*(0.700)*			*(0.784)*		
2005																		
Mean	31.66	37.94	33.39	2.11	3.21	2.41	3.60	7.23	4.60	23.02	26.74	24.01	3.34	7.18	4.40	2.61	3.49	2.85
T-test	*(0.165)*			*(0.003)****			*(0.185)*			*(0.433)*			*(0.247)*			*(0.259)*		
Median	35.37	40.92	35.95	2.04	3.14	2.28	3.77	5.05	3.82	25.49	27.15	25.57	3.94	3.71	3.89	2.25	2.86	2.43
M-W	*(0.212)*			*(0.000)****			*(0.154)*			*(0.957)*			*(0.662)*			*(0.307)*		
K-S	*(0.171)*			*(0.000)****			*(0.081)**			*(0.400)*			*(0.202)*			*(0.216)*		
2006																		
Mean	36.16	43.02	38.08	1.96	2.84	2.21	3.15	6.18	3.99	20.89	23.33	21.57	3.29	3.56	3.37	2.06	3.64	2.51
T-test	*(0.145)*			*(0.006)***			*(0.099)**			*(0.535)*			*(0.571)*			*(0.021)***		
Median	34.50	44.38	37.17	1.89	2.54	1.96	3.41	4.08	3.44	21.65	19.82	21.60	3.53	3.32	3.39	1.83	3.33	1.90
M-W	*(0.079)**			*(0.001)****			*(0.064)**			*(0.800)*			*(0.940)*			*(0.012)***		
K-S	*(0.094)**			*(0.002)****			*(0.025)***			*(0.471)*			*(0.579)*			*(0.011)***		
2007																		
Mean	42.47	39.76	41.73	1.97	2.69	2.18	2.72	4.30	3.17	18.93	20.14	19.27	3.05	3.36	3.13	1.87	3.39	2.30
T-test	*(0.449)*			*(0.028)***			*(0.102)*			*(0.607)*			*(0.312)*			*(0.027)***		
Median	33.53	38.96	35.53	1.83	2.40	1.98	2.84	4.51	2.96	21.22	22.19	21.37	2.85	2.74	2.77	1.58	2.38	1.77
M-W	*(0.420)*			*(0.006)***			*(0.008)***			*(0.432)*			*(0.911)*			*(0.026)***		
K-S	*(0.498)*			*(0.019)***			*(0.000)***			*(0.637)*			*(0.187)*			*(0.031)***		
All Years																		
Mean	40.38	46.45	46.10	2.28	3.28	3.06	3.35	6.03	3.88	22.36	24.52	21.07	3.55	5.20	4.55	2.30	3.60	2.50
T-test	*(0.048)***			*(0.000)****			*(0.018)***			*(0.557)*			*(0.115)*			*(0.001)****		
Median	36.42	43.38	37.73	1.92	2.66	2.14	3.12	4.13	3.32	22.46	22.12	22.42	3.48	3.59	3.50	1.77	2.50	1.87
M-W	*(0.005)****			*(0.000)****			*(0.000)****			*(0.916)*			*(0.015)***			*(0.001)****		
K-S	*(0.006)****			*(0.000)****			*(0.018)***			*(0.557)*			*(0.115)*			*(0.001)****		

Notes: *,** ,*** denote statistical significance at the 10%, 5% and 1% significance level respectively. Null Hypothesis for the T-test: equal means in CB/IB (equal variances are not assumed). M-W is the Mann Whitney test. Null Hypothesis is that medians in CB/IB are equal. KS is the Kolmogorov-Smirnov 2-sample test Null Hypothesis is that the samples of CB/IB are drawn from different distributions (equal higher moments). CTI=Cost/Income; NIE=Net Interest Revenue ROA=Return on Assets; ROE=Return on Equity; NIM= Net Interest Margin; OOI= Other Operating Income. Numbers in brackets are p-values.

Figure 3. Real GDP Growth (Annual Percentage Change) in the GCC Region.



Source: IMF

Table 8. Normal and Bootstrapped p-values for the equality of means test.

	CTI	NIE	ROA	ROE	NIM	OOI
2004						
P value	(0.024)**	(0.040)**	(0.716)	(0.379)	(0.169)	(0.191)
P value (b=999)	(0.044)**	(0.095)*	(0.736)	(0.399)	(0.277)	(0.262)
P value (b=9999)	(0.043)**	(0.094)*	(0.755)	(0.386)	(0.272)	(0.238)
P value (b=99999)	(0.044)**	(0.090)*	(0.746)	(0.386)	(0.262)	(0.241)
2005						
P value	(0.165)	(0.003)***	(0.185)	(0.433)	(0.247)	(0.259)
P value (b=999)	(0.186)	(0.011)**	(0.395)	(0.474)	(0.429)	(0.335)
P value (b=9999)	(0.195)	(0.008)***	(0.379)	(0.479)	(0.411)	(0.345)
P value (b=99999)	(0.197)	(0.009)***	(0.366)	(0.473)	(0.401)	(0.347)
2006						
P value	(0.145)	(0.006)***	(0.099)*	(0.535)	(0.571)	(0.021)**
P value (b=999)	(0.207)	(0.013)**	(0.260)	(0.507)	(0.596)	(0.028)**
P value (b=9999)	(0.238)	(0.015)**	(0.276)	(0.546)	(0.615)	(0.034)**
P value (b=99999)	(0.236)	(0.015)**	(0.271)	(0.545)	(0.607)	(0.034)**
2007						
P value	(0.449)	(0.028)**	(0.102)	(0.607)	(0.312)	(0.027)**
P value (b=999)	(0.751)	(0.058)*	(0.114)	(0.660)	(0.777)	(0.039)**
P value (b=9999)	(0.729)	(0.061)*	(0.104)	(0.657)	(0.762)	(0.043)**
P value (b=99999)	(0.731)	(0.059)*	(0.103)	(0.661)	(0.761)	(0.044)**
Pooled						
P value	(0.048)**	(0.000)***	(0.018)**	(0.557)	(0.115)	(0.001)***
P value (b=999)	(0.046)**	(0.001)***	(0.060)*	(0.554)	(0.246)	(0.003)***
P value (b=9999)	(0.047)**	(0.001)***	(0.065)*	(0.554)	(0.260)	(0.003)***
P value (b=99999)	(0.039)**	(0.002)***	(0.069)*	(0.540)	(0.295)	(0.005)***

Notes: *,** ,*** denote statistical significance at the 10%, 5% and 1% significance level respectively. Numbers in brackets are p-values. CTI=Cost/Income; NIE=Net Interest Revenue; ROA=Return on Assets ROE=Return on Equity; NIM= Net Interest Margin; OOI= Other Operating Income.

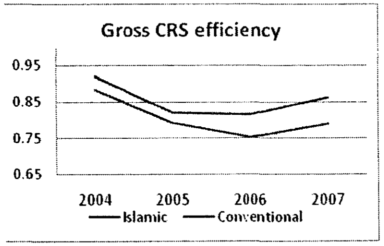
Table 9. Results of the DEA Analysis/Gross, Net and Type Efficiencies/Mean and Median Values.

	Gross Efficiency									Net Efficiency									Bank Type Efficiency					
	CRS			VRS			SE			CRS			VRS			SE			CRS			VRS		
	CB	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**
2004																								
Mean	0.919	0.885	0.910	0.945	0.919	0.938	0.973	0.963	0.971	0.927	0.934	0.929	0.951	0.958	0.953	0.976	0.974	0.975	0.992	0.946	0.979	0.994	0.957	0.984
T-test	*(0.229)*			*(0.312)*			*(0.476)*			*(0.765)*			*(0.719)*			*(0.918)*			*(0.000)******			*(0.003)******		
Median	0.909	0.922	0.913	0.964	0.964	0.964	0.995	0.984	0.988	0.927	1.000	0.942	0.978	1.000	1.000	0.994	1.000	0.997	1.000	0.932	0.999	1.000	0.964	1.000
M-W	*(0.609)*			*(0.707)*			*(0.527)*			*(0.160)*			*(0.135)*			*(0.256)*			*(0.000)******			*(0.004)******		
K-S	*(0.329)*			*(0.575)*			*(0.384)*			*(0.156)*			*(0.177)*			*(0.283)*			*(0.000)******			*(0.002)******		
2005																								
Mean	0.822	0.794	0.815	0.917	0.899	0.912	0.896	0.879	0.891	0.906	0.875	0.897	0.947	0.950	0.948	0.957	0.916	0.945	0.905	0.903	0.904	0.968	0.943	0.961
T-test	*(0.535)*			*(0.589)*			*(0.578)*			*(0.426)*			*(0.878)*			*(0.109)*			*(0.933)*			*(0.232)*		
Median	0.813	0.797	0.811	0.930	0.991	0.938	0.914	0.926	0.915	0.911	0.975	0.914	0.953	1.000	0.979	0.967	0.975	0.967	0.908	0.916	0.912	0.993	0.994	0.994
M-W	*(0.604)*			*(0.667)*			*(0.930)*			*(0.807)*			*(0.143)*			*(0.786)*			*(0.798)*			*(0.852)*		
K-S	*(0.400)*			*(0.481)*			*(0.680)*			*(0.209)*			*(0.156)*			*(0.180)*			*(0.788)*			*(0.499)*		
2006																								
Mean	0.815	0.754	0.798	0.875	0.831	0.863	0.931	0.904	0.924	0.909	0.836	0.889	0.932	0.915	0.927	0.976	0.914	0.959	0.894	0.901	0.896	0.938	0.908	0.930
T-test	*(0.233)*			*(0.321)*			*(0.346)*			*(0.131)*			*(0.682)*			*(0.045)****			*(0.783)*			*(0.233)*		
Median	0.786	0.698	0.782	0.885	0.819	0.877	0.964	0.918	0.960	0.901	0.905	0.904	0.939	1.000	0.972	0.995	0.991	0.994	0.898	0.917	0.898	0.975	0.897	0.967
M-W	*(0.144)*			*(0.569)*			*(0.598)*			*(0.419)*			*(0.225)*			*(0.556)*			*(0.625)*			*(0.343)*		
K-S	*(0.107)*			*(0.524)*			*(0.440)*			*(0.048)****			*(0.192)*			*(0.202)*			*(0.977)*			*(0.151)*		
2007																								
Mean	0.863	0.790	0.843	0.905	0.840	0.887	0.954	0.943	0.951	0.907	0.917	0.910	0.938	0.953	0.942	0.967	0.962	0.966	0.949	0.858	0.924	0.964	0.877	0.940
T-test	*(0.053)**			*(0.095)**			*(0.504)*			*(0.731)*			*(0.552)*			*(0.773)*			*(0.000)******			*(0.003)******		
Median	0.842	0.785	0.824	0.958	0.856	0.903	0.986	0.969	0.981	0.918	1.000	0.929	0.984	1.000	1.000	0.992	1.000	0.995	0.976			1.000	0.875	0.988
M-W	*(0.049)****			*(0.147)*			*(0.161)*			*(0.252)*			*(0.212)*			*(0.205)*			*(0.000)******			*(0.005)******		
K-S	*(0.133)*			*(0.363)*			*(0.192)*			*(0.151)*			*(0.250)*			*(0.151)*			*(0.000)******			*(0.001)******		
All Years																								
Mean	0.855	0.806	0.806	0.911	0.872	0.900	0.939	0.922	0.934	0.912	0.891	0.906	0.942	0.944	0.942	0.969	0.942	0.961	0.935	0.902	0.926	0.966	0.922	0.954
T-test	*(0.020)****			*(0.036)****			*(0.186)*			*(0.231)*			*(0.870)*			*(0.015)****			*(0.006)******			*(0.000)******		
Median	0.862	0.803	0.852	0.930	0.893	0.924	0.974	0.969	0.972	0.914	0.985	0.923	0.970	1.000	0.987	0.986	0.997	0.990	0.972	0.917	0.948	0.998	0.962	0.996
M-W	*(0.049)****			*(0.247)*			*(0.422)*			*(0.303)*			*(0.006)******			*(0.390)*			*(0.010)******			*(0.002)******		
K-S	*(0.006)******			*(0.042)****			*(0.451)*			*(0.004)******			*(0.001)******			*(0.006)******			*(0.008)******			*(0.000)******		

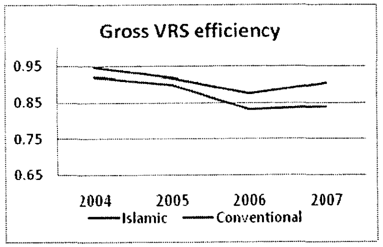
Notes: *,** ,*** denote statistical significance at the 10%, 5% and 1% significance level respectively. Null Hypothesis for the T-test: equal means in CB/IB (equal variances are not assumed). M-W is the Mann Whitney test. Null Hypothesis is that medians in CB/IB are equal. KS is the Kolmogorov-Smirnov 2-sample test Null Hypothesis is that the samples of CB/IB are drawn from different distributions (equal higher moments). CRS=Constant Returns to Scale; VRS=Variable Returns to Scale SE=Scale Efficiency. Numbers in brackets are p-values.

Figure 4. Evolution of DEA Efficiencies/Mean and Median Values.

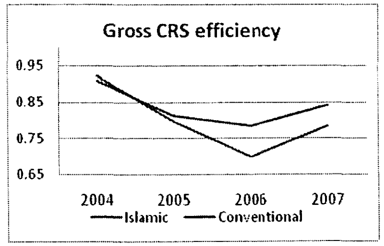
Means | **Medians**



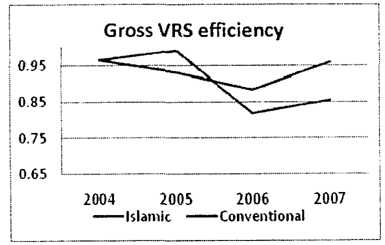
Gross CRS Efficiency



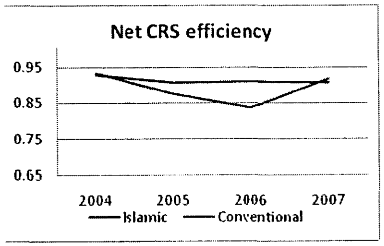
Gross VRS Efficiency



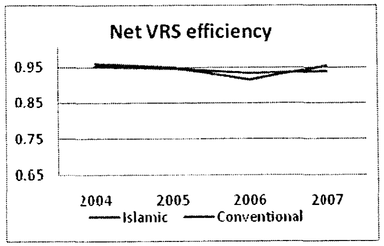
Gross CRS Efficiency



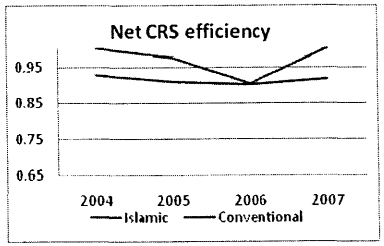
Gross VRS Efficiency



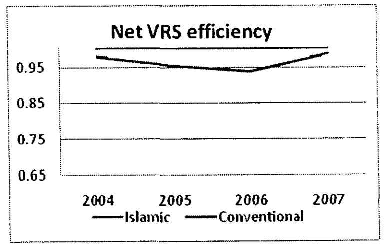
Net CRS Efficiency



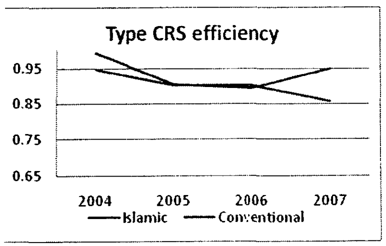
Net VRS Efficiency



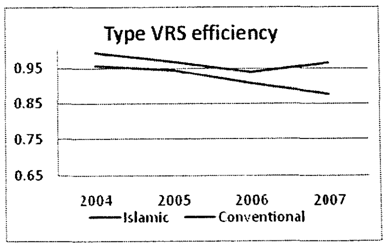
Net CRS Efficiency



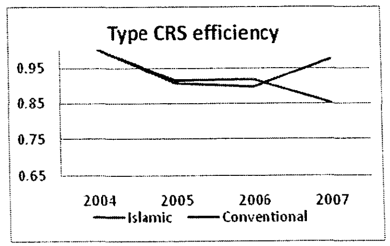
Net VRS Efficiency



Type CRS Efficiency



Type VRS Efficiency



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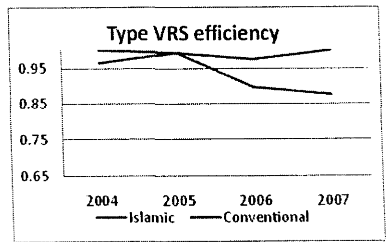

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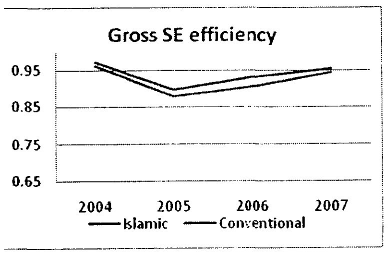
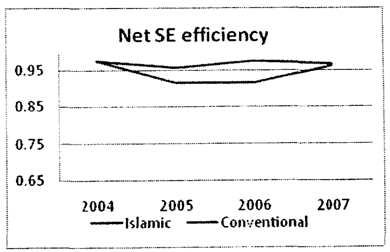
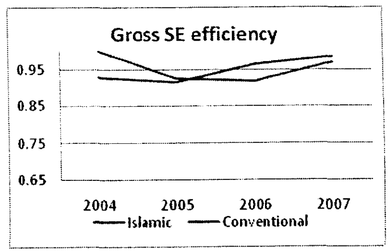


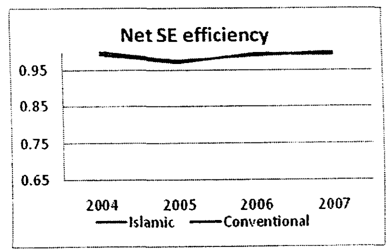
Gross SE Efficiency



Net SE Efficiency



Gross SE Efficiency



Net SE Efficiency

Table 10. Summary of DEA results.

				Model with equity					
	CRS			VRS			SE		
Efficiency	**Difference**	**Best**	**S. Level**	**Difference**	**Best**	**S. Level**	**Difference**	**Best**	**S. Level**
Gross	4.9%	CB	5%	3.9%	CB	5%	1.7%	CB	-
Net	2.1%	CB	-	0.2%	IB	-	2.7%	CB	5%
Type	3.3%	CB	1%	4.4%	CB	1%			
				Model without equity					
	CRS			VRS			SE		
Efficiency	**Difference**	**Best**	**S. Level**	**Difference**	**Best**	**S. Level**	**Difference**	**Best**	**S. Level**
Gross	6.1%	CB	10%	4.1%	CB	10%	4.5%	CB	10%
Net	6.7%	CB	5%	0.8%	CB	-	8%	CB	1%
Type	0.2%	IB	-	3.3%	CB	1%			

Notes: Gross efficiency is decomposed into Net (managerial incompetencies) and Type (modus operandi). CRS=Constant Returns to Scale; VRS=Variable Returns to Scale; SE=Scale Efficiency.

Table 11. DEA Efficiency Scores and Financial Ratios by Country.

		Bahrain	**Kuwait**	**Oman**	**Qatar**	**Saudi**	**UAE**
Gross Efficiency	**CRS**	0.855	0.779	0.826	0.866	0.799	0.875
	VRS	0.910	0.858	0.870	0.917	0.913	0.908
	SE	0.940	0.906	0.948	0.945	0.875	0.963
Net Efficiency	**CRS**	0.928	0.837	0.897	0.926	0.874	0.934
	VRS	0.958	0.900	0.922	0.961	0.927	0.957
	SE	0.966	0.931	0.974	0.964	0.945	0.976
Type Efficiency	**CRS**	0.922	0.925	0.917	0.934	0.912	0.935
	VRS	0.949	0.950	0.942	0.954	0.984	0.947
Financial Ratios	**CTI**	54.05	39.16	48.88	36.56	29.29	42.65
	NIE	3.28	2.63	3.35	2.17	2.48	2.68
	ROA	3.83	4.50	2.86	5.33	4.94	4.45
	ROE	13.72	25.36	20.84	32.12	34.95	22.43
	NIM	4.30	3.47	4.73	5.35	5.49	3.77
	OOI	3.07	3.14	1.54	2.30	2.38	2.90

Notes: CRS=Constant Returns to Scale; VRS=Variable Returns to Scale; SE=Scale Efficiency. CTI=Cost/Income; NIE=Net Interest Revenue; ROA=Return on Assets; ROE= Return on Equity; NIM= Net Interest Margin; OOI= Other Operating Income.

Table 12. Market Structure in the GCC banking sector.

	2004	**2005**	**2006**	**2007**
Bahrain	0.150	0.148	0.140	0.141
Kuwait	0.090	0.092	0.084	0.096
Oman	0.079	0.071	0.127	0.138
Qatar	0.192	0.160	0.196	0.186
Saudi Arabia	0.030	0.034	0.032	0.035
UAE	0.057	0.054	0.053	0.051

Notes: Table shows the normalized Herfindahl index of market concentration. $HI^* < 0.1 \Leftrightarrow$ Competitive market; $0.1 < HI^* < 0.18 \Leftrightarrow$ Moderately concentrated market; $HI^* > 0.18 \Leftrightarrow$ Highly concentrated market.

Source: US Department of Justice

Table 13. Spearman correlations (ρ) between DEA Efficiency Scores and Financial Ratios.

		CTI		NIE		ROA		ROE		NIM		OOI	
Gross CRS	2004	0.271	*(0.013)***	0.211	*(0.041)***	-0.008	*(0.527)*	0.058	*(0.318)*	-0.030	*(0.596)*	-0.221	*(0.965)*
	2005	0.260	*(0.015)***	0.411	*(0.000)****	-0.224	*(0.968)*	-0.098	*(0.788)*	-0.087	*(0.761)*	-0.318	*(0.996)*
	2006	0.185	*(0.065)**	0.433	*(0.000)****	-0.322	*(0.996)*	-0.120	*(0.835)*	-0.083	*(0.750)*	-0.484	*(1.000)*
	2007	0.230	*(0.032)*	0.431	*(0.000)****	-0.347	*(0.998)*	-0.035	*(0.611)*	-0.434	*(1.000)*	-0.446	*(1.000)*
	Pooled	0.126	*(0.019)***	0.304	*(0.000)****	-0.271	*(1.000)*	-0.109	*(0.964)*	-0.111	*(0.966)*	-0.389	*(1.000)*
Gross VRS	2004	0.290	*(0.008)****	0.220	*(0.035)***	-0.046	*(0.354)*	0.047	*(0.351)*	0.035	*(0.388)*	-0.326	*(0.997)*
	2005	0.208	*(0.043)***	0.248	*(0.020)***	-0.049	*(0.655)*	-0.022	*(0.572)*	-0.174	*(0.924)*	-0.106	*(0.807)*
	2006	0.224	*(0.033)***	0.290	*(0.008)****	-0.147	*(0.884)*	0.065	*(0.298)*	-0.056	*(0.676)*	-0.280	*(0.990)*
	2007	0.247	*(0.023)***	0.330	*(0.003)****	-0.325	*(0.996)*	-0.025	*(0.578)*	-0.343	*(0.998)*	-0.386	*(0.999)*
	Pooled	0.176	*(0.002)****	0.239	*(0.000)****	-0.159	*(0.996)*	-0.006	*(0.537)*	-0.099	*(0.948)*	-0.279	*(1.000)*
Net CRS	2004	0.194	*(0.056)**	0.130	*(0.143)*	-0.012	*(0.539)*	-0.006	*(0.521)*	0.039	*(0.374)*	-0.198	*(0.948)*
	2005	0.192	*(0.057)**	0.181	*(0.068)**	-0.080	*(0.742)*	-0.061	*(0.691)*	0.008	*(0.475)*	-0.132	*(0.860)*
	2006	0.029	*(0.406)*	0.235	*(0.027)***	-0.245	*(0.978)*	-0.232	*(0.972)*	-0.077	*(0.735)*	-0.358	*(0.999)*
	2007	0.035	*(0.390)*	0.216	*(0.039)***	-0.292	*(0.992)*	-0.154	*(0.894)*	-0.531	*(1.000)*	-0.277	*(0.988)*
	Pooled	0.066	*(0.141)*	0.173	*(0.002)****	-0.177	*(0.998)*	-0.138	*(0.989)*	-0.119	*(0.975)*	-0.253	*(1.000)*
Net VRS	2004	0.170	*(0.083)**	0.127	*(0.150)*	-0.022	*(0.573)*	-0.017	*(0.556)*	0.122	*(0.159)*	-0.323	*(0.996)*
	2005	0.234	*(0.026)***	0.060	*(0.312)*	0.114	*(0.176)*	0.031	*(0.400)*	0.036	*(0.384)*	0.051	*(0.338)*
	2006	-0.011	*(0.537)*	-0.011	*(0.534)*	-0.059	*(0.684)*	-0.032	*(0.603)*	-0.108	*(0.810)*	-0.088	*(0.761)*
	2007	0.121	*(0.166)*	0.178	*(0.074)**	-0.154	*(0.893)*	-0.058	*(0.680)*	-0.393	*(0.999)*	-0.132	*(0.856)*
	Pooled	0.097	*(0.056)**	0.085	*(0.082)**	-0.044	*(0.763)*	-0.029	*(0.683)*	-0.076	*(0.895)*	-0.128	*(0.982)*
Type CRS	2004	0.271	*(0.013)***	0.227	*(0.030)***	-0.069	*(0.712)*	0.150	*(0.109)*	-0.001	*(0.503)*	-0.185	*(0.934)*
	2005	0.127	*(0.149)*	0.408	*(0.000)****	-0.357	*(0.999)*	-0.178	*(0.929)*	-0.157	*(0.901)*	-0.400	*(1.000)*
	2006	0.193	*(0.058)**	0.298	*(0.007)****	-0.179	*(0.928)*	-0.009	*(0.529)*	-0.173	*(0.921)*	-0.294	*(0.993)*
	2007	0.214	*(0.042)***	0.394	*(0.000)****	-0.345	*(0.998)*	0.040	*(0.375)*	-0.199	*(0.947)*	-0.464	*(1.000)*
	Pooled	0.081	*(0.092)**	0.249	*(0.000)****	-0.272	*(1.000)*	-0.071	*(0.879)*	-0.103	*(0.956)*	-0.347	*(1.000)*
Type VRS	2004	0.371	*(0.001)****	0.279	*(0.010)****	-0.115	*(0.826)*	0.107	*(0.190)*	-0.109	*(0.813)*	-0.199	*(0.948)*
	2005	0.186	*(0.063)**	0.366	*(0.001)****	-0.077	*(0.735)*	0.001	*(0.495)*	-0.224	*(0.968)*	-0.184	*(0.935)*
	2006	0.345	*(0.002)****	0.348	*(0.002)****	-0.053	*(0.667)*	0.148	*(0.114)*	-0.002	*(0.505)*	-0.233	*(0.972)*
	2007	0.253	*(0.020)***	0.363	*(0.001)****	-0.374	*(0.999)*	0.006	*(0.479)*	-0.232	*(0.971)*	-0.473	*(1.000)*
	Pooled	0.189	*(0.001)****	0.279	*(0.000)****	-0.185	*(0.999)*	0.034	*(0.289)*	-0.102	*(0.953)*	-0.289	*(1.000)*

Notes: *,**,*** denote statistical significance at the 10%, 5% and 1% significance level respectively. CRS=Constant Returns to Scale; VRS=Variable Returns to Scale SE=Scale Efficiency. CTI=Cost/Income; NIE=Net Interest Revenue; ROA=Return on Assets; ROE=Return on Equity; NIM= Net Interest Margin OOI= Other Operating Income. Table reports the Spearman rank correlation and the p-values are given in parenthesis.

Null hypothesis is that $\rho = 0$ against the alternative $\rho > 0$.

Table 14. Malmquist Productivity analysis.

	Malmquist index				**Efficiency change index (E)**				**Technology change index (T)**			
	2004-2007		E.A.A.P.I.		2004-2007		E.A.A.P.I.		2004-2007		E.A.A.P.I.	
CRS	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
CB	0.989	0.992	0.997	0.998	0.939	0.947	0.984	0.986	1.061	1.082	1.015	1.020
IB	1.077	0.968	1.019	0.992	0.901	0.859	0.974	0.963	1.179	1.152	1.042	1.036
All	1.013	0.988	1.003	0.997	0.928	0.925	0.981	0.981	1.094	1.098	1.023	1.024
T-test	*(0.404)*				*(0.401)*				*(0.136)*			
MW	*(0.768)*				*(0.134)*				*(0.041)***			
KS	*(0.440)*				*(0.019)***				*(0.111)*			
VRS												
CB	0.990	0.996	0.998	0.999	0.958	1.000	0.989	1.000	1.040	1.071	1.010	1.017
IB	1.108	0.976	1.026	0.994	0.915	0.904	0.978	0.975	1.204	1.134	1.048	1.032
All	1.023	0.994	1.006	0.999	0.946	0.997	0.986	0.999	1.085	1.078	1.021	1.019
T-test	*(0.289)*				*(0.235)*				*(0.109)*			
MW	*(0.883)*				*(0.210)*				*(0.122)*			
KS	*(0.634)*				*(0.374)*				*(0.180)*			

Notes: *, ** , *** denote statistical significance at the 10%, 5% and 1% significance level respectively. Numbers in parenthesis are p-values for the respective tests. Null Hypothesis for the T-test: equal means in CB/IB (equal variances are not assumed). M-W is the Mann Whitney test. Null Hypothesis is that medians in CB/IB are equal. KS is the Kolmogorov-Smirnov 2-sample test. Null Hypothesis is that the samples of CB/IB are drawn from different distributions (equal higher moments).
E.A.A.P.I. = Equivalent Annual Average Productivity Index

Table A1: Results of the DEA Analysis/Gross, Net and Type Efficiencies/Mean and Median Values/Model without Equity.

	Gross Efficiency									Net Efficiency									Bank Type Efficiency					
	CRS			VRS			SE			CRS			VRS			SE			CRS			VRS		
2004	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**	**CB**	**IB**	**ALL**
Mean	0.555	0.486	0.536	0.912	0.856	0.896	0.605	0.553	0.591	0.759	0.739	0.754	0.922	0.923	0.922	0.824	0.782	0.812	0.727	0.663	0.709	0.989	0.928	0.972
T-test	*(0.051)**			*(0.103)*			*(0.316)*			*(0.763)*			*(0.978)*			*(0.450)*			*(0.122)*			*(0.000)****		
Median	0.523	0.469	0.512	0.921	0.889	0.915	0.562	0.500	0.561	0.750	0.896	0.751	0.924	1.000	0.959	0.819	0.896	0.820	0.744	0.649	0.706	1.000	0.924	1.000
M-W	*(0.057)**			*(0.135)*			*(0.104)*			*(0.946)*			*(0.276)*			*(0.989)*			*(0.045)***			*(0.000)****		
K-S	*(0.095)*			*(0.103)*			*(0.107)*			*(0.015)***			*(0.192)*			*(0.028)***			*(0.022)***			*(0.000)****		
2005																								
Mean	0.703	0.666	0.693	0.885	0.863	0.879	0.792	0.764	0.784	0.853	0.736	0.821	0.927	0.923	0.923	0.919	0.788	0.883	0.815	0.913	0.842	0.953	0.937	0.948
T-test	*(0.508)*			*(0.553)*			*(0.560)*			*(0.046)***			*(0.898)*			*(0.010)****			*(0.002)****			*(0.485)*		
Median	0.690	0.651	0.676	0.890	0.831	0.889	0.801	0.731	0.795	0.847	0.651	0.843	0.939	1.000	0.963	0.918	0.795	0.910	0.821	0.961	0.849	0.985	0.996	0.990
M-W	*(0.427)*			*(0.817)*			*(0.600)*			*(0.124)*			*(0.256)*			*(0.111)*			*(0.003)****			*(0.916)*		
K-S	*(0.660)*			*(0.481)*			*(0.892)*			*(0.002)****			*(0.262)*			*(0.004)****			*(0.001)****			*(0.788)*		
2006																								
Mean	0.723	0.662	0.706	0.825	0.783	0.813	0.877	0.824	0.862	0.834	0.740	0.808	0.901	0.877	0.894	0.926	0.825	0.898	0.863	0.894	0.872	0.914	0.895	0.909
T-test	*(0.337)*			*(0.415)*			*(0.232)*			*(0.136)*			*(0.627)*			*(0.024)***			*(0.315)*			*(0.524)*		
Median	0.692	0.638	0.686	0.820	0.816	0.816	0.950	0.893	0.905	0.825	0.811	0.817	0.909	1.000	0.921	0.934	0.859	0.925	0.915	0.867	0.898	0.971	0.906	0.966
M-W	*(0.266)*			*(0.665)*			*(0.430)*			*(0.337)*			*(0.346)*			*(0.123)*			*(0.480)*			*(0.762)*		
K-S	*(0.133)*			*(0.469)*			*(0.338)*			*(0.037)***			*(0.314)*			*(0.013)***			*(0.595)*			*(0.801)*		
2007																								
Mean	0.774	0.699	0.753	0.865	0.817	0.851	0.888	0.837	0.874	0.845	0.810	0.835	0.910	0.903	0.908	0.923	0.879	0.911	0.908	0.853	0.893	0.944	0.907	0.934
T-test	*(0.202)*			*(0.312)*			*(0.280)*			*(0.536)*			*(0.861)*			*(0.268)*			*(0.034)***			*(0.122)*		
Median	0.779	0.708	0.770	0.889	0.856	0.863	0.951	0.869	0.949	0.869	0.808	0.856	0.969	1.000	0.979	0.968	0.977	0.969	0.938	0.832	0.906	0.994	0.897	0.981
M-W	*(0.216)*			*(0.486)*			*(0.428)*			*(0.893)*			*(0.316)*			*(0.861)*			*(0.024)***			*(0.128)*		
K-S	*(0.588)*			*(0.788)*			*(0.411)*			*(0.726)*			*(0.647)*			*(0.202)*			*(0.008)****			*(0.374)*		
All Years																								
Mean	0.689	0.628	0.672	0.871	0.830	0.860	0.790	0.745	0.778	0.823	0.756	0.805	0.915	0.907	0.913	0.898	0.818	0.876	0.829	0.831	0.829	0.950	0.917	0.941
T-test	*(0.051)*			*(0.051)*			*(0.101)*			*(0.027)***			*(0.657)*			*(0.001)****			*(0.905)*			*(0.005)****		
Median	0.670	0.609	0.661	0.885	0.848	0.882	0.814	0.741	0.797	0.818	0.803	0.816	0.926	1.000	0.955	0.913	0.890	0.876	0.845	0.834	0.840	0.999	0.945	0.995
M-W	*(0.057)*			*(0.168)*			*(0.245)*			*(0.392)*			*(0.028)***			*(0.203)*			*(0.734)*			*(0.005)****		
K-S	*(0.095)*			*(0.181)*			*(0.361)*			*(0.000)****			*(0.002)****			*(0.000)****			*(0.562)*			*(0.010)****		

Notes: *,** ,*** denote statistical significance at the 10%, 5% and 1% significance level respectively. Null Hypothesis for the T-test: equal means in CB/IB (equal variances are not assumed). M-W is the Mann Whitney test. Null Hypothesis is that medians in CB/IB are equal. KS is the Kolmogorov-Smirnov 2-sample test Null Hypothesis is that the samples of CB/IB are drawn from different distributions (equal higher moments). CRS=Constant Returns to Scale; VRS=Variable Returns to Scale SE=Scale Efficiency. Numbers in brackets are p-values.

Chapter 3
Failure Risk in Islamic and Conventional Banks

Abstract

This chapter compares the hazard of failure in Islamic and conventional commercial banks using survival models. The sample consists of 421 banks from 20 Middle and Far Eastern countries observed during the 1995 to 2010 period. The conditioning variables are of both bank-level and country-type. The analysis suggests that Islamic banks have lower failure risk and are less interconnected which reduces the likelihood of domestic co-failure. Differences are revealed in the role played by various bank-level indicators. This has implications regarding the information that should be monitored by regulators to identify fragile banks. For instance, higher leverage increases the failure risk of conventional banks whereas the effect is instead favorable for Islamic banks. At macroeconomic level, a relevant finding for policymakers is that failure risk is more strongly driven by inflation for Islamic banks.

3.1 Introduction

During the recent global financial crisis, a number of conventional commercial banks (CBs) and other financial institutions in the US and elsewhere have experienced massive losses on mortgages and mortgage-backed securities. Those losses were amplified by leverage from derivatives tied to them. Primary events were the collapse of Lehman Brothers and the bailout of various commercial banks by national governments. Concerns regarding bank solvency, declines in credit availability and damaged investor confidence adversely affected stock markets. More general features were the decline in output and employment and rising fiscal deficits (Reinhart and Rogoff 2009). Clearly, a sound banking system that maintains the flow of credit to the private sector is a primary objective of policymakers and bank regulators around the world (Levine and Zervos 1998). With this *débâcle* there is renewed interest in the analysis of bank failure risk.

Islamic banking industry attracted a lot of attention in the recent years for a number of reasons. Firstly, the increase of Muslim population as well as its increasing desire to have financial instruments that comply with its religious beliefs (Seidel *et al.* 2009). Secondly, the high profitability, solvency and asset growth that Islamic banks experienced during the financial crisis increasing the appeal of Islamic investment products (Čihák and Hesse 2010). Islamic banking is no longer confined to Muslim countries but has expanded to Australia, Europe and the USA. The UK and Luxembourg promote themselves as major hubs serving the need for Islamic finance in Europe. The 2008 financial crisis caused S&P (Standard & Poor's) 500 and the Dow Jones Industrial Average, two of the most well known equity indices, to fall by 38.5% and 33.8% respectively (Financial Services Authority 2009). By contrast, the Dow Jones Islamic Financial Index recorded a 7% loss for the same year highlighting the resilience of Islamic finance. Despite the negative climate in the financial markets, growth in Islamic assets across the world reached almost 30%, far greater than the 16.3% of the top 1000 conventional banks (The Banker report 2009). In countries with substantial Islamic banking presence[26] during the 1995-2010 period there has been a higher number of failures involving conventional rather than Islamic banks. In addition, the 25 most costly failures during the 2008 financial crisis only involved conventional banks as shown in table 1.

[Table 1 here]

Banking failure has been studied in an impressive body of literature (Kaminsky and Reinhart 1999; Caprio *et al.* 2000). A bank failure can be due to idiosyncratic reasons (i.e. risk mismanagement) or associated with economic downturn; hence put in a context of banking crisis. Banking crises can start when a shock hits the economy or because economic agents expect them (Diamond and Dybvig 1983). The shock can be an increase in the interest rate (Mishkin 1999), borrowing and lending currency mismatch (Akerlof and Romer 1993; Drees and Pazarbasioglou 1995)or speculative attack by foreign investors taking advantage of high interest rates and loose monitoring systems in developing countries (Calvo *et al.* 1994). An extensive part of the literature studies the factors that can predict bank failure. Factors related to the macroeconomic environment such as real GDP growth or real interest rates (Demirgüç and Detragiache 1998)and to the banking sector such as private sector credit/GDP, a proxy for financial liberation (Levine and Zevros 1998; Demirgüç-Kunt and Huizinga 2001) are used to capture the cause of financial distress in the banking system. Accounting information reflects an individual bank's financial situation.

In the conventional banking system fixed interest is given on deposits. However returns on investments are driven by economic cycles. Consequently the conventional bank-

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[26] Albania, Bahrain, Bangladesh, Brunei, Egypt, Indonesia, Iran, Jordan, Kuwait, Malaysia, Mauritania, Pakistan, Palestine, Qatar, Saudi Arabia, Sudan, Tunisia, Turkey, UAE and Yemen.

ing sector becomes fragile and prone to crisis as pressure to meet the fixed obligations builds up (Diamond and Dybvig 1983; Ali 2004). Islamic banking promotes ethical investments by prohibiting any involvement in business lines related with alcohol, pork and weapons. Furthermore businesses that their debt is higher than 30% of their total assets are screened out. Sale of debt instruments, derivatives as well as short-sales is forbidden. Equity-based contracts are the main financial products promoted in Islamic banking; however because the industry is still young there is little standardization which can lead to higher costs. As a consequence Islamic banking is mainly practiced in project financing of large infrastructure projects rather than retail banking. In addition fee-based contracts (*i.e.* Ijarah) have prevailed over equity-based ones (*i.e.* Mudarabah) because of the lower risk they entail, their lower costs and shorter commitment of capital.

Islamic banks are partners with both entrepreneurs and depositors. The deposit accounts available in an Islamic bank treat depositors as preferred stock holders allowing them residual claiming on the bank profits and not offering any capital protection (Pellegrina 2008). Islamic banks use deposits to expand and as a type of leverage, alternative to equity increases or debt issuing in conventional banks (Karim and Ali 1989). This enables the bank to take on higher risk in its projects but at the same time the risk is passed through to depositors whose remuneration is a share ratio tied to the bank's projects rather than being an interest rate as in conventional banks (Olson and Zoubi 2008). All the aforementioned make Islamic banking a unique product in the financial world.

There has been theoretical work arguing why Islamic banking is inherently more stable and enhances economic growth (Haque and Mirakhor 1986; Sundarajan and Errico

2002; Archer and Karim 2007). First, Islamic banks are able to pass through all risks related to their investments to their depositors, which are similar to investment accounts, with no guaranteed return. Secondly, as Islamic banks act as business partners in their financing operations, moral hazard and adverse selection issues are reduced (Harris and Raviv 1991). Moreover, the investment type of deposit accounts shifts part of the monitoring task to the depositors (Čihák and Hesse 2010). Nevertheless, the lack of standardization of products and procedures leads Islamic banks to focus on the financing of big scale projects (*i.e.* real estate, infrastructure). The additional, legal mostly, complexities of Islamic financial products are impediments to Islamic banks' expansion in the west.

Our research is motivated by the increased interest in banking failure during periods of crisis and the rising interest in Islamic finance. The purpose of this chapter is to compare and contrast the information contained in accounting statements preceding bank distress in Islamic and conventional banks. The aim is to identify whether Islamic banks are more/less prone to default relative to conventional banks and whether similar indicators affect their hazard functions. To this aim we use bank-level data (drawn from Bankscope[27]) for 421 banks, with 315 conventional and 106 Islamic, covering 96 failure episodes in 20 countries – Albania, Bahrain, Bangladesh, Brunei, Egypt, Indonesia, Iran, Jordan, Kuwait, Malaysia, Mauritania, Pakistan, Palestine, Qatar, Saudi Arabia, Sudan, Tunisia, Turkey, UAE, Yemen – over the 1995-2010 period. As banking failures can also be associated with economic

[27] The Bankscope database, run by Bureau van Dijk (http://www.bvdep.com/en/index.html) contains information on 30,000 banks around the world.

downturns, a set of publicly available macroeconomic variables is included[28] (Reinhart and Rogoff 2009).

This chapter contributes to the sparse empirical research on this issue in two directions. First, we utilize survival-time analysis to determine whether IBs are less prone to failure than CBs. Formal tests of this hypothesis are carried out both *unconditionally* (on the basis of observed bank failures only) and *conditionally* on available information at bank-level and country-level. The conventional banking literature has shown that relatively parsimonious survival-time models can serve as effective early warning tools (Lane *et al.* 1986; Whalen 1991; Männasoo and Mayes 2009) . Survival analysis has been recognized as superior to conventional classification techniques such as discriminant analysis or binary logit modeling[29] because: i) it can provide estimates of the expected time to failure; ii) estimation can be handled by partial maximum likelihood without invoking assumptions on the distribution of the time to failure; iii) it recognizes the continuous-time nature of the failure probability (Hosmer and Lemeshow 1999; Kalbfleish and Prentice 2002).

Second, we investigate differences between IBs and CBs regarding the role of firm-level characteristics — balance sheet (stock), income statement (flow) and financial ratios — macroeconomic/structural indicators and latent domestic factors in explaining the hazard of bank failure. This is achieved through the Cox Proportional Hazards model which provides estimates of the probability that a bank with a given set of characteristics and operating in a given environment will survive longer than some specified length into the fu-

28 Sources: IMF, The World Bank

29 Logit models are very widely applied in the early warning of crises although, more often than not, without controlling for duration dependence (see e.g., Bussiére and Fratzscher, 2006, Fuertes and Kalotychou, 2007).

ture. For instance, the level of cost-to-income will plausibly influence failure risk for both bank types but the marginal effect could be different. Country-level variables are included to accommodate heterogeneities in economic environment (*e.g.* real GDP growth and inflation) and in financial structure (*e.g.* banking sector concentration). Given that most IB contracts are asset-backed (*i.e.* collateralized by real estate or commodities), that IBs tend to be more closely involved in the construction sector and large infrastructure projects, and are unable to use conventional inflation-hedging instruments, they could be more exposed to macroeconomic cycles than CBs (Hasan and Dridi 2010; IMF 2011b).

As a preview of our key findings, unconditional non-parametric survival probability estimators and tests that exploit exclusively the observed frequency of bank failures indicate that IBs are about 55% less hazardous than CBs. Conditional survival models also support the hypothesis that, controlling for bank-level and country-level factors, the hazard of failure is significantly lower for IBs. The analysis highlights noteworthy contrasts in the sensitivity of bank failure risk to various covariates. Lower capitalization ratios make IBs significantly less hazardous whereas the opposite is shown for CBs. This maybe be linked to the fact that IBs tend to be under-leveraged (or over-capitalized) relative to CBs and hence, further decreases in leverage for IBs could hinder profitable business operations.

The growth of administrative expenses is favorably linked to survival rates for IBs which may be explained by the relatively important human resource development process taking place in them. Failure risk is positively tied to net interest margins for CBs but negatively so for IBs, a finding that may relate to differences in their main clientele. IBs are often involved in large government-related infrastructure projects, and name lending practices prevail as usual clients of IBs are large family-owned conglomerates; in both cases, an "Islamicity premium" can be charged. At a macro level, high inflation contributes toward bank financial distress for both bank types. Yet the effect is more pronounced for IBs possibly due to their larger cash reserves and widespread use of commodities as collateral. Finally, latent country-type factors are found to have a significant impact on survival rates, albeit only for CBs. Such latent effects give rise to a domestic correlation in CB failure risk and could reflect expectation of domestic contagion. The latter is plausibly smaller for IBs given their lesser interconnectedness which stems from their peculiar business model.

The chapter continues as follows. Section 2 provides a review on the literature on banking fragility, survival analysis models utilized in banking failure studies and corroborates on some of the theoretical arguments supporting the resilience of Islamic banks. Section 3 outlines the survival analysis methodology used and Section 4 discusses the data and transformations used. The empirical findings are presented in Section 5. A final section concludes.

3.2 Literature Review

In this section we provide a brief discussion on the literature. The section is divided in three subsections; literature on banking fragility, on survival analysis studies and on Islamic banking and fragility. In the first subsection we define bank failure and why is different to other firm failures. Next, we describe the factors that can lead a single bank to fail. We distinguish between internal factors, those being under the bank's control, and external factors that relate to the macroeconomic environment where the bank operates. Negative externalities arising from a single bank failure and endanger the rest are also addressed. The subsection ends by presenting empirical studies that investigate the determinants of banking failure. The second subsection builds on the first by summarizing studies that use survival analysis methodology to examine which factors explain banking failure. The third subsection expands the previous ones by introducing the theoretical arguments that Islamic banking literature puts forward about Islamic banks being less prone to failure. The subsection presents arguments that counter this perception and ends by leading directly to our empirical investigation of whether Islamic banks are indeed less fragile with their survival being affected by different factors than the conventional commercial banks.

3.2.1 Literature on Banking Fragility

The analysis of banking failures and banking crises has attracted significant attention in economics, with extensive literature addressing the issue from different perspectives. Banking crises have been experienced by developed and developing economies to a greater or lesser degree. In the event of a banking crisis, the available credit to households and enterprises is restricted thus reducing savings, consumption and investment which in turn will force many firms into bankruptcy. Unemployment, a drop in GDP and social unrest are likely to follow potentially undermining the country's reputation thus losing part of the foreign markets' confidence. Single bank failures, where a single bank or financial institution is affected, can be separated from extended banking events, or banking crises, where a larger number of financial institutions fail at the same time period.

Failure of banks is not as straightforward as a company's due to the former's unique role in the economic system, intermediating between surplus and deficit units. Cash flow insolvency occurs when a firm is no longer able to pay its debts as they fall due. When a firm has liabilities exceeding its assets then it is balance sheet insolvent. It is possible for a firm to be "cash flow insolvent" but "balance sheet solvent" if it holds illiquid assets (such as buildings or machinery) at its balance sheet which will counter-weigh against its liabilities as the latter fall due. Nevertheless, banks' assets, such as bonds and certificates of deposit, are in a form that could be easily liquidated (UK Insolvency Act 1986). For banks, cash flow insolvency can lead to balance sheet insolvency if it is required to sell assets at a great discount. At the point when the market value of the bank's assets is less than that of its liabilities, the bank is unable to meet its obligations. The regulators decide whether to let the bank go bankrupt or intervene by a restructuring plan and/or financial support. The bank can also become an acquisition (M&A) target by another bank; thus cease to exist as the single entity it used to. However, insolvency is not the only prerequisite for M&A to take place. Capital injection from shareholders might also be decided help through financial distress and to avoid potential insolvency. All the aforementioned cause an identification problem in all statistical analysis as there is time difference between insolvency, an economic event which may not be observed immediately by the outsiders of the bank, and failure, which is a regulatory event (Whalen 1991). The problem was particularly profound in the 80's in the USA where holding companies were facing financial problems mainly attributed to some of their larger subsidiaries although smaller subsidiary banks were reported as healthy. Authorities were attempting to dispose of the entire holding company without taking into account some financially sound, though small, subsidiaries (Whalen 1991; Wheelock and Wilson 1995). Banks can be led to failure due to internal, external factors or a combination of them.

Internal factors that can lead to bank failure are related to the bank's management, decision making process and risk-taking behavior. Hence, choices regarding the bank's optimal level of capitalization, the diversification of the bank's investment portfolio, the duration mismatch between assets and liabilities and over-exposure to a particular market play a vital role to the long-run viability of the bank. Poor management decisions will be reflected upon bank-specific factors like financial ratios, equity prices, bond yields, credit default swap spreads and credit rating scores. Financial ratios that have been found to affect the bank's risk profile are regulated by micro-prudential guidelines like the Basel agreement.

By contrast, external factors, like changes in interest rates, money supply, real GDP growth, uncertainty, business-cycle related events, a drop in asset prices (*e.g.* real estate), would affect all banks. Banks with a stronger internal financial profile are more likely to withstand an adverse macroeconomic shock than banks with poor economic record are more likely to experience difficulties leading to their potential failure. A problem arises for financially stronger banks in the case that they are forced to pay a much higher premium, dictated by some banks in distress, than the one defined by their own financial situation. This higher premium can be a higher interbank borrowing rate, a higher deposit withdrawal rate or a falling market value. Negative externalities originating from informational asymmetries and lack of creditworthiness on behalf of the government can give rise to contagion putting more pressure to banks.

Banks have certain attributes that make them vulnerable to contagion. First of all banks are highly leveraged, as they only maintain a small percentage of the deposits in the form of cash while they lend or invest the rest. Secondly, maturity transformation is taking place as banks' investments maturities do not coincide with those of the depositors'. Thirdly, illiquid assets may not be able to liquidate fast enough (or even at all if the market for such an asset has collapsed, due to a bubble for instance) or without a discount when in need. Contagion is the increased linkage between two (or more) financial institutions that occurs when turmoil exists. The fact that banks possess superior information regarding the financial condition of their borrowers which can be concealed from regulators and depositors facilitates contagion (Diamond and Dybvig 1983; Cole and Gunther 1995). Following a banking failure, and given that the necessary measures to prevent contagion are not taken, (It has been argued that Protectionism is a way to prevent contagion. Protectionism occurs when an economy is insulated from external shocks by restricting the flows of foreign capital. According to the World Bank, 17 out of G20 countries were reported as imposing trade restrictive measures shortly after the burst of the 2008 Financial crisis, though in the London summit, the G20 had pledged not to impose such policies) the loss of confidence from the public to the troubled lender will disseminate to other lenders. Flight-to-liquidity is the phenomenon where investors try to load their portfolios with highly-liquid and riskless assets, such as cash or T-bills. This puts pressure in banks as they need to sell illiquid assets (*e.g.* bonds or real assets) with the aforementioned problems, thus a liquidity shortage problem could arise making insolvency more likely.

Informational asymmetries exist because depositors have imperfect information on the extent that an economic shock affects the bank. Consequently depositors not only withdraw deposits from troubled banks, but from banks that would have been untouched by the shock. The creditworthiness of the deposit insurance mechanism plays a crucial role in limiting the contagious impact of a bank-run. Deposit guarantee schemes usually offer less than total protection, thus leaving depositors with large deposited funds exposed. Furthermore the deposit guarantee scheme is designed to withstand a limited number of bank-failures. However the exact limitations of the system are not known to the depositors. Therefore when an economic shock hits the economy and banks face problems, depositors will react based on their expectations about i) what is the minimum number of banks that can fail before the deposit insurance mechanism collapses; ii) what are the expectations from the government. Is it likely that the government will provide adequate and timely support to the mechanism? In the occurrence of a bank run, there is an incentive to be among the first to withdraw deposits as the insurance scheme's resources might be insufficient and also due to the bureaucracy involved which means that it could take a considerable amount of time between the bank run and the compensation from the deposit insurance scheme. Hence depositors will display "herding behavior" in the sense that a few agents withdrawing money from a troubled bank may turn into a bank run affecting other banks' depositors as well (Hermosillo *et al.* 1996). Moreover, banking crises can unravel quickly when they are initiated by changes in the macroeconomic environment.

First, an increase on the interest rate offered on deposits, which could happen due to increased inflation or an increase in the international interest rates can start a banking crisis (Mishkin 1999). The increase will decrease the bank's profits as the interest rate charged on loans cannot be adjusted quickly enough. Additionally, an increase on the interest rate on loans is likely to render borrowers unable to repay thus increasing the fraction of non-performing loans.

A second reason for a banking crisis to start is related to borrowing and lending currency mismatch. This has caused several banking crises in the past, for instance, Chile in 1981, Mexico in 1995 and the Nordic countries in the early 90s (Akerlof and Romer 1993; Mishkin 1999; Drees and Pazarbasioglou 1995). Even if currency risk is shifted to borrowers, by issuing foreign denominated loans, devaluation could still threaten the bank's viability through a rise in non-performing loans.

A third reason for the emergence of a banking crisis can be foreign investors seeking to exploit the higher interest rates in conjunction with the inadequate or loose monitoring usually following financial liberalization enactment in developing countries. The initial large inflows of foreign capital into countries will be withdrawn at the smallest sign of discomfort, be it some equalization between international and host-country interest rates taking place or political turmoil, causing illiquidity to the banking system and making a banking crisis more likely (Calvo *et al.* 1996). According to Obstfeld and Rogoff (1996) a speculative attack on a country's currency, when the country maintains a fixed exchange rate system, may cause distress among depositors who would send the money to foreign deposit accounts in fear of a devaluation thus restricting liquidity in the banking system.

However, banking crises do not need an economic shock to emerge. Hence a forth reason can be that economic agents are expecting them. In other words if depositors believe that funds are being withdrawn, they will rush to withdraw their funds as well causing others to imitate them and consequently starting a bank run out of nowhere as the "self-fulfilling" principle dictates (Diamond and Dybvig 1983). For the likelihood and magnitude of such an event to be reduced, many countries have opted for a deposit insurance system which will prevent economic agents from rushing to the bank as they will be confident that their money are guaranteed by the government (or some insurance agency). However for the scheme to operate properly it has to be accompanied by effective judicial and regulatory systems. The judicial system must prevent "looting" practises, like in the case of Chile where managers invested in very-risky projects only to obtain some personal benefit, by not leaving any events to elude punishment (Akerlof and Romer 1993). The regulatory system needs to be closely monitoring the banks as they, in the presence of the deposit insurance scheme, have incentives to choose riskier investments (moral hazard) (Kane 1989).

Once a banking crisis has started, authorities will respond quickly to prevent the crisis from gaining greater magnitude and expanding into other sectors of the economy. Authorities can use a variety of instruments to achieve this such as bailouts and quantitative easing (Demirgüç and Detragiache 1998). However, ex post rescue operations can cause trouble with the government's budget, inefficient banks with inadequate management and risk assessment controls may be granted a second chance on tax-payers' or financially sound banks' money. Moreover, expectations about future bailouts are created causing bank managers to take excess risks knowing that they will not be left to fail by the state.

In addition, quantitative easing can trigger hyperinflation and speculative attacks against the country through the currency market especially if the country is maintaining a fixed exchange rate (Demirgüç and Detragiache 1998). Next we are presenting some empirical studies with an aim to identify some of the early warning signals of banking crises.

Accounting data have been found to be relevant in modelling firms' likelihood of default (Bartelsman *et al.* 2005; Duffie *et al.* 2007). In a banking context accounting data have been used by Lane *et al.* (1986), Whalen (1991), Gonzalez-Hermosillo *et al.* (1997) and Männasoo and Mayes (2009) among others. Macroeconomic factors (*i.e.* GDP growth and concentration) that also affect the likelihood of failure of a bank have been incorporated in several studies.

One of the first comprehensive studies in the field was the one by Demirgüç and Detragiache (1998). They investigate using logit model approach the macroeconomic factors that were related to banking crises during the period 1980-1994 in a number of countries. They conclude that low real GDP growth, worsening in the terms of trade; high real interest rates, external vulnerability (*i.e.* M2-to-reserves ratio) and inefficient judicial system increase the probability of a banking crisis. Similarly, the existence of a deposit insurance scheme increases the likelihood of a banking crisis. The authors fail to find any statistically significant evidence that financial liberalization, as measured by the credit to the private sector-to-GDP ratio and the change in real credit could increase financial instability. Moreover, the government surplus as a percentage of GDP, a proxy used to reflect the government's ability to address long-standing issues with banks (*i.e.* weak balance sheets, bad credit practises), does not have any relationship with banking failure. Financial development was found not to endanger the stability of the financial system; however it has positive effects on economic growth (Stulz 1999).

These positive effects of development of financial systems is verified statistically by Stultz (1999)and Levine and Zevros (1998). They find that financial systems' development has significant impact upon economic growth and firm profitability (Stulz 1999; Levine and Zevros 1998). As argued by Demirgüç-Kunt and Maksimovic (1998), firms operating in a highly developed financial system grow faster than what their individual characteristics suggest. The impact of different stages of financial development and structure, as a country's financial system develops and evolves from bank-based to market-based, upon the performance of the banking sector is investigated in Demirgüç-Kunt and Huizinga (2000).

Central bank's size is likely to be much more pronounced in developing countries. By contrast market-capitalisation-to-GDP and value of traded stock-to-GDP will be very low for developing countries as stock markets are either non-existent or very little trading takes place (Demirgüç-Kunt and Huizinga 2000). Bank-based financial systems have higher bank credit-to-GDP ratios as banks play a more important role in firm financing. In underdeveloped financial systems the ratio of deposits-to-GDP tends to be significantly lower than developed countries. A plausible explanation could be the lower number of firms operating, the lower wealth and the people's lack of confidence on government which leads them to keep their money in a form that will not depreciate (*e.g.* gold) (Cagan 1956). By contrast in market-based systems firms can resort to stock markets to finance their operations or expansionary projects. Demirgüç-Kunt and Huizinga (2000)use a statistical approach to verify the above mentioned points.

The methodology followed by Demirgüç-Kunt and Huizinga (2000) is standard regression techniques with two profitability measures (profit-to-total assets and net margin-to-total assets) on a set of bank specific, macroeconomic and financial development and structure variables. According to their findings, banks operating in developed countries are less profitable than those in developing ones, possibly due to tougher competition (Demirgüç-Kunt and Huizinga 2000). Moreover the presence of stock markets enhances bank profits. This can be attributed to the more funding alternatives enjoyed by companies leading to a greater expansion of the business sector without the banks incurring all default risks (as companies will also get financing from stock and capital markets). Additionally greater transparency and dissemination of firm-related information is enforced in the presence of stock markets thereby reducing monitoring costs previously incurred only by banks. However this effect is subject to decreasing returns to scale. In other words there is an optimum level of stock market development at which banks gain most (Demirgüç-Kunt and Maksimovic 1998). Consequently banks in developing countries are the ones to benefit the most from stock market development. So far Demirgüç-Kunt and Huizinga (2000) have established a relationship between different degrees of financial development and different levels of financial structure. The next step is to see how these are related to banking fragility, a topic addressed by Ruiz-Porras (2006, 2008).

Ruiz-Porras (2006, 2008)in two of his studies links financial development and banking fragility. Using data on banking crises worldwide extracted from Caprio and Klingebiel (1996) and explanatory variables from Beck *et al.* 2006he finds that financial development, defined as the level of efficiency, know-how and technical innovation existing in banks and stock markets, is higher in market-based systems and particularly during periods of banking crises. Moreover banking crises encourage the transition from a bank-based system to a market-based one, a result consistent with previous studies (Allen and Gale 2000). The author does not give any explanation regarding the factors that might drive such changes. A plausible explanation could be attributed to the fact that banking insolvency episodes could cost above 15% of a country's GDP to "clean up", a cost that will ultimately be shifted to taxpayers and potentially endanger the government's stay in power (Caprio and Klingebiel 1996). Additionally there are increasing returns to scale by the development of a stock market both for the country's economy and the banking sector's profitability (Demirgüç-Kunt and Huizinga 2000). In his second study, Ruiz-Porras (2006, 2008), he concludes that market-based systems are less likely to experience banking crises. However there is an optimum level of financial development[30] (for instance financial liberalization is comprised within the financial development category) after which the likelihood of banking fragility increases (Loayza and Ranciere 2006; Diaz-Alejandro 1985). Finally the author fails to find any statistical significant link between concentration and bank fragility.

Maechler *et al.* (2005) limit their study within the European territory. They investigate whether Eastern and Central European (ECE) countries have a different risk profile compared to some of the least advanced EU-12 members (*i.e.* Greece, Portugal, Spain or EU-3). ECE countries were considered developing countries[31] at the time the paper was published which makes the study close related to Demirgüç-Kunt and Huizinga (2000). The

[30] The author has already shown that market-based systems enhance financial development (Ruiz-Porras, 2006).

[31] Eastern and Central European countries, especially the new-EU members, are now considered as "graduated developing countries" according to the IMF and UN.

study focuses on the effect of financial risks (liquidity, credit and exchange risk) upon the risk of banking default and the differences between groups of European countries. The selected methodology involves the z-score as the dependent variable regressed (pooled OLS) on a set of explanatory variables necessary to reflect bank-related sources of risk as well as macroeconomic and supervisory ones. Findings show that EU-3 countries are less capitalized and profitable but with lower earnings volatility than ECE countries, which is attributed, according to the authors, to lower lending opportunities. The finding is consistent with Demirgüç-Kunt and Huizinga (2000) who also find that underdeveloped financial systems are more profitable than developed ones. Additionally the direct relationship between inflation and the likelihood of default found by the authors is also validated by Demirgüç-Kunt and Detragiache (1998). Credit growth enhances banking stability through increased activity, particularly when directed to the private sector (*i.e.* a rise in credit to private sector-to-GDP ratio is observed), a finding that is usually associated with financial development (Demirgüç-Kunt and Huizinga 2000). Nevertheless, excessive high growth can jeopardize banking fragility through rises in bank portfolios' risk and non-performing loans. The non-linear effect of credit growth expansion which was also evidenced by Demirgüç-Kunt and Detragiache (1998) is also found to be statistically significant here (Maechler *et al.* 2005). The author's finding that more liquid banks are more likely to experience insolvency problems is probably sample-specific. ECE countries bear higher country risk than other EU members mainly because they are undergoing a convergence process to become affiliated with the rest of EU. This involves undertaking a lot of measures to improve transparency and governance. Changes to the exchange rate regime may also have to be taken. All these implementations could be problematic and lead to turmoil. Hence the higher likelihood for bank default may be more associated with country-specific risk, which would also explain the riskier profile of foreign bank also found in the study, than pure liquidity risk. Finally the authors fail to find any statistically significant link between bank size and banking fragility in spite of the literature arguing that larger banks are less likely to fail (Demirgüç-Kunt and Detragiache 1998).

In this subsection we defined bank failure, summarized the factors that can lead a bank to fail and how can this turn into a bank crisis. Finally we reviewed some empirical studies in order to see which variables have been found to be statistically significant in identifying troubled banks. The next subsection continues from where this one finished but now we review only studies that used survival analysis methods as it is the one we implement later on.

3.2.2 Literature on Survival Analysis

Survival analysis has been used extensively in medical statistics and industrial reliability studies, however, results from the seminal paper of Lane *et al.* (1986)show that the methodology can be applied within finance and economics context. The benefits of the application of the survival analysis methodology[32] in finance can be summarized below. Firstly, regression analysis and logit model techniques estimate the probability that a bank with some given characteristics will (or will not) fail at some point in time within an interval set by

[32] The authors make use of the Cox Proportional Hazards model which is a semi-parametric approach in the survival analysis methodology. It would be more appropriate therefore to say the benefits of the Cox methodology in finance. However, as the Cox model has not been formally introduced yet (see methodology section) we believe that the used term will lessen confusion among the readers not familiar with survival analysis methodology.

the study design (Whalen 1991). Survival analysis, as opposed to regression analysis and logit models, incorporates the bank's time to failure as a variable in the analysis instead of whether it failed or not (Dabos and Escudero 2004). This allows subjects with different history before the event to be included in the analysis. Hence observations one year prior to failure can be mixed with observations three years prior to failure (Lane *et al.* 1986). Most importantly, survival analysis assumes that the probability of failure is not constant over time, as such it is preferred to logit models (Männasoo and Mayes 2009). Secondly, parametric models of survival analysis are known to have shortcomings when certain assumptions (*e.g.* distribution of variables) are violated. By contrast the Cox model, which is a non-parametric survival analysis model, has been very useful due to its lack of underlying assumptions (Crowley and Hu 1977).

The seminal paper of Lane *et al.* (1986) focuses on banking failures and whether an early warning system could identify them prior to their actual failure date. They focus their analysis in the USA and their sample ranges from 1979-1984. At that time, the three regulatory agencies of the USA, namely the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve Board and the Office of the comptroller of the currency had resorted to the CAMEL rating system to assess a bank's soundness. CAMEL stands for capital, asset quality, management, earnings quality and liquidity comprising the five categories in which accounting ratios are divided into. The CAMEL system was adopted in 1978 but since then there has been little consensus on which variables are the best predictors of banking failure. Given that stock market data are only available for the largest banks, accounting data need to be used for the sample size to be relatively large. However, accounting data suffer from low update frequency (as financial statements are usually published yearly or quarterly) and creative accounting, which can distort results (Randall 1989).

Lane *et al.* (1986)use 21 accounting ratios covering all five categories of the CAMEL system. According to the authors' findings, an increase in the commercial and industrial loans-to-total loans as well as total operating expense-to-total operating income results in decreased survival probability. Similarly, a rise in loans-to-deposits ratio leads to decreased survival probability for the banks. Conversely, an increase in total capital-to-total assets ratio is associated with an increase in bank's survival probability. Although the study is primarily about the determinants of banking fragility in the United States, the efficiency of the CAMEL rating system is implicitly tested. According to the authors, there is no statistically significant connection between any of the asset (loan) quality ratios (i.e. provision for loan losses-to-total operating income, net loan recoveries/total loans) and banking failure. However a measure of non-performing loans, which is considered to be a better leading indicator of asset quality problems that could lead to bank failure, is not included in the pool of asset (loan) quality variables as only a few banks at that time were reporting such an index (Whalen 1991). There has been some criticism on the Lane *et al.* (1986) paper focusing mainly on two points that are discussed next.

The first point of criticism relates to the sampling method employed by the authors. In a survival analysis study the sample needs to comprise an adequate number of failed banks so that reliable results can be reached. Random sampling does not ensure that too few failed banks might be included (Whalen 1991). In the matched sample approach, which is used by Lane *et al.* (1986), the researcher adds one or more non-failed banks for every failed bank in the sample. The non-failed banks are selected according to some characteristic that they have in common with the failed ones such as (Lane *et al.* 1986):

i. Geographic location

ii. Charter status (state or national bank)

iii. Size (according to assets, deposits or loans)

iv. Age

The shortcoming of the matched sample approach is firstly its vulnerability to subjective judgements (i.e. which cut-off size value should be selected) and secondly its inability to be applied in countries with a small number of banks (Whalen 1991).

The second point of criticism to Lane *et al.* (1986) was the lack of any macroeconomic variable in their analysis. Whalen (1991) addresses mainly the matter of non-inclusion of macroeconomic variables and identifies several issues regarding the inclusion of macroeconomic variables in a model. At first a selection of the area represented by the macroeconomic variables needs to be made. For countries such as the USA covered in the study of Whalen (1991), macroeconomic variables can be chosen at the state level, at metropolitan areas level, at local level which would be identified by the researcher (*i.e.* Mainland and coastline areas, urban and rural areas-higher degree of monopoly power and/or profitability is more likely to be observed in rural areas (Cole and Gunther 1995), or finally at the country level. Secondly, sector-specific macroeconomic variables, like farm or energy sector, should not be included although they have been found to be correlated with bank failures. The author argues that there is no reason to assume that the pattern will repeat itself in the future. Hence he supports the use of variables that cover a larger area such as unemployment or production level (Whalen 1991). Thirdly, as macroeconomic variables are published with a certain lag it is reasonable to assume that economic agents form expectations on these variables and act according to these. Using forecasted values for these variables or the difference between expected and realized values might yield better results (Goudie 1987).

Whalen (1991) includes the percentage change in state residential housing permits over the three-year period preceding the bank failure to account for the different economic background. The estimated coefficient has a negative sign giving indication that a positive change in the construction of new houses increases the survival probability of banks. This is attributable to the good economic climate that motivates agents to shift from renting a house to buy one. Other variables used in the model comprise return on assets and non-performing loans-to-average assets a rise in which results in higher survival probability. By contrast, loans-to-assets, operating expenses-to-assets and certificate of deposit dependence ratio are negatively associated with the bank's probability of survival. An extension to the papers of Lane *et al.* (1986)and Whalen (1991) comes when Wheelock and Wilson (1995) combine methodologies from survival analysis, bank fragility and cost efficiency studies.

In their paper Wheelock and Wilson (1995) combine the methodology found in technical and cost efficiency studies with survival analysis in order to assess the linkage between poor management and banking failure or acquisition. A competing risks framework is used under which every bank can either fail or be acquired by another bank. Moreover the Cox model is enhanced by using time-varying covariates[33] which allow for more information on

[33] The Cox model with time-varying explanatory variables (covariates) is called "extended Cox" as opposed to Cox Proportional Hazards which assumes constant variables (Kalbfleisch and Prentice, 1980).

the banks' condition throughout the experiment. The selected explanatory variables cover all five areas of the CAMEL ratings system. Under the management category however, the authors have used variables (cost inefficiency, technical inefficiency) estimated by Data Envelopment Analysis (DEA). Several miscellaneous factors are also incorporated so that size, the presence of holding companies and restrictive bank-branching laws are considered. The fact that a bank might be part of a holding company could increase its survival probability due to the transfer of financial and other resources from the parent company to the subsidiary. Additionally the dissolution of a subsidiary bank could be more complicated and more costly than a stand-alone one; hence increasing the time between insolvency and failure (Cole and Gunther 1995). The ban of bank branching could expose banks to idiosyncratic risk, like in the case of oil-dependent states in the USA during the oil-price shock of the late 1980's, which led to a higher number of bank failures (Cole and Gunther 1995; Brown and Hill 1988). Results show that managerial inefficient banks are more likely to fail. However as cost efficiency rises, the likelihood of a bank being acquired drops indicating that costs for reorganization and other potential problems discourage takeover by ambitious managers. The authors also find that bank survival is higher among states permitting state/nation-wide branching, which is in favour of the claim that unrestrained branching enhances diversification and lowers the exposure to localized risks.

The impact of bank concentration on bank failures for developed and developing countries is examined using parametric survival analysis techniques in Evrensel (2008). Banking concentration has caused a lot of contradiction in the literature. Some studies find that a higher level of banking concentration leads to higher survival time for banks mainly for two reasons. Firstly, concentration lessens competition and increases profits and capital buffers; hence managers can lead an "easy life" without taking excessive risks, an argument known as "franchise value" (Keeley 1990; Schaeck *et al.* 2009). Secondly, the regulatory mechanism may be working in a less costly and inefficient way, partly because high competition can undermine banks' prudent behavior (Evrensel 2008; Hellman *et al.* 2000). As stated by Mishkin (1999), welfare may be decreased in the presence of high competition. In addition to this point, Allen and Gale (2000) claim that competition may be less socially preferable to concentration. By contrast more concentration may create very large banks that implicitly fall under the "too-big-to-fail" doctrine which can lead to more loans being granted, potentially without so stringent credit rationing (Stiglitz 1972; O'Hara and Shaw 1990). However, to get a clearer picture of the differences that affect bank failures in developed and developing countries several other factors need to be taken into account. For instance the presence and type of a deposit insurance scheme is analyzed in Matutes and Vives (2006) and Cordella and Yeyatti (2002) as well as the political system's impact in terms of banking restrictions, entry barriers and government intervention which are examined within Kaminsky and Reinhart (1999), DeNicolo *et al.* (2003) and Beck *et al.* (2006).

Evrensel'sstudy (2007a)focuses in the period 1980-1997 having a sample of 79 countries and 50 episodes of banking crises. Because some countries (e.g. Malaysia, Turkey) faced more than one episode during the examined period, the data can be described as multiple-failure data rendering the study the first one to do so. The explanatory variables are selected to capture the macroeconomic, financial and regulatory specialities of every country. The findings, which are consistent with Beck *et al.* (2006) and Schaeck *et al.* (2009), show that, higher values of concentration, banking restrictions (*i.e.* restrictions in bank ownership, operating in real estate market and insurance), banking freedom (i.e. whether banks can operate freely, degree of regulation in the financial markets), real GDP growth, economic freedom (i.e. policies related to trade, wages and government finances) and political accountability in the banking sector are associated with higher survival probability. Conversely, higher levels of moral hazard-reflected in the generosity of the deposit insurance scheme, money growth rates, inflation rates and real interest rates decrease the banks' survival probability.

Although the study reaches some conclusion on how certain variables affect banking fragility, it fails to produce robust results on the difference of these factors between developing and developed countries. For instance the author finds that higher concentration is associated to lower hazard but for the developing countries, where concentration is higher, banking fragility is also higher. Clearly the channels among concentration, competition and bank failures have not been fully investigated (Matutes and Vives 1996; Claessens and Laeven 2004; Beck *et al.* 2006; Schaeck *et al.* 2009). A possible explanation could be that concentration in developing countries is imposed by government practises (governments in developing countries intervene in the market for political reasons) rather than being the outcome of market pressure leading to a more consolidated and efficient banking sector (Evrensel 2008). As far as bank regulations are concerned, it could be the case that in developing countries they are not properly enforced due to corruption or inadequacies of the judicial system (Evrensel 2008).

The studies presented so far examine the survival time of banks given some financial ratios relating solely to the bank (*i.e.* technical inefficiency) or the banking industry (*e.g.* loans-to-deposits). The studies reviewed next take a macroeconomic shock as the starting point of their approach in the context of a generalized financial crisis.

The collapse of the Mexican peso in December 1994 is an adequate macroeconomic shock to cause a banking crisis. Although no banks were liquidated during the crisis, the majority of banks received various forms of financial assistance from the Mexican government (Hermosillo *et al.* 1996). The most commonly used support mechanisms comprise financial support from the deposit guarantee fund, temporary recapitalization and sale of bad loans to the government. The deposit guarantee fund is financed by the banks in proportion to their deposits and according to the cap set by the government/regulator. At that time the Mexican government guaranteed all deposits. In Europe the deposit insurance limit is in the range of 35-50,000 euro, although some countries temporarily eliminated it – or raised the limit - during the 2008 financial crisis. During distressed times banks will get funds from the guarantee fund. Temporary recapitalization involves the problem bank getting an emergency budget from the government or some other organization for a pre-negotiated period of time (*e.g.* 6 months). During this period the bank needs to establish a restructuring plan, to identify the reasons for that led it to financial distress and to restore its viability (World Bank website). Finally the government can buy at a discount a portion or the whole of the banks' non-performing loans. The last method was used in case of "Northern Rock" when it was returned to public ownership in January 2010 stripped of its book of bad loans, which remained under government possession (Guardian 2010).

Hermosillo *et al.* (1996) examine the determinants of banking failure and provide a case study for Mexico during the currency crisis. To their aim they make use of logit models and survival analysis techniques to estimate the impact of bank-specific, bank-sector and macroeconomic factors upon the probability of failure and the survival time of banks. They find that higher values of *Non-performing loans*, *Non-securitised loans* and more *Interbank deposits* are associated with a higher probability of failure. By contrast, they fail to find any statistical significant link between profitability, as measured by *Return on Assets (RoA)*, *Return on Equity (RoE)* and *Profit margin*, and liquidity, as measured by *Liquid assets to total assets* and bank size, proxied by *Bank assets to total banking assets*. The theoretical grounds for the statistical significance of the first three variables are self-explanatory; thus non-performing and non-securitised loans are a measure of banks' exposure to credit risk. Additionally increased interbank activity could signify higher exposure to risk as the problematic bank seeks for additional funds to prevent insolvency. However we would expect profitability to be negatively related with probability of survival as a more profitable bank would have higher financial flexibility, higher operational efficiency, greater research and development capabilities and more efficient risk management (Willison 2009). On one hand, liquidity would be expected to be positively related to banks' survival, especially when the economic shock comes from the macroeconomic environment, thus affects all banks. Hence when interbank lending is restricted due to the uncertainty for other banks' creditworthiness, the bank with the more liquid assets would clearly be in a better position as it would have a larger cushion to absorb shocks. On the other hand, if the economic shock comes from within the bank then the impact of liquidity may not be as straightforward since high levels of liquidity could be related with inactivity. Therefore bank inactivity, proxied by liquidity and not liquidity per se, would be the reason for financial instability. Size and the "too big to fail" doctrine has gained a lot of popularity lately after the bailouts in the US and the UK that followed the 2008 financial crisis. Moreover, larger banks are more able to diversify credit risk and enjoy more flexibility in financial markets (Cole and Gunther 1995). Therefore it would be expected that size would be positively related to banks' survival time.

An adverse macroeconomic shock can affect the banking environment of another country. A number of studies that have examined the effects of the Mexican devaluation upon the banking systems of Argentina (Dabos and Escudero, 2004), Brazil (Sales and Tannuri-Pianto 2005), Venezuela (Molina 2002) and Colombia (Gonzalez and Kiefer 2009), are presented below.

Dabos and Escudero (2004) examine in one of their studies the impact of the Mexican devaluation upon the Argentinean banking sector. The selected explanatory variables cover all five categories of the CAMEL ratings system. The sample period 1994-1996 is selected and the Cox model is used. Their findings give support to the positive effect of increased liquidity and profitability, as measured by cash plus public securities-to-deposits and return on equity respectively, upon banking survival. By contrast, higher levels of equity-to-assets, as a proxy for capitalization, and less efficient management, evidenced by higher levels of expenses-to-liabilities, have a negative effect upon banking survival. Similar to the study of Lane *et al.* (1986), the authors here fail to reach robust results (significance level and sign of the variable is not consistent between the two groups of banks selected by the authors) regarding the impact of asset (loan) variables upon the soundness of the banking system. However this could be due to their poor choice of proxy variables (they selected arrears portfolio minus loss provisions-to-equity) which is not found anywhere else in the related literature.

The impact of the Mexican currency crisis upon the fragility of the Brazilian banking system is studied by Sales and Tannuri-Pianto (2007). The examined period covers 1994 to 1998 and parametric survival models are used by the authors. Brazil uses the INDCON system which, similarly to the CAMEL ratings system in the USA, uses quarterly financial ratios at the bank-level. Similarly to the CAMEL system, financial ratios in the INDCON system use the same classification. Macroeconomic variables (consumer price index, industrial production indicator, and average spread of Brazilian over US government bonds) and contagion variables (total loans-to-monthly GDP, monthly percentage change of loans) are also included. Contagion variables are used to assess the effect of the government's attempt to minimize the likelihood of a system-wide banking crisis by promoting mergers and bank restructuring[34]. Results show that an increase in two financial ratios (recovery of the administrative expenses through service's income-a proxy for efficiency and loan reserve coverage, a proxy for credit risk) decrease the probability of a bank failure. Conversely in all other statistically significant variables (industrial production as a proxy for economic environment, atypical assets-to-total assets, a proxy for fraud risk, operational margin, a measure of profitability, leverage ratio and other liabilities-to-total liabilities as proxies for

34 The Brazilian Central Bank launched the "Proer" (Program of incentives to the restructuring and strengthening of the national financial system which ended in 2001 when the enactment of the Fiscal Responsibility Law forbid any state support to troubled banks (Sales and Pianto 2007).

credit risk and non-performing loans-to-total loans, a measure of asset (loan) quality) of the model will increase the probability of a bank failure. The authors' results agree with Rocha (1999) who used the Cox proportional hazards model for the period 1995-1996. However they are not supportive of Janot (2001) probably because of the sample choice (1994-1995) as the effect of the Mexican devaluation (occurred in December 1994) would have taken some time to impact on the, already, cash-flow problematic Brazilian banks (Central Bank of Brazil website).

The financial turmoil of the mid-90s in Latin America had an impact upon Venezuela, which is examined by Molina (2002). During that time the weak and volatile macroeconomic environment of the region, the inadequate banking supervision and regulation coupled with bankers' corruption, mismanagement and the untrustworthy government as well as the shift of all interest rate restrictions fuelled the Venezuelan banking crisis (Garcia 1997). The sample period ranges from January 1994 to August 1995 when 17 banks, accounting for more than half of the system's assets, failed. Due to the less developed banking system of the country, there are no financial indicators for all categories of the CAMEL ratings system. Moreover, the percentage of bad loans at the bank-level was unavailable at that time. The paper's findings are that banks with higher return-on-assets and a greater investment in government bonds than loans have higher survival probability. During the mid 90's, Venezuelan government bonds were considered as a low-risk/medium-return investment, hence banks would discard the risky loans and assign a higher proportion of their assets to government bonds, in accordance to the flight-to-quality principle. Lower operational costs in association with more financial expenses give rise to higher default probability. The author's explanation for this finding is that troubled banks cut operating expenses and increase the interest rate offered on deposits to attract more depositors. Similar results have been also found to hold for the USA and the UK (Weelock and Wilson 1995; Logan 2001).

Colombia's banking system was also affected by the mid-90's crisis of Latin America (Gonzalez and Kiefer 2009). A total of 53 banks, accounting for more than 20 percent of the system's assets, failed between 1998 and 2001. Before the nineties, Colombia's financial system was heavily regulated with high reserve requirements, constraints on foreign investment and a large proportion of nationalized banks. Financial liberalization started during the nineties and led to a rise in the operating financial institutions, a higher percentage of foreign assets circulating in the system and a transfer of the previously government-owned financial institutions to private ownership. The credit boom that followed led the ratio of loans-to-GDP to grow steadily until 1998 when a capital reversion followed by deterioration in the terms of trade coupled with the country's abandonment of the pegged exchange rate system over a free floating one, caused the worst banking crisis in Colombia's history. Utilizing the Cox proportional hazards model and a, rather limited, set of bank-specific explanatory variables, the authors find that a rise in capitalization (equity-to-assets) affects positively the survival time of the banks. Moreover they find that the effect diminishes as the banks' capitalization level increases. Size and profitability (proxied by annualized profits-to-average annual assets) also affect the survival of a bank in a positive way. Larger banks are expected to be less likely to fail given their higher diversification capabilities, economies of scale and publicity. When management efficiency or loan quality data are unobservable by the public, profitability is more likely to be used as a proxy for them (Molina 2002). Hence more profitable banks are expected to have a larger clientele particularly in distressed times.

In this subsection we reviewed some of the literature on banking fragility that used survival analysis. All literature with survival analysis methodology focuses on fragility of conventional banks whereas there is no comparative empirical study between Islamic and conventional banks. There are however, theoretical arguments that Islamic banks are more resilient to financial crisis and are they do not share the same early warning indicators to conventional banks. The next subsection presents these arguments as well as their counter arguments, leading to the methodological part of this chapter where all the arguments are empirically tested.

3.2.3 Islamic Banking and Fragility

In the conventional banking system fixed interest is given on deposits. However returns on investments fluctuate according to the economic cycles. Consequently the conventional banking sector is fragile and prone to crisis as pressure to meet the fixed obligations builds up (Diamond and Dybvig 1983; Ali 2004). There has been a lot of theoretical work arguing on why Islamic banking is inherently more stable and enhances economic growth (Haque and Mirakhor 1986; Sundarajan and Errico 2002; Archer and Karim 2007; Mehta 2008). Below we summarize some of the arguments that are in favour of Islamic banks enhancing the stability of the financial system and present some of the counter-arguments as well.

First, Islamic banks are able to pass through all risks related to their investments to their depositors. This is possible because of the way balance is maintained in the accounting statements of Islamic banks. Islamic banks do not use interest to channel funds; they rely mostly on fees for simple "trade contracts" and on equity for "partnership contracts". *Murabahah* for example can be classified as a "trade contract". In the contract of *Murabahah*, the Islamic bank buys an asset and sells it at a mark-up which takes into account the bank's expenses and profit margin. Partnership contracts work on the profit and loss sharing (PLS) principle on the asset and liability side of the bank. The PLS principle is similar to preferred stock without contractually agreed interest payments (Ebrahim 1999). On the asset side the Islamic bank will contract with the entrepreneur so that the former provides the necessary capital and the latter the expertise. Profits of the joint venture will be distributed on a pre-agreed profit share ratio between the bank and the entrepreneur. In case of losses, the bank will be the only part to bear the financial loss. On the liability side the Islamic bank has two types of deposit accounts. A safekeeping account where all the money is 100% available on request but a zero rate of return is offered and an investment account where money is not guaranteed and its rate of return is tied to the bank's investments. The rate of return is unknown beforehand as it is directly related to the performance of the bank's investments. If the investments are profitable, a higher rate of return is offered. However the account does not guarantee a minimum rate of return or even explicit capital protection. In case of some shock, due to the special link between depositors and investors offered by Islamic banks, the liability side will always adjust automatically to the value of the asset side. In other words, Islamic banks are able to pass through all risks related to a venture (i.e. credit, default, market) to their depositors thus enhancing stability and avoiding bank runs (Ali 2004; Iqbal and Mirakhor 2007; Gangopadhyay and Singh 2000).

A second benefit to the financial system by Islamic banks is the elimination of moral hazard and adverse selection issues (Harris and Raviv 1991). This is ensured by a more frequent monitoring of the entrepreneur by the bank, because the latter acts as a business partner who has an interest in ensuring that the joint-venture is profitable, to ensure his own profit share (Iqbal and Mirakhor 2007). In other words, Islamic banks, tie the remuneration to the project's performance which is different to the conventional banks tying the remuneration to the input of capital (Haque and Mirakhor 1986). Moreover, the use of PLS transfers part of the monitoring task to the depositors as they share the risks and are closer to equity investors rather than holders of debt (Čihák and Hesse 2010).

Thirdly, Islamic banking does not aggravate the down-phase of the economy as is the case with conventional banking (Iqbal and Mirakhor 1999). In the event of a crisis, banks restrict liquidity in the financial system by increasing the interest rate on loans or halting them completely for certain ventures. This can be worsened further if banks need to make adjustments to comply with liability management policies, which align the behavior of all banks. An increase of deposit interest rates at that time to attract more depositors has occurred many times in the past and most of the times it has led to a banking crisis. By contrast, Islamic banks do not need to adjust any deposit rate. In fact they do not have one to adjust. The profit of the depositors is tied to the performance of the bank's portfolio and will adjust by itself.

However, Islamic banks also face problems that could invalidate the aforementioned arguments in favour of financial stability besides making their expansion more difficult. First of all operational risk is much higher partly because of the lack of standardization of products and procedures in the business and partly due to the complexities involved in PLS contracts. Islamic banks are not yet fully standardized, hence working at the micro level would incur higher costs as contracts need to be created from scratch every time. Consequently they are forced to operate mainly at the macro level financing big scale projects, like real estate and infrastructure projects. Secondly, the legal system, especially in non-Muslim countries and the incompatibilities with the Shariah Law which Islamic banking abides by, can invalidate Islamic banking contracts. Shariah compliance risk is caused when a financial product offered by an Islamic bank is deemed as unlawful and thus void. As most Islamic banks operate in countries with dual banking system, competition from conventional banks, which face no investment restrictions, is severe. Islamic banks need to cover the investment needs of their clients which lead to research for new products that could potentially be unlawful (Sundararajan and Errico 2002; Iqbal and Llewellyn 2002). Thirdly, competition from conventional banks and guidelines from various organizations (*i.e.* World Bank, IMF, BIS) necessitate the practise of profit smoothing in Islamic banks. A set of reserves is created which act as buffer for hard times so that profit can still be distributed. Although this, in theory, is opposite to Islamic banking it is found that Islamic banks in many countries do profit smoothing to a greater or lesser degree (Sundararajan 2005).

Despite the theoretical arguments about the difference of Islamic banking and its unique risks, there is lack of empirical analysis in the context of financial stability. Questions like Islamic banks being less vulnerable to systemic shocks than conventional ones or simply that they are affected by different factors have not been adequately addressed. Reasons for this lack of empirical work comprise the much smaller size of the Islamic banking sector, the unavailability of reliable and high frequency data, differences in how Islamic banking is perceived and practised (*e.g.* Malaysia versus GCC states), inconsistencies between databases on how to measure (the equivalent of) interest income and how to make accounting statements from conventional and Islamic banks comparable. So far only one empirical study comparing conventional and Islamic banks has been brought to our knowledge.

The study of Čihák and Hesse (2010) is the first one to address the issue of comparing banking fragility profiles for the two types of banks. In their sample 18 countries with adequate presence of Islamic banks are included. The range covered is 1993-2004 while Islamic banks account for less than one-fifth of the total sample. The methodology, similar to Maechler *et al.* (2005), involves regressing the banks' z-score indicator, a measure of how close a bank is to being insolvent, on a set of bank specific and macroeconomic explanatory variables necessary to reflect both the economic events and regulatory or governance issues. The authors find that size is inversely related to the likelihood of a crisis in an Islamic bank. This is opposite to what literature has found for conventional banks where size seems to affect positively survival (Demirgüç-Kunt and Detragiache 1998; Maecher *et al.* 2005). The finding is plausibly attributed to the problems faced by Islamic banks due to the lack of standardization in products and procedures. As contracts need to be redesigned from scratch and be tailored specifically to each client, operational risk is significant. Moreover larger banks are more likely to be involved in profit-and-loss sharing which is riskier than the non-PLS contracts (*e.g.* Murabahah, Ijarah) used by small banks[35]. With regards to conventional banking, the authors find small Islamic banks to be less likely to face insolvency than small conventional ones. However when bank size gets bigger, the situation is reversed. The rest of the results comply with the rest of the literature with increases in loan-to-assets and cost-to-income ratios leading to increased banking fragility. Income diversity and bank size (which is likely to be biased by the high proportion of conventional banks in the sample) tend to decrease the likelihood of banking failure when they increase. Last but not least better governance would lead to higher z-scores, hence higher survival probability (Maechler *et al.* 2005; Evrensel 2008).

In this subsection we reviewed some of the reasons put forward about Islamic banks being less affected compared to conventional ones by financial crises. Next we will be introducing the survival analysis methodology that we will be using to assess whether the aforementioned arguments can be verified empirically.

3.3 Methodology

In this section we outline the survival analysis methodology we will be using. We start by comparing survival analysis with linear regression. Then we summarize the key characteristics of non-parametric (Kaplan-Meier), semi-parametric (Cox model) and parametric

35 The authors use arbitrarily a cut-off value of $1 billion assets.

ways of implementing survival analysis. Moreover some basic concepts referring to data organization are presented, like censoring, different explanatory variables that could be included and "ties". Finally we describe the robust standard errors and the model selection methodology.

In survival analysis the time to the occurrence of an event is analyzed. Time is usually measured in years, months, days but can have any measurement unit. The event monitored varies depending on the area of research; it could be related to engineering, the time until a piece of machinery fails, to medicine, the time until a patient infected by some disease dies or economics, the time until a firm goes bankrupt. The event needs not be a failure, although it is very common in the literature to refer to the time to an event as "time to failure". There are studies where the event is the employment of an individual (Yamaguchi 1992).

3.3.1 Survival Analysis and Linear Regression

Survival analysis estimates the instantaneous rate of failure (force of mortality or hazard function) subject to time and a set of explanatory variables affecting the subject's history. Suppose we have the following dataset (Table 2) where $time$ measures the time till the occurrence of an event and x is an explanatory variable (covariate) (Cleaves *et al.* 2010).

[Table 2 here]

A linear regression model would be of the following forms:

$$
\begin{aligned}
time_j &= \beta_0 + \beta_1 x_j + \varepsilon_j \quad \varepsilon_j \tilde{} N(0, \sigma^2) && (3.1) \\
\ln(time_j) &= \beta_0 + \beta_1 x_j + \varepsilon_j \quad \varepsilon_j \tilde{} N(0, \sigma^2) && (3.2)
\end{aligned}
$$

There are however problems if linear regression is applied in a survival analysis context. The most important problem is that the residuals are assumed to follow the normal distribution. However, there are many cases in survival analysis context that we need to assume that subjects might face constant hazard (risk of an event occurring) or that hazard can be bimodal. For instance, after having a heart transplant the patient might die very shortly after the operation or some days later. Although linear regression is known to be robust to small deviations from normality, it is not safe to assume that the deviations inherent in a survival analysis context fall in this category as they can be very asymmetric or multi-modal.

Other problems rendering linear regression unsuitable exist but they can be circumvented. The fact that time to failure cannot be negative is not in line with the normal distribution. Censoring is very frequently encountered in survival analysis. Linear regression models can be modified to handle such problems with tobit models being the most widely used. The following two subsections give a more detailed presentation of censoring, a problem unique to survival analysis, and different explanatory variables that can be used within survival analysis. Thirdly, survival analysis assumes the probability of failure is not constant over time, as such it is preferred to logit models (Männasoo and Mayes 2009).

3.3.2 Censoring

Censoring is a form of missing data problem that arises in survival analysis studies. It is observed because we cannot run an experiment starting at $t = 0$ at the birth of a new subject (a living organism, a firm, one's employment) and wait until the subject fails because of the unknown time the experiment would take, the fact that a failure may not occur and even if we run the experiment the results would be outdated by the time the experiment ended. Hence we choose to run an experiment for a pre-specified time and this causes various types of censoring.

Right censoring happens because some subjects do not fail within the time bounds of the experiment. An independent right-censoring method ensures that the failure rates applicable to the observed subjects are the same if right-censoring did not exist in the data. In other words, the hazard conditional on the process hazard at time t should only depend on survival to time t.

Left censoring occurs when the subjects start date is not observed. Patients may only be diagnosed for AIDS after their annual exams which cannot tell us exactly how many days is the patient sick. A bank is in existence for some time before the sample period. In the same sense if we are modelling the survival of a bank according to its age and do not have the necessary financial statement going back to $t = 0$ when the bank was founded, we could use the first of the available financial statements from, say $t = 10$, in which case left censoring arises.

Other forms of censoring exist like (the combination of right and left censoring) *interval censoring* meaning that failure time falls within some time frame rather than a specific date. *Random censoring* occurs if a subject leaves the experiment not by the exit we are currently studying. For instance, an insurance policy holder may cancel his policy without dying. A bank may be "lost" from the database for reasons other than failure, for example the bank may choose to stop publishing its accounts with Bankscope or any other database. However there can be other causes of random censoring. Subjects may move away from the study area for various reasons (students may leave their current school as they changed house, or an investment bank may be forced to work as a commercial bank thus leaving the group of investment banks that the researcher was monitoring. Subjects facing deteriorating or improving condition may move to a different category (patients with AIDS in the monitoring room with certain characteristics may deteriorate; thus moving to emergencies or improve; thus leaving the hospital, banks may move from a high growth category to a low growth one. Random censoring can be informative, when the subjects that moved away from the experiment, may have some effect on the survival time (AIDS positive individuals being studied and some are imported in the hospital as ill) or non-informative when subjects leaving are independent of life time; thus not introducing bias to the results. *Type I censoring* occurs when all the subjects will be censored at a specific time known in advance. An application could be to pension schemes where individuals retire at 65 years of service. *Type II censoring* occurs when the experiment will go on until a certain number of failures has been achieved. Applications of this type of censoring are largely found in the industry where machinery (*e.g.* motors) is tested until a certain proportion has failed (Nelson and Hahn 1972). Table 3 summarizes all types of censoring[36].

[36] As survival analysis was primarily designed for medical and engineering experiments some types of censoring are hard to to be found in economics context. For example Type II censoring is hard to imagine

[Table 3 here]

For studies involving banks and our study in particular right censoring is the most relevant. Banks that are right censored are those that have survived till the end of the experiment and we cannot observe what happens after that time. The way we deal with this problem involves using a dummy variable for every period that takes the value of 1 when the bank fails and 0 when the bank has survived that particular time period. Once a bank has been classified as failed (state 1), it stops from being monitored and cannot return to the pool with the survived banks (state 0). Because only banks identified by the dummy variable are the ones that actually failed, the analysis is not biased. This approach has been used extensively to deal with this problem in the literature (Hermosillo *et al.* 1996; Dabos and Escudero 2004).

3.3.3 Explanatory Variables

The most basic survival analysis approach is the non-parametric which makes use of the Kaplan Meier estimators of survival rate. It is a mechanical process that estimates the survival function from a pool of observations where failures occur. The formulae describing the Kaplan-Meier estimator are introduced formally in a later paragraph. One drawback of a non-parametric estimator is that it does not take into account various characteristics of the sample. So if we carry out the same experiment again by simply changing the sample, results can be completely different. The cause of this is that non-parametric estimators do not incorporate variables that allow us to categorize a sample. For instance, we might

in a bank failure example as typically firms and banks fail once. However, a situation where the event is an agent being fired (or hired) can be subject to Type II censoring.

want to examine separately males from females only, commercial from investment banks or firms with more than 1 million in assets. Variables like these are known as explanatory variables or covariates in the survival analysis context and have a dual role. First they are used as categorical variables to separate the sample into different and mutually exclusive categories (strata). Secondly they are used as explanatory variables when a model is fitted. Covariates are split into three categories according to what data they represent and into two categories according to how many times their values are recorded during an experiment. Hence we can have:

- A direct quantitative measure (age, weight, assets, loans, return on assets)
- A dummy variable indicating two different and mutually exclusive categories (sex, smoker, member of EU, Islamic bank)
- A dummy variable indicating more than two different and mutually exclusive categories. This is used to give some quantitative representation on qualitative data and the number of states is chosen arbitrarily. (mg of dosage taking 5 different values, GDP growth of country taking 6 different values)

Covariates are also categorized as:

- Time independent, where their value is recorded once, usually before the start of the experiment, and does not change until the end of the experiment

- Time varying, where for every period of the experiment we have a new value for every observed variable. Time varying covariates can be further split into external and internal
  - External are the covariates that affect the time to failure but they are not affected by failure occurrences. They can be classified as fixed, where their value is measured in before the experiment starts and does not change for its duration and are practically the same as time independent covariates; defined, when the future evolution of the variable is known to the researcher a possible application being a temperature factor that varies in a predetermined way to assess its impact on machinery; ancillary, where the future evolution of the variable follows a stochastic process and is not affected by the experiment.
  - Internal covariates are the covariates that the subject generates while under study. Their values can carry information useful to predict the time of failure and in many cases after the subject has failed, it is not possible to obtain information on them. The essential difference from defined or ancillary external covariates is that internal covariates can affect and be affected by the failure time.

3.3.4 Parametric Models

We mentioned previously that the distribution of the residuals cannot be assumed to be normal. Parametric survival analysis requires imposing a certain distribution on the residuals which can be done in two formations; the Proportional Hazards (PH) formation and the

Accelerated Failure Time (AFT) or log-time metric. The linear regression (1) introduced in a previous paragraph can be rewritten as follows:

$$h_j(t) = h_0(t)\exp(\beta_0 + x_j\beta_x) \tag{3.3}$$

$$\ln(t_j) = x_j\beta_x + \varepsilon_j \tag{3.4}$$

Equation 3 is known as the PH formation. The distributional assumption we impose on the error term of the residual in equation 1 is now embedded within the baseline hazard function $h_0(t)$. The proportional hazards terminology refers to the fact that the hazard faced by the subject is multiplicative to the baseline hazard. In parametric survival models we can fit a positive function for $h_0(t)$ that describes out data in the best way. Some of the most commonly used distributions are presented below alongside with their baseline hazard functions, their instantaneous and cumulative hazard functions and their survival functions:

[Table 4 here]

Once the appropriate distribution is selected, the coefficients of the covariates can be estimated. A positive coefficient shows that an increase on the covariate leads to higher survival rate, hence lower hazard for the subject. By contrast, a negative coefficient shows that an increase on the covariate means that survival rate is lowered, hence the subject faces higher hazard. When a distribution with more than one parameter is selected, for instance the Weibull has a scale and a shape parameter (p), the covariates are used to model the scale parameter while the shape parameter is assumed to be constant. However, we can choose to model the shape parameter in the case we have evidence that the shape of the hazard function might be different for two groups of observations (*e.g.* gender, bank type). In other words we allow the baseline survivor function to be different in the groups we have specified. This is referred to as a stratified model. Extending the notion of creating separate groups from the full sample based on some identification variable, we have the shared frailty concept. Shared frailty is the equivalent of random effects on a survival model. Shared frailty is an unobserved factor that causes observations within groups to be correlated. In other words, these subjects will be facing an additional source of risk (*e.g.* some random-effect) whose variance can be estimated from the data and measures the extent of different frailty quantities in the groups . The frailty for each group is usually assumed to follow a gamma or inverse-Gaussian distribution and is described by equation 5 where denotes the groups and the observations within a group.

$$h_j(t) = \alpha_i h_{ij}(t) \tag{3.5}$$

In the accelerated time formation (equation 4) the distribution assumption is embedded in the quantity:

$$\ln(\tau_j) = \exp(-x_j \beta_x) t_j \tag{3.6}$$

Equation 6 is then used to substitute the residual term in equation 4 giving equation 7:

$$\ln(t_j) = x_j \beta_x + \ln(\tau_j) \tag{3.7}$$

Depending on the values the acceleration parameter, $exp(-x_j\beta_x)$, takes we identify three cases:

- $exp(-x_j\beta_x) > 1 \Leftrightarrow \tau_j > t_j$: Failure of the subject is expected to occur sooner, as time for the subject is accelerated.
- $exp(-x_j\beta_x) < 1 \Leftrightarrow \tau_j < t_j$: Failure of the subject is expected to occur later, as time for the subject is decelerated.
- $exp(-x_j\beta_x) = 1 \Leftrightarrow \tau_j = t_j$: Time for the subject passes at its normal rate.

Hence in the equation 6, the distribution of $\ln(\tau_j)$ is restricted to follow a certain distribution. Some of the most commonly used are the gamma, the log-normal and the log-logistic. Interpretation of the coefficients for an accelerated failure time model states that an increase in the covariate having a positive coefficient leads to increased time to failure, which is equivalent to decreased hazard rate.

Conversely to PH formation, the AFT gives more weight to the analysis time. This formation is preferable when predictions of failure time are our priority. However, there is a problem associated with this approach. The problem relates to the use of time-varying covariates in conjunction with failure time predictions. In essence we are calculating $E(\ln(t_j|x_j)$ for different values of x_j. Given that different values of x_j are only available for the recorded observations and timings there is no way of obtaining the values in intermediate times or times outside those observed. For instance we might have: $t = 1; x = 5.2$ and $t = 2; x = 4.9$. Assigning a value for x at $t = 3$ is required to predict the time to failure, however this requires some assumptions to be made. Should we assume that the quantity measured by x continues to drop? And what rate would that be?

Due to the problem mentioned above as well as our desire to maintain as much comparability of our results with other approaches we opt for the PH formation of parametric models.

3.3.5 Semi-Parametric Models

Parametric models can be problematic when an inappropriate distribution for the data is selected. An alternative would be to remove any assumptions we impose on the time to failure by focusing instead on the ordering of the events. Going back to the sample dataset of table 2, suppose that the first failure in our dataset has occurred, and we want to calculate the probability of failure after being at risk for $time = 1$, which leads to an application of logistic regression. In fact we could have chosen to analyze the second event, that is at $time = 5$ or the third at $time = 9$. Nevertheless, by not selecting the first we are missing some information due to the observations we are not considering. Semi-parametric models and Cox (1972) in particular proposed a solution that overcomes this selection problem by fitting a conditional logistic model, conditioned on the fact that only one observation fails in each analysis. The analysis is repeated for every failure time and the results are combined (Cleves *et al.* 2010). The benefit is that the combination of the analyses imposes no assumption on the distribution of failure times, indeed time is only used to order the observations. Therefore time is not parameterized, but the covariates are. Hence the method falls under the category of semi-parametric models of survival analysis.

The Cox (1972) model is the most popular choice of semi-parametric models and its hazard function is defined as:

$$h_j(t) = h_{0(t)} \exp(x_j \beta_x) \tag{3.8}$$

Where $h_0(t)$ is the baseline hazard function which in the case of semi-parametric models is not assumed to follow any distribution. Nevertheless, all subjects are required to have the same baseline hazard function. The reason why we do not parameterize the baseline hazard function is that it drops out from further calculations since our analysis is confined only to times when failures occur. To realize how this is the case, we use the data of table 5 to demonstrate the analysis.

[Table 5 here]

Suppose that at time $t = 9$ only subjects $3, 4, 5$ survive and subject 3 fails. Using the hazard equation 8 we get:

$$h_3(t = 9) = h_0(9) \exp(\beta_0 + 4\beta_x) \tag{3.9}$$

$$h_4(t = 9) = h_0(9) \exp(\beta_0 + 9\beta_x) \tag{3.10}$$

$$h_5(t = 9) = h_0(9) \exp(\beta_0 + 10\beta_x) \tag{3.11}$$

Since only one failure occurs at $time = 9$, the probability that subject 3 has failed is:

$$\Pr(3\ fails|failure) = \frac{h_3(9)}{h_3(9)+h_4(9)+h_5(9)} = \tag{12}$$

$$= \frac{h_0(9)\exp(\beta_0+4\beta_x)}{h_0(9)\exp(\beta_0+4\beta_x)+h_0(9)\exp(\beta_0+9\beta_x)+h_0(9)\exp(\beta_0+10\beta_x)} = \tag{13}$$

$$= \frac{\exp(4\beta_x)}{\exp(4\beta_x)+\exp(9\beta_x)+\exp(10\beta_x)} \tag{14}$$

Hence, the baseline hazard function has dropped out.

3.3.6 Ties

A shortcoming of the semi-parametric model coming from the fact that only failures times enter the estimation procedure is that two or more failures can occur at the same time. Consequently we cannot be sure which subject failed first and this can affect the estimates. To deal with the problem there are four approaches; the marginal and the partial calculations as well as two approximations; the Breslow (1974) and Efron (1977). The marginal approach assumes that because time is continuous, ties do not really exist, consequently some subjects failed earlier than others. However we do not know the exact ordering of the events, hence this approach assumes that we can calculate the probabilities for all possible orderings of the events and use this sum for further calculations. Suppose we have 5 subjects $(n_1, n_2, n_3, n_4, n_5)$ and at time $t = 1$ two failures are recorded (n_2, n_3) we do not know whether n_2 failed out of a sample of 4 subjects (n_1, n_3, n_4, n_5) or 3 subjects (n_1, n_4, n_5). A drawback of this method is the computational time required if there is a large number of events within a period. For instance, if we have 5 failures in a year, all possible orderings are $5! = 120$. The partial approach is similar to the marginal but it assumes that the subjects fail at the same time and this is not down to incorrect measurement of time but because we are assuming time is discrete. Consequently the calculated conditional probabilities will be altered to accommodate that. These methods do not deviate much from one another, they do however pose calculation difficulties in case of big samples or many tied events; hence two approximations are most commonly used. Breslow (1974) uses the largest pool of data as we do not know the precise ordering of the events. Hence in our previous example subjects (n_2, n_3) both failed from the pool of $(n_1, n_2, n_3, n_4, n_5)$. This is the faster method but if ties are many, it will give misleading results. The Efron (1977) approach assumes that the first (arbitrarily) subject failed from the pool $(n_1, n_2, n_3, n_4, n_5)$ while the second either from the pool (n_1, n_3, n_4, n_5) or (n_1, n_2, n_4, n_5). Hence there is 50% probability of n_2 and n_3 to be in the second pool. So $0.5 \times (n_2+n_3)+n_1+n_4+n_5$. Efron's approach is more accurate but more time consuming than the Breslow. We are using the Efron's approximation as it is the best of compromise between accuracy and time.

3.3.7 Extensions to the Cox PH model

Strata and Frailty

The baseline hazard function can be different among subgroups of the full sample while the estimated coefficients remain the same. In other words, every subgroup is allowed to have its unique shape of a baseline hazard function upon which the covariates act. Different models for every subgroup also allow for different shapes of the baseline hazard functions but they give different coefficient estimates at the same time. In that way the stratified Cox PH model is a more efficient way when we are not concerned about how different variables affect different groups but we are looking for a single, efficient estimate (Cleves *et al.* 2010). Provided that the hazards of the groups are proportional, then the estimates of the two methods, stratified Cox as opposed to a model with an indicator variable for every group, would give very similar results. The greater the deviation among the results, the more likely the hazard is not proportional at which case the stratified model should be preferred (Cleves *et al.* 2010). Strata can be defined by a single dummy variable or by a categorical variable to identify more than two strata. The Stratified Cox model is used to identify groups.

$$h_j(t) = h_{0,i}(t)\exp(x_j\beta_x) \tag{3.15}$$

Shared frailty can also be applied to the Cox PH model to account for increased correlation within a subgroup of observations. Equation 4.10 is the Cox PH model with shared frailty:

$$h_{ij}(t) = h_0(t)\alpha_i\exp(x_{ij}\beta_x) \tag{3.16}$$

Which can also be written as:

$$h_{ij}(t) = h_0(t)\exp(x_{ij}\beta_x + \nu_i) \tag{3.17}$$

A use of the shared frailty model is to identify omitted variables at which case the estimated variance (θ) will be significant. This is because the omitted variable might be a source of unobserved heterogeneity that is captured by the frailty model; however once accounted for, the frailty term will lose its significance. Given that the group effect is directly incorporated in the hazard function, we can obtain estimates of the α_i or ν_i the of every group and since we can get an estimate of the least frail and frailest group. In terms of interpretation, the highest the value of the , the higher the hazard for the group.

$$\nu_i < 0 \Longleftrightarrow \alpha_i < 1 \Longleftrightarrow hazard \downarrow \tag{3.18}$$

$$\nu_i > 0 \Longleftrightarrow \alpha_i > 1 \Longleftrightarrow hazard \uparrow \tag{3.19}$$

Testing the Proportional Hazards Assumption

The proportional hazards assumption states that the effect of the covariates does not change over time. In other words the interaction of analysis time with covariates should have no explanatory power if included in the model. The ways of testing the validity of this assumption can be divided into two categories; the first requires additional models to be estimated so that the interaction between analysis time and the covariates is incorporated in the model. If these variables turn out to be statistically insignificant then we can conclude that the proportional hazards assumption is not violated as it would mean that the effects do not change in ways besides the ones we have already accounted for. The second way involves the use of the scaled Schoenfeld (1982) residuals from the original estimation and test whether they are have a statistically significant relationship with some specified function of time. The statistical test is essentially a test of a non-zero slope of the fitted line on residuals (Grambsch and Therneau 1994).

If we define an explanatory variable x_u with $u = 1,..,k$ and j observations with $j = 1, \ldots, n$ then the Schoenfeld residual is defined, at the time when a subject has failed

$j = 1$, as the difference between the covariate value for the subject that failed and the weighted covariate average of the non-failed (at-risk) subjects.

$$r_{u,j} = x_{u,j} - \frac{\sum_{j=1}^{n} x_{u,j} \exp(x_j \hat{\beta}_x)}{\sum_{j=1}^{n} \exp(x_j \hat{\beta}_x)} \tag{3.20}$$

If the coefficient on x_u does not vary with time, as the proportional hazards assumption requires, then $q_j = 0$ and time, expressed as a function $g(t)$, does not have an impact.

$$\beta_u(t) = \beta_u + q_j g(t) \tag{3.21}$$

It can be shown (Grambsch and Thernau 1994)that the Schoenfeld residuals can be scaled and re-arrange the previous equation into:

$$E(r^*_{u,j}) + \beta_u = \beta_u(t) \tag{3.22}$$

Where $r^*_{u,j}$ is the scaled Schoenfeld residual. Consequently plotting $r^*_{u,j}$ versus time would lead to a graphical assessment of the proportional hazards assumption where the latter will hold if the slope of the best fit line is zero. A formal statistical test of zero slope can also be performed the null hypothesis being $H_0 : q_j = 0$

Time-Varying Covariates – The Extended Cox Model

The proportional hazards assumption is a way of verifying whether measuring covariates one time for the experiment is adequate. If there is not supportive evidence of the PH assumption then the extended Cox should be used. The extended Cox allows for time-varying covariates, thus allowing multiple values of the covariates, obtained at different times, to be used in the analysis. The equation giving the instantaneous hazard rate is given in the equation below where is the time index indicating that covariates vary with respect to time:

$$h_j(t) = h_0(t)\exp(x_{j,t}\beta_x) \tag{3.23}$$

Time-varying covariates can be combined with strata and shared frailty. However there might be some additional reasons to why an extended Cox model should be used even when the proportional hazards assumption is not violated. First of all the proportional hazards assumption says nothing about other variables that are not included in the model. An explanatory variable might be insignificant in capturing banks' failure dynamics in one year but in subsequent years the variable might become significant. Hence moving from a proportional hazards Cox model to an extended Cox could lead to the inclusion of certain variables that otherwise would have been rejected.

Secondly while both methods are an ex-ante way of modelling survival rates, in a long time frame (*e.g.* four years) deviations within a variable will always be monitored by a small lag (which is going to be the examination period selected by the researcher (*e.g.* years, months etc) using the extended Cox. By contrast, a proportional hazards Cox model will ignore completely these deviations.

Thirdly estimated coefficients from the extended Cox model are likely to correct for any bias that the Cox proportional hazards might introduce. To clarify the point made above, suppose that 15% of the banks that are included in the sample fail in the first year whereas in each of the subsequent years the failure ratio is much smaller. Using a proportional hazards model will introduce upward bias in this case as the variables will be measured just before the failure of 15% of banks; therefore the hazard ratios will be greater than what they should be as the model implies that this high ratio of failures will be repeated in the rest of the examined period. By contrast an extended Cox model will be taking measurements of variables at the intervals specified; hence the coefficients will be adjusted for any bias.

Interpretation of Coefficients

Inspecting again the Cox PH model, equation 8 repeated here for convenience, we can have two alternative formulations of the estimated coefficients; the first being the linear and the second the exponential. In survival analysis we refer to the first as "coefficient" and the second as "hazard ratio".

$$h_j(t) = \exp(x_j \beta_x) \tag{3.24}$$

The coefficient (β_x) makes discrimination between two variables, one increasing the risk of a subject and the other decreasing it, easier as the first would have a positive sign and the second a negative sign. To convert to hazard ratios we need to take the exponential of the coefficient $e^{\beta} = HR$. Now the variable that decreases the risk of an event has a hazard rate lower than 1. Conversely, the variable increasing the risk has a higher than 1 hazard ratio. The advantage of this formulation is that we get an estimate of how much the risk of an event will decrease (or increase) by a 1-unit change in the explanatory variable. To give an example we assume that we are interested to measure the impact of weight (in kilos), sex and doctor's fee (in hundred pounds) in the hazard of an event (death) happening after an operation. Suppose the model is estimated and the following results are obtained:

[Table 6 here]

A rise by 1-unit (1 kilo) in the patient's weight leads to a 20.30% rise in the risk of an event ($e^{0.185} = 1.203$). By the same token, a rise by 1-unit (100 pounds) in the doctor's fee leads to a 57.00% decrease in the hazard of an event occurring. Lastly, females face a hazard 42.50% lesser than males. The coefficient has another significant attribute as it allows us to scale the results for use with another measurement scale. Suppose that we want the weight to be measured in pounds rather than kilos. Knowing that $1\,\mathrm{kg} = 2.2\,\mathrm{lb}$ we can obtain the new coefficient expressed in pounds simply by dividing $0.185/2.2 = 0.084$ and then the new hazard ratio is $e^{0.084} = 1.087$ which means that a rise in the patient's weight by 1 pound (0.45 kilos) increases the hazard faced by the patient by 8.70%

Diagnostic Tests

The goodness of fit of the Cox PH model can be assessed using the Cox-Snell (1968) residuals. The model fits the data well if the plotted cumulative hazard of the Cox-Snell residuals approximates a line with slope of one (Cleaves *et al.* 2008). Nevertheless, this measure's effectiveness is reduced as the ratio of failures in the sample increases; thus some variability around the diagonal line is expected as analysis time increases.

Besides goodness of fit tests, additional checks for outliers and highly influential points can be done. The approach followed is to compare the estimated coefficient $\hat{\beta}_x$ from the full model to the coefficient obtained after an observation j (the outlier or assumed outlier) is removed from the sample and the model is re-estimated yielding $\hat{\beta}_x^{(j)}$. If the difference $\hat{\beta}_x^{(j)} - \hat{\beta}_x$ is close to zero then the observation is not considered to be an outlier. However, this approach has the disadvantage of having to repeat the process $k(n-1)$ times, where n is the number of observations and k the number of covariates. Moreover, discrepancies might appear as an observation might be classified as an outlier when one covariate is examined and not as an outlier for another covariate. An alternative that reduces calculations is to use $\mathbf{D} \times \mathbf{V}(\hat{\beta}_x)$ where $\mathbf{D}$ is a matrix containing the efficient score residuals and $\mathbf{V}$ is the variance-covariance matrix of the estimated coefficients. This way we get k different outcomes. Another alternative is to explore the impact on the model of several observations including all covariates. This can be achieved by using either the likelihood displacement values or the LMAX scores (Colletti 2003). The likelihood displacement value for subject is given by:

$$2[\log L(\hat{\beta}_x) - \log L(\hat{\beta}_x^{(j)})] \tag{3.25}$$

The value $L(\cdot)$ is the partial likelihood from fitting the Cox PH model. If there is large discrepancy between the two coefficient vectors then the observation is identified as influential. LMAX works in a similar way but it is making use of the efficient score residuals ($\mathbf{D}$) and the variance-covariance matrix of the estimated coefficients (Cleaves *et al.* 2008). LMAX represents absolute values of a B matrix, where:

$$B = \mathbf{D} \times \mathbf{V}(\hat{\beta}_x) \times \mathbf{D}' \tag{3.26}$$

The largest values in the B matrix correspond to the most influential observations. Outliers and influential points in survival analysis should not be removed from the sample before their attributes are checked. Influential points might turn out to be the subjects that have failed; hence they should be kept in the analysis.

Parametric and Semi-Parametric Models: A Comparison

The semi-parametric approach is a combination of separate binary outcomes as we are combining individual analyses that occurred exactly at the times when an event was recorded. For instance in our example the first two analyses would be:

$$\Pr(failure|time = 1) \tag{3.27}$$

$$\Pr(failure|time = 5) \tag{3.28}$$

A way to increase the efficiency of our estimates, by decreasing the standard errors, is to include more analyses. For instance:

$$\Pr(failure|time = 1.1) \tag{3.29}$$

$$\Pr(failure|time = 1.2) \tag{3.30}$$

However, doing this implies some assumptions about the distribution of time to failure which is only the case in the parametric approach. Due to this fact, the parametric approach is entirely different to the semi-parametric. The fact that no failures are observed at a time interval is informative for parametric analysis but not for semi-parametric analysis. Suppose the following profile of a subject where time is measured in a certain unit, x is a covariate and outcome takes the value of 1 when the subject fails:

[Table 7 here]

If this is the only subject in the experiment, then the rise in the value of the covariate between $time = 1$ and $time = 2$ will have no effect in the case of semi-parametric approach as no failure has occurred in that interval. If the rise had not taken place the result would have been the same. By contrast, in parametric analysis this rise will be informative as with this approach all data points up to the failure are taken into account. If our assumption is that higher values of x lead to higher failure rates, then under parametric approach we can argue that the effect of the covariate might not be as strong as we assumed ex ante since the subject managed to survive its rise. The semi-parametric approach would have ignored completely the rise in the covariate value, unless failures of other subjects had been recorded at that interval, thus being more inefficient.

Another drawback of semi-parametric models as opposed to parametric ones is that the former require the observation of the subjects to overlap each other. If the first and only subject in our pool fails before the second comes under investigation then the semi-parametric approach cannot be used as it only takes into account the timing of the failures and not the time passed between them (Cleves *et al.* 2002).

Non-Parametric Models

Semi-parametric models sacrifice some of the efficiency in favour of less distribution assumptions. However, under semi-parametric models the assumptions on the way covariates affect the survival probability are not relaxed. Non-parametric models are a way of loosening the restrictions even further. Non-parametric regressions using splines or local polynomial regressions cannot deal effectively with censoring which is present in survival analysis data (Cleves *et al.* 2002; Kaplan and Meier 1958; Nelson 1972; Aalen 1978) proposed ways of estimating the survival probability when no covariates are included, or the covariates used are qualitative and are used to distinguish between homogeneous subgroups (*e.g.* gender, age, bank type).

The Kaplan and Meier (1958)estimator calculates the probability of survival after some time and it is given by:

$$\hat{S}_{(t)} = \prod\nolimits_{j|t_j \leq t} (\frac{n_j - d_j}{n_j}) \tag{3.31}$$

Where n_j is the number of subjects at risk and d_j the number of subjects that have failed up till time t_j. By contrast, the Nelson (1972)and Aalen (1978)estimator is a formula for the empirical cumulative hazard function given by:

$$\hat{H}_{(t)} = \sum\nolimits_{j|t_j \leq t} \frac{d_j}{n_j} \tag{3.32}$$

Where n_j and d_j follow the same definition as above. The two estimators are linked via the equation given below:

$$\hat{S}_{(t)} = e^{-\hat{H}_{(t)}} \tag{3.33}$$

According to Klein and Moeschberger (2003) the two estimators are consistent. However for small samples the Kaplan and Meier gives superior estimates for the survival function while the Nelson-Aalen should be preferred for the cumulative hazard function (Cleaves *et al.* 2008).

After the survival functions have been estimated, statistical tests can be used to test if they are different across two or more groups. Most approaches available rely on the rank test methodology but differ on the weights they assign to observations. The rank methodology assumes there are $i = 1, \ldots, r$ groups and k distinct failure times (t_i). At each failure time (t_i) a matrix can be created to tabulate the subjects at risk (n_{ij}), the failed (d_{ij}) and the survived $(n_{ij} - d_{ij})$ for every group. The matrix would look like the following:

[Table 8 here]

The whole duration of the experiment is taken into account with the rank tests rather than comparing the functions at a distinct time. Under the null hypothesis that the survival functions of the groups are the same; hence at time t_j we only need to know the number of failures for group A, (d_{Aj}), and the number of subjects at risk for the two groups (n_{1j}, n_{2j}) to calculate the conditional probability:

$$\Pr(d_{Aj}|d_j, n_{1j}, n_{2j}) = \frac{\binom{n_{Aj}}{d_{Aj}} p^{d_{Aj}}(1-p)^{n_{Aj}-d_{Aj}} \times \binom{n_{Bj}}{d_{Bj}} p^{d_{Bj}}(1-p)^{n_{Bj}-d_{Bj}}}{\binom{n_j}{d_j} p^{d_j}(1-p)^{n_j-d_j}} \tag{3.34}$$

$$= \frac{\binom{n_{Aj}}{d_{Aj}} \times \binom{n_{Bj}}{d_{Bj}}}{\binom{n_j}{d_j}} \tag{3.35}$$

Because d_{Aj} follows a hypergeometric distribution it can be shown that the expected number of failures in group i is:

$$E_{ij} = \frac{n_{ij} d_j}{n_j} \tag{3.36}$$

The hypothesis test is based on the chi-squared distribution with $r - 1$ degrees of freedom. The test statistic is calculated as $\mathbf{u}'\mathbf{V}^{-1}\mathbf{u}$ with $\mathbf{u}$ and $\mathbf{V}$ defined as:

$$\mathbf{u}' = \sum\nolimits_{j=1}^{k} W(t_j)(d_{Aj} - E_{Aj}, ..., d_{rj} - E_{rj}) \tag{3.37}$$

$$\mathbf{V}_{il} = \sum\nolimits_{j=1}^{k} \frac{W^2(t_j) n_{ij} d_j (n_j - d_j)}{n_j(n_j - 1)} (\delta_{il} - \frac{n_{ij}}{n_j}) \tag{3.38}$$

where $W(t_j)$ is the weight function; $i = 1, ..., r$ and $l = 1, ..., r$ while the following restrictions $\delta_{il} = 1 \forall i = l$ and $\delta_{il} = 0 \forall i \neq l$ also hold.

According to the specification of the test, a different weighting scheme is selected. The log-rank test, which is an extension of the Mantel-Haenszel (1959) test, assumes that $W(t_j) = 1$. The log-rank test is used when the hazards differ in a proportional way as it is the most powerful (Cleves *et al.* 2007). By contrast, when hazard are expected to differ in a non-proportional way, two variations of the Wilcoxon test are considered more appropriate. The Breslow (1970) and Gehan (1965) version of the Wilcoxon assumes that the weighting is equal to the number of subjects at risk at every point in time, $W(t_j) = n_j$. The advantage of the Wilcoxon test is that it does not assume that the hazards differ at a proportional way. The drawbacks are that it can be it's not clear that a single group has higher hazard or in other words if the hazard functions are crossing. Another issue is that the weighting scheme assumes that as the experiment evolves the number of subjects at risk decreases; consequently the earlier observations carry a bigger weight. However the weighting scheme will be influenced by the rate of delayed entries in the experiment. Another specification of the Wilcoxon test is the one proposed by Tarone and Ware (1977) where $W(t_j) = \sqrt{n_j}$ which can be thought of as a mid-point between the equally-weighted log-rank and the early weighted Wilcoxon of Gehan and Breslow. The Peto-Peto-Prentice test uses an estimate of the overall survivor function as a weight (Peto and Peto 1972; Prentice 1978). The weight is given as $W(t_j) = \tilde{S}(t_j)$ where the estimate of the survivor function is similar to the Kaplan-Meier estimator. Finally the Fleming-Harrington (1982) test assumes that the weight function is:

$$W(t_j) = \{\tilde{S}(t_j)\}^p\{1 - \tilde{S}(t_j)\}^q \tag{3.39}$$

$\tilde{S}(t_j)$ is the Kaplan-Meier estimator and p, q are positive numbers used to control the weighting scheme with respect to time. When $p > q$ more weight is given to earlier failure times; when $p < q$ more weight is given to later failure times. When $p = q = 0$ the test collapses to the log-rank.

Robust Standard Errors and Model Selection

In the Ordinary Least Squares estimator the squared residuals are summed while in the robust estimators (unclustered and clustered) the residuals are multiplied by the predictors then squared and summed. For clustered robust errors the summation takes place within each cluster. Under the OLS assumptions correlation between explanatory variables and residuals should be zero $corr(x_i, e_i) = 0$ If not then the robust estimator would provide a better estimate of the variance of the coefficients as the OLS estimator would be overestimating (or underestimating depending on the nature of correlation) the variances. In the case of sampling for survival analysis, we have sampled the subjects we are interested in (banks in this case) but we believe that a bank failure in a certain country is more likely to increase the probability of another bank failing in the same country. In other words, correlation on failure times might be observed for banks within a country. The clustered estimator provides a more precise estimate without making any model assumptions about the underlying correlation process. Stated differently, the clustered estimator not only preserves the panel nature of the data, but allows ensures that a high correlation in one sub-panel does not affect the estimates elsewhere.

The OLS variance estimator is given below:

$$V_{OLS} = s^2 \times (X'X)^{-1} \tag{3.40}$$

where:

$$s^2 = \frac{1}{N-k} \times \sum\nolimits_{i=1}^{N} e_i^2 \tag{3.41}$$

The robust (unclustered) variance estimator is given below:

$$V_{ROB} = (X'X)^{-1} \times [\sum\nolimits_{i=1}^{N} (e_i \times x_i)' \times (e_i \times x_i)] \times (X'X)^{-1} \tag{3.42}$$

The robust (clustered) variance estimator is given below:

$$V_{CLU} = (X'X)^{-1} \times [\sum\nolimits_{j=1}^{n_c} u_j' \times u_j] \times (X'X)^{-1} \tag{3.43}$$

where:

$$u_j = \sum_{j=1}^{n_c} e_i \times x_i \tag{3.44}$$

and n_c is the number of clusters, e_i is the residual for the i observation and x_i is a row vector of predictors.

Stepwise selection algorithms can implement a general-to-specific or a specific-to-general approach. In the general-to-specific the algorithm starts with the full model and step by step the insignificant explanatory variables are eliminated. The specific-to-general is the exact opposite. When the number of candidate variables in the model is large there are many different "paths" as removing one variable will affect the significance of the remaining ones. Hence the use of an algorithm that exploits all possible alternative "paths" is necessary. This technique is known as forward and backward elimination and the algorithm's goal is to minimize the specified information criterion (*i.e.* Akaike, Schwarz, Hannan-Quinn). Other methods of assessing each model include the likelihood ratio and the wald tests.

The likelihood ratio test is based on the deviance, which is $-2 \times \log likelihood$ on a fitted model. The lower the deviance is, the better the fit. In the case of two nested models, with the restricted model having less explanatory variables than the unrestricted one, the difference in deviance between the two models is used to construct the likelihood ratio test. The number of covariates (q) dropped from the unrestricted model are the degrees of freedom and the chi-square distribution is used for the test (χ^2_q). The null hypothesis is that the restricted model is better while the alternative is that the unrestricted should be used. If the difference in deviance is higher than the critical value we reject the null; therefore the variable(s) we dropped should be put back into the model.

Alternatively a Wald test could be used to test the joint significance of the variables that are about to be dropped. The null hypothesis that all the selected variables equal zero is tested against the alternative that they are not. If the calculated Wald statistic is higher than the critical chi-square with degrees of freedom equal to the variables in null hypothesis, then the null hypothesis is rejected in favour of the alternative and the variables cannot be dropped.

We adopt a forward-and-backward elimination approach is followed until a satisfactory regressor set is encountered. For each full set of K bank-level (*i.e.*, balance sheet, income statement or financial ratio) variables and macro variables we start by comparing the K regressor and $K-1$ regressor models and one model is retained on the basis of two criteria: insignificance of covariates according to the p-values of individual LR tests, and the models' degrees-of-freedom-adjusted explanatory power as given by the Akaike Information Criterion (AIC). The term forward-and-backward refers to the fact that the algorithm both drops and adds covariates sequentially.

3.4 Data and Variables

Annual accounting data from 1995 to 2010 are obtained from *Bankscope* for 421 banks located in 20 Middle and Far Eastern countries.[37] The sample countries host about 77% of

[37] Bankscope is run by Bureau van Dijk (http://www.bvdep.com/en/index.html). The countries are: Albania (4 CBs/ 1 IB), Bahrain (9/17), Bangladesh (28/2), Brunei (2/3), Egypt (31/2), Indonesia (74/1), Iran (0/15), Jordan (11/2), Kuwait (6/8), Malaysia (35/14), Mauritania (2/1), Pakistan (21/6), Palestine (1/1), Qatar

the total IB industry but have also a large CB sector (excluding Iran, Sudan and Brunei where the IB share is above 50%). A bank is deemed as "failed" when at least one of the following criteria is met: bankruptcy, dissolution, liquidation, negative net worth, state intervention, forced (involuntary) merger, and acquisition (Heffernan 2005). The data pertain to 106 IBs and 315 CBs with 8% and 28% failures in each group, respectively.

The restricted models include an *Islamic Bank Dummy* that equals 1, where the bank operates under Islamic finance law, and 0 otherwise. All other bank-specific covariates are stochastic and represent the three dimensions of the accounting statement: balance sheet, income statement and financial ratios.[38] Financial ratios are subcategorized in four groups (Capital quality, Asset quality, Earnings and Liquidity) following the CAMELS system.[39] The country-level covariates are controls for the macroeconomic conditions and banking sector structural indicators. Table 9 provides a full list of the covariates.

[Table 9 around here]

We consider as potential drivers of failure hazard the firm-level variables listed in Table 1 in levels or logarithmic levels for those that preclude non-positive values, and (log) growth rates. Variables from the balance sheet (stock) and income statement (flow) are inflation-adjusted using the appropriate country GDP deflator.

(6/4), Saudi Arabia (10/3), Sudan (2/8), Tunisia (11/1), Turkey (41/4), United Arab Emirates (UAE;16/9) and Yemen (5/4). We focus on countries where IBs have a non-negligible share of the financial system. Following Cihak and Hesse (2010) we select all the countries where IBs account for more than 1% of total assets in the banking system during at least one year in the observation period. The banks included within each country are dictated by data availability.

38 CBs and IBs are required to follow national and international regulatory requirements under the supervision of the banking authorities of their host country. Both bank types adhere to the same accounting standards. IBs must also abide by the Shariah supervisory board which monitors the compliance of financial products with the Islamic law (Alexakis and Tsikouras, 2009).

39 Variables from the Management and Sensitivity to risk categories are not included due to data unavailability.

The country-level variables are *Growth of Real GDP*, *Inflation*, *Unexpected Inflation*, *Banking Sector Concentration*, *Sovereign Credit Rating*, *FX Rate Depreciation*, *Financial Openness* and *Islamic Bank Share*.

3.4.1 Variable Definitions and Transformations

Income diversity, which is a measure of the diversification of the bank's operations. The higher the *income diversity*, the more diversified the bank is. According to Čihák and Hesse (2010) it is defined as:

$$ID=1-\left|\frac{Net\ Interest\ Revenue\text{-}Other\ Operating\ Income}{Net\ Income}\right| \tag{3.45}$$

Z-score is a measure of bank fragility (Čihák and Hesse 2010) defined as follows. Banks with higher values of *z-score* are considered less prone to insolvency.

$$Z=\frac{\frac{Equity}{Assets}+RoA}{Volatility\ of\ RoA} \tag{3.46}$$

Volatility of RoA is proxied by the standard deviation of the RoA. According to Maechler *et al.* (2007), *return on assets (RoA)* should be used on a moving average basis[40] rather than the current value. We experimented with this approach but found it to underperform compared to the version utilizing the current value of RoA.

Inflation is computed as the year-on-year logarithmic change of the GDP deflator. *Unexpected Inflation* is computed as the difference between forecasted or anticipated in-

[40] A backward moving average is one that in period t averages only periods before time t, that is t-1, t-2, t-3 and so on. By contrast, a centre weighted moving average is one that averages periods equidistant from time t, that is t-2, t-1, t, t+1, t+2 and so on. We opted for the backward as data on t+1 and t+2 are not known in time t (though agents could be using expectations of them that we, however do not have access)

flation of the next period (*i.e.* year) minus the actual inflation that occurred. To estimate the forecasted inflation we fit an ARMA(p, q) model on the inflation series and generate 1-step ahead forecasts for the period of the analysis. The models are fitted with respect to minimize the Bayesian information criterion (BIC)[41]. The rationale for the inclusion of the unexpected inflation is that a high inflation that is forecasted can be incorporated in the contracts of the bank. By contrast, the bank will not be hedged if the actual inflation turns out to be higher than expected. Following Busse *et al.* (2007) and others, our *Banking Sector Concentration* covariate is the Herfindahl-Hirschmann Index (HHI) computed as the sum of squared normalized market shares at year end. As in recent studies, the market share of a bank is calculated according to total assets (Bikker and Haaf 2002; Čihák and Hesse 2010). The HHI measure is bounded by 0 (highest competition) and can take a maximum value of 1 (monopoly). There are two opposing schools of thought on the link between banking sector concentration and stability. One view sustains the "too-big-to-fail" tenet according to which a more highly concentrated (*i.e.* monopolistic) banking environment increases moral hazard and risk-taking behavior. Another view suggests the opposite by the argument that larger profits in more highly concentrated banking sectors lessen the need for excessive risk-taking. *Sovereign Credit Rating* takes a value of 1 for countries with a Standard & Poor's rating BBB^- or better (investment grade), 0.5 for BB^+ or below (non-investment grade), and 0 for not-rated countries using year-end data. A sound economic system with sustainable output growth, low inflation, an appreciating currency and a high credit rating

41 We are using the BIC as it settles for a more parsimonious model than the AIC. In ARIMA methodology using the AIC leads to overfitting whereas the stricter BIC settles for lower order models. In this case the AR(1) model was selected at over 90% of the cases.

is expected to have a favorable influence on bank survival rates. A positive year-on-year logarithmic change in the spot exchange rate, defined as local currency *vis-à-vis* US$, represents currency depreciation. *Financial Openness* is a composite measure capturing the extent of capital controls within a country. We use the Chinn and Ito (2007) measure due to its wide coverage across countries and time. Chinn and Ito (2007) report that their measure is highly correlated with the Quinn (1997) and the IMF's AREAER measures of financial openness that are also widely used in the literature. *Islamic Bank Share* is defined as total assets managed by IBs over total banking assets at year end. A negative coefficient for this indicator in the restricted (all-banks) hazard model would indirectly suggest that the larger the presence of IBs in a country, the greater the stability of its financial system. We have converted the index to a percentage scale where 100% indicates the most open economy.

Finally we define *Duration* for every bank in the analysis as in Evrensel (2008):

$$Duration = Establishment\ Year\ \text{-}\ Current\ Year \qquad (3.47)$$

3.4.2 Preliminary Data Analysis

The summary accounting profiles for different bank categories are set out in Table 10 alongside mean difference pairwise t-tests. The averages reported are for the original variables without transformations. Balance sheet and income statement variables are reported in $US millions and financial ratios in percentages. Although the main comparison is between CBs and IBs, we further subdivide the two bank types into those that failed and those that survived within the 16-year sample period. We also proceed in reverse: we first group the entire sample of banks into failed and survivors, and further subcategorize each group into CBs and IBs. In the columns of Table 10 labelled Fail we report averages pertaining to the accounting statement on the year-end prior to the failure event.

[Table 10 around here]

The first two columns reveal significant differences between CBs and IBs. On average the total *Equity* stands at US$ 0.40 billion for IBs against about US$ 0.50 billion for CBs. The mean size of total *Deposits* is only US$ 2.78 billion (IBs) against US$ 4.00 (CBs) and, similarly, total *Assets* are US$ 3.65 billion (IBs) against US$ 4.94 billion (CBs). These balance sheet statistics confirm that IBs are small by conventional banking standards. The income statement profile also bears this out. *Net Income* for CBs is US$ 227 million on average compared with only US$166 million for IBs. A break-down of *Net Income* into earnings from interest bearing financial products (*Net Interest Revenue*) and fee-based services (*Other Operating Income*) reveals interesting information.[42] CBs and IBs generate comparable fee-based income (US$ 71.08 million and US$ 64.31 million respectively). By contrast, *Net Interest Revenue* is higher for CBs (US$ 155.90 million) than IBs (US$ 103.60 million) because most IBs, except relatively large ones, prefer to use fee-based contracts than PLS ratio arrangements due to their lower administration costs and complexities, shorter duration and lower risk (Khalil *et al.* 2002).

In respect of the financial ratios, on average IBs exhibit significantly larger liquidity buffers than CBs as borne out by a *Liquid Assets/Deposits* ratio of 55.6% (IBs) and 40.3%

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42 IBs do not offer interest but share ratios of profits instead. However, the same "net interest margin" principle applies. Depositors are offered a *low* share ratio of the bank's profits whereas banks charge a *high* share ratio when taking part in a venture through a business loan.

(CBs), and a *Net Loans/Assets* ratio of 49.8% (IBs) and 51.5% (CBs). The higher liquidity of IBs has been attributed to managerial choice rather than to lack of investment opportunities (Pellegrina 2008; Olson and Zoubi 2008). Large liquidity buffers are a crucial feature of IBs for two reasons. First, IBs need more protection against deposit withdrawal given their limited access to liquidity from interbank, conventional money markets and lender-of-last resort because Islamic finance law prohibits any interest payment (*riba*).[43] Second, they cannot utilize hedging instruments as a way of mitigating liquidity risk.

Low leverage is one of the cornerstones of Islamic finance as borne out by Equity/Assets and Liabilities/Equity ratios at 21.7% and 9.0% for IBs which are significantly different from the corresponding 10.8% and 15.8% for CBs. Leverage levels are expected to be lower for IBs compared to CBs because Islamic finance law discourages debt-based funding and promotes asset-backed investments. Bonds issued by IBs need to be backed by tangible assets (*e.g.*, real estate or commodities) which puts a constraint on leverage. The most common sources of funding for IBs are profit-sharing investment accounts and safe-keeping (Hasan and Dridi 2010). Low leverage can have a favorable effect on survival time by reducing business risk *ceteris paribus*. As IBs do not offer deposit insurance schemes, lower leverage can signal a higher degree of bank solvency (Galloway *et al.* 1997; Kahane 1977). There is evidence in the recent literature that the higher leverage of IBs is related to their business model rather than managerial inadequacies (Johnes *et al.* 2012).

43 However, there are regulatory requirements that force them to maintain an interest-bearing account with the central bank in order to obtain a banking license. To maintain their ethical principles, any interest income is typically donated to charity.

IBs are significantly better capitalized than CBs as borne out by respective average Tier 1 ratios of 25.0% and 15.8%. This is in line with IBs having to withhold more capital to balance their greater exposure to liquidity risk (Bashir 1999). On the other hand, asset quality indicators such as *Loan Loss Reserves/Loans* suggest a tendency for IBs to hold lower reserves than CBs, which can be linked to their greater ability to pass risks on to depositors (Olson and Zoubi 2008). In terms of profitability, the results in columns 1-2 of Table 10 suggest that, while IBs show significantly larger *Return on Assets (RoA)* than CBs, the opposite applies to *Return on Equity (RoE)*. Given that IB contracts are based on asset-backed transactions (*e.g.*, collateralized by real estate), the direction of the discrepancy for *RoA* can relate to the fact that IBs also earn income by letting those assets. Moreover, the higher RoA of IBs can also be linked to their large involvement (relative to CBs) in major governmental infrastructure projects which offer a safer income than private sector projects. The significantly larger *Cost/Income Ratio* of IBs is in line with existing evidence which suggests that IBs are typically less cost efficient than CBs and have larger operational risk (Čihák and Hesse 2010).

Table 10 also sub-classifies *survivors* (cols. 5-6) and *failed* banks (cols. 7-8) into CBs and IBs. As noted above, for the failed banks the reported means are based on accounting figures for the year-end prior to the failure event. Notable differences are observed in the accounting profile of survivor IBs and CBs but those differences narrow for banks prior to failure. The only clear exceptions are in the income statement where failed IBs show significantly lower *Net Interest Revenue*, *Net Income* and *Overheads* than failed CBs. Overall it seems fair to conclude that the accounting profiles of IBs and CBs get very close once they get into severe distress, ending in failure. However, it cannot be inferred from mean difference t-tests that the marginal influence of accounting factors on failure risk is identical for both bank types. For instance, a 1% reduction in liquidity could have a stronger effect on failure risk (reducing the time to failure at a faster rate) for IBs than CBs even though, once banks fail, their mean liquidity levels could be similar.

Next we split the entire cross-section of 421 banks into those that survived during the observation window and those that failed (cols. 3-4). Unsurprisingly, failed banks are in a significantly worse financial position on the year prior to failure than survivors. For instance, they show significantly lower *Net Income* and *RoA,* and inferior capital quality ratios (*i.e.*, smaller *Equity/Assets* and *Equity/Net Loans*) and liquidity ratios (i.e., larger *Net Loans/Assets*). Such differences become apparent two years prior to the failure event. For instance, the average *Assets*, *Net Interest Revenue* and *Tier 1 Ratio* for failed banks in the year-end prior to failure (year t) are US$ 1.81 billion, US$ 59 million and 13.1% against US$1.87 billion, US$63 million and 12.1% in year $t-1$ which suggests that failed banks show early signs of vulnerability. Columns 9 (survivor CBs) and 10 (failed CBs) reveal significant differences in all balance sheet and income statement information and various financial ratios (*e.g.* capitalization, liquidity). Likewise, survivor IBs and failed IBs (last 2 cols.) show significant differences in balance sheet and income statement variables but their mean financial ratios are indistinguishable, the only exception being *Net Interest Margin* (*NIM*) which is significantly greater for survivor IBs. Regarding profitability, failed CBs show significantly lower *RoA* than survivor CBs, and although the direction of the discrepancy in *RoA* for failed IBs against survivor IBs is the same, the magnitude is much smaller and statistically insignificant.

To sum up, this preliminary analysis provides *prima facie* evidence that: *i*) it is possible to distinguish between IBs and CBs on the basis of financial information obtained from company balance sheets, income statements and financial ratios; and *ii*) for both CBs and IBs the accounting profile of survivors presents significant differences from that of failed banks. Taken together, both aspects suggest that IBs and CBs may need separate attention in the design of appropriate early warning systems.

Table 11 presents summary statistics for the country-level covariates over the 1995-2010 period. Among the 10 largest banking systems by assets are those of Gulf Cooperation Council (GCC) countries: Bahrain, Kuwait, Saudi Arabia, Qatar and the UAE.[44]

[Table 11 around here]

The table show large country heterogeneity. Qatar has the highest real GDP growth rate at 11.8% while that of Saudi Arabia is 2.8%. Iran, ranked 2^{nd} by total banking assets, suffers from high inflation and low GDP growth. Mauritania, Yemen and Palestine have the smallest banking systems. The average annual inflation rate for Turkey at 43.2% is by far the highest among all the sample countries and is reflective of persistent economic problems during the 1990s that brought the country to recession in 2001. The Turkish lira, which was pegged to the US$ prior to the 2001 crisis, had to be floated and lost an important amount of its value. The 2001 financial meltdown shrank the number of banks in Turkey from 72 to 31 (with only one IB among the failures). The Malaysian banking system is the

44 The GCC region also includes Oman which is excluded from our analysis because it does not have IBs.

least concentrated, with a HHI of 10%, and the highest degree of concentration is observed in Palestine (76.6%), Albania (46.4%) and Mauritania (38.9%). Within the GCC group, Saudi Arabia (12.7%) and the UAE (10.4%) show the lowest concentration. After Iran, whose banking system is exclusively Islamic, the largest *Islamic Bank Share* is observed in Sudan followed by Brunei. Indonesia has the lowest IB presence.

3.5 Results

3.5.1 Non-Parametric Analysis

Figure 1 shows the Kaplan-Meier survival estimator separately for conventional and Islamic banks. This estimator is testing the hypothesis that failure risk is lower for IBs than CBs using a non-parametric estimator of the survival function $S(t)$. These estimates are *unconditional* because they are based only on the observed frequency of bank failures; *i.e.*, 8/106 and 89/315 for IBs and CBs, respectively. Hence, this approach does not control for differences in bank-specific accounting characteristics nor for different macroeconomic conditions of the country in which a bank is located.

[Figure 1 here]

It can be observed that Islamic banks have higher survival rate than conventional banks for all the examined period. The majority of Islamic banks are established after 1975 and only a few exist before 1950. Dubai Islamic Bank, established in 1975, is regarded as the world's first private interest-free bank. The first Islamic bank in the sample is established in 1908 in Iran. The flat line in the graph for Islamic banks for analysis time higher than approximately 30 is explained by the few Islamic banks in existence at that time and the lack of any failure. The probability of survival beyond 20 years is 91% (IBs) against 84% (CBs) and 86%, falling beyond 30 years to 86% (IBs) and 77% (CBs).

Table 12 shows the numerical value of the survivor function (Kaplan-Meier Estimator) and the cumulative hazard function estimator (Nelson-Aalen Estimator) which are calculated after every failure separately for the two bank types. The Net Lost column combines the information from censored subjects and late entries into one number. Hence at every time t:

$$Net\ Lost_t = Censored_t - Late\ Entries_t \tag{3.48}$$

[Table 12 here]

In order to assess whether the differences are statistically significant, we deploy a non-parametric rank test for the equality of survival functions among the two types of banks: up to 20 years (log-rank 4.09; p-value 0.043); and up to 30 years (log-rank 4.17; p-value 0.041). For our relatively large sample, cross-sectionally (421 banks) and in time span (16 years including the post-Lehman crisis), these findings suggest that the failure risk of IBs is significantly lower than that of CBs. A drawback of the log-rank test is its reliance on the assumption that hazards differ at a proportional way. The Wilcoxon test relaxes this assumption by allowing the hazard functions to differ in non-proportional ways. Result of the Wilcoxon test suggests that hazard do not vary in non-proportional ways (p-value 0.155). Hence the Log-Rank test is correctly used. However, as Islamic banks have been in existence for fewer years than the conventional ones, it may be plausible to assume that giving more weight to newer banks corrects the bias introduced by a non-weighting test like the log-rank. The Fleming-Harrington test allows for a customized weighting scheme of the failure times. Hence, when earlier failure times, or equivalently banks that have been in existence for a few years, are given more weight then the survival functions are different at the 5% significance level. To conclude, there is statistical evidence, especially for the more recent past, that the survival functions between the two bank types are different. In addition subsequent modelling using the Cox PH model can be applied. Table 13 summarizes the results of the statistical tests.

[Table 13 here]

3.5.2 Cox PH Results

The Cox Proportional Hazards model is fitted separately on the three parts of the accounting statement; namely balance sheet, income statement and financial ratios.

In every of the three parts of the accounting statement we estimate four models:

i) a restricted

ii) a semi-restricted

iii) a semi-generalised

iv) a generalized

The models differ according to the assumptions imposed on the baseline hazard functions of the two bank types as well as the application of the stepwise selection algorithm.

In the restricted we are asserting that conventional and Islamic banks face the proportional risks over time and that the same explanatory variables can explain their probability of failure. An Islamic bank dummy variable is included to measure the difference in risk faced by the two bank types. The advantage of this model is that we can quantify the difference in the Islamic banks risk profile with respect to the conventional ones. The drawback is that the same explanatory variables might not be appropriate for modeling both bank types fragility. As the model assumes that risks faced by the two bank types are proportional to each other the only difference is on the mean level of risk (captured by the Islamic bank dummy) but not on higher moments of the baseline hazard function. In other words, the baseline survival functions are assumed to have the same shape (but different levels). The selection of the explanatory variables is based on the stepwise algorithm employed on conventional and Islamic banks.

The semi-restricted model does not restrict the baseline hazard function to differ in a proportional way between the two bank types. The semi-restricted is in essence a stratified Cox model estimated for the pooled sample of conventional and Islamic banks. The semi-restricted model imposes the same explanatory variables for both bank types which are obtained from the restricted model. Hence no further optimization with respect to explanatory variables occurs between the restricted and semi-restricted models.

However it might be argued that as Islamic banks have a different modus operandi then the same indicators might not be revealing the same information; hence a semi-generalised model is also proposed. If the two bank types share the same characteristics then the covariates selected by the stepwise procedure should have the same significance levels when applied separately to Islamic and conventional banks. The semi-generalised model is estimated separately for conventional and Islamic banks but uses the explanatory variables from the restricted model and inferences can be drawn from coefficient magnitudes and significances between the two bank types. Hence the restricted, the semi-restricted and the generalized share the same explanatory variables.

Finally a generalized model is proposed which, in addition to the semi-generalized models, makes use of the stepwise selection algorithm for conventional and Islamic banks separately. This model allows the baseline hazard functions and the explanatory variables to be different.

The bank-level variables represent information from either the balance sheet (stock), income statement (flow) or financial ratios, entered separately in three sets of models. The restricted, semi-restricted and semi-generalized models for the Balance Sheet, Income Statement and Financial Ratios sections are presented in tables 14 through 19.

[Tables 14 - 19 here]

Among the diagnostics reported in Tables 14-19 are: a) a test of the proportional-hazards assumption, b) a test for overall model significance, and c) a pseudo-R^2. The proportional-hazards assumption is assessed via the Schoenfeld residuals-based test which is equivalent to testing via a LR statistic that the specific influence of the covariates (or log hazard-ratio function) on the level of failure risk is time independent; the time variation in failure risk is dictated by the baseline hazard function $h_0(t)$ as formalized in equations in the methodology section. Consistently across all models shown in Tables 14-19, we find no evidence against this assumption. Finally, the Wald test statistic ($\mathrm{H}_0 : \boldsymbol{\beta} = 0$) is strongly significant in most cases for the CBs which serves to validate the PH Cox models as statistically significant. For IBs there is evidence that a model with only bank-specific covariates is not able to adequately capture their failure risk. Hence in the next section we enhance our analysis by including macroeconomic variables.

Under all three data sections (i.e. Balance Sheet, Income Statement and Financial Ratios) the *semi-restricted models* have better fit than the *restricted* according to the AIC. However, the hazards between the two bank types are proportional at conventional significance levels according to the relevant statistical test. The *generalized model* has superior fit compared to the *semi-generalized* with the analysis of financial ratios displaying the greatest differences between the two bank types. This emphasizes the necessity to identify the determinants of failure risk individually for the two bank types. The common conclusion from the three parts of the accounting statement is that the Islamic bank dummy is statistically significant with a negative coefficient suggesting that IBs exhibit about 66% lower failure risk than conventional banks.

Balance Sheet Data

The models based on the Balance Sheet are presented in Tables 14 and 15. The positive coefficients on *Assets* for conventional and Islamic banks indicate that large banks of either type are substantially more likely to fail than small banks *ceteris paribus*. The coefficient of *Assets* around 0.6 for conventional banks is notably smaller than that for Islamic banks at about 2.3 which indicates that large IBs are substantially more likely to fail than large CBs. This confirms a similar finding in Čihák and Hesse (2010), despite their different sample period and methodology, suggesting that large commercial banks tend to be financially stronger than large Islamic banks. Large Islamic banks tend to become more involved in PLS partnerships which are relatively risky and difficult to monitor whereas small Islamic banks tend to engage in low-risk investments and fee income contracts (Khalil *et al.* 2002).[45] Furthermore, a large IB is more likely to have expanded its operations in other countries, especially Western economies where legal issues can arise due to lack of compatibility of the Western laws and the Islamic law for the IB contracts to be valid (Archer and Karim 2007).

Equity-type contracts (represented by *Loans*) because of their aforementioned problems are utilized by the largest Islamic banks. The negative and statistically significant coefficient is attributed to the utilization of such contracts to finance large infrastructure and real estate projects on which IBs can charge a premium (Khalil *et al.* 2002).

The coefficient estimates of *Other Earning Assets* are significant but have a larger marginal effect to the failure risk of Islamic banks. In particular, a rise of *Other Earning Assets* by 1% decreases the risk faced by a conventional bank and an Islamic bank by 29.53% and 62.93%. This can be attributed to the fact that Islamic banks rely heavily on trade (fee based) contracts rather than the equity-type (PLS) contracts. These contracts are tailor-made as many of the relevant parameters (such as maturity, repayments and collateral) are specific for every client. The bank, as the financier, needs to conduct a feasibility and profitability analysis for equity-type contracts; this is costly and time-consuming. Second an Islamic bank needs to gain approval for its financial products from the Shariah board of the bank. This is done for every Islamic bond issue (sukuk) and also for the majority of equity-based contracts, although the fee-based contracts are more standardized and hence

45 Frequently used trade contracts are lease contracts (Ijarah) and cost plus profit sale (Murabahah).

rarely require the approval of the Shariah board. Hence the lack of standardization in products and practices leads to greater administration costs, higher operational risk as well as the greater monitoring costs (Sadr and Iqbal 2001). Secondly, Islamic banks are highly regulated as to where investments can be placed; hence complex derivatives or conventional finance products are prohibited.

Income Statement Data

The models based on the Income Statement (Tables 16 and 17) suggest that *Net Interest Revenue* is statistically significant only for conventional banks. An explanation is that an Islamic bank operates mainly with fee-based contracts rather than the equity-type (PLS). The estimated coefficient of *Other Operating Income* suggests that the marginal effect for Islamic banks upon failure risk is larger than that of conventional banks. An increase in the *Other Operating Income* by 1-unit leads to $1 - e^{-0.017} = 1.69\%$ and $1 - e^{-0.002} = 0.20\%$ decrease in risk for Islamic and conventional banks respectively.

Growth of overheads (administrative expenses) is statistically significant at the 10% and 1% significance level for conventional and Islamic banks respectively. An increase in the overheads reduces hazard in both bank types but has a more pronounced for Islamic banks. Reputation and relationship management are high priorities for IBs. Consequently they rely and spend more on human resources compared to CBs (Pellegrina 2008). Education and technical expertise in Islamic finance have increased significantly in recent years. Ahmad *et al.* (1998) find that staff members in the IB industry are not sufficiently qualified. Hence the negative and statistically significant coefficient of the *Growth of Overheads* for IBs can be explained by the human resource development process taking place. A more recent study of Johnes *et al.* (2012) documents improvements of the managerial efficiency in Islamic banks due to the increased investments in human resources in recent years. As a consequence Islamic banking is promoted to the general public using, for example, marketing campaigns[46].

The *generalized* model verifies that survival of the two bank types is explained by different factors although the results are not very different to the previous models. Examining table 17 we find that higher levels of *Net Income* decrease the risk for Islamic banks whereas for conventional banks this effect has the opposite direction though much less pronounced. This is possibly a reflection of our broad definition of "failure" which includes merger and acquisitions (M&A) activity. To date, however, there is no instance of M&A among IBs.

Financial Ratios

The models based on financial ratios (Tables 18 and 19) suggest that larger *Cost/Income* ratios have an adverse effect on failure risk but the magnitude of the effect is more pronounced for IBs.

The coefficient of the *Equity/Assets* ratio reveals opposite effects for both bank types. The negative sign appearing in the conventional banks shows that better capitalization decreases the hazard of a bank failure. By contrast, in an Islamic bank the opposite is true. A rise of 1% in *Equity/Assets* (better capitalization) decreases the failure risk by

46 To this end, Bank Syariah Mandiri in Indonesia sponsors documentaries on Islamic finance while Emirates Bank in the UAE waives loan payments during the Ramadan as part of marketing campaigns (Bloomberg).

$1 - e^{-0.039} = 3.82\%$ for conventional banks, while it increases it by $e^{0.047} = 4.81\%$ for Islamic banks. These contrasting findings are consistent with the stylized fact that CBs are typically less liquid and more highly leveraged than IBs. They are also broadly in line with the accounting profile presented in an earlier section where failed CBs show lower *Equity/Assets* ratios than survivor CBs, but failed IBs show lower (or similar) leverage levels than survivor IBs. This evidence supports the notion that the failure of an IB is less likely (than that of a CB) to have wide implications for the banking system. CBs are often deemed "too big too fail" not only on account of their asset size but also of their high leverage. Liquidity, represented by *Liquid Assets/Deposits*, although not statistically significant for either bank it is closely linked to the capitalization ratio. In particular, better liquidity for Islamic banks is negatively associated with the hazard of an event happening. The finding is plausibly associated to the increased importance of liquidity management in Islamic banks business model which constrains access to money markets (interbank) and lender-of-last-resort (Iqbal and Mirakhor 2007). By contrast, in conventional banks higher liquidity increases the likelihood of bank failure. This is because conventional banks are able to obtain liquidity from the interbank market or via secondary markets without having to forgo revenues by the retention of large liquidity buffers.

Coming now to the other variables we find z-score to be marginally insignificant for Islamic banks with the sign suggested in the literature (Čihák and Hesse 2010). By contrast, for conventional banks, despite the high significance of the estimate, the sign is not the expected. Considering also the descriptive statistics from a previous section we believe that this proxy of bank failure is not performing very well. It is possible that the few variables included in the calculation of this ratio are not able to capture the complexities of failure risk.

Net Interest Margin (NIM) shows the profit margin of a bank's traditional activity, borrowing at a low interest rate and lending at a higher one. For IBs, the same concept applies but with reference to the profit-loss share ratio instead. The results suggest that for a 1% increase in NIM the failure hazard of CBs increases significantly by about 10.4% while the effect goes in the opposite direction for IBs by a magnitude of 16.4%. The contrasting impact of the NIM covariate on failure hazard for the two types of banks is plausible given important differences in their clientele. These results are in line with the accounting profile shown earlier in the section of descriptive statistics, namely, IBs show significantly higher NIM than CBs on average. CBs working mainly in the retail sector face strong competition and can lose market share if NIMs are high. The primary source of NIM for IBs are large infrastructure and real estate projects via PLS contracts on which they can charge a premium. IBs are known to rely on connections with large and often family-owned conglomerates and name lending is widespread (IMF 2011b). Typical IB clientele are governments that pay more attention to the ethics aspect of the investment than to its high cost (had they instead sought financing in a CB); this is termed "Islamicity Premium" in the literature (Khalil *et al.* 2002).

Baseline Survivor Functions

The estimated baseline survivor functions from the previous models are presented in the sets of figures 2-4 for each of the three parts of the accounting statement. The graphs reveal two findings. First the baseline survival function is decreasing across time meaning that both bank types face increasing hazard with respect to time. Secondly the slope of the baseline hazard function is varying both across time and among the three parts of the accounting statement. Using the Income Statement, the survival curve decreases more rapidly, or conversely the hazard increases faster, across time. A steeper slope of the baseline survival function suggests that the respective set of the explanatory variables is less informative about the hazard of an event occurring.

[Figures 2-4 here]

To realize how this is true we consider a Cox PH model with no explanatory variables. The estimated baseline survivor function in that case would coincide with the non-parametric Kaplan-Meier estimator. In that case failure would be explained solely by time. However it is not time per se that causes the failure of subjects; it is rather used as a proxy for things that can not be measured. For example an old man has higher probability of dying not due to time itself but due to fatigue of his organism or deterioration of his immunity system which may not be measured perfectly. It's not time itself that is responsible for the failure but some latent variable that is correlated with time. By contrast, in a perfect model we would be able to measure and include such covariates. Then we would have shifted all the explanatory power from time and place it on the covariates themselves. In that case the estimated baseline survivor function would have been a straight and flat line[47] (Cleves *et al.* 2007).

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47 A downward slopping straight line means that time has a constant effect on survival. A straight and flat line indicates that time has no effect on the survival - everything is explained by the covariates.

All three baseline survivor functions have varying slopes (there is no straight line) we can see that the Financial ratios model is the most informative, based on the smoother slope of the baseline hazard function, followed by the Balance Sheet and the Income Statement. The result is not surprising as the Financial ratios combine information present in Balance Sheet and Income Statement. Between the latter two parts of the accounting statement, the Balance Sheet is a continuing record of the banks operations (stock) as opposed to the only one year that the Income Statement covers (flow). Hence, the Income Statement provides the least information to assess a bank's failure risk. Islamic banks have lower failure risk at any point in time, a consistent finding among all three parts of the accounting statement.

3.5.3 Macro Cox PH Results

The four specifications utilized in the previous section can be split into two categories. *Restricted* and *Semi-restricted* are a single model for both bank types while *Semi-generalized* and *Generalized* models are separate for CB/IB. In this section we augment with macroeconomic covariates the best specifications of the two categories; the *Semi-restricted* and the *Generalized* models. Tables 20-22 present the results of the survival models augmented by macroeconomic covariates. Panel A of every table is the *Semi-restricted* model and Panels B and C are the *Generalized* models for CB/IB respectively.

[Tables 20-22 here]

At this stage we fit separate models for each of the eight macroeconomic variables under consideration to assess the different impact on the failure risk for the two bank types. There have been arguments suggesting that Islamic banks are more closely linked to the productive economy, due to their investments in real estate and infrastructure (Haque and Mirakhor 1986; Aziz and Yilmaz 2009).

Controlling for macroeconomic characteristics leads to better models under all parts of the accounting statement as evidenced by the lower information criteria in these models compared to those of the previous sections. Hence, both banking systems are affected by the macroeconomic condition of the country they are operating in. Failure risk is more strongly influenced by inflation for Islamic banks. Our findings are robust across all three different datasets and they are described next.

We find that the evolution of the business cycle as measured by the lagged *Growth of Real GDP* influences the hazard of bank failure. The coefficient is significant for conventional banks and suggests that an increase in economic growth by 1% materializes in about $1 - e^{-0.099} = 9.43\%$ reduction in default risk. By contrast the the impact of *Growth of Real GDP* on Islamic banks is not statistically significant.

Inflation is found to increase the risk of failure for both bank types; however the effect is more pronounced for Islamic banks due to the larger coefficient. A 1% increase in lagged inflation leads to about $e^{0.017} = 1.71\%$ and $e^{0.031} = 3.15\%$ higher risk for conventional and Islamic banks respectively. The stronger effect for Islamic banks is plausibly attributed to the special attributes of the financial products being utilized. In particular, equity-based contracts once entered into, they cannot be changed till the maturity. Hence Islamic banks do not offer any equivalent of inflation linked bonds or inflation adjusted financial products. Their profit share ratios are made based on inflation forecasts.

In line with Beck *et al.* (2006) and Evrensel (2008) *inter alios*, our survival-time analysis suggests that banking *sector concentration* (Herfindahl index) has a favorable effect on survival time for CBs. An increase of 1% in concentration reduces dramatically the failure risk of CBs which is in line with the notion that competition has an adverse effect in the banking sector possibly because it can undermine prudent bank behavior by encouraging excessive risk taking or "gambling". However, for IBs the effect of banking sector concentration on survival time is economically more muted and statistically insignificant. The effect of concentration upon Islamic banks is not as clear; however it seems to suggest that the Islamic banking system would not benefit, in terms of stability, if some M&A activity were to take place. Despite their lower efficiency with regards to the conventional banking system as well as standardization and operational risk problems there is no statistically significant evidence that a rise of concentration in the sector would be beneficial (Johnes *et al.* 2012; Hasan and Dridi 2010).

The *credit risk score* of sovereign states appears positively linked with bank survival rates generally for both CBs and IBs, as one would expect, albeit the effect is significant only in the Financial Ratios section. which may suggest that sovereign credit ratings are primarily reflective of Balance Sheet and Income Statement information.

Foreign Exchange depreciation is only significant in the Income Statement section with a sign suggestive that a depreciation of the home currency against the USD would increase failure risk for conventional banks. The fact that FX Depreciation is only significant in the Income statement may be related to the short-lived hazard of currency depreciation. From the bank's point of view any new investments would be adjusted quickly to take into account the recent developments in the currency markets; hence there may not be any significant contribution to failure risk would last maximum one year. Islamic banks do not engage into complex hedging instruments (currency swaps). In fact any currency exchange for an Islamic bank can only take place at par value; hence any hazard arising from foreign exchange depreciation does not have any significant contribution to an Islamic bank's failure risk.

Financial openness is positively related to failure risk. The effect is significant for conventional banks but more muted for Islamic banks. The finding may be reflective of our broad definition of failure that includes mergers and acquisitions, similar to bank concentration. M&A activity following the East Asian crisis in countries like Malaysia and Indonesia that had been particularly open to foreign investors during the years leading to the outbreak of the crisis is likely to be driving this result.

Finally, *unexpected inflation* and Foreign Exchange depreciation is not found to have any significant relation with banking failure.

Figures 5-7 present the baseline survivor functions of the Semi-restricted Cox PH with macroeconomic variables for the three parts of the accounting statement. Similarly to the findings of the previous paragraph, the Financial ratios model is the most informative due to the more gentle slope of the baseline hazard function followed by the Balance sheet and the Income statement. The varying explanatory power of the macroeconomic variables can be assessed from the flatness of the baseline survivor functions. Indeed, *Real GDP growth* and *Inflation* are consistently the most informative macroeconomic determinants of failure risk.

[Figures 5-7 here]

3.5.4 Shared Frailty Cox PH Results

Tables 23-25 present the results of the shared frailty models for the three parts of the accounting statement, Balance Sheet, Income Statement, and Financial Ratios, respectively. We report two specifications according to the cluster variables that define the intra-group correlations for the frailty specification. First according to bank type (*Islamic banking dummy*) (column 4) and the second according to *Country* (column 5). As the frailty models provide a correction for omitted variables they are reported alongside the *Restricted* and *Semi-restricted* models for comparison.

[Tables 23-25 here]

When the cluster variable is set to *Country*, the random effects are highly significant (LR test=39.12; p-value=0.000). The estimated coefficients appear slightly different than the original restricted and semi-restricted models due to the omitted variables correction. However these differences are minor with signs and statistical significances not changing qualitatively. The hidden country factors captured by the estimated random effects imply that there are significant differences across countries that need to be accounted for by the inclusion of macroeconomic variables. Most interestingly, the *Islamic banking dummy* retains its significance (At the 5% level) while the exponentiated coefficient suggests that Islamic banks are $1 - e^{-1.058} = 65.29\%$ less hazardous than conventional banks when the Balance Sheet is used. When the Income statement and the Financial Ratios are used there is no significant difference between the two bank types. When the *Islamic banking* *dummy* is the specified cluster variable, we observe that the random effect term is statistically significant (LR test=5.36; p-value=0.010). Therefore there is significant within-group correlation meaning that the failure patterns in one group (conventional banks) is different to the other (Islamic banks). Our main argument that hazard rates in IBs are different than CBs is also verified by the random effects model.

Table 26 and Figure 8 report the estimated log frailty when the frailty identifier is set to the *Country* variable, for every part of the accounting statement and separately for CB/IB.

[Table 26 here]

[Figure 8 here]

The least frail country is the one with the most negative estimated frailty. By contrast, the most frail country is the one with the highest. The interpretation of the coefficients now needs to be conditioned on the frailty for every country. Given that coefficient estimates do not change significantly from the non-frailty models we can focus on the interpretation of the log frailties (v_i) for every country which may be considered as a measure of "opportunity cost" in hazard terms of a bank operating in country A rather than country B. In other words the log-frailty estimates provide a classification of the banking environments according to how "favorable" they are. To explain "favorable" better we refer to how random effects are specified within the Cox model:

$$v_i = \log(\alpha_i) \Longleftrightarrow \exp^{\nu_i} = \alpha_i \tag{3.49}$$

Hence a favorable banking environment can be interpreted as a country bonus in the hazard function contributions of the explanatory variables. Take for example the hazard functions of Jordan and Brunei for the Balance Sheet specification:

$$h_{J,i(t)} = h_0(t) \times e^{-1.462} \times e^{(0.783A-6.336GoA-0.092GoE-0.001LA-0.483OEA-1.058ISL)} \quad (3.50)$$

$$h_{B,i(t)} = h_0(t) \times e^{0.726} \times e^{(0.783A-6.336GoA-0.092GoE-0.001LA-0.483OEA-1.058ISL)} \quad (3.51)$$

where A stands for *Assets*, GoA for *Growth of Assets*, GoE for *Growth of Equity*, LA for *Liquid Assets*, OEA for *Other Earning Assets* and ISL is the *Islamic dummy*. As the two functions differ only by the log frailties we realize that a bank with the same characteristics would have $1 + e^{-1.462+0.726} = 1 - e^{-0.751} = 52.8\%$. The estimated frailties from the three sections of the accounting statement give broadly the same ranking with Egypt and Yemen being two exceptions.

Table 27 and Figure 9 present the estimated frailties when the frailty is defined by bank type. We evidence significant differences on failure risk of the two bank types under all three sections of the accounting statement. The results verify that Islamic banks are less hazardous. However, the correction for omitted variables leads to a revised estimate that Islamic banks have about 13.8% lower failure risk than conventional banks. The largest difference between the two bank types is evidenced in the Balance Sheet data (19.5%) while the Financial ratios give rise to the smallest (9.4%).

[Table 27 here]
[Figure 9 here]

3.5.5 Shared Frailty Macro Cox PH

Heterogeneity can exist among groups when a variable has not been accounted for. So far the frailty models did not take account of the macroeconomic environment; therefore the differences found previously could be explained by greater financial growth or higher concentration. By contrast, failure to eliminate the shared frailty would mean that there is a latent variable or process that affects the banking sector of a country and cannot be explained by the differences in macroeconomic characteristics. In a previous section we have found significant evidence that both bank types are affected by the macroeconomic environment. Here we combine into a shared frailty model bank-specific and macroeconomic indicators. Tables 28 - 30 present the estimation results for the *Restricted* (Panel A) and *Generalized* (Panels B & C)[48].

[Tables 28 - 30 here]

Frailty is present when the pooled dataset is considered under the *Restricted* specification (Panel A of Tables 28 - 30); however when the *Generalized* model is utilized we find that conventional banks always have a statistically significant random effect. In further analysis, the LR tests for the significance of the latent country effects or shared frailty ($H_0 : \theta = 0$), suggests that unobserved factors induce within-country clusters of correlation in the hazard of bank failure for CBs but not for IBs. These contrasting findings indirectly suggest that there is larger within-country heterogeneity among IBs which could relate to their modus operandi, namely, their less uniform and standardized nature in terms of fi-

48 We have opted for the *restricted* as opposed to the better, in terms of AIC, *semi-restricted* version due to the Islamic banking dummy whose explanation in terms of difference between the two bank types is more straightforward.

nancial products and nature of contracts. Moreover, severe distress and failure of one bank can easily spread to other banks in the case of CBs — due to their large size and leverage levels, and strong bank interconnectedness articulated through interbank lending in money markets. Thus, contagion can play the role of a latent country factor linking the failure risk of CBs. When a CB is severely distressed, the state typically intervenes to minimize negative externalities and avoid possible bank runs. This creates moral hazard problems. By contrast, the business model of IBs makes them less interconnected thus more insulated meaning that if an IB is in financial distress, the effect is less likely to spread to the rest of the banking sector. Consequently state intervention to rescue IBs may be far less expected to take place.

From the shared frailty models with bank-specific and macroeconomic variables we can get the estimates of the individual frailty quantities for each country separately for conventional and Islamic banks. Results are presented in tables 31-33 and figures 10-12.

[Tables 31-33 here]

[Figures 10-12 here]

The rankings of the countries do not change significantly from the frailty model without the macroeconomic variables. This gives evidence in support of some hidden characteristics applicable for every country that cannot be accounted solely with the inclusion of macroeconomic variables. Differences in the ranking of the countries separately for CB/IB reveal that the latent factor does not always have the same impact on both bank types. These variances in the rankings provide additional evidence of the different risk profile of the two bank types. For example Egypt (under the Balance sheet data) has a negative log frailty -

yet this is not statistically significant - for Islamic banks (see Table 31); thus hazard is reduced. By contrast, conventional banks appear to have a positive log frailty (see Table 31); hence they experience a rise in hazard due to operating in this country. Hence, a conventional bank in Egypt faces $(e^{0.24-0.069} - 1) \times 100 = 18.65\%$ higher failure risk compared to the an Islamic bank of the same country, ceteris paribus.

3.5.6 Robustness Checks

In this section we perform some standard robustness checks for the models we fitted previously. We have supportive evidence for the proportional hazards assumption. First the respective tests reported after every model show no sign of violation. Secondly the magnitude of the coefficients between the *Restricted* and the *Semi-Restricted* versions of the same model (see Tables 14, 16 and 18) shows no significant variation (Cleves *et al.* 2007). Here we present a test for the proportional hazards assumption using the Schoenfeld (1982) residuals for every explanatory variable in the three blocks of the accounting statement as well as the global test which has been reported in the tables of the previous sections. In addition we have run the proportional tests separately on every stratum for the *Semi-resticted* models. Tables 34 - 36 present the test statistic and the p-values in brackets. Results show that the proportional hazards assumption is not violated with a minor exception in the generalized version of the Balance Sheet model. Further investigation on that showed that the explanatory variable *Growth of Loans* is the one disturbing the proportionality of hazards. To correct for this we can fit *Growth of Loans Squared* which is in-line with the literature arguing about an optimal Growth rate of loans above which excessive lending is considered dangerous for the stability of the bank. Yet that term was not statistically significant at conventional levels hence dropped.

[Table 34 - 36 here]

Figure 13 reports the Cox-Snell residuals plotted against the Nelson-Aalen cumulative hazard function as a measure of the goodness of fit for the *Semi-Restricted* (first column) and *Generalized* models (second column for CB, third for IB).

[Figure 13 here]

The model for the conventional banks shows better fit across the different datasets used; an expected result due to the richer dataset for the conventional banking industry. By contrast, the fit on the Islamic banks is not as good particularly when balance sheet data are used. Financial ratios data show much better fit. The variability at the right-hand tail and the more jagged lines are expected due to the reduced sample effectiveness because of past failures.

[Figure 14 here]

Figure 14 shows the influential banks in the analysis. Influential points are detected using the log-likelihood displacement and LMAX values methodologies for the stratified samples under each data specification. The further the bank lies from the x-axis the more influential it is. Visual inspection of the graphs shows that there are some influential points (identified by their ID number). Contrary to other methodologies where influential points could be removed, in survival analysis these are not treated as outliers as they might be informative. In other words it would not be correct to remove any of the outliers that are failed banks. Bank IDs show that the influential points are all failed banks hence they should not be removed from the analysis (outliers with an ID higher than 1000 indicate Islamic banks).

3.5.7 A Full Variable Model

In this section we develop a set of *Full Models* which utilize the stepwise algorithm for both bank-specific and macroeconomic variables. Hence these models can have more than one macroeconomic variables at every time. Shared frailty is selected only for Conventional banks as it was found to be insignificant for Islamic banks in a previous section. We report the *Restricted* and the *Semi-Generalized* set-ups. The Semi-Generalized is the least restrictive between the two on its assumptions for the hazard functions of the two bank types. Consistent with our initial approach of treating Balance Sheet, Income Statement and Financial Ratios individually. The optimization phase with the stepwise algorithm takes place in the *Restricted* setup with both bank-specific and macroeconomic variables (micro+macro model in Table 38) and then the macroeconomic variables are dropped (micro model). The tables 37-39 present our results for the Balance sheet, Income statement and Financial Ratios respectively.

[Tables 37-39 here]

The contributions of the explanatory variables remain unchanged from the previous analysis so we avoid any further repetition. In particular, the coefficient of the Islamic Banking dummy implies that, controlling for differences in bank-level accounting characteristics, macroeconomic environment and latent country effects Islamic banks have about 55% less hazardous than CBs. The main benefit from the *Full models* is a much improved, in terms of explanatory power, model of failure risk as can be evidenced by the increased $pseudo - R^2$. A comparison of the McFadden pseudo-R^2 of each Micro+Macro model reported in Tables 37-39 and the corresponding Micro model suggests that bank-level fundamentals not only significantly affect the probability of bank failure, but also explain a significant proportion of it.[49] However, country-level indicators add further explanatory power, particularly, for IBs. The increase in the pseudo-R^2 from each Micro model to the corresponding Micro+Macro model ranges from 5% to 11% for CBs and from 18% to 26% for IBs;[50] the same qualitative conclusion is reached by measuring the change in AIC, BIC and log-likelihood. For instance, in the context of the generalized Cox PH model for financial ratios, the improvement in the log-likelihood of the Micro+Macro model against the corresponding Micro model is 4% for CBs and 38% for IBs. This finding suggests that the macroeconomic environment (mainly *Inflation*) matters to IB failure risk, which is plausible given the asset-backed aspect of their business model and their greater involvement in real estate and the construction sector.

To conclude the empirical analysis, we gather all the Balance sheet, Income statement, Financial ratio and country-level indicators retained by the stepwise variable-selection algorithm, as shown in Tables 37-39, and include them in a "Full-Variable" *Restricted* Cox PH model for pooled data on all banks. This model allows us to corroborate empirically the absence of omitted variable bias in the balance sheet, income statement and financial ratio

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49 The McFadden pseudo-R^2 is computed as 1 minus the ratio of log-likelihoods of two PH Cox models: the corresponding "full" model as reported in each table and the "intercept" model which is a simplified version including only the baseline hazard function without explanatory variables.

50 The unreported shared-frailty Cox PH models for IBs produce similar evidence, namely, the increase in the pseudo-R^2 is 24% (balance sheet), 18% (income statement) and 25% (financial ratios).

models. Indeed the coefficient estimates reported in Table 40 are similar in magnitude to those reported earlier in Tables 37 to 39.

[Table 40 here]

3.6 Conclusion

This chapter has been motivated by the lack of empirical evidence, supportive or contradicting, to theoretical arguments that Islamic finance promotes economic growth and enhances financial stability (Haque and Mirakhor 1986). In addition, there has been evidence that Islamic banks have managed to weather the recent financial crisis due to their different banking model as well as their excess liquidity (Hasan and Dridi 2010).

We conduct a comparative analysis of Islamic banks and conventional commercial banks from the viewpoint of failure risk. A novel research strategy is adopted for the comparison based on both unconditional and conditional survival-time models. We assess the relative importance of various accounting indicators and macroeconomic fundamentals as early waning signals of bank financial distress. The firm-level covariates pertain to the three blocks of the accounting statement, balance sheet, income statement and financial ratios, whereas the system-wide indicators reflect the country business cycle and financial structure. The survival-time methodology adopted controls for unobserved country factors that induce within-country correlation clusters in default rates. A total of 421 banks, of which 106 are Islamic and 315 conventional, are observed during the 16-year period from 1995 to 2010. The banks are located in 20 Middle and Far Eastern countries.

The unconditional non-parametric estimators of survival rates suggest that Islamic banks are less prone to failure than commercial banks. The conditional hazard functions reveal that Islamic banks are about 55% less hazardous than conventional banks ceteris paribus. We uncover important differences in the drivers of the survival rate for the two banking systems. Better capitalization (inverse of leverage), as proxied by Equity/Assets, reduces the failure risk for conventional banks; yet it increases it for Islamic banks. The default risk of Islamic banks is more strongly linked to macroeconomic factors (*e.g.* inflation) than that of commercial banks. This is attributed to the IBs having to invest in tangible goods (*i.e.* commodities, real estate) affects them to a greater degree by the macroeconomic environment (real GDP growth, inflation) than CBs. Specifically, IBs are more affected by inflation whereas CBs by real GDP growth. The reason for this is that IBs cannot protect themselves against rising inflation as CBs do by the use of hedging instruments. Latent country factors significantly increase the probability of co-default in commercial banks but are less important for Islamic banks.

The contrasting findings documented for the two banking systems can be attributed to fundamental differences in their business models. The results indirectly imply that Islamic banks contribute favorably to the soundness of the overall financial system. This research has very important implication for policy makers and regulators, and the risk management of individual banks.

We find that the two bank types display important differences under the three blocks of the accounting statement, namely the Balance Sheet, the Income Statement and the Financial Ratios, with Islamic banks being less fragile than the conventional ones.

Firstly, growth of assets has a greater impact on Islamic banks while there is a significant relation between real GDP growth and growth of assets only for Islamic banks verifying their being closer to the real economy as argued by Haque and Mirakhor (1986). In addition, the macroeconomic environment affects the survival of Islamic banks to a larger degree than it does for conventional banks. Merger and acquisition activity led many conventional banks to merge their business in many countries; thus leading to higher concentration of the industry. As a result more concentration reduces the hazard for conventional banks; however the opposite is true, though not statistically significant, for Islamic banks.

Secondly, the equity-to-assets shows that better capitalization is desirable for conventional banks but not for Islamic banks. Better capitalization (inverse of leverage), as proxied by Equity/Assets, reduces the failure risk for conventional banks; yet it increases it for Islamic banks. The contrast may reflect the downward pressure to profitability that Islamic banks face from their constraints on leverage. Moreover it seems that Islamic banks have the necessary mechanisms in place that discipline them more effectively than conventional banks on the use and abuse of leverage. Such mechanisms may relate to the equity-type contractual agreements with depositors, the so-called investment account holders. These agreements induce depositors to monitor bank performance due to the uncertainty of their payout. On the bank's end, such depositors imply larger withdrawal risk than in conventional banks. In addition, the applicability of displaced commercial risk specifically to IBs suggests that leverage imposes stronger market discipline in Islamic banks (e.g. incentives to stronger loan screening standards and monitoring) and reduces moral hazard.

Thirdly, we find evidence in support of the claims that Islamic banking is operating more using fee-based contracts as opposed to partnership contracts due to the insignificance of the net interest revenue explanatory variable under the income statement data specification. In addition, the other operating income coefficient is more negative for the Islamic than the conventional banks which could mean that an increase in the covariate has a greater, hazard lessening, effect upon the former.

Fourthly, we find evidence that there is a significant "country effect" for conventional banks. The effect can be considered as a proxy for political risk or regulatory efficiency. In essence it is a bonus decrease in the hazard function of banks operating in country A than country B. The effect retains its significance even after correcting for the macroeconomic environment.

Additionally, increased within-country correlation for conventional banks would mean that they are more vulnerable to banking crises, as there is a latent process causing them to behave in the same way implying a higher vulnerability to contagion. By contrast, Islamic banks do not have significant within group correlation, meaning that it is more likely financial distress in an Islamic bank to be contained rather than spreading to the rest banking system. Less standardization of products and practices in Islamic banking as well as a more "private banking" character might be responsible for this. Such finding can have important policy implications as governments would intervene to bail out a failed conventional banks for fears of adverse economic impact on the country's banking system. However the results suggest that such action is not likely to take place for Islamic banks as the effect is unlikely to spread to other banks.

Tunisia, Jordan and Kuwait have the most favorable banking background whereas Turkey, Brunei and Indonesia have the least. For Islamic banks in particular the most favorable environment is found in Malaysia, Kuwait and the UAE; conversely the worst is found in Bangladesh, Brunei and Turkey. Finally, all results are verified no matter which part of the accounting statement is used; however as subtle differences exist among them, inspection of all is necessary and one set cannot be used to substitute another.

Main policy implication from this chapter is the fact that Islamic banks are less prone to failure than conventional banks. In addition they are sensitive to different variables which has implications for their regulation and monitoring. Moreover the presence of Islamic banks in the system reduces potential contagion effects as these banks appear to be less interconnected.

3.7 Tables

Table 1. The 25 most costly failures during the 2008 Financial crisis.

	Acquired	Acquirer	Country	Value	Type	Date
1	American International Group	United States Government	USA	182 bil	Insurance company	Sep-08
2	Fannie Mae & Freddie Mac	United States Government	USA	160 bil	Subprime mortgage lender	Sep-08
3	Northern Rock	Government of the UK	UK	60 bil	Retail and mortgage bank	Feb-08
4	Merrill Lynch	Bank of America	USA	44 bil	Investment bank	Sep-08
5	HBOS	Lloyds TSB	UK	21.9 bil	Diversified financial services	Sep-08
6	Wachovia	Wells Fargo	USA	15 bil	Retail and investment banking	Oct-08
7	IndyMac	IMB Management Holdings	USA	13.9 bil	Savings and loan association	Jan-09
8	Commerce Bancorp	Toronto-Dominion Bank	USA	8.5 bil	Commercial Bank	Oct-08
9	Fortis	Government of the Netherlands BNP Paribas	Belgium Netherlands Luxemburg	7.6 bil	Diversified financial services	Sep-08
10	Caja de Ahorros	Banco de España	Spain	7.1 bil	Savings and loan association	Mar-09
11	National City Bank	PNC Financial Services	USA	5.6 bil	Commercial Bank	Oct-08
12	Countrywide Financial	Bank of America	USA	4 bil	Subprime mortgage lender	Jul-08
13	Derbyshire Building Society	Nationwide Building Society	UK	3.9 bil	Building society	Sep-08
14	Cheshire Building Society	Nationwide Building Society	UK	2.7 bil	Building society	Sep-08
15	Bear Sterns	JP Morgan Chase	USA	2.2 bil	Investment bank	Apr-08
16	BTA Bank	Government of Kazakhstan	Kazakhstan	2.1 bil	Commercial Bank	Feb-09
17	Washington Mutual	JP Morgan Chase	USA	1.9 bil	Savings and loan association	Sep-08
18	Sovereign Bank	Banco Santander SA	USA	1.9 bil	Commercial Bank	Oct-08
19	Lehman Brothers	Barclays plc	USA	1.3 bil	Investment bank	Sep-08
20	Roskilde Bank	Danmarks Nationalbank	Denmark	0.89 bil	Retail bank	Aug-08
21	BankWest	Commonwealth Bank of Australia	Australia	0.67 bil	Commercial Bank	Oct-08
22	Alliance & Leicester	Grupo Santander	UK	0.63 bil	Retail and Mortgage bank	Jul-08
23	CajaSur	Banco de España	Spain	0.42 bil	Savings and loan association	May-10
24	Barnsley Building Society	Yorkshire Building Society	UK	0.21 bil	Building society	Oct-08
25	Chesham Building Society	Skipton Building Society	UK	0.14 bil	Building society	Feb-10
26	Catholic Building Society	Chelsea Building Society	UK	25.93 mil	Building society	Sep-08

Sources: Federal Deposit Insurance Corporation; Bloomberg; National Audit Office. Value in USD

Table 2. Time to an event.

Time	X
1	3
5	2
9	4
20	9
22	-4

Table 3. Types of Censoring.

Type	Description
Left	Start date is not observed
Right	End date is not observed
Interval	Start & End dates are not observed
Random	Subject leaving the experiment for other than the reason under study
Type I	The end date is fixed
Type II	The experiment goes on until a certain number of failures are reached

Table 4. Parametric Survival Models.

Distribution	Baseline Hazard	Parameters	Hazard shape	Uses
Exponential	$h_0(t) = \exp(\beta_0)$ $h_j(t) = h_0(t)\exp(x_j\beta_x) =$ $= \exp(\beta_0 + x_j\beta_x)$ $H_j(t) = \exp(\beta_0 + x_j\beta_x)t$ $S_j(t) = \exp(-\exp(\beta_0 + x_j\beta_x)t)$	β_0, β'_x	Constant	A young individual at good health. Hazard would reflect death from unnatural causes. A bank facing constant hazard throughout its lifetime.
Weibul	$h_0(t) = pt^{p-1}\exp(\beta_0)$ $h_j(t) = h_0(t)\exp(x_j\beta_x)$ $= pt^{p-1}\exp(\beta_0 + x_j\beta_x)$ $H_j(t) = \exp(\beta_0 + x_j\beta_x)t^p$ $S_j(t) = \exp(-\exp(\beta_0 + x_j\beta_x)t^p)$	β_0, β'_x, p	Monotonically increasing or decreasing	Patients recovering from a surgery where hazard is higher during the first hours after the operation. A bank having more hazard in the first years of operation.
Gompetz	$h_0(t) = \exp(\beta_0)\exp(\gamma t)$ $h_j(t) = h_0(t)\exp(x_j\beta_x)$ $= exp(\gamma t)\exp(\beta_0 + x_j\beta_x)$ $H_j(t) = \gamma^{-1}\exp(\beta_0 + x_j\beta_x)(\exp(\gamma t) - 1)$ $S_j(t) = \exp[-\gamma^{-1}\exp(\beta_0 + x_j\beta_x)(\exp(\gamma t) - 1)]$	$\beta_0, \beta'_x, \gamma$	Exponential hazard	Hazard from a complex surgery in young ages as opposed to elders. A bank having more hazard in the first years of operation then decreasing and rising again.

Table 5. Semi-Parametric Analysis.

Subject	Time	X
1	1	3
2	5	2
3	9	4
4	20	9
5	22	-4

Table 6. Interpretation of Coefficients and Hazard Ratios.

Explanatory Variables	Coefficient	Hazard Ratio	Hazard Change
Weight (kilos)	0.185	1.203	+20.30%
Sex (1 female; 0 male)	-0.554	0.575	-42.50%
Doctor's fee (hundred pounds)	-0.843	0.430	-57.00%

Table 7. Comparison of Parametric and Semi-Parametric Analysis.

Time	X	Outcome
0	5	0
1	20	0
2	20	0
3	5	0

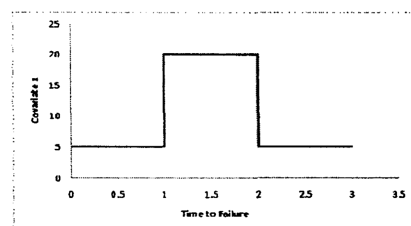


Table 8. Rank tests methodology.

		Time $t_j = 1$	
Groups	**Survived** $(n_{ij} - d_{ij})$	**Failed** (d_{ij})	**At risk** (n_{ij})
A	$n_{Aj} - d_{Aj}$	d_{Aj}	n_{Aj}
B	$n_{Bj} - d_{Bj}$	d_{Bj}	n_{Bj}
Total	$n_j - d_j$	$d_{ij} = d_{Aj} + d_{Bj}$	$n_j = n_{Aj} + n_{Bj}$

Table 9. Classification of conditioning variables.

Accounting Variables

I. Balance Sheet

Loans	Deposits and Short term funding
Assets	Equity
Other Earning Assets	Liabilities
Reserves for Impaired Loans/NPL	Liquid Assets

II. Income Statement

Net Interest Revenue	Net Income
Other Operating Income	General Admin. Expenses (Overheads)

III. Financial Ratios

Capital Quality	*Earnings*
Equity/Assets	Net Interest Margin
Equity/Net Loans	Return on Average Assets (RoA)
Equity/Deposits and Short term funding	Return on Average Equity (RoE)
Liabilities/Equity	Cost to Income
Z-score	Income Diversity
Asset Quality	*Liquidity*
Loan Loss Reserves/Loans	Net Loans/Assets
Tier 1 Ratio	Liquid Assets/Deposits and Short term funding

Macroeconomic Variables

Business Cycle	*Financial structure*
Growth of Real GDP	Banking Sector Concentration
Inflation	Islamic Banks Share
FX Rate Depreciation	Sovereign Rating
Unexpected Inflation	Financial Openness

The source for the accounting variables is *Bankscope* whereas the macroeconomic data are obtained from the *IMF/World Bank* databases. NPL denotes Non-Performing Loans.

Table 10. Accounting profile by bank category.

					Surv		Fail		CB		IB	
	CB	IB	Surv	Fail	CB	IB	CB	IB	Surv	Fail	Surv	Fail
No. of banks	315	106	324	97	226	98	89	8	226	89	98	8
Balance Sheet												
Assets	4941***	3651	5140***	1810	5492***	3858	1888*	941.7	5492***	1888	3858***	941.7
Equity	482.6***	400.2	5120***	184.4	537.8***	418.0	186.3	163.1	537.8***	186.3	418.0***	163.1
Liabilities	4459***	3251	4628***	1625	4954***	3440	1701*	778.6	4954***	1701	3440***	778.6
Loans	2452**	2107	2617***	1013	2720***	2237	1070**	385.5	2720***	1070	2237***	385.5
Deposits	3996***	2782	4115***	1455	4442***	2914	1502	857.5	4442***	1502	2914***	857.5
Other Earn. Assets	1848***	1003	1845***	557.1	2062***	1048	562.8	484.7	2062***	562.8	1048**	484.7
Reserves Imp Loans	156.8***	114.2	165.6***	60.45	175.1***	119.4	61.29	43.32	175.1***	61.29	119.4**	43.32
Liquid Assets	1287***	867.2	1320***	357.1	1433***	910.4	358.3	340.6	1433***	358.4	910.4***	340.6
Income Statement												
Net Interest Revenue	155.9***	103.6	159.2***	58.64	172.58***	109.7	62.71***	13.31	172.6***	62.71	109.7***	13.31
Other Oper. Income	71.08	64.31	77.69***	22.59	80.43	67.61	23.42	13.32	80.40***	23.42	67.61***	13.32
Net Income	227.1***	166.1	236.6***	81.23	253.11***	174.8	86.13***	26.63	253.1***	86.13	174.8***	26.63
Overheads	111.3***	84.65	116.1***	46.13	123.44***	89.13	48.44***	16.68	123.4***	48.44	89.13***	16.68
Financial Ratios												
Tier 1 Ratio	15.85***	25.01	17.51**	13.10	16.05***	25.08	13.10	n/a	16.05	13.10	25.08	n/a
Loan Loss Res./Loans	7.884***	6.683	7.813	8.109	8.082***	6.487	8.008	10.57	8.082	8.008	6.487	10.57
Equity/Assets	10.81***	21.68	13.22***	8.541	11.02***	21.25	6.993	28.15	11.02***	6.993	21.25	28.15
Equity/Net Loans	27.67***	68.23	36.19***	21.56	28.36***	66.26	15.51*	97.60	28.36***	15.51	66.26	97.60
Equity/Deposits	18.09***	55.06	25.88***	15.29	18.03***	55.35	13.41	43.14	18.03	13.41	55.35	43.14
Liabilities/Equity	15.82***	9.050	15.08	10.87	16.60***	9.420	11.43	3.750	16.60	11.43	9.420	3.750
Z-score	15.55***	22.86	16.62**	35.56	15.03***	22.88	36.68	21.29	15.03**	36.68	22.88	21.29
Income Diversity	-5.43	-4.10	-4.96	-15.41	-5.18	-4.08	-16.22	-6.92	-5.18	-16.22	-4.08	-6.92
Net Interest Margin	4.081***	6.557	4.486	4.407	3.887***	6.716	4.592*	1.989	3.887	4.592	6.716***	1.989
RoA	0.940***	2.126	1.293***	-0.728	1.055***	2.162	-0.890**	1.131	1.055***	-0.890	2.162	1.131
RoE	14.10**	11.26	13.13	9.728	13.67*	11.17	9.415	13.11	13.67	9.415	11.17	13.11
Cost/Income	56.48**	62.61	57.31*	78.06	55.79***	63.09	79.33	60.70	55.79**	79.33	63.09	60.70
Net Loans/Assets	51.52**	49.82	50.82**	55.49	51.02	50.05	56.22	46.32	51.02***	56.22	50.05	46.32
Liquid Assets/Depos.	40.29***	55.56	43.60	40.11	40.34***	55.71	40.14	39.79	40.34	40.14	55.71	39.79

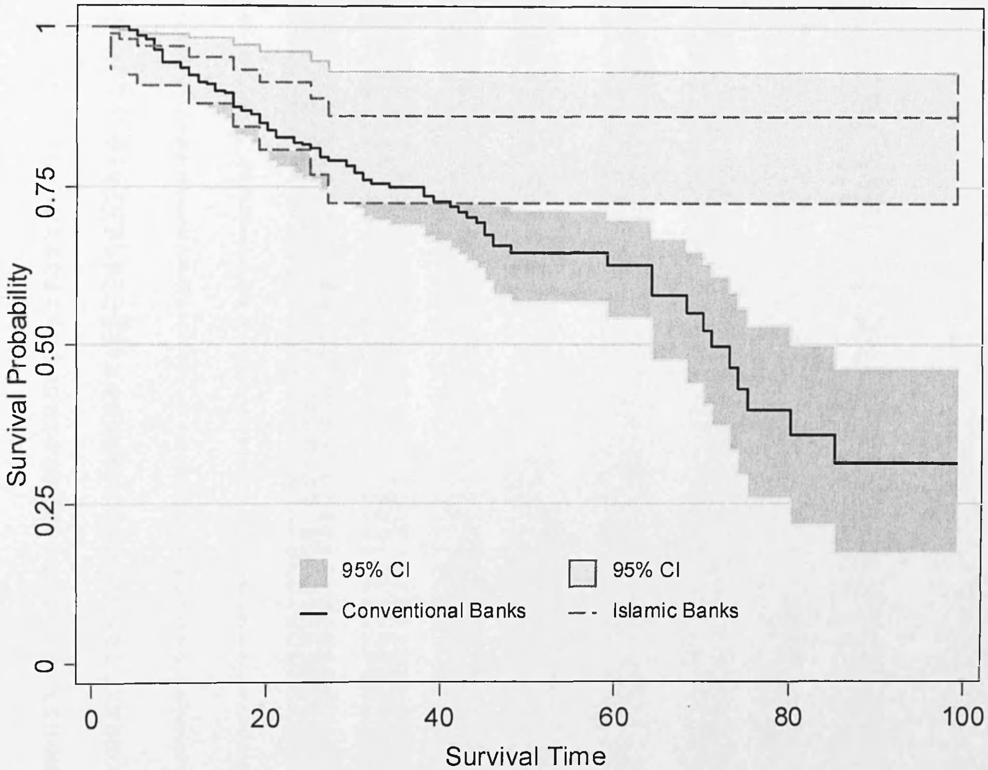
All figures are US$ millions except financial ratios, which are in percentages. Surv stands for survivor bank and Fail for banks that failed at some point during the sample period 1995-2010. Columns labelled Fail report averages of the accounting indicators on the year prior to the banking failure event. *, ** and *** denote significance of the mean difference t-test at the 10%, 5% and 1% significance levels, respectively. n/a refers to data unavailability for the particular cohort.

Table 11. Descriptive Statistics of Macroeconomic Variables.

	Real GDP Growth	Inflation	Unexpected Inflation	Banking Sector Concentration	Credit Rating	FX Rate Depreciation	Financial Openness
Albania	5.64	4.11	8.52	0.46	0	-0.037	33.24
Bahrain	5.92	6.21	4.97	0.24	1	0.000	96.32
Bangladesh	5.57	4.79	-4.84	0.10	0	0.038	17.42
Brunei	1.78	7.07	2.83	0.31	0	-0.001	43.04
Egypt	4.88	7.10	-1.33	0.13	0	0.034	82.02
Indonesia	4.92	16.20	26.00	0.10	0.5	0.113	75.76
Iran	5.02	19.03	-0.88	0.15	0	0.150	24.65
Jordan	5.39	4.44	-0.33	0.32	0	0.000	89.08
Kuwait	5.26	8.50	0.14	0.30	1	-0.007	74.29
Malaysia	4.77	3.55	-0.08	0.10	1	0.018	49.26
Mauritania	3.95	7.46	-0.98	0.38	0	0.048	17.31
Pakistan	4.38	10.54	0.98	0.14	0.5	0.060	15.23
Palestine	4.04	1.67	-3.07	0.76	0	-0.003	43.04
Qatar	11.74	5.86	-0.97	0.30	1	0.000	100
Saudi Arabia	2.78	4.55	-5.06	0.12	1	0.000	75.55
Sudan	7.04	13.85	-9.62	0.27	0	0.034	30.17
Tunisia	4.81	3.47	-2.61	0.12	1	0.016	17.83
Turkey	3.77	43.20	-8.28	0.13	0.5	0.307	21.15
UAE	5.82	7.33	2.68	0.10	1	0.000	100
Yemen	4.58	14.65	-9.51	0.19	0	0.072	90.48

Note: Real GDP Growth is year-on-year logarithmic change in real GDP. Inflation is year-on-year log change in the GDP deflator. FX Rate Depreciation is year-on-year change in log spot exchange rate defined as local currency vis-a-vis US$ (positive changes represent depreciation). Banking Sector Concentration is the normalized HHI. Islamic Bank Share is the market share of IBs in each country at year end. Sovereign Rating takes value of 1 for investment grade sovereign bonds, 0.5 for speculative grade and 0 for unrated countries. Financial Openness takes the value of 100 for the most open economy and 0 for the most restricted.

Figure 1. Unconditional survivor functions.



The figure reports non-parametric Kaplan-Meier survival rate estimates and their 95% confidence interval from 1 to 100 years. The survival rates are 84% (after 20 years) and 77% (after 30 years) for conventional commercial banks, and 91% (20 years) and 86% (30 years) for Islamic banks.

Table 12(a). Non Parametric Analysis by Bank Type / Conventional Banks.

Time	Total Banks	Failure	Net Lost	Survivor Function	St. Error	Upper 95% CI	Lower 95% CI	Cumulative Hazard	St. Error	Upper 95% CI	Lower 95% CI
4	315	1	0	0.9968	0.0032	0.9777	0.9996	0.0032	0.0032	0.0004	0.0225
5	314	3	0	0.9873	0.0063	0.9665	0.9952	0.0127	0.0064	0.0048	0.0339
6	311	2	1	0.9810	0.0077	0.9581	0.9914	0.0192	0.0078	0.0086	0.0426
7	308	5	1	0.9650	0.0104	0.9377	0.9805	0.0354	0.0107	0.0196	0.0639
8	302	6	2	0.9459	0.0128	0.9143	0.9660	0.0553	0.0134	0.0344	0.0889
9	294	0	3	0.9459	0.0128	0.9143	0.9660	0.0553	0.0134	0.0344	0.0889
10	291	2	3	0.9394	0.0135	0.9066	0.9609	0.0621	0.0143	0.0396	0.0974
11	286	4	7	0.9262	0.0148	0.8910	0.9504	0.0761	0.0159	0.0506	0.1146
12	275	3	2	0.9161	0.0158	0.8792	0.9421	0.0870	0.0171	0.0592	0.1279
13	270	1	2	0.9127	0.0161	0.8753	0.9393	0.0907	0.0175	0.0622	0.1324
14	267	3	4	0.9025	0.0169	0.8634	0.9308	0.1020	0.0186	0.0713	0.1459
15	260	1	12	0.8990	0.0172	0.8594	0.9279	0.1058	0.0190	0.0744	0.1506
16	247	6	4	0.8772	0.0190	0.8343	0.9095	0.1301	0.0215	0.0942	0.1798
17	237	1	3	0.8735	0.0192	0.8301	0.9064	0.1343	0.0219	0.0976	0.1848
18	233	2	7	0.8660	0.0198	0.8216	0.9000	0.1429	0.0227	0.1047	0.1951
19	224	3	11	0.8544	0.0206	0.8085	0.8900	0.1563	0.0240	0.1157	0.2111
20	210	3	7	0.8422	0.0215	0.7946	0.8795	0.1706	0.0256	0.1275	0.2283
21	200	2	1	0.8337	0.0221	0.7851	0.8723	0.1806	0.0263	0.1357	0.2403
22	197	0	3	0.8337	0.0221	0.7851	0.8723	0.1806	0.0263	0.1357	0.2403
23	194	2	1	0.8251	0.0227	0.7754	0.8649	0.1909	0.0273	0.1442	0.2527
24	191	1	3	0.8208	0.0230	0.7705	0.8611	0.1961	0.0278	0.1485	0.2590
25	187	1	2	0.8164	0.0233	0.7656	0.8573	0.2015	0.0283	0.1530	0.2654
26	184	3	8	0.8031	0.0241	0.7506	0.8457	0.2178	0.0299	0.1665	0.2849
27	173	1	8	0.7985	0.0244	0.7454	0.8416	0.2236	0.0304	0.1713	0.2919
28	164	0	3	0.7985	0.0244	0.7454	0.8416	0.2236	0.0304	0.1713	0.2919
29	161	2	4	0.7886	0.0251	0.7342	0.8331	0.2360	0.0316	0.1814	0.3069
30	155	2	3	0.7784	0.0258	0.7227	0.8242	0.2489	0.0329	0.1920	0.3226
31	150	2	6	0.7680	0.0265	0.7111	0.8152	0.2622	0.0343	0.2030	0.3388
32	142	1	6	0.7626	0.0268	0.7050	0.8105	0.2693	0.0350	0.2087	0.3473
33	135	0	8	0.7626	0.0268	0.7050	0.8105	0.2693	0.0350	0.2087	0.3473
34	127	1	5	0.7566	0.0273	0.6981	0.8054	0.2771	0.0359	0.2151	0.3571
35	121	0	7	0.7566	0.0273	0.6981	0.8054	0.2771	0.0359	0.2151	0.3571
36	114	0	2	0.7566	0.0273	0.6981	0.8054	0.2771	0.0359	0.2151	0.3571
37	112	0	4	0.7566	0.0273	0.6981	0.8054	0.2771	0.0359	0.2151	0.3571
38	108	2	4	0.7426	0.0285	0.6816	0.7937	0.2957	0.0382	0.2296	0.3808
39	102	1	2	0.7353	0.0292	0.6730	0.7879	0.3055	0.0394	0.2372	0.3933
40	99	0	2	0.7353	0.0292	0.6730	0.7876	0.3055	0.0394	0.2372	0.3933
41	97	1	3	0.7277	0.0298	0.6641	0.7813	0.3158	0.0407	0.2452	0.4066
42	93	1	4	0.7199	0.0305	0.6549	0.7747	0.3265	0.0421	0.2536	0.4205
43	88	1	0	0.7117	0.0313	0.6453	0.7679	0.3379	0.0436	0.2623	0.4352
44	87	1	3	0.7035	0.0319	0.6358	0.7611	0.3494	0.0451	0.2712	0.4500
45	83	2	2	0.6866	0.0333	0.6161	0.7468	0.3735	0.0482	0.2900	0.4811
46	79	2	3	0.6692	0.0347	0.5961	0.7321	0.3988	0.0514	0.3097	0.5135
47	74	0	2	0.6692	0.0347	0.5961	0.7321	0.3988	0.0514	0.3097	0.5135
48	72	1	2	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
49	69	0	6	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
50	63	0	7	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
52	56	0	5	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
53	51	0	2	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
54	49	0	2	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
55	47	0	2	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
56	45	0	2	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
57	43	0	1	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
58	42	0	1	0.6599	0.0354	0.5854	0.7242	0.4127	0.0533	0.3204	0.5315
59	41	1	1	0.6438	0.0381	0.5639	0.7128	0.4371	0.0586	0.3361	0.5684
60	39	0	1	0.6438	0.0381	0.5639	0.7128	0.4371	0.0586	0.3361	0.5684
61	38	0	2	0.6438	0.0381	0.5639	0.7128	0.4371	0.0586	0.3361	0.5684
62	36	0	1	0.6438	0.0381	0.5639	0.7128	0.4371	0.0586	0.3361	0.5684
63	35	0	2	0.6438	0.0381	0.5639	0.7128	0.4371	0.0586	0.3361	0.5684
64	33	2	0	0.6048	0.0446	0.5114	0.6858	0.4977	0.0726	0.3739	0.6624
65	31	0	1	0.6048	0.0446	0.5114	0.6858	0.4977	0.0726	0.3739	0.6624
67	30	0	1	0.6048	0.0446	0.5114	0.6858	0.4977	0.0726	0.3739	0.6624
68	29	1	1	0.5839	0.0477	0.4845	0.6707	0.5322	0.0804	0.3958	0.7155
70	27	1	0	0.5623	0.0506	0.4574	0.6546	0.5692	0.0885	0.4197	0.7720
71	26	1	3	0.5407	0.0531	0.4313	0.6378	0.6077	0.0965	0.4451	0.8295
73	22	1	0	0.5161	0.0561	0.4014	0.6192	0.6531	0.1067	0.4742	0.8995
74	21	1	0	0.4915	0.0585	0.3728	0.5997	0.7007	0.1168	0.5054	0.9715
75	20	1	0	0.4670	0.0606	0.3453	0.5796	0.7507	0.1271	0.5388	1.0461
79	19	0	2	0.4670	0.0606	0.3453	0.5796	0.7507	0.1271	0.5388	1.0461
80	17	1	0	0.4395	0.0629	0.3146	0.5574	0.8096	0.1400	0.5768	1.1362
82	16	0	1	0.4395	0.0629	0.3146	0.5574	0.8096	0.1400	0.5768	1.1362
85	15	1	1	0.4102	0.0652	0.2825	0.5335	0.8762	0.1551	0.6194	1.2396
89	13	0	1	0.4102	0.0652	0.2825	0.5335	0.8762	0.1551	0.6194	1.2396
96	12	0	1	0.4102	0.0652	0.2825	0.5335	0.8762	0.1551	0.6194	1.2396
104	11	0	2	0.4102	0.0652	0.2825	0.5335	0.8762	0.1551	0.6194	1.2396
105	9	0	1	0.4102	0.0652	0.2825	0.5335	0.8762	0.1551	0.6194	1.2396
111	8	1	1	0.3589	0.0745	0.2178	0.5022	1.0012	0.1992	0.6779	1.4787
114	6	0	1	0.3589	0.0745	0.2178	0.5022	1.0012	0.1992	0.6779	1.4787
125	5	0	2	0.3589	0.0745	0.2178	0.5022	1.0012	0.1992	0.6779	1.4787
134	3	0	1	0.3589	0.0745	0.2178	0.5022	1.0012	0.1992	0.6779	1.4787
137	2	1	0	0.1795	0.1323	0.0186	0.4766	1.5012	0.5382	0.7435	3.0312
146	1	0	1	0.1795	0.1323	0.0186	0.4766	1.5012	0.5382	0.7435	3.0312

Note: Survivor Function and Cumulative Hazard Function are the Kaplan-Meier and Nelson-Aalen estimators respectively. Net $Lost_t$=$Censored_t$-Late $Enties_t$

Table 12(b). Non Parametric Analysis by Bank Type / Islamic Banks.

Time	Total Banks	Failure	Net Lost	Survivor Function	St. Error	Upper 95% CI	Lower 95% CI	Cumulative Hazard	St. Error	Upper 95% CI	Lower 95% CI
2	106	1	3	0.9906	0.0094	0.9349	0.9987	0.0094	0.0094	0.0013	0.0670
3	102	1	3	0.9809	0.0134	0.9256	0.9952	0.0192	0.0136	0.0048	0.0769
4	98	0	11	0.9809	0.0134	0.9256	0.9952	0.0192	0.0136	0.0048	0.0769
5	87	1	4	0.9696	0.0174	0.9083	0.9901	0.0307	0.0178	0.0099	0.0957
6	82	0	6	0.9696	0.0174	0.9083	0.9901	0.0307	0.0178	0.0099	0.0957
7	76	0	3	0.9696	0.0174	0.9083	0.9901	0.0307	0.0178	0.0099	0.0957
8	73	0	4	0.9696	0.0174	0.9083	0.9901	0.0307	0.0178	0.0099	0.0957
9	69	0	3	0.9696	0.0174	0.9083	0.9901	0.0307	0.0178	0.0099	0.0957
10	66	0	2	0.9696	0.0174	0.9083	0.9901	0.0307	0.0178	0.0099	0.0957
11	64	1	1	0.9544	0.0228	0.8807	0.9830	0.0464	0.0237	0.0170	0.1262
12	62	0	6	0.9544	0.0228	0.8807	0.9830	0.0464	0.0237	0.0170	0.1262
13	56	0	3	0.9544	0.0228	0.8807	0.9830	0.0464	0.0237	0.0170	0.1262
14	53	0	4	0.9544	0.0228	0.8807	0.9830	0.0464	0.0237	0.0170	0.1262
15	49	0	1	0.9544	0.0228	0.8807	0.9830	0.0464	0.0237	0.0170	0.1262
16	48	1	2	0.9345	0.0297	0.8436	0.9734	0.0672	0.0316	0.0268	0.1687
17	45	0	1	0.9345	0.0297	0.8436	0.9734	0.0672	0.0316	0.0268	0.1687
19	44	1	1	0.9133	0.0358	0.8091	0.9619	0.0899	0.0389	0.0385	0.2099
20	42	0	1	0.9133	0.0358	0.8091	0.9619	0.0899	0.0389	0.0385	0.2099
21	41	0	1	0.9133	0.0358	0.8091	0.9619	0.0899	0.0389	0.0385	0.2099
23	40	0	2	0.9133	0.0358	0.8091	0.9619	0.0899	0.0389	0.0385	0.2099
24	38	0	1	0.9133	0.0358	0.8091	0.9619	0.0899	0.0389	0.0385	0.2099
25	37	1	4	0.8886	0.0425	0.7700	0.9480	0.1169	0.0474	0.0529	0.2586
26	32	0	1	0.8886	0.0425	0.7700	0.9480	0.1169	0.0474	0.0529	0.2586
27	31	1	3	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
28	27	0	3	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
29	24	0	3	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
30	21	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
31	20	0	2	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
32	18	0	4	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
33	14	0	2	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
34	12	0	4	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
36	8	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
47	7	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
56	6	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
70	5	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
79	4	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
83	3	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
96	2	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167
99	1	0	1	0.8600	0.0499	0.7257	0.9315	0.1492	0.0573	0.0703	0.3167

Note: Survivor Function and Cumulative Hazard Function are the Kaplan-Meier and Nelson-Aalen estimators respectively. Net $Lost_t$=$Censored_t$-Late $Enties_t$

Table 13. Log-rank tests for equality of survival functions.

Bank Type	**Log-rank test**		**Peto & Prentice**		**Wilcoxon**		**Fleming-Harington (p>q)**		**Fleming-Harington (p<q)**	
	Events Observed	**Events Expected**	**Events Observed**	**Events Expected**	**Events Observed**	**Events Expected**	**Events Observed**	**Events Expected**	**Events Observed**	**Events Expected**
Conventional	89	82.11	89	82.11	89	82.11	89	82.11	89	82.11
Islamic	8	14.89	8	14.89	8	14.89	8	14.89	8	14.89
Total	97	97.00	97	97.00	97	97.00	97	97.00	97	97.00
χ_1^2 **value**	3.87		3.29		2.02		4.33		2.59	
p − value	*(0.049)*		*(0.069)*		*(0.155)*		*(0.037)*		*(0.107)*	

Note: In the Fleming-Harington test, when $p > q$ more weight is given to earlier failures; when $p < q$ more weight is given to later failures
In all tests the null hypothesis is that the two survival functions are the same.

Table 14. Restricted / Semi-Restricted / Semi-Generalized Cox PH / Balance Sheet.

	Restricted	Semi-Restricted	Semi-Generalized	
	All banks	**All banks**	**Conventional**	**Islamic**
Assets (ln)	0.638	0.649	0.610	0.813
(p-value)	*(0.000)*	*(0.000)*	*(0.001)*	*(0.007)*
Growth of Assets	-0.094	-0.091	-0.093	-0.082
(p-value)	*(0.000)*	*(0.000)*	*(0.001)*	*(0.177)*
Growth of Equity	-0.102	-0.115	-0.114	-0.216
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.651)*
Liquid Assets	-0.001	-0.001	-0.001	-0.001
(p-value)	*(0.003)*	*(0.004)*	*(0.007)*	*(0.179)*
Other Earning Assets (ln)	-0.390	-0.386	-0.350	-0.463
(p-value)	*(0.003)*	*(0.002)*	*(0.038)*	*(0.014)*
Islamic	-1.207	–	–	–
(p-value)	*(0.002)*			
AIC	711.82	665.61	626.62	48.72
BIC	749.82	697.27	657.19	72.20
$LogL$	-349.91	-327.81	-308.31	-19.36
$Pseudo - R^2(\%)$	10.51	9.50	9.25	13.88
No. of banks	419	419	315	104
No. of failures	96	96	89	7
No. of obs	4155	4155	3345	810
Wald test (χ^2)	79.70	68.86	64.62	11.09
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.049)*
PH test (χ^2)	7.02	4.92	8.07	1.17
(p-value)	*(0.319)*	*(0.425)*	*(0.152)*	*(0.947)*

Note: The table reports estimates of the restricted, semi-restricted and semi-generalized Cox PH models conditional on firm-level balance sheet information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. Assets and Other Earning Assets are in natural logs.

Table 15. Generalized Cox PH / Balance Sheet.

	Generalized	
	Conventional	Islamic
Growth of Loans	-1.595	–
(p-value)	*(0.002)*	
Loans	–	-0.003
(p-value)		*(0.057)*
Growth of Equity	-0.108	–
(p-value)	*(0.000)*	
Liquid Assets	-0.001	–
(p-value)	*(0.011)*	
Other Earning Assets (ln)	-0.410	-0.756
(p-value)	*(0.009)*	*(0.028)*
Assets (ln)	0.640	2.305
(p-value)	*(0.000)*	*(0.012)*
Growth of Assets	–	-0.137
(p-value)		*(0.092)*
AIC	622.65	38.83
BIC	653.22	57.57
$LogL$	-306.32	-15.42
$Pseudo - R^2(\%)$	9.83	31.08
No. of banks	315	100
No. of failures	89	7
No. of obs	3340	800
Wald test (χ^2)	57.93	18.99
(p-value)	*(0.000)*	*(0.001)*
PH test (χ^2)	13.92	4.96
(p-value)	*(0.016)*	*(0.291)*

Note: The table reports estimates of the generalized Cox PH models conditional on firm-level balance sheet information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for of all explanatory variables. Assets and Other Earning Assets are in natural logs. A dash "–" indicates that the variable was thrown out by the variable selection algorithm.

Table 16. Restricted / Semi-Restricted / Semi-Generalized Cox PH / Income Statement.

	Restricted	Semi-Restricted	Semi-Generalized	
	All banks	**All banks**	**Conventional**	**Islamic**
Growth of Overheads	-0.087	-0.085	-0.074	-0.947
(p-value)	*(0.036)*	*(0.041)*	*(0.077)*	*(0.002)*
Net Income	0.007	0.006	0.006	-0.166
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.005)*
Net Interest Revenue	-0.002	-0.002	-0.002	-0.012
(p-value)	*(0.008)*	*(0.006)*	*(0.009)*	*(0.373)*
Other Operating Income	-0.002	-0.002	-0.002	-0.011
(p-value)	*(0.016)*	*(0.035)*	*(0.040)*	*(0.385)*
Islamic	-1.025	–	–	–
(p-value)	*(0.009)*			
AIC	712.19	666.71	624.13	42.01
BIC	743.76	691.97	648.55	60.65
$LogL$	-351.09	-329.35	-308.06	-17.01
$Pseudo-R^2(\%)$	4.54	3.25	3.19	23.35
No. of banks	418	418	315	103
No. of failures	91	91	84	7
No. of obs	4089	4089	3308	781
Wald test (χ^2)	33.40	22.15	20.35	10.37
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.035)*
PH test (χ^2)	5.08	4.37	5.30	1.64
(p-value)	*(0.407)*	*(0.358)*	*(0.258)*	*(0.802)*

Note: The table reports estimates of the restricted, semi-restricted and semi-generalized Cox PH models conditional on firm-level income statement information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables.

Table 17. Generalized Cox PH / Income Statement.

	Generalized	
	Conventional	**Islamic**
Growth of Overheads	-0.074	-0.969
(p-value)	*(0.077)*	*(0.002)*
Net Income	0.006	-0.194
(p-value)	*(0.000)*	*(0.000)*
Net Interest Revenue	-0.002	–
(p-value)	*(0.009)*	
Other Operating Income	-0.002	-0.017
(p-value)	*(0.040)*	*(0.025)*
AIC	624.13	40.88
BIC	648.54	54.91
$LogL$	-308.06	-17.44
$Pseudo - R^2(\%)$	3.19	1.13
No. of banks	315	104
No. of failures	84	7
No. of obs	3308	793
Wald test (χ^2)	20.35	9.84
(p-value)	*(0.000)*	*(0.020)*
PH test (χ^2)	5.30	1.13
(p-value)	*(0.257)*	*(0.769)*

Note: The table reports estimates of the generalized Cox PH models conditional on firm-level income statement information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. A dash "–" indicates that the variable was thrown out by the variable selection algorithm.

Table 18. Restricted / Semi-Restricted / Semi-Generalized Cox PH / Financial Ratios.

	Restricted	Semi-Restricted	Semi-Generalized	
	All banks	All banks	Conventional	Islamic
Z score	0.004	0.003	0.004	0.001
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.750)*
ROA	-0.025	-0.026	-0.026	-0.127
(p-value)	*(0.055)*	*(0.051)*	*(0.055)*	*(0.373)*
CTI	0.003	0.004	0.004	-0.013
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.473)*
Net Loans/Assets	0.015	0.015	0.018	-0.015
(p-value)	*(0.046)*	*(0.042)*	*(0.026)*	*(0.355)*
Islamic	-1.021	–	–	–
(p-value)	*(0.033)*			
AIC	878.08	839.79	798.59	46.39
BIC	910.11	865.42	823.37	65.37
$LogL$	-434.04	-415.89	-395.48	-19.60
$Pseudo - R^2(\%)$	3.52	2.85	3.23	2.10
No. of banks	415	415	315	100
No. of failures	87	87	82	5
No. of obs	4476	4476	3624	852
Wald test (χ^2)	31.65	24.37	26.37	4.52
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.341)*
PH test (χ^2)	1.59	0.98	0.69	4.55
(p-value)	*(0.902)*	*(0.912)*	*(0.953)*	*(0.337)*

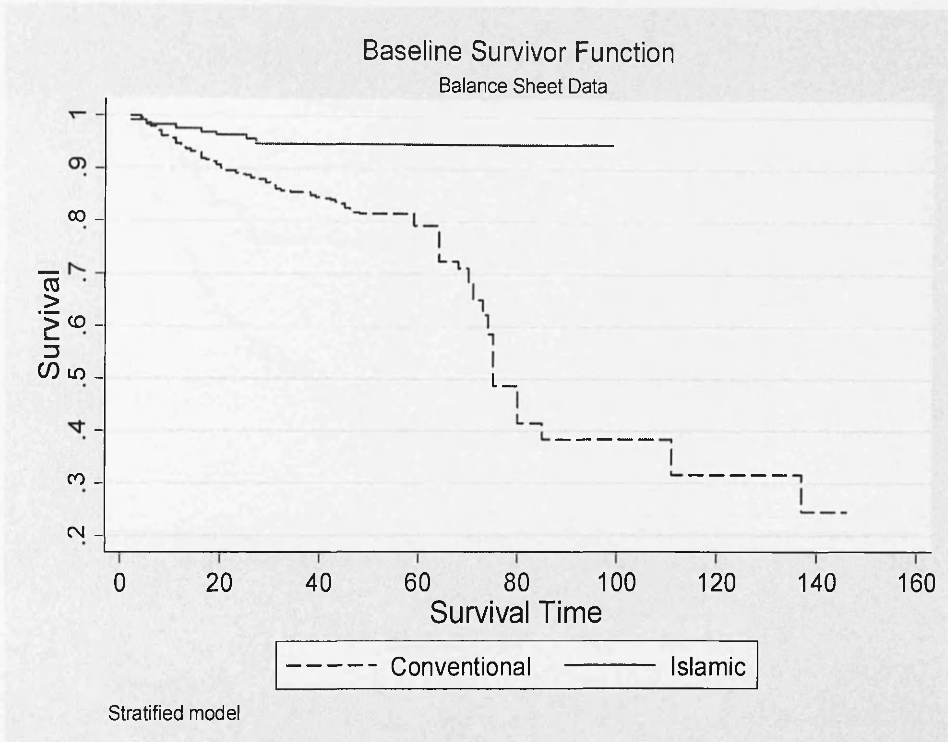
Note: The table reports estimates of the restricted, semi-restricted and semi-generalized Cox PH models conditional on firm-level financial ratios information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables.

Table 19. Generalized Cox PH / Financial Ratios.

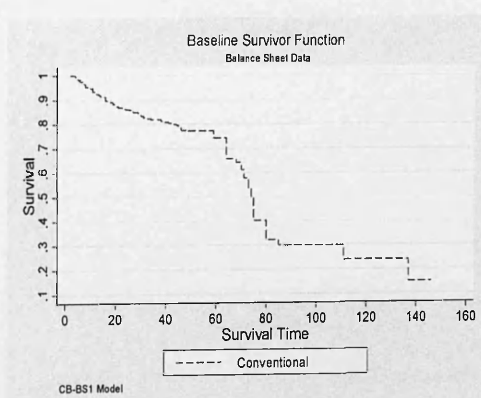
	Generalized	
	Conventional	**Islamic**
Z score	0.007	-0.003
(p-value)	*(0.000)*	*(0.113)*
ROA	–	0.040
(p-value)		*(0.813)*
CTI	0.003	0.017
(p-value)	*(0.003)*	*(0.410)*
Equity/Assets	-0.039	0.047
(p-value)	*(0.000)*	*(0.000)*
NIM	0.099	-0.179
(p-value)	*(0.000)*	*(0.077)*
Income Diversity	-0.001	-0.051
(p-value)	*(0.097)*	*(0.009)*
Liquid Assets/Deposits	0.003	-0.011
(p-value)	*(0.406)*	*(0.357)*
AIC	552.48	37.51
BIC	589.07	69.87
$LogL$	-270.24	-11.75
$Pseudo - R^2(\%)$	8.34	27.63
No. of banks	315	102
No. of failures	82	5
No. of obs	3624	755
Wald test (χ^2)	49.19	8.98
(p-value)	*(0.000)*	*(0.254)*
PH test (χ^2)	1.19	1.19
(p-value)	*(0.977)*	*(0.991)*

Note: The table reports estimates of the generalized Cox PH models conditional on firm-level income statement information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. A dash "–" indicates that the variable was thrown out by the variable selection algorithm.

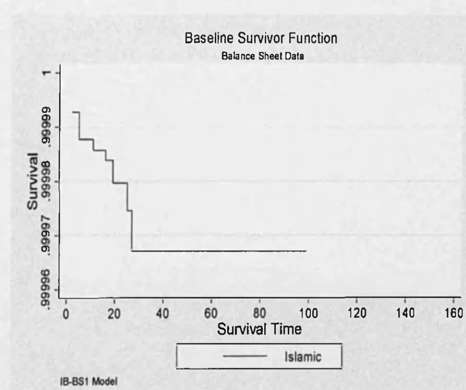
Figure 2. Baseline Survivor Function / Semi-Restricted Model / Balance Sheet.



a) All banks

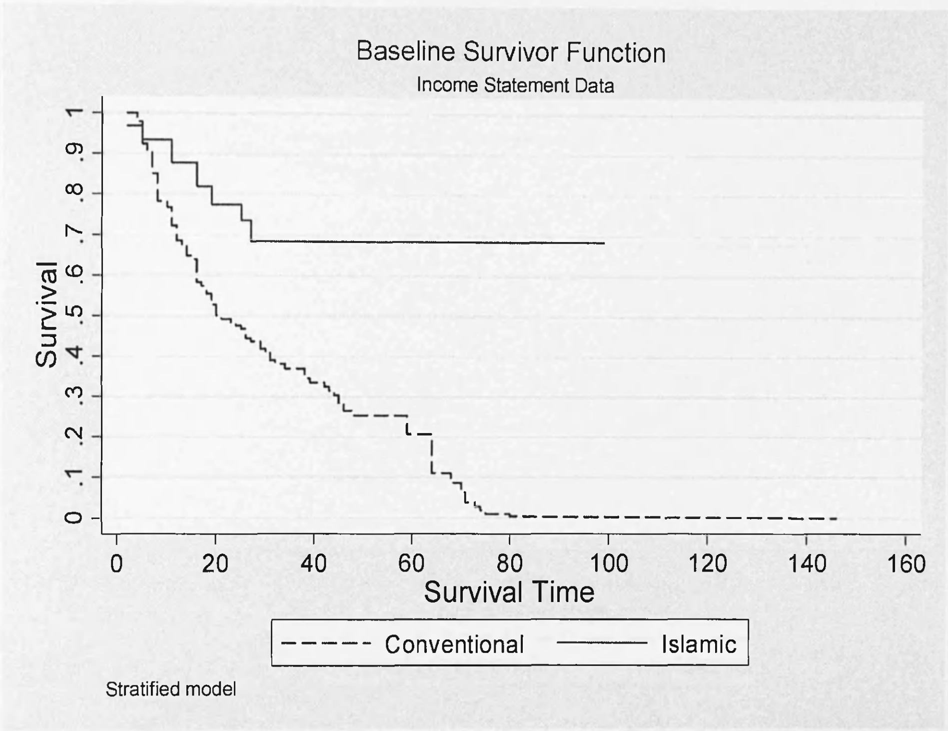


b) Conventional Banks

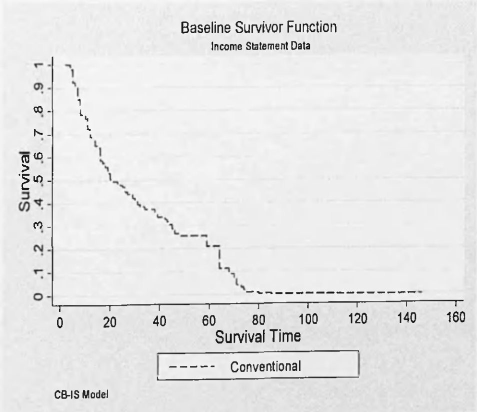


c) Islamic Banks

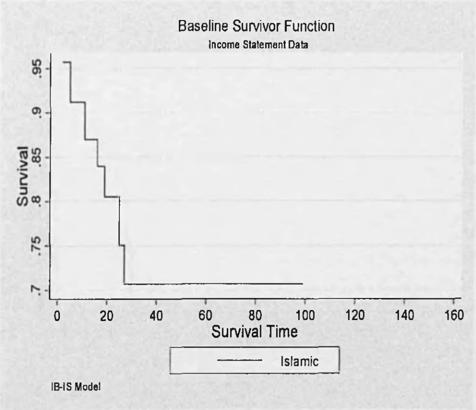
Figure 3. Baseline Survivor Function / Semi-Restricted Model / Income Statement.



a) All banks

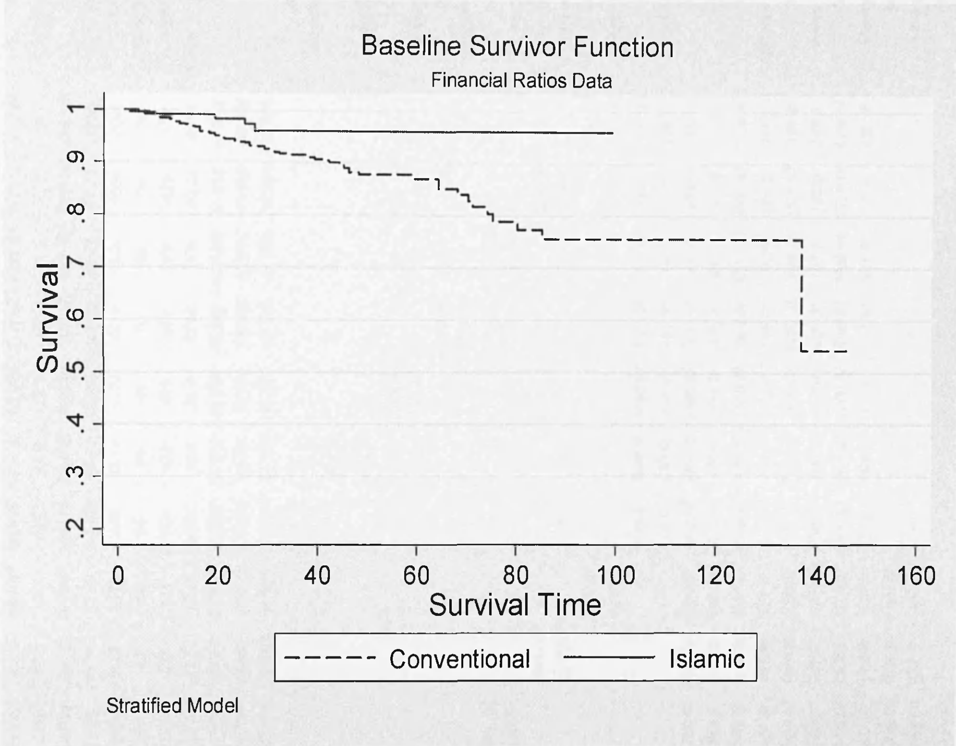


b) Conventional Banks

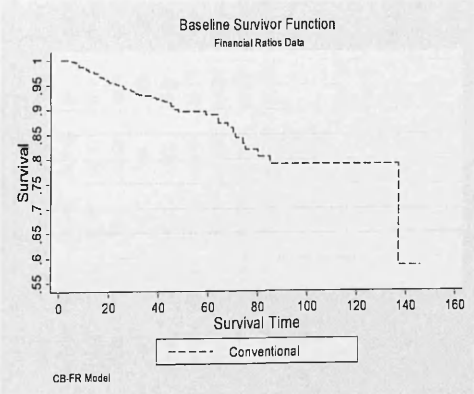


c) Islamic Banks

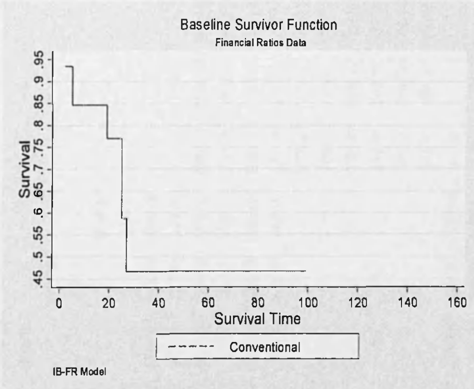
Figure 4. Baseline Survivor Function / Semi-Restricted Model / Financial Ratios.



a) All banks



b) Conventional Banks



c) Islamic Banks

Table 20. Macro Cox PH Results / Balance Sheet.

	Panel A							Panel B							Panel C						
	Semi-Restricted													Generalized							
	All banks							Conventional banks							Islamic banks						
Loans	–	–	–	–	–	–	–	–	–	–	–	–	–	–	*-0.003*	*-0.002*	*-0.003*	*-0.003*	*-0.003*	*-0.003*	*-0.003*
(p-value)															*(0.013)*	*0.000*	*(0.001)*	*(0.017)*	*(0.012)*	*(0.000)*	*(0.057)*
Gr. of Loans	–	–	–	–	–	–	–	*-1.400*	*-1.455*	*-1.609*	*-1.521*	*-1.614*	*-1.486*	*-1.510*	–	–	–	–	–	–	–
(p-value)								*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.006)*	*(0.000)*							
Gr. of Equity	*-0.083*	*-0.101*	*-0.116*	*-0.115*	*-0.113*	*-0.106*	*-0.123*	*-0.083*	*-0.098*	*-0.109*	*-0.110*	*-0.105*	*-0.102*	*-0.117*	–	–	–	–	–	–	–
(p-value)	*(0.069)*	*(0.023)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.003)*	*(0.073)*	*(0.029)*	*(0.006)*	*(0.006)*	*(0.007)*	*(0.000)*	*(0.005)*							
Liquid Assets	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	–	–	–	–	–	–	–
(p-value)	*(0.001)*	*(0.004)*	*(0.004)*	*(0.005)*	*(0.003)*	*(0.004)*	*(0.001)*	*(0.003)*	*(0.008)*	*(0.004)*	*(0.006)*	*(0.004)*	*(0.012)*	*(0.001)*							
Oth.E. Assets(l)	*-0.414*	*-0.485*	*-0.387*	*-0.334*	*-0.393*	*-0.401*	*-0.424*	*-0.456*	*-0.530*	*-0.411*	*-0.333*	*-0.437*	*-0.425*	*-0.443*	*-0.799*	*-0.771*	*-0.793*	*-0.774*	*-0.742*	*-0.804*	*-0.770*
(p-value)	*(0.001)*	*(0.000)*	*(0.002)*	*(0.010)*	*(0.001)*	*(0.000)*	*(0.002)*	*(0.003)*	*(0.001)*	*(0.008)*	*(0.051)*	*(0.004)*	*(0.007)*	*(0.005)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.031)*
Assets (l)	*0.707*	*0.709*	*0.648*	*0.549*	*0.693*	*0.665*	*0.749*	*0.728*	*0.728*	*0.638*	*0.515*	*0.705*	*0.659*	*0.754*	*2.399*	*2.096*	*2.357*	*2.339*	*2.303*	*2.424*	*2.304*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.010)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.011)*
Gr. of Assets	*-0.085*	*-0.081*	*-0.092*	*-0.087*	*-0.092*	*-0.085*	*-0.091*	–	–	–	–	–	–	–	*-0.128*	*-0.129*	*-0.144*	*-0.139*	*-0.136*	*-0.136*	*-0.159*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*								*(0.020)*	*(0.025)*	*(0.029)*	*(0.023)*	*(0.019)*	*(0.035)*	*(0.085)*
Gr. of GDP(-1)	*-0.103*							*-0.099*							0.040						
(p-value)	*(0.000)*							*(0.000)*							*(0.426)*						
Inflation (-1)		*0.018*							*0.017*							*0.031*					
(p-value)		*(0.000)*							*(0.000)*							*(0.000)*					
U. Inflation			-0.001							-0.001							-0.023				
(p-value)			*(0.875)*							*(0.798)*							*(0.242)*				
Sect. Conc/tion				*-0.038*							*-0.051*							0.019			
(p-value)				*(0.047)*							*(0.027)*							*(0.601)*			
Credit Risk Sc.					-0.376							-0.431							-0.136		
(p-value)					*(0.180)*							*(0.148)*							*(0.889)*		
FX Depr/tion						0.745							0.611							*4.156*	
(p-value)						*(0.159)*							*(0.264)*							*(0.032)*	
Fin. Openness							*0.012*							*0.014*							0.001
(p-value)							*(0.001)*							*(0.001)*							*(0.941)*
AIC	648.38	641.81	667.57	662.60	665.73	664.97	655.25	608.03	603.92	624.57	617.88	622.43	622.65	612.06	39.68	36.19	40.05	40.65	40.81	39.38	40.12
BIC	686.20	679.63	705.57	700.59	703.72	702.94	693.12	644.67	640.57	661.27	654.57	659.11	659.31	648.74	62.46	58.98	63.47	64.07	64.24	62.79	63.00
LogL	-318.19	-314.91	-327.79	-325.30	-326.86	-326.48	-321.62	-298.02	-295.96	-306.29	-302.95	-305.75	-305.32	-300.03	-14.84	-13.10	-15.03	-15.33	-15.41	-14.69	-15.06
$Pseudo - R^2$(%)	11.88	12.80	9.51	10.20	9.76	9.81	11.09	12.14	12.76	9.84	10.84	10.16	10.07	11.69	31.86	39.85	32.84	31.49	31.13	34.32	31.07
No. of banks	419	419	419	419	419	419	411	315	315	315	315	315	315	315	100	100	100	100	100	100	92
No. of failures	96	96	96	96	96	96	96	89	89	89	89	89	89	89	7	7	7	7	7	7	7
No. of obs	4034	4036	4155	4155	4155	4155	4073	3318	3320	3340	3340	3340	3329	3340	704	704	800	800	800	797	718
Wald test (χ^2)	*85.81*	*92.44*	*72.76*	*73.87*	*70.74*	*70.29*	*80.19*	*82.38*	*86.55*	*66.92*	*73.61*	*69.07*	*68.38*	*79.45*	*16.75*	*55.26*	*25.64*	*24.72*	*22.44*	*21.31*	*13.58*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.005)*	*(0.000)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.001)*	*(0.018)*
PH test (χ^2)	5.03	4.33	5.34	5.99	8.23	6.56	5.89	9.48	7.11	9.77	10.00	14.17	9.86	9.00	5.44	4.36	5.37	6.76	5.89	3.92	5.54
(p-value)	*(0.540)*	*(0.633)*	*(0.501)*	*(0.425)*	*(0.222)*	*(0.363)*	*(0.436)*	*(0.148)*	*(0.311)*	*(0.134)*	*(0.124)*	*(0.027)*	*(0.131)*	*(0.174)*	*(0.364)*	*(0.499)*	*(0.372)*	*(0.239)*	*(0.317)*	*(0.560)*	*(0.354)*

Note: The table reports estimates of the semi-restricted and generalized Cox PH models conditional on firm-level balance sheet information and macroeconomic characteristics. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion Wald test for the joint significance of all explanatory variables. Assets and Other Earning Assets are in natural logs.
A dash "–" indicates that the variable was thrown out by the variable selection algorithm.

Table 21. Macro Cox PH Results / Income Statement.

	Panel A							Panel B							Panel C						
	Semi-Restricted													Generalized							
	All banks							Conventional banks							Islamic banks						
Gr. of Overheads	-0.044	-0.055	-0.085	-0.088	-0.085	-0.076	-0.082	-0.032	-0.044	-0.074	-0.077	-0.073	-0.064	-0.070	-0.924	-0.920	-1.109	-0.958	-0.976	-0.999	-1.252
(p-value)	(0.303)	(0.186)	(0.041)	(0.034)	(0.043)	(0.071)	(0.195)	(0.671)	(0.568)	(0.300)	(0.069)	(0.304)	(0.370)	(0.329)	(0.006)	(0.004)	(0.002)	(0.008)	(0.003)	(0.004)	(0.001)
Net Income	0.007	0.007	0.006	0.006	0.006	0.007	0.006	0.007	0.007	0.006	0.006	0.006	0.007	0.006	-0.191	-0.189	-0.200	-0.195	-0.210	-0.198	-0.226
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.003)	(0.002)	(0.005)	(0.000)	(0.004)	(0.003)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Int. Revenue	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	-0.001	-0.001	-0.002	–	–	–	–	–	–	–
(p-value)	(0.007)	(0.004)	(0.006)	(0.002)	(0.009)	(0.008)	(0.022)	(0.042)	(0.037)	(0.036)	(0.003)	(0.045)	(0.048)	(0.028)							
Oth.Op. Income	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.019	-0.015	-0.016	-0.017	-0.015	-0.016	-0.017
(p-value)	(0.054)	(0.121)	(0.035)	(0.079)	(0.042)	(0.091)	(0.048)	(0.135)	(0.230)	(0.101)	(0.109)	(0.106)	(0.195)	(0.043)	(0.026)	(0.047)	(0.023)	(0.052)	(0.022)	(0.024)	(0.023)
Gr. of GDP(-1)	-0.105							-0.109							0.031						
(p-value)	(0.000)							(0.000)							(0.650)						
Inflation(-1)		0.018							0.018							0.031					
(p-value)		(0.000)							(0.000)							(0.000)					
U. Inflation			0.000							0.001							-0.031				
(p-value)			(0.958)							(0.853)							(0.291)				
Sect. Conc/tion				-6.199							-7.846							-0.005			
(p-value)				(0.002)							(0.003)							(0.928)			
Credit Risk Sc.					-0.237							-0.233							-0.632		
(p-value)					(0.378)							(0.418)							(0.362)		
FX Depr/tion						1.142							1.161							1.642	
(p-value)						(0.021)							(0.023)							(0.524)	
Fin. Openness							0.005							0.006							-0.012
(p-value)							(0.146)							(0.097)							(0.141)
AIC	648.39	639.70	668.71	655.48	667.92	663.61	665.67	606.31	601.74	626.10	610.43	625.45	621.04	623.33	41.98	37.73	41.72	42.87	42.38	42.56	40.29
BIC	679.83	671.15	700.28	687.06	699.50	695.17	697.15	636.79	632.24	656.62	640.95	655.97	651.54	653.85	60.18	55.93	60.42	61.58	61.08	61.24	58.56
$LogL$	-319.20	-314.85	-329.35	-322.74	-328.96	-326.80	-327.84	-298.15	-295.87	-308.05	-300.22	-307.73	-305.52	-306.67	-16.98	-14.86	-16.86	-17.44	-17.19	-17.28	-16.15
$Pseudo-R^2(\%)$	5.92	7.21	3.25	5.20	3.37	3.93	3.55	6.16	6.88	3.20	5.66	3.30	3.92	3.64	21.93	31.69	24.61	22.03	23.13	22.74	26.08
No. of banks	418	418	418	418	418	418	410	315	315	315	315	315	315	315	104	104	104	104	104	104	96
No. of failures	91	91	91	91	91	91	91	84	84	84	84	84	84	84	7	7	7	7	7	7	7
No. of obs	3977	3979	4089	4089	4089	4089	4007	3288	3308	3308	3308	3308	3297	3308	700	700	793	793	793	790	711
Wald test (χ^2)	40.21	48.95	22.15	35.38	22.94	40.73	24.11	39.13	62.82	26.07	36.05	21.03	24.95	23.15	21.13	32.59	19.98	27.15	21.30	22.60	21.33
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
PH test (χ^2)	4.63	4.49	4.48	4.39	8.24	6.16	5.45	5.78	4.57	5.37	4.50	9.41	6.71	6.69	0.43	0.35	2.62	0.71	0.69	0.54	0.25
(p-value)	(0.463)	(0.481)	(0.483)	(0.495)	(0.143)	(0.291)	(0.363)	(0.328)	(0.471)	(0.373)	(0.479)	(0.093)	(0.244)	(0.245)	(0.980)	(0.986)	(0.623)	(0.950)	(0.925)	(0.970)	(0.993)

Note: The table reports estimates of the semi-restricted and generalized Cox PH models conditional on firm-level income statement information and macroeconomic characteristics. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. "–" indicates that the variable was thrown out by the variable selection algorithm.

Table 22. Macro Cox PH Results / Financial Ratios.

	Panel A							Panel B							Panel C						
	Semi-restricted							Generalized													
	All banks							Conventional banks							Islamic banks						
Z score	*0.007*	*0.006*	*0.004*	*0.003*	*0.003*	*0.003*	*0.004*	*0.007*	*0.007*	*0.007*	*0.006*	*0.007*	*0.007*	*0.006*	*-0.005*	*-0.006*	*-0.006*	*-0.005*	*-0.005*	*-0.005*	*-0.006*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.026)*	*(0.086)*	*(0.070)*	*(0.082)*	*(0.039)*	*(0.068)*	*(0.063)*
ROA	-0.004	-0.012	-0.010	-0.022	-0.024	-0.025	-0.026	–	–	–	–	–	–	–	-0.114	*-0.402*	*-0.246*	*-0.207*	*-0.174*	-0.189	*-0.200*
(p-value)	*(0.809)*	*(0.501)*	*(0.589)*	*(0.232)*	*(0.166)*	*(0.137)*	*(0.135)*								*(0.623)*	*(0.019)*	*(0.002)*	*(0.032)*	*(0.097)*	*(0.150)*	*(0.062)*
CTI	*0.004*	*0.004*	*0.004*	*0.003*	*0.003*	*0.003*	*0.003*	*0.005*	*0.005*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	0.006	-0.016	0.000	0.004	0.006	0.002	0.003
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.002)*	*(0.001)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.762)*	*(0.461)*	*(0.999)*	*(0.734)*	*(0.658)*	*(0.897)*	*(0.849)*
Net Loan/Assets	*0.025*	*0.018*	*0.015*	*0.005*	*0.016*	*0.016*	*0.015*	*0.036*	*0.037*	*0.030*	*0.023*	*0.031*	*0.031*	*0.032*	*-0.022*	-0.017	*-0.025*	*-0.024*	*-0.021*	*-0.025*	*-0.022*
(p-value)	*(0.000)*	*(0.008)*	*(0.027)*	*(0.471)*	*(0.015)*	*(0.018)*	*(0.026)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.013)*	*(0.001)*	*(0.001)*	*(0.000)*	*(0.005)*	*(0.411)*	*(0.012)*	*(0.022)*	*(0.069)*	*(0.003)*	*(0.048)*
Equity/Assets	–	–	–	–	–	–	–	*-0.031*	*-0.032*	*-0.043*	*-0.045*	*-0.043*	*-0.042*	*-0.049*	*0.052*	0.087	*0.069*	*0.057*	*0.063*	*0.058*	*0.063*
(p-value)								*(0.003)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.006)*	(0.000)	*(0.002)*	*(0.003)*	*(0.000)*	*(0.000)*	*(0.000)*
NIM	–	–	–	–	–	–	–	*0.128*	*0.075*	*0.126*	*0.122*	*0.125*	*0.116*	*0.143*	*-0.086*	-0.206	-0.162	-0.110	*-0.119*	*-0.146*	*-0.118*
(p-value)								*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.311)*	*(0.195)*	*(0.276)*	*(0.257)*	*(0.050)*	*(0.238)*	*(0.038)*
Inc. Diversity	–	–	–	–	–	–	–	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	*-0.055*	*-0.049*	-0.045	*-0.048*	*-0.057*	*-0.051*	*-0.054*
(p-value)								*(0.194)*	*(0.173)*	*(0.136)*	*(0.162)*	*(0.166)*	*(0.152)*	*(0.148)*	*(0.019)*	*(0.038)*	*(0.131)*	*(0.039)*	*(0.003)*	*(0.013)*	*(0.016)*
Gr. of GDP (-1)	*-0.132*							*-0.123*							0.034						
(p-value)	*(0.000)*							*(0.000)*							*(0.606)*						
Inflation		*0.013*							*0.016*							*0.060*					
(p-value)		*(0.006)*							*(0.000)*							*(0.000)*					
U. Inflation			*0.019*	–	–					0.003							-0.050				
(p-value)			*(0.004)*							*(0.595)*							*(0.228)*				
Sect. Conc/tion				*-0.060*							*-0.052*							0.033			
(p-value)				*(0.002)*							*(0.051)*							*(0.359)*			
Credit Risk Sc.					*-0.558*							-0.126							-0.706		
(p-value)					*(0.035)*							*(0.687)*							*(0.379)*		
FX Depr/tion						0.132							0.525							3.262	
(p-value)						*(0.743)*							*(0.315)*							*(0.172)*	
Fin. Openness							-0.001							*0.011*							-0.011
(p-value)							*(0.721)*							*(0.011)*							*(0.172)*
AIC	637.06	645.58	833.95	829.99	836.96	830.73	840.68	514.39	524.83	540.71	535.57	540.77	539.75	534.23	38.47	30.79	36.76	38.65	38.69	37.69	38.28
BIC	668.63	677.15	865.98	862.02	868.98	862.70	872.62	557.05	567.49	583.42	578.27	583.48	582.43	576.94	74.48	66.79	73.77	75.66	75.70	74.67	74.38
LogL	-313.53	-317.79	-411.97	-409.99	-413.47	-410.36	-415.34	-250.19	-255.41	-263.35	-260.78	-263.38	-262.87	-260.11	-11.24	-7.39	-10.38	-11.32	-11.34	-10.84	-11.14
$Pseudo - R^2(\%)$	8.85	7.62	3.76	4.23	3.41	2.86	2.85	15.02	13.25	10.69	11.56	10.68	10.78	11.79	28.90	53.21	35.85	30.02	29.90	32.98	29.25
No. of banks	414	414	415	415	415	415	415	313	313	313	313	313	313	313	100	100	100	100	100	100	92
No. of failures	87	87	87	87	87	87	87	77	82	77	77	77	77	77	5	5	5	5	5	5	5
No. of obs	4081	4083	4476	4476	4476	4421	4387	3277	3321	3298	3298	3298	3287	3298	666	663	755	755	755	752	673
Wald test (χ^2)	*60.88*	*52.41*	*32.31*	*36.18*	*29.21*	*24.20*	*24.36*	*88.44*	*125.58*	*63.06*	*68.20*	*63.00*	*63.56*	*69.55*	*25.67*	*65.65*	*23.20*	*21.94*	*35.86*	*32.65*	*36.10*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.004)*	*(0.000)*	*(0.005)*	*(0.000)*	*(0.000)*	*(0.000)*
PH test (χ^2)	4.92	4.78	1.51	1.64	4.00	1.37	2.53	2.54	2.93	2.79	3.10	4.50	2.51	4.33	1.53	3.32	11.65	0.65	0.99	1.05	0.90
(p-value)	*(0.425)*	*(0.444)*	*(0.912)*	*(0.896)*	*(0.550)*	*(0.927)*	*(0.772)*	*(0.924)*	*(0.892)*	*(0.904)*	*(0.875)*	*(0.721)*	*(0.926)*	*(0.742)*	*(0.992)*	*(0.912)*	*(0.167)*	*(0.999)*	*(0.998)*	*(0.997)*	*(0.998)*

Note: The table reports estimates of the semi-restricted and generalized Cox PH models conditional on firm-level financial ratios information and macroeconomic characteristics. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. A dash "–" indicates that the variable was thrown out by the variable selection algorithm.

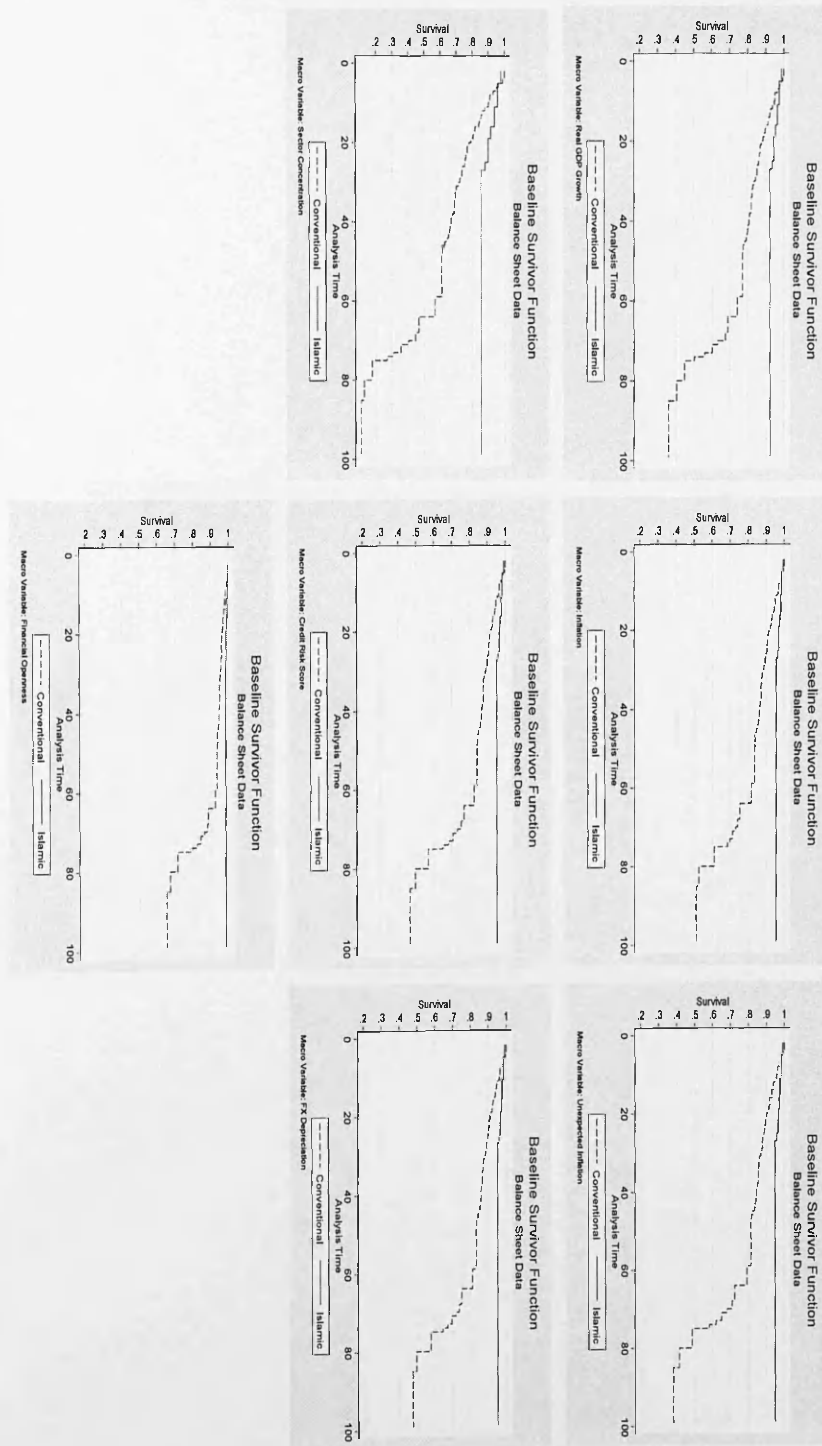


Figure 5. Baseline Survivor Function / Semi-Restricted Macro Cox PH / Balance Sheet.

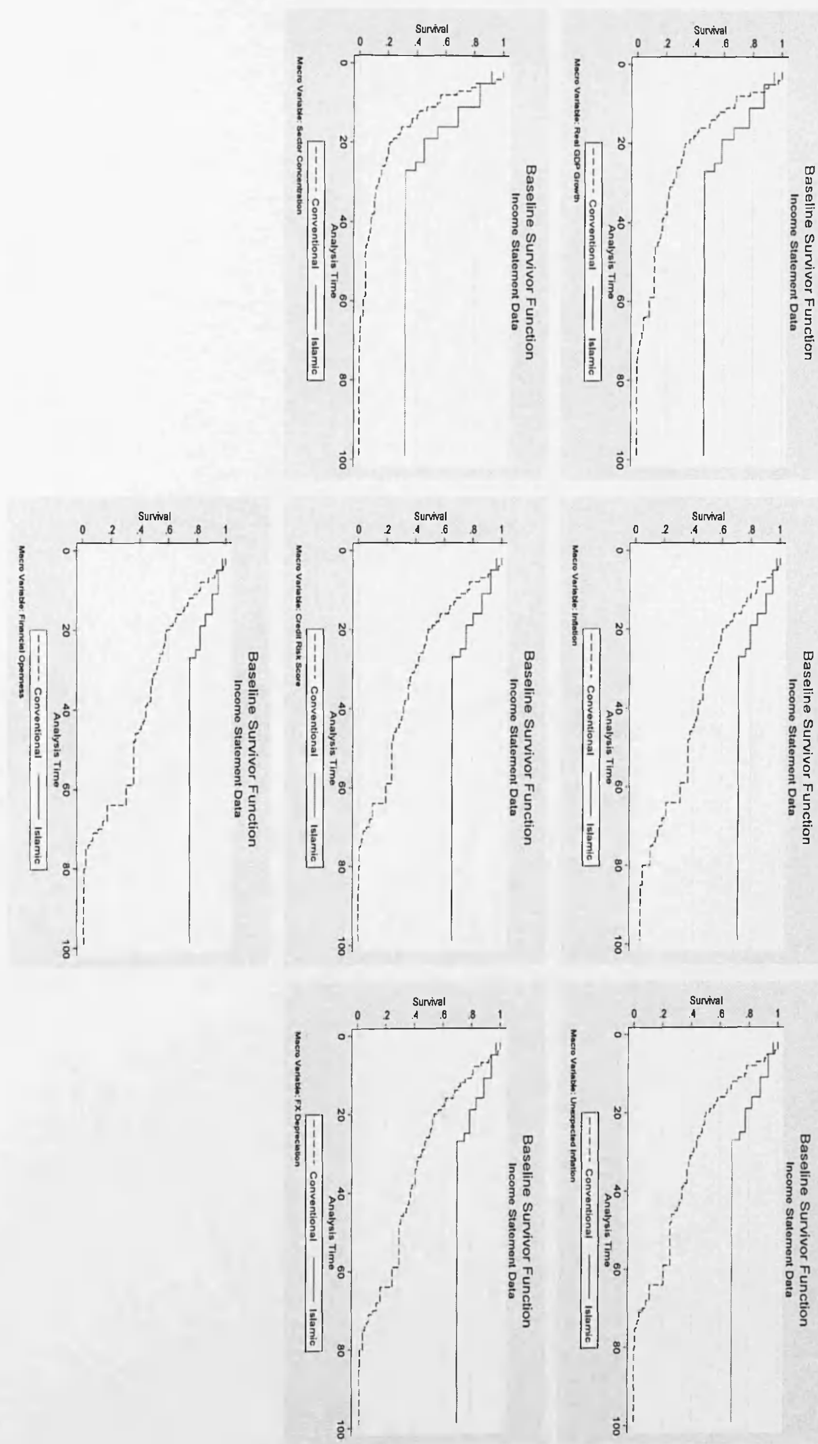


Figure 6. Baseline Survivor Function / Semi-Restricted Macro Cox PH / Income Statement.

Figure 7. Baseline Survivor Function / Semi-Restricted Macro Cox PH / Financial Ratios.

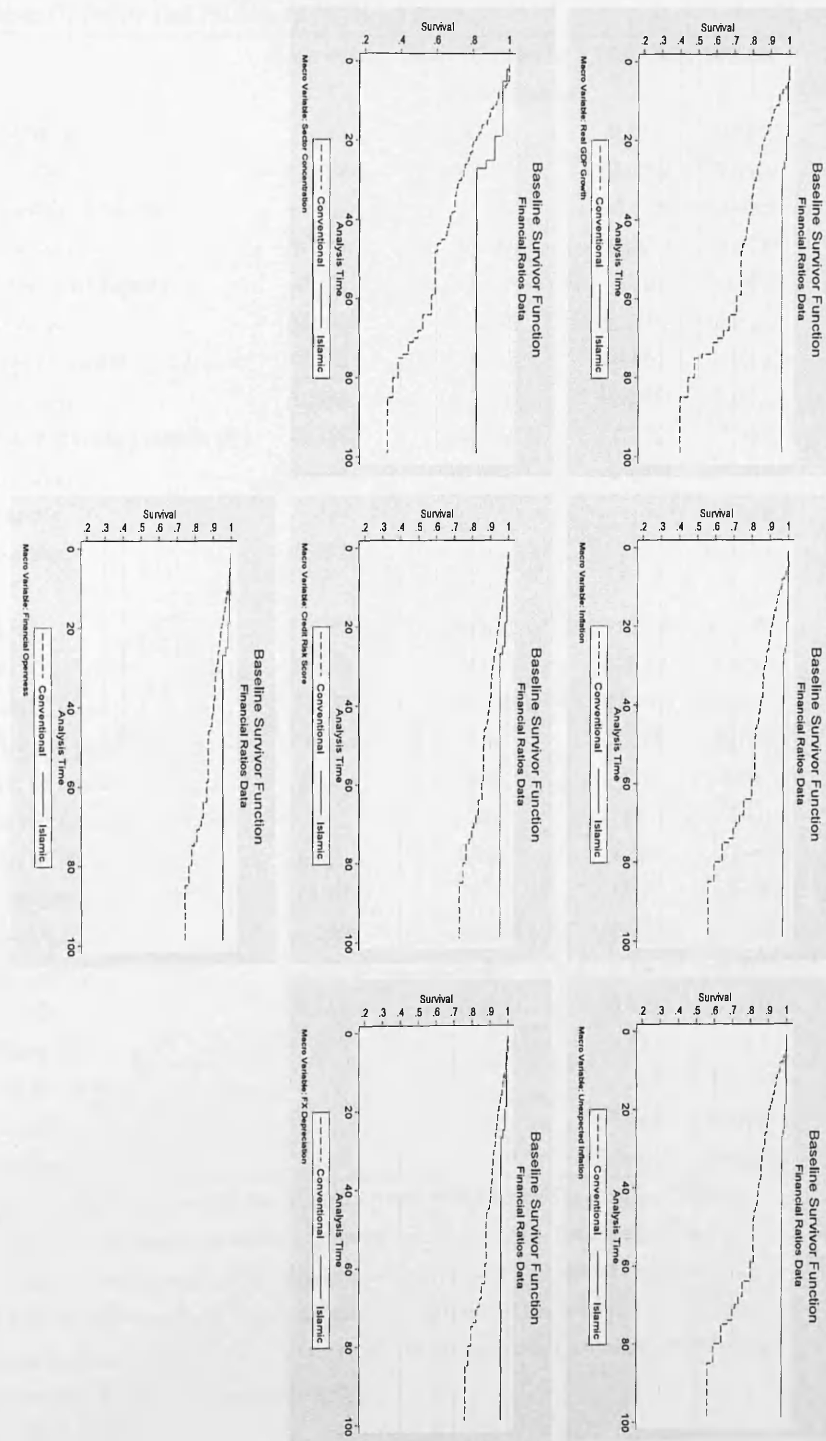


Table 23. Frailty Cox PH Results / Balance Sheet.

	Restricted	Semi-Restricted	Random Effects	
		All Banks		
Assets (l)	*0.638*	*0.649*	*0.618*	*0.783*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Growth of Assets	*-9.407*	*-9.132*	*-9.498*	*-6.336*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.005)*
Growth of Equity	*-0.102*	*-0.115*	*-0.102*	*-0.092*
(p-value)	*(0.000)*	*(0.000)*	*(0.003)*	*(0.009)*
Liquid Assets	*-0.001*	*-0.001*	*-0.001*	*-0.001*
(p-value)	*(0.003)*	*(0.004)*	*(0.001)*	*(0.001)*
Other Earning Assets (l)	*-0.390*	*-0.386*	*-0.372*	*-0.483*
(p-value)	*(0.003)*	*(0.002)*	*(0.002)*	*(0.001)*
Islamic	*-1.207*	–	–	*-1.058*
(p-value)	*(0.002)*			*(0.020)*
AIC	711.82	665.61	716.21	672.70
BIC	749.82	697.27	747.87	710.69
$LogL$	-349.91	-327.81	-353.10	-330.35
$Pseudo - R^2(\%)$	10.51	9.50	29.71	31.72
No. of banks	419	419	419	419
No. of failures	96	96	96	96
No. of obs	4155	4155	4155	4155
Wald test (χ^2)	*79.70*	*72.47*	*53.01*	*45.28*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
PH test (χ^2)	7.02	4.92	4.94	4.20
(p-value)	*(0.319)*	*(0.425)*	*(0.423)*	*(0.649)*
Theta (θ)	–	–	0.257	1.381
LR test $\theta = 0$			*5.360*	*39.120*
(p-value)			*(0.010)*	*(0.000)*
Frailty Group	–	–	Islamic	Country

Note: The table reports estimates of the restricted, semi-restricted and random effects Cox models conditional on firm-level balance sheet information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. LR test is for the null that the latent factors are insignificant. θ is the variance of the unspecified probability distribution from which the random effects are drawn.

Table 24. Frailty Cox PH Results / Income Statement.

	Restricted	Semi-Restricted	Random Effects	
		All Banks		
Growth of Overheads	-0.087	-0.085	-0.087	-0.064
(p-value)	*(0.036)*	*(0.041)*	*(0.166)*	*(0.360)*
Net Income	0.007	0.006	0.007	0.006
(p-value)	*(0.000)*	*(0.000)*	*(0.004)*	*(0.013)*
Net Interest Revenue	-0.002	-0.002	-0.002	-0.002
(p-value)	*(0.008)*	*(0.006)*	*(0.022)*	*(0.013)*
Other Operating Income	-0.002	-0.002	-0.002	-0.001
(p-value)	*(0.016)*	*(0.035)*	*(0.038)*	*(0.301)*
Islamic	-1.025	–	–	-0.611
(p-value)	*(0.009)*			*(0.169)*
AIC	712.19	666.71	715.86	660.46
BIC	743.76	691.97	741.12	685.81
$LogL$	-351.09	-329.35	-353.93	-326.27
$Pseudo-R^2(\%)$	4.54	3.25	29.54	32.56
No. of banks	418	418	418	418
No. of failures	91	91	91	91
No. of obs	4089	4089	4089	4089
Wald test (χ^2)	36.53	24.27	18.68	16.04
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
PH test (χ^2)	5.08	4.37	4.82	1.67
(p-value)	*(0.407)*	*(0.358)*	*(0.306)*	*(0.796)*
Theta (θ)			0.172	2.088
LR test $\theta = 0$			2.890	51.720
(p-value)			*(0.044)*	*(0.000)*
Frailty Group			Islamic	Country

Note: The table reports estimates of the restricted, semi-restricted and random effects Cox models conditional on firm-level income statement information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. LR test is for the null that the latent factors are insignificant. θ is the variance of the unspecified probability distribution from which the random effects are drawn.

Table 25. Frailty Cox PH Results / Financial Ratios.

	Restricted	Semi-Restricted	Random Effects	
		All Banks		
Z score	*0.004*	*0.003*	*0.004*	*0.003*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.002)*
ROA	*-0.025*	*-0.026*	-0.026	*-0.017*
(p-value)	*(0.055)*	*(0.051)*	(0.141)	*(0.346)*
CTI	*0.003*	*0.004*	*0.003*	*0.004*
(p-value)	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*
Net Loans/Assets	*0.015*	*0.015*	*0.015*	0.010
(p-value)	*(0.046)*	*(0.042)*	*(0.024)*	*(0.180)*
Islamic	*-1.021*	–	–	-0.457
(p-value)	*(0.033)*			*(0.389)*
AIC	878.08	839.79	881.36	859.64
BIC	910.11	865.42	906.98	891.67
$LogL$	-434.04	-415.89	-436.67	-424.82
$Pseudo - R^2(\%)$	3.52	2.85	13.08	12.19
No. of banks	415	415	415	415
No. of failures	87	87	87	87
No. of obs	4476	4476	4476	4476
Wald test (χ^2)	*51.91*	*50.40*	*38.25*	*28.71*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
PH test (χ^2)	1.59	0.98	0.89	1.22
(p-value)	*(0.902)*	*(0.912)*	*(0.926)*	*(0.943)*
Theta (θ)			0.144	1.101
LR test $\theta = 0$			1.32	*21.16*
(p-value)			(0.125)	*(0.000)*
Frailty Group			Islamic	Country

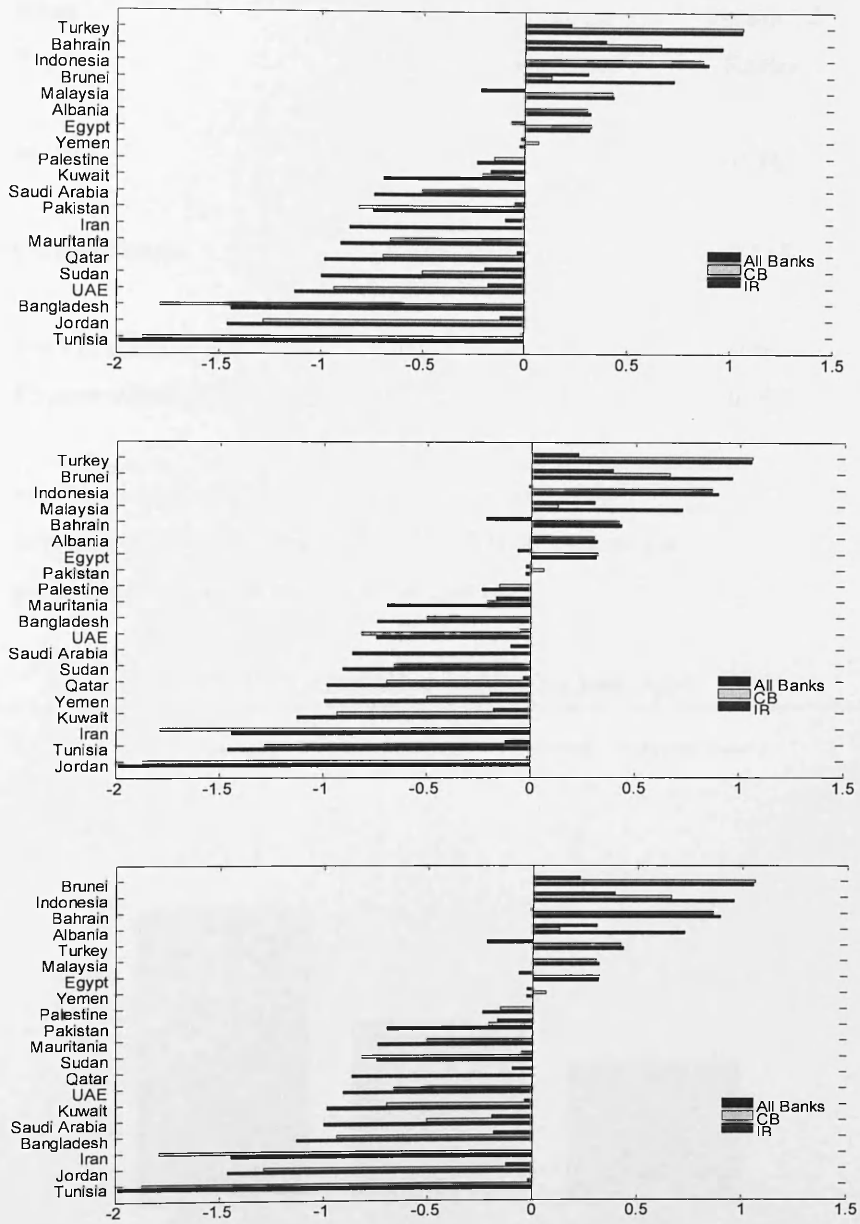
Note: The table reports estimates of the restricted, semi-restricted and random effects Cox models conditional on firm-level financial ratios information. Estimated coefficients are reported while p-values are in brackets. AIC is Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. LR test is for the null that the latent factors are insignificant. θ is the variance of the unspecified probability distribution from which the random effects are drawn.

Table 26. Estimated Log frailties (ν_i) for countries according to data and bank type.

	Balance Sheet Bank Type			Income Statement Bank Type			Financial Ratios Bank Type		
	All	**CB**	**IB**	**All**	**CB**	**IB**	**All**	**CB**	**IB**
Albania	0.318	0.303	0.000	0.342	0.233	0.000	0.649	0.387	0.000
Bahrain	0.961	0.663	0.394	0.480	0.480	0.133	0.684	0.431	0.012
Bangladesh	-1.443	-1.788	0.007	-1.127	-1.600	0.801	-1.223	-1.700	1.205
Brunei	0.726	0.129	0.306	1.202	0.436	1.395	1.097	0.397	1.945
Egypt	0.316	0.323	-0.067	-0.345	-0.292	-0.682	0.302	0.124	-1.939
Indonesia	0.896	0.865	-0.010	1.196	1.121	-0.155	0.773	0.908	-0.111
Iran	-0.862	0.000	-0.097	-1.746	0.000	-0.967	-1.409	0.000	-1.814
Jordan	-1.462	-1.284	-0.120	-2.087	-1.726	-0.505	-1.477	-1.215	-0.908
Kuwait	-0.695	-0.208	-0.166	-1.736	-0.944	-0.668	-1.113	-0.468	-2.869
Malaysia	0.434	0.423	-0.217	0.908	0.989	-0.664	0.350	0.936	-1.543
Mauritania	-0.906	-0.661	-0.002	-0.974	-0.584	-0.778	-0.383	-0.220	-0.767
Pakistan	-0.745	-0.815	-0.050	-0.459	-0.397	-0.805	-0.340	-0.495	-1.511
Palestine	-0.236	-0.150	-0.004	-0.538	-0.302	-0.112	-0.279	-0.120	-0.077
Qatar	-0.985	-0.695	-0.036	-1.606	-1.122	-0.240	-0.861	-0.637	-1.066
Saudi Arabia	-0.740	-0.502	-0.001	-1.390	-1.179	-0.014	-1.174	-0.962	-0.527
Sudan	-0.998	-0.502	-0.194	-1.566	-0.633	-1.098	-0.742	-0.355	-1.866
Tunisia	-1.988	-1.871	-0.016	-1.967	-1.612	-0.388	-1.573	-1.370	-0.691
Turkey	1.055	1.060	0.224	1.252	1.185	1.013	0.605	0.654	0.622
UAE	-1.128	-0.935	-0.180	-1.284	-0.992	-0.821	-0.884	-0.718	-1.347
Yemen	-0.028	0.064	-0.023	-1.674	-1.116	-0.812	0.235	-0.419	-0.777

Note: The table shows the estimates of the random effects from the shared-frailty Cox model. A negative (positive) coefficient suggests a decreasing (increasing) contribution of the country to the bank's hazard. $\nu_i = \log(\alpha_i)$.

Figure 8. Estimated Log frailties for countries according to bank and data type.



The figure plots the latent country factor estimates, (ν_i), for the shared-frailty Cox PH model that conditions on accounting information indicators. The bars represent the estimated log frailties obtained in the balance sheet, income statement and financial ratio models. In each country we distinguish conventional and Islamic banks separately. $\nu_i > 0$ $(\nu_i < 0)$ implies that the latent country factor has an upward (downward) effect on bank failure risk.

Table 27. Estimated Log frailties (ν_i) for bank type.

Bank Type	Balance Sheet	Income Statement	Financial Ratios
Islamic	-0.582	-0.432	-0.367
Conventional	0.365	0.301	0.268
Difference (Log)	-0.217	-0.131	-0.099
Exponentiated Difference	0.195	0.123	0.094

Note: Exponentiated difference is the hazard ratio of the difference in the log frailties. Islamic banks are $9.4\% - 19.5\%$ lower failure risk than conventional banks when bank-specific indicators are used.

Figure 9. Exponentiated frailties for bank type.

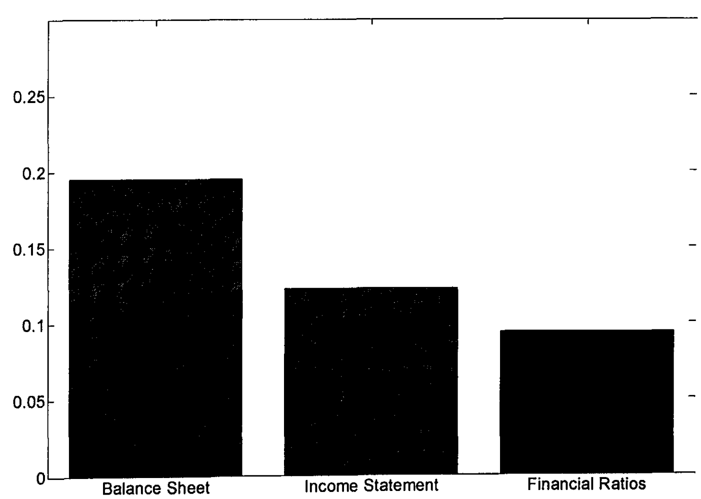


Table 28. Macro Frailty Cox PH Results / Balance Sheet.

	Panel A							Panel B							Panel C						
	Restricted													Generalized							
	All banks							Conventional Banks							Islamic Banks						
Loans	–	–	–	–	–	–	–	–	–	–	–	–	–	–	*-0.003*	-0.002	*-0.003*	*-0.003*	*-0.003*	*-0.003*	*-0.003*
(p-value)															*(0.071)*	*(0.105)*	*(0.070)*	*(0.058)*	*(0.065)*	*(0.037)*	*(0.061)*
Gr. of Loans	–	–	–	–	–	–	–	*-1.112*	*-1.156*	*-1.273*	*-1.205*	*-1.249*	*-1.291*	*-1.224*	–	–	–	–	–	–	–
(p-value)								*(0.003)*	*(0.003)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*							
Gr. of Equity	-0.058	*-0.067*	*-0.096*	*-0.097*	*-0.092*	*-0.093*	*-0.097*	-0.077	*-0.093*	*-0.115*	*-0.111*	*-0.106*	*-0.111*	*-0.113*	–	–	–	–	–	–	–
(p-value)	*(0.123)*	*(0.062)*	*(0.006)*	*(0.006)*	*(0.009)*	*(0.009)*	*(0.006)*	*(0.121)*	*(0.060)*	*(0.019)*	*(0.016)*	*(0.020)*	*(0.018)*	*(0.015)*							
Liquid Assets	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	–	–	–	–	–	–	–
(p-value)	*(0.001)*	*(0.003)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.003)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*							
Oth.E. Assets(l)	*-0.536*	*-0.543*	*-0.471*	*-0.477*	*-0.479*	*-0.482*	*-0.469*	*-0.536*	*-0.516*	*-0.429*	*-0.397*	*-0.442*	*-0.432*	*-0.415*	*-0.785*	*-0.764*	*-0.776*	*-0.770*	*-0.714*	*-0.796*	*-0.754*
(p-value)	*(0.000)*	*(0.000)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.002)*	*(0.002)*	*(0.003)*	*(0.014)*	*(0.027)*	*(0.011)*	*(0.013)*	*(0.019)*	*(0.042)*	*(0.028)*	*(0.032)*	*(0.023)*	*(0.051)*	*(0.034)*	*(0.037)*
Assets (ln)	*0.862*	*0.824*	*0.772*	*0.741*	*0.783*	*0.782*	*0.774*	*0.909*	*0.831*	*0.768*	*0.711*	*0.789*	*0.778*	*0.762*	*2.276*	*1.997*	*2.227*	*2.331*	*2.217*	*2.376*	*2.255*
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.018)*	*(0.031)*	*(0.013)*	*(0.010)*	*(0.014)*	*(0.010)*	*(0.013)*
Growth of Assets	*-0.062*	*-0.064*	*-0.064*	*-0.060*	*-6.365*	*-6.406*	*-0.063*	–	–	–	–	–	–	–	-0.132	*-0.133*	*-0.140*	*-0.140*	-0.139	*-0.139*	*-0.159*
(p-value)	*(0.007)*	*(0.005)*	*(0.005)*	*(0.008)*	*(0.005)*	*(0.005)*	*(0.006)*								*(0.125)*	*(0.096)*	*(0.087)*	*(0.093)*	*(0.104)*	*(0.087)*	*(0.090)*
Islamic Dummy	*-0.987*	*-0.927*	*-1.049*	*-1.064*	*-1.034*	*-1.062*	*-1.083*	–	–	–	–	–	–	–							
(p-value)	*(0.032)*	*(0.044)*	*(0.021)*	*(0.020)*	*(0.023)*	*(0.020)*	*(0.017)*														
Gr. of GDP (-1)	*-0.077*							*-0.080*							0.061						
(p-value)	*(0.001)*							*(0.001)*							*(0.642)*						
Inflation		*0.017*							*0.013*							0.032					
(p-value)		*(0.000)*							*(0.007)*							*(0.108)*					
U. Inflation			*-0.014*							-0.013							-0.025				
(p-value)			*(0.017)*							*(0.024)*							*(0.329)*				
Sect. Conc/tion				*-0.043*	–						-0.049							0.018			
(p-value)				*(0.085)*							*(0.087)*							*(0.689)*			
Credit Risk Sc.					-0.336							-0.428							-0.260		
(p-value)					*(0.609)*							*(0.517)*							*(0.794)*		
FX Depr/tion						-0.121							-0.362							4.196	
(p-value)						*(0.821)*							*(0.511)*							*(0.180)*	
Fin. Openness							*0.014*							*0.015*							0.001
(p-value)							*(0.071)*							*(0.061)*							*(0.987)*
AIC	662.34	660.27	668.89	671.25	674.45	674.55	670.97	576.52	580.00	582.87	584.65	587.74	587.59	584.64	39.52	36.14	39.89	40.65	40.70	39.36	40.11
BIC	706.45	704.39	713.22	715.58	718.77	718.85	715.15	613.16	616.65	619.56	621.33	624.42	624.25	621.32	62.30	58.92	64.07	64.13	64.13	62.76	62.99
LogL	-324.17	-323.13	-327.45	-328.62	-330.22	-330.27	-328.48	-282.25	-284.00	-285.44	-286.32	-287.87	-287.79	-286.32	-14.76	-13.07	-15.32	-15.35	-15.35	-14.68	-15.05
$Pseudo-R^2(\%)$	35.49	35.69	34.83	34.60	34.28	34.27	34.63	36.13	35.74	35.41	35.21	36.61	34.88	35.21	54.74	59.92	53.03	53.01	52.93	54.99	53.84
No. of banks	419	419	419	419	419	419	419	315	315	315	315	315	315	315	100	100	100	100	100	100	92
No. of failures	96	96	96	96	96	96	96	89	89	89	89	89	89	89	7	7	7	7	7	7	7
No. of obs	4034	4036	4155	4155	4155	4141	4073	3318	3320	3340	3318	3318	3318	3318	704	704	800	800	797	797	718
Wald test (χ^2)	54.23	45.74	49.53	47.97	45.81	45.35	47.17	48.53	45.70	42.24	40.91	32.19	38.88	41.26	6.03	8.54	7.52	7.16	6.72	7.89	6.85
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.304)*	*(0.129)*	*(0.184)*	*(0.209)*	*(0.242)*	*(0.162)*	*(0.232)*
PH test (χ^2)	4.48	9.40	7.65	5.95	15.31	6.43	5.34	6.38	8.05	6.95	6.81	14.62	6.84	6.73	5.38	4.30	6.16	6.15	5.28	5.28	5.37
(p-value)	(0.723)	(0.225)	0.364	0.545	0.032	0.491	0.618	0.381	0.234	0.325	0.338	0.023	0.335	0.346	0.371	0.506	0.291	0.292	0.386	0.383	0.372
LR test $\theta = 0$	33.78	33.38	44.91	37.03	37.65	45.35	30.65	31.52	23.92	41.71	33.24	34.69	35.05	27.42	0.16	0.06	0.16	0.01	0.11	0.03	0.01
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.345)*	*(0.404)*	*(0.343)*	*(0.471)*	*(0.370)*	*(0.433)*	*(0.460)*
Theta (θ)	1.278	1.341	1.541	1.380	1.350	1.379	1.415	1.094	0.908	1.242	1.105	1.102	1.179	1.235	0.699	0.283	0.483	0.089	0.434	0.180	0.174

Note: The table reports estimates of the restricted and generalized shared frailty Cox models conditional on bank-level balance sheet information and macroeconomic characteristics. Estimated coefficients are reported while p-values are given in brackets. AIC is the Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. Frailty group: Country. "-" indicates that the variable was thrown out by the variable selection algorithm.

Table 29. Macro Frailty Cox PH Results / Income Statement.

				Panel A							**Panel B**							**Panel C**			
				Restricted											**Generalized**						
				All banks							**Conventional Banks**							**Islamic Banks**			
Gr. of Overheads	-0.040	-0.045	-0.054	-0.068	-0.064	-0.064	-0.062	-0.018	-0.028	-0.032	-0.047	-0.045	-0.045	-0.043	-0.992	-0.861	-1.137	-1.023	-1.109	-1.050	-1.189
(p-value)	(0.579)	(0.511)	(0.464)	(0.347)	(0.359)	(0.361)	(0.380)	(0.842)	(0.734)	(0.744)	(0.607)	(0.597)	(0.599)	(0.624)	(0.149)	(0.113)	(0.101)	(0.154)	(0.123)	(0.128)	(0.108)
Net Income	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	-0.134	-0.151	-0.123	-0.141	-0.141	-0.134	-0.155
(p-value)	(0.011)	(0.007)	(0.011)	(0.011)	(0.013)	(0.014)	(0.010)	(0.008)	(0.006)	(0.010)	(0.010)	(0.012)	(0.012)	(0.009)	(0.224)	(0.097)	(0.197)	(0.206)	(0.177)	(0.184)	(0.160)
Net Int. Revenue	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.016	-0.021	-0.019	-0.016	-0.018	-0.018	-0.015
(p-value)	(0.017)	(0.046)	(0.018)	(0.007)	(0.013)	(0.013)	(0.009)	(0.025)	(0.059)	(0.025)	(0.010)	(0.019)	(0.019)	(0.015)	(0.399)	(0.350)	(0.367)	(0.417)	(0.357)	(0.364)	(0.398)
Oth.Op. Income	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.011	-0.007	-0.005	-0.009	-0.005	-0.007	-0.006
(p-value)	(0.285)	(0.287)	(0.210)	(0.254)	(0.304)	(0.303)	(0.261)	(0.410)	(0.393)	(0.308)	(0.429)	(0.437)	(0.432)	(0.412)	(0.726)	(0.712)	(0.726)	(0.739)	(0.771)	(0.743)	(0.771)
Islamic Dummy	-0.487	-0.462	-0.611	-0.696	-0.594	-0.610	-0.588	–	–	–	–	–	–	–	–	–	–	–	–	–	–
(p-value)	(0.273)	(0.304)	(0.169)	(0.123)	(0.182)	(0.170)	(0.187)														
Gr. of GDP (-1)	-0.065							-0.073							0.065						
(p-value)	(0.003)							(0.001)							(0.690)						
Inflation		0.017							0.016							0.035					
(p-value)		(0.000)							(0.001)							(0.032)					
U. Inflation			-0.018							-0.016							-0.035				
(p-value)			(0.004)							(0.009)							(0.225)				
Sect. Conc/tion				-0.052							-0.065							-0.017			
(p-value)				(0.047)							(0.031)							(0.742)			
Credit Risk Sc.					-0.438							-0.349							-1.560		
(p-value)					(0.559)							(0.618)							(0.284)		
FX Depr/tion						0.022							0.023							1.945	
(p-value)						(0.967)							(0.966)							(0.516)	
Fin. Openness							0.020							0.018							-0.020
(p-value)							(0.046)							(0.069)							(0.250)
AIC	652.26	647.22	654.09	657.73	662.13	662.40	658.33	570.09	569.51	573.98	575.25	580.64	580.80	577.94	42.74	38.07	42.17	43.49	42.45	43.24	41.40
BIC	689.99	684.95	691.99	695.62	700.03	700.27	696.11	600.58	600.00	604.50	605.77	611.16	611.31	608.46	65.42	60.75	65.47	66.79	65.75	66.53	64.15
LogL	-320.13	-317.61	-321.05	-322.86	-325.07	-325.19	-323.16	-280.05	-279.75	-281.99	-282.62	-285.32	-285.41	-283.97	-16.37	-14.04	-16.08	-16.74	-16.23	-16.62	-15.70
$Pseudo - R^2(\%)$	36.29	36.79	36.11	35.75	35.31	35.28	35.69	36.63	36.70	36.19	36.05	35.44	35.42	35.74	49.80	56.96	50.68	48.66	50.24	49.03	51.86
No. of banks	418	418	418	418	418	418	410	315	315	315	315	315	315	315	103	103	103	103	103	103	95
No. of failures	91	91	91	91	91	91	91	84	84	84	84	84	84	84	7	7	7	7	7	7	7
No. of obs	3977	3979	4089	4089	4089	4075	4007	3288	3308	3308	3308	3308	3297	3308	689	689	781	781	781	778	699
Wald χ^2	24.43	28.04	23.04	19.98	16.44	16.05	19.60	24.51	23.74	19.35	18.29	13.92	13.63	16.88	5.05	10.66	5.41	5.41	6.22	5.67	6.69
(p-value)	(0.000)	(0.000)	(0.001)	(0.003)	(0.012)	(0.014)	(0.003)	(0.001)	(0.000)	(0.002)	(0.003)	(0.016)	(0.018)	(0.004)	(0.410)	(0.059)	(0.368)	(0.368)	(0.285)	(0.340)	(0.244)
PH test (χ^2)	2.00	7.71	6.30	3.41	18.70	5.76	2.46	2.71	6.06	4.97	3.35	13.90	5.30	2.51	1.54	2.04	2.95	1.51	2.93	1.73	1.55
(p-value)	(0.919)	(0.260)	(0.390)	(0.755)	(0.004)	(0.450)	(0.873)	(0.744)	(0.301)	(0.419)	(0.646)	(0.016)	(0.381)	(0.775)	(0.908)	(0.843)	(0.707)	(0.912)	(0.710)	(0.885)	(0.907)
LR test $\theta = 0$	42.85	36.57	60.09	43.09	51.37	46.57	52.20	36.22	32.23	52.11	35.18	44.81	40.23	45.39	0.18	0.00	0.63	0.51	1.20	0.45	0.35
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.336)	(0.500)	(0.213)	(0.238)	(0.137)	(0.252)	(0.278)
Theta (θ)	1.881	1.740	2.433	1.892	2.049	2.069	2.852	1.437	1.265	1.857	1.318	1.575	1.587	2.256	2.152	0.000	2.718	2.674	3.117	2.477	1.968

Note: The table reports estimates of the restricted and generalised shared frailty Cox models conditional on bank-level income statement information and macroeconomic characteristics. Estimated coefficients are reported while p-values are given in brackets. AIC is the Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. Frailty group: Country. "-" indicates that the variable was thrown out by the variable selection algorithm.

Table 30. Macro Frailty Cox PH Results / Financial Ratios.

	Panel A							Panel B							Panel C						
	Restricted							Generalised													
	All Banks							Conventional Banks							Islamic Banks						
Z score	*0.006*	*0.006*	*0.003*	*0.003*	*0.003*	*0.003*	*0.003*	*0.006*	*0.006*	*0.005*	*0.006*	*0.006*	*0.006*	*0.006*	-0.002	-0.001	-0.001	-0.001	-0.003	-0.001	-0.002
(p-value)	*(0.000)*	*(0.000)*	*(0.001)*	*(0.004)*	*(0.002)*	*(0.003)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.852)*	*(0.910)*	*(0.867)*	*(0.896)*	*(0.860)*	*(0.946)*	*(0.882)*
ROA	0.001	-0.001	-0.007	-0.014	-0.017	-0.021	-0.010	-0.004	-0.005	-0.007	-0.003	-0.004	-0.004	-0.004	0.148	0.157	0.082	0.085	0.103	0.093	0.087
(p-value)	*(0.967)*	*(0.933)*	*(0.681)*	*(0.477)*	*(0.346)*	*(0.278)*	*(0.597)*	*(0.777)*	*(0.737)*	*(0.698)*	*(0.867)*	*(0.823)*	*(0.814)*	*(0.797)*	*(0.254)*	*(0.217)*	*(0.353)*	*(0.363)*	*(0.280)*	*(0.323)*	*(0.335)*
CTI	*0.004*	*0.005*	*0.004*	*0.004*	*0.004*	*0.004*	*0.005*	*0.005*	*0.005*	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*	–	–	–	–	–	–	–
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*							
Net Loan/Assets	*0.024*	*0.022*	*0.012*	0.007	0.010	0.009	0.017	*0.034*	*0.034*	*0.028*	*0.026*	*0.028*	*0.028*	*0.027*	-0.009	0.014	-0.011	-0.014	-0.019	-0.013	-0.015
(p-value)	*(0.001)*	*(0.003)*	*(0.088)*	*(0.364)*	*(0.167)*	*(0.235)*	*(0.023)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.002)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.657)*	*(0.534)*	*(0.580)*	*(0.451)*	*(0.342)*	*(0.483)*	*(0.438)*
Equity/Assets	–	–	–	–	–	–	–	*-0.029*	*-0.027*	*-0.039*	*-0.042*	*-0.039*	*-0.040*	*-0.040*	0.012	0.018	0.009	0.005	0.016	0.006	0.013
(p-value)								*(0.026)*	*(0.049)*	*(0.003)*	*(0.002)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.552)*	*(0.366)*	*(0.655)*	*(0.788)*	*(0.483)*	*(0.751)*	*(0.565)*
NIM	–	–	–	–	–	–		*0.102*	*0.073*	*0.095*	*0.094*	*0.092*	*0.094*	*0.096*	-0.176	-0.213	-0.140	-0.139	-0.152	-0.152	-0.138
(p-value)								*(0.001)*	*(0.014)*	*(0.001)*	*(0.001)*	*(0.002)*	*(0.002)*	*(0.001)*	*(0.228)*	*(0.159)*	*(0.253)*	*(0.297)*	*(0.260)*	*(0.263)*	*(0.285)*
Inc. Diversity	–	–	–	–	–	–	–	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	*-0.001*	-0.057	-0.058	-0.042	-0.043	-0.045	-0.042	-0.043
(p-value)								*(0.066)*	*(0.096)*	*(0.055)*	*(0.084)*	*(0.088)*	*(0.084)*	*(0.081)*	*(0.211)*	*(0.158)*	*(0.215)*	*(0.223)*	*(0.205)*	*(0.238)*	*(0.202)*
Islamic Dummy	*-1.532*	*-1.466*	-0.504	-0.567	-0.427	-0.538	-0.508														
(p-value)	*(0.004)*	*(0.006)*	*(0.341)*	*(0.292)*	*(0.424)*	*(0.308)*	*(0.341)*														
Gr. of GDP (-1)	*-0.097*							*-0.090*							0.021						
(p-value)	*(0.000)*							*(0.000)*							*(0.907)*						
Inflation		*0.016*							*0.015*							0.049					
(p-value)		*(0.000)*							*(0.003)*							*(0.046)*					
U. Inflation			*0.015*							*-0.011*							-0.031				
(p-value)			*(0.017)*							*(0.075)*							*(0.308)*				
Sect. Conc/tion				*-0.061*							-0.035							0.003			
(p-value)				*(0.009)*							*(0.237)*							*(0.951)*			
Credit Risk Sc.					-0.679							-0.271							-2.027		
(p-value)					*(0.304)*							*(0.679)*							*(0.214)*		
FX Depr/tion						-0.749							-0.064							2.580	
(p-value)						*(0.175)*							*(0.919)*							*(0.405)*	
Fin. Openness							*-0.025*							0.005							-0.021
(p-value)							*(0.001)*							*(0.590)*							*(0.295)*
AIC	636.44	637.08	855.95	853.73	860.61	855.57	850.98	498.23	502.73	511.34	512.84	514.28	514.33	514.16	50.19	44.66	51.07	52.07	50.39	51.48	50.58
BIC	674.32	674.96	894.38	892.17	899.05	893.93	889.30	546.99	551.49	560.15	561.65	563.09	563.11	562.97	81.82	76.29	83.59	84.58	82.90	83.97	82.31
$LogL$	-312.22	-312.54	-421.97	-420.87	-424.31	-421.78	-419.49	-241.12	-243.36	-247.67	-248.42	-249.14	-249.16	-249.08	-18.09	-15.33	-18.53	-19.03	-18.19	-18.74	-18.29
$Pseudo-R^2(\%)$	37.86	37.80	16.02	16.24	15.56	16.06	16.52	45.44	44.93	43.96	43.79	43.63	43.62	43.64	44.52	52.99	43.16	41.63	44.21	42.53	43.91
No. of banks	414	414	415	415	415	415	407	313	313	313	313	313	313	313	100	100	100	100	100	100	92
No. of failures	87	87	87	87	87	87	87	77	77	77	77	77	77	77	7	7	7	7	7	7	7
No. of obs	4081	4083	4476	4476	4476	4421	4387	3277	3279	3298	3298	3298	3287	3298	678	678	769	769	769	766	687
Wald χ^2	66.20	63.24	33.96	35.17	29.64	30.19	38.94	71.44	67.00	59.08	57.23	56.36	56.17	56.19	3.62	7.38	4.28	3.27	4.41	3.86	4.11
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.822)*	*(0.390)*	*(0.747)*	*(0.859)*	*(0.732)*	*(0.796)*	*(0.766)*
PH test (χ^2)	5.14	7.07	2.75	2.75	19.76	1.63	4.45	3.90	4.16	4.31	3.84	15.92	3.60	3.61	2.72	1.77	4.19	2.18	2.99	2.39	2.32
(p-value)	0.526	0.315	0.839	0.840	0.003	0.950	0.616	0.865	0.842	0.828	0.872	0.043	0.891	0.891	0.907	0.971	0.757	0.949	0.885	0.935	0.939
LR test $\theta = 0$	37.59	44.09	16.28	13.53	15.13	13.30	27.80	17.75	23.60	30.99	24.47	28.05	27.03	21.61	1.49	0.42	1.87	1.48	1.90	1.51	1.37
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.111)*	*(0.258)*	*(0.086)*	*(0.112)*	*(0.084)*	*(0.109)*	*(0.121)*
Theta (θ)	1.447	1.548	1.241	1.332	1.267	1.181	2.405	0.898	0.971	1.289	1.041	1.130	1.127	1.133	3.836	2.050	3.907	3.498	3.806	3.896	3.042

Note: The table reports estimates of the restricted and generalised shared frailty Cox models conditional on bank-level financial ratios information and macroeconomic characteristics. Estimated coefficients are reported while p-values are given in brackets. AIC is the Akaike Information Criterion. Wald test for the joint significance of all explanatory variables. Frailty group: Country. "-" indicates that the variable was thrown out by the variable selection algorithm.

Table 31. Country log frailties conditional on bank specific and macroeconomic variables / Balance Sheet.

	Panel A							Panel B							Panel C						
	Restricted							Generalised													
	All Banks							Conventional Banks							Islamic Banks						
	GDP	INF	U.INF	HHI	STR	FX	OPEN	GDP	INF	U.INF	HHI	STR	FX	OPEN	GDP	INF	U.INF	HHI	STR	FX	OPEN
Albania	0.414	0.443	0.457	0.631	0.339	0.386	0.452	0.340	0.335	0.355	0.540	0.252	0.291	0.436	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bahrain	0.964	1.011	0.934	1.133	1.077	0.911	0.512	0.708	0.693	0.687	0.886	0.801	0.648	0.289	0.554	0.399	0.546	0.143	0.500	0.277	0.242
Bangladesh	-1.419	-1.264	-1.535	-1.776	-1.535	-1.427	-0.941	-1.726	-1.549	-1.900	-2.101	-1.891	-1.811	-0.281	-0.009	0.002	-0.006	0.004	0.008	-0.002	-0.001
Brunei	0.521	0.731	0.769	0.971	0.625	0.701	0.826	-0.052	0.157	0.164	0.376	0.064	0.117	0.209	0.596	0.308	0.441	0.091	0.356	0.201	0.171
Egypt	0.344	0.429	0.180	0.035	0.150	0.261	-0.050	0.377	0.426	0.266	0.135	0.199	0.310	-0.033	-0.145	-0.061	-0.092	-0.016	-0.098	-0.038	-0.034
Indonesia	0.926	0.948	1.270	0.594	0.857	0.962	0.587	0.826	0.872	1.150	0.534	0.746	0.876	0.555	-0.022	-0.005	-0.006	-0.002	-0.015	-0.007	-0.005
Iran	-0.676	-0.709	-0.823	-0.737	-0.794	-0.730	-0.483	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.159	-0.091	-0.134	-0.025	-0.135	-0.049	-0.004
Jordan	-1.548	-1.321	-1.821	-1.151	-1.750	-1.666	-1.924	-1.180	-0.996	-1.357	-0.816	-1.348	-1.327	-1.788	-0.212	-0.061	-0.173	-0.042	-0.173	-0.062	-0.066
Kuwait	-1.007	-0.838	-1.199	-0.684	-0.909	-1.060	-0.824	-0.201	-0.174	-0.235	-0.108	-0.157	-0.213	-0.259	-0.255	-0.107	-0.180	-0.055	-0.197	-0.081	-0.095
Malaysia	0.545	0.787	0.587	0.251	0.818	0.604	0.511	0.295	0.564	0.423	0.126	0.673	0.402	0.518	-0.473	-0.125	-0.294	-0.053	-0.257	-0.098	-0.125
Mauritania	-1.305	-1.107	-1.442	-0.704	-1.357	-1.292	-0.619	-0.735	-0.577	-0.723	-0.280	-0.701	-0.675	-0.432	-0.005	-0.003	-0.002	-0.001	-0.003	-0.001	-0.001
Pakistan	-0.424	-0.320	-0.468	-0.666	-0.559	-0.462	-0.299	-0.700	-0.572	-0.819	-0.986	-0.922	-0.841	-0.359	-0.116	-0.024	-0.057	-0.012	-0.073	-0.021	-0.030
Palestine	-0.263	-0.161	-0.334	-0.030	-0.297	-0.273	-0.214	-0.143	-0.090	-0.170	-0.012	-0.160	-0.161	-0.139	-0.015	-0.003	-0.007	-0.002	-0.006	-0.002	-0.002
Qatar	-0.841	-0.888	-1.227	-0.695	-0.913	-1.068	-1.442	-0.523	-0.539	-0.770	-0.392	-0.544	-0.716	-1.115	-0.106	-0.063	-0.070	-0.012	-0.041	-0.018	-0.020
S.Arabia	-1.109	-0.889	-1.237	-1.132	-0.906	-1.055	-0.862	-0.517	-0.411	-0.552	-0.564	-0.392	-0.514	-0.599	-0.001	-0.002	-0.002	0.000	-0.001	0.000	-0.001
Sudan	-1.176	-1.199	-1.667	-1.019	-1.421	-1.348	-0.795	-0.430	-0.421	-0.606	-0.364	-0.536	-0.517	-0.396	-0.451	-0.202	-0.331	-0.055	-0.271	-0.116	-0.114
Tunisia	-1.764	-1.494	-2.011	-2.015	-1.633	-1.772	-1.552	-1.860	-1.525	-1.979	-2.022	-1.594	-1.851	-1.443	-0.033	-0.011	-0.022	-0.004	-0.018	-0.010	-0.008
Turkey	1.071	0.245	0.905	0.843	0.996	1.100	1.433	1.033	0.495	0.865	0.866	0.947	1.118	1.454	0.428	-0.018	0.180	0.069	0.269	0.042	0.126
UAE	-1.027	-0.988	-1.180	-1.421	-0.928	-1.131	-1.675	-0.876	-0.810	-0.960	-1.186	-0.698	-0.959	-1.494	-0.379	-0.104	-0.221	-0.045	-0.203	-0.090	-0.098
Yemen	-0.016	-0.081	-0.246	-0.089	-0.166	-0.093	-0.393	0.152	0.082	-0.029	0.080	-0.001	0.055	-0.267	-0.043	-0.020	-0.040	-0.006	-0.034	-0.012	-0.015

Note: Table shows estimates of the random effects from the shared-frailty Cox model conditional on bank-specific and macroeconomic variables.
A negative (positive) coefficient suggests a decreasing (increasing) contribution of the country to the bank's hazard. $\nu_i = \log(\alpha_i)$.
GDP=Real GDP Growth(-1); INF=Inflation(-1); U.INF=Unexpected Inflation; HHI=Banking Sector Concentration;
STR=Credit Risk Score; FX=FX Depreciation; OPEN=Financial Openness.

Table 32. Country log frailties conditional on bank specific and macroeconomic variables / Income Statement.

	Panel A							Panel B							Panel C						
	Restricted													Generalised							
	All Banks							Conventional Banks							Islamic Banks						
	GDP	INF	U.INF	HHI	STR	FX	OPEN	GDP	INF	U.INF	HHI	STR	FX	OPEN	GDP	INF	U.INF	HHI	STR	FX	OPEN
Albania	0.267	0.354	0.337	0.665	0.172	0.255	0.440	0.241	0.295	0.307	0.614	0.171	0.233	0.422	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bahrain	0.701	0.774	0.663	0.912	0.881	0.646	-0.263	0.524	0.573	0.500	0.834	0.628	0.479	-0.161	0.162	0.349	0.285	0.148	0.811	0.205	0.615
Bangladesh	-1.096	-0.979	-1.375	-1.604	-1.338	-1.202	-0.680	-1.474	-1.348	-1.771	-1.947	-1.708	-1.596	-1.154	0.732	0.668	0.824	0.744	0.660	0.813	0.447
Brunei	1.069	1.210	1.254	1.408	1.116	1.198	1.333	0.326	0.436	0.467	0.599	0.383	0.433	0.555	1.346	1.097	1.575	1.475	1.326	1.452	1.198
Egypt	-0.317	-0.232	-0.517	-0.643	-0.540	-0.395	-1.181	-0.221	-0.147	-0.393	-0.498	-0.413	-0.292	-0.903	-0.600	-0.308	-0.806	-0.769	-1.181	-0.750	-0.301
Indonesia	1.075	1.099	1.481	0.697	0.968	1.103	0.539	1.068	1.112	1.470	0.721	1.007	1.119	0.686	-0.136	-0.061	-0.052	-0.192	-0.276	-0.190	-0.097
Iran	-1.170	-1.159	-1.400	-1.240	-1.380	-1.269	-0.777	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.830	-0.660	-1.006	-1.082	-1.469	-0.883	-0.057
Jordan	-1.878	-1.650	-2.241	-1.377	-2.141	-2.020	-3.202	-1.588	-1.341	-1.903	-0.899	-1.813	-1.715	-2.722	-0.402	-0.164	-0.543	-0.446	-0.873	-0.466	-0.212
Kuwait	-1.405	-1.236	-1.708	-0.969	-1.287	-1.504	-2.251	-0.866	-0.715	-1.102	-0.411	-0.808	-0.936	-1.484	-0.561	-0.356	-0.721	-0.630	-0.377	-0.614	-0.482
Malaysia	0.862	1.085	0.827	0.469	1.150	0.891	0.868	0.920	1.141	0.954	0.565	1.180	0.989	1.033	-0.620	-0.237	-0.585	-0.816	-0.333	-0.562	-0.713
Mauritania	-0.846	-0.724	-1.033	-0.392	-0.963	-0.877	-0.726	-0.546	-0.443	-0.694	-0.166	-0.634	-0.579	-0.477	-0.635	-0.372	-0.811	-0.729	-1.400	-0.847	-1.089
Pakistan	-0.427	-0.333	-0.526	-0.741	-0.622	-0.493	0.227	-0.360	-0.261	-0.420	-0.589	-0.501	-0.397	0.908	-0.811	-0.480	-0.654	-0.935	-1.266	-0.785	-1.111
Palestine	-0.409	-0.299	-0.589	-0.041	-0.521	-0.466	-0.589	-0.260	-0.173	-0.375	-0.011	-0.330	-0.298	-0.372	-0.171	-0.038	-0.121	-0.064	-0.195	-0.100	-0.108
Qatar	-1.204	-1.291	-1.725	-0.989	-1.274	-1.495	-2.697	-0.826	-0.901	-1.277	-0.552	-0.967	-1.114	-2.072	-0.253	-0.076	-0.368	-0.234	-0.108	-0.207	-0.079
S. Arabia	-1.387	-1.172	-1.627	-1.488	-1.168	-1.378	-2.120	-1.201	-0.959	-1.379	-1.178	-1.025	-1.171	-1.789	-0.009	-0.003	-0.019	-0.018	-0.006	-0.012	-0.010
Sudan	-1.084	-1.155	-1.736	-0.914	-1.391	-1.281	-1.320	-0.519	-0.525	-0.822	-0.334	-0.681	-0.627	-0.667	-0.771	-0.801	-1.507	-1.088	-1.716	-1.176	-1.352
Tunisia	-1.785	-1.577	-2.167	-2.117	-1.664	-1.848	-1.691	-1.485	-1.264	-1.821	-1.699	-1.424	-1.538	-1.421	-0.356	-0.158	-0.444	-0.472	-0.205	-0.382	-0.543
Turkey	1.201	0.404	0.917	0.935	1.086	1.211	1.704	1.154	0.441	0.937	0.928	1.078	1.178	1.672	0.930	0.280	0.675	1.021	1.016	0.854	0.718
UAE	-1.115	-1.090	-1.308	-1.576	-0.982	-1.236	-2.304	-0.870	-0.831	-1.049	-1.283	-0.805	-0.989	-1.865	-0.763	-0.394	-0.847	-0.953	-0.445	-0.753	-0.355
Yemen	-1.414	-1.402	-1.898	-1.433	-1.655	-1.544	-2.660	-0.966	-0.955	-1.389	-0.890	-1.191	-1.109	-1.958	-0.659	-0.491	-0.930	-0.880	-1.229	-0.939	-0.359

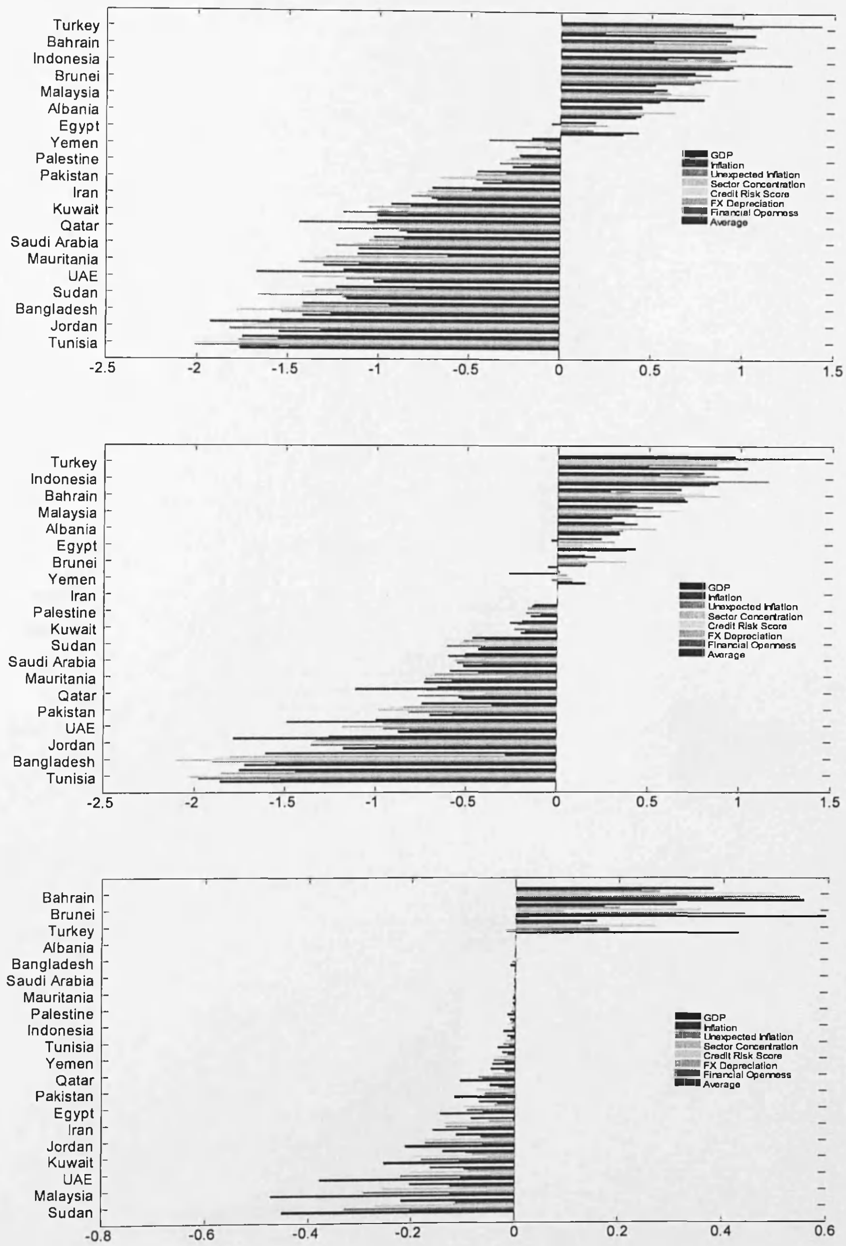
Note: Table shows estimates of the random effects from the shared-frailty Cox model conditional on bank-specific and macroeconomic variables.
A negative (positive) coefficient suggests a decreasing (increasing) contribution of the country to the bank's hazard. $\nu_i = \log(\alpha_i)$.
GDP=Real GDP Growth(-1); INF=Inflation(-1); U.INF=Unexpected Inflation; HHI=Banking Sector Concentration;
STR=Credit Risk Score; FX=FX Depreciation; OPEN=Financial Openness.

Table 33. Country log frailties conditional on bank specific and macroeconomic variables / Financial Ratios.

	Panel A							Panel B							Panel C						
	Restricted							Generalised													
	All Banks							Conventional Banks							Islamic Banks						
	GDP	INF	U.INF	HHI	STR	FX	OPEN	GDP	INF	U.INF	HHI	STR	FX	OPEN	GDP	INF	U.INF	HHI	STR	FX	OPEN
Albania	0.417	0.492	0.658	0.926	0.599	0.612	0.613	0.381	0.419	0.437	0.524	0.358	0.383	0.424	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bahrain	0.751	0.811	0.687	1.145	1.078	0.609	1.361	0.427	0.461	0.450	0.600	0.502	0.416	0.325	0.134	0.337	0.500	0.385	1.119	0.422	0.898
Bangladesh	-1.029	-0.925	-0.538	-1.223	-0.785	-0.674	-2.422	-1.534	-1.580	-1.897	-1.892	-1.818	-1.726	-1.543	1.104	0.865	1.115	1.103	0.994	1.144	0.876
Brunei	0.882	1.074	1.261	1.559	1.160	1.226	1.246	0.280	0.403	0.450	0.505	0.378	0.405	0.424	1.679	1.430	1.789	1.629	1.445	1.771	1.479
Egypt	0.392	0.439	0.191	-0.408	-0.046	0.043	-0.206	0.212	0.187	0.026	-0.014	-0.002	0.083	-0.013	-1.149	-0.465	-1.198	-1.106	-1.888	-1.222	-0.669
Indonesia	1.088	1.164	0.693	-0.068	0.569	0.745	1.247	0.852	0.886	1.184	0.775	0.872	0.965	0.877	-0.087	-0.032	-0.034	-0.079	-0.120	-0.111	-0.050
Iran	-1.741	-1.858	-1.720	-1.891	-1.942	-1.775	-2.996	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.557	-1.155	-1.472	-1.398	-2.120	-1.500	-1.116
Jordan	-1.664	-1.542	-1.666	-1.160	-1.866	-1.809	-2.158	-0.921	-0.935	-1.343	-0.844	-1.302	-1.235	-1.358	-0.528	-0.092	-0.718	-0.709	-1.176	-0.701	-0.328
Kuwait	-1.187	-1.180	-1.369	-0.899	-1.007	-1.497	-1.141	-0.377	-0.396	-0.529	-0.293	-0.409	-0.465	-0.490	-1.908	-0.986	-1.954	-1.722	-1.080	-1.696	-1.357
Malaysia	0.500	0.764	0.226	-0.506	0.705	0.065	0.205	0.747	0.986	0.915	0.739	1.061	0.922	0.969	-1.275	-0.413	-1.266	-1.224	-0.484	-1.208	-1.270
Mauritania	-0.703	-0.683	-0.523	-0.188	-0.624	-0.552	-1.428	-0.197	-0.191	-0.263	-0.105	-0.248	-0.224	-0.184	-0.609	-0.314	-0.461	-0.475	-0.829	-0.603	-0.654
Pakistan	-0.436	-1.206	-0.177	-0.509	-0.391	-0.292	-1.569	-0.346	-0.309	-0.543	-0.597	-0.600	-0.520	-0.371	-1.024	-0.165	-0.684	-0.853	-1.427	-0.878	-1.231
Palestine	-0.295	-0.223	-0.380	-0.010	-0.459	-0.434	-0.665	-0.081	-0.070	-0.137	-0.017	-0.127	-0.116	-0.109	-0.097	-0.022	-0.063	-0.068	-0.093	-0.056	-0.056
Qatar	-0.919	-1.201	-1.040	-0.635	-0.708	-1.092	-0.777	-0.357	-0.550	-0.749	-0.419	-0.574	-0.646	-0.738	-1.241	-0.977	-1.260	-0.900	-0.386	-0.936	-0.396
S. Arabia	-1.664	-1.520	-1.397	-2.145	-1.035	-1.536	-1.272	-0.866	-0.834	-1.142	-1.030	-0.900	-1.001	-1.038	-0.475	-0.256	-0.460	-0.380	-0.120	-0.397	-0.222
Sudan	-0.943	-1.069	-0.988	-0.833	-1.213	-0.967	-1.724	-0.236	-0.285	-0.437	-0.233	-0.375	-0.348	-1.038	-1.017	-0.268	-1.388	-1.205	-2.015	-1.536	-1.651
Tunisia	-1.825	-1.726	-1.730	-2.401	-1.299	-0.954	-3.034	-1.263	-1.232	-1.518	-1.403	-1.263	-1.317	-0.324	-0.723	-0.282	-0.660	-0.563	-0.236	-0.644	-0.912
Turkey	0.923	0.285	0.764	0.257	0.347	0.901	-0.303	0.562	0.062	0.470	0.513	0.572	0.654	-1.228	0.940	-0.353	0.297	0.749	0.393	0.498	0.414
UAE	-1.300	-1.316	-1.057	-1.698	-0.598	-0.547	-0.383	-0.642	-0.721	-0.755	-0.843	-0.610	-0.731	0.771	-1.131	-0.696	-1.109	-1.012	-0.470	-1.092	-0.544
Yemen	0.008	-0.036	0.116	0.134	-0.041	0.262	0.284	-0.266	-0.335	-0.552	-0.402	-0.481	-0.445	-0.870	-0.572	-0.275	-0.736	-0.628	-0.942	-0.982	-0.243

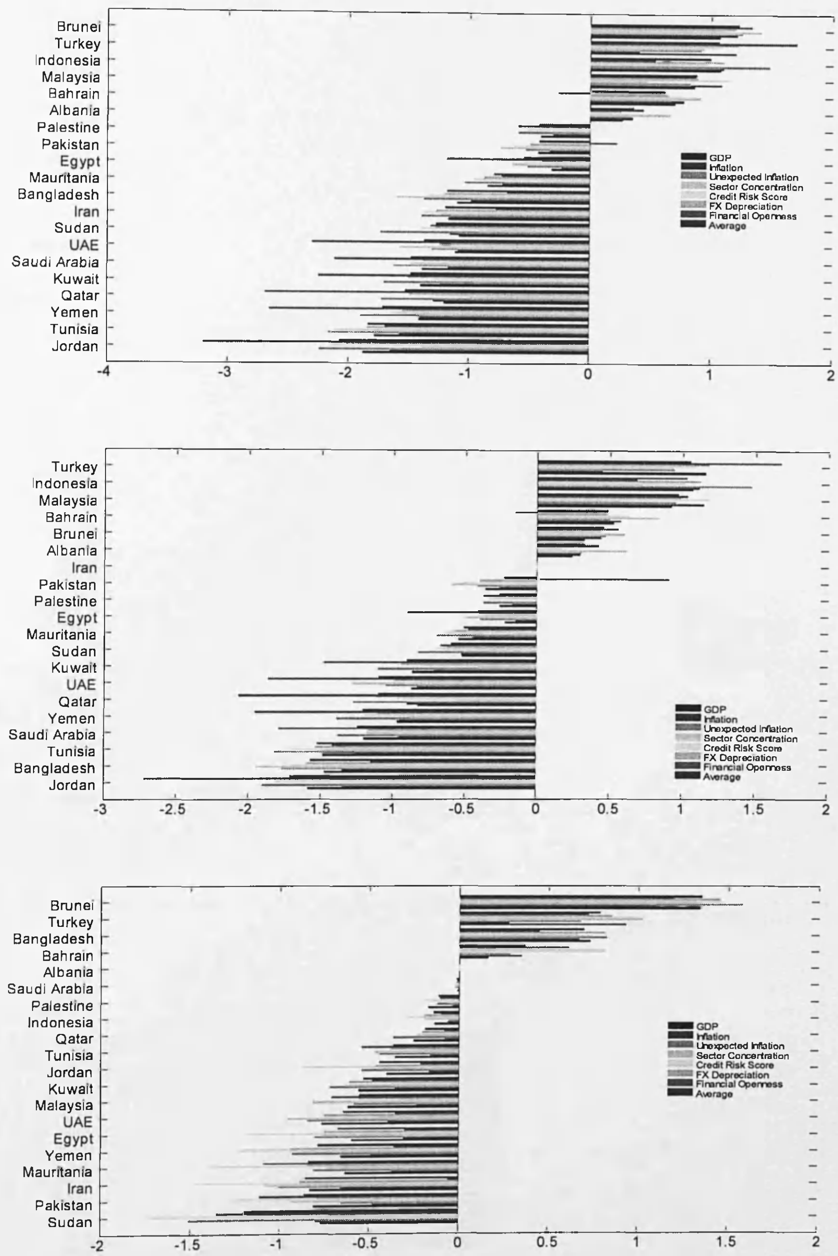
Note: Table shows estimates of the random effects from the shared-frailty Cox model conditional on bank-specific and macroeconomic variables.
A negative (positive) coefficient suggests a decreasing (increasing) contribution of the country to the bank's hazard. $\nu_i = \log(\alpha_i)$.
GDP=Real GDP Growth(-1); INF=Inflation(-1); U.INF=Unexpected Inflation; HHI=Banking Sector Concentration;
STR=Credit Risk Score; FX=FX Depreciation; OPEN=Financial Openness.

Figure 10. Exponentiated frailties for countries / Balance Sheet.



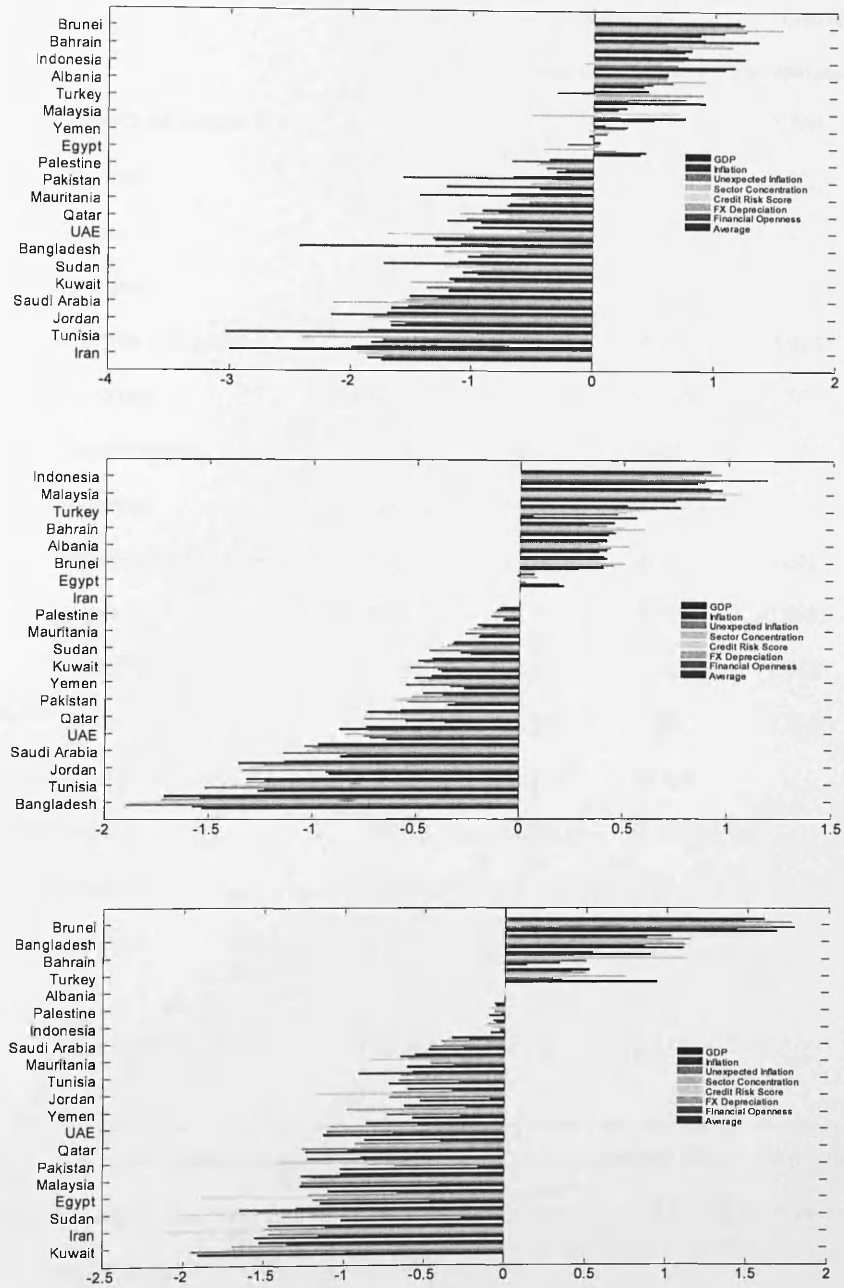
The figure plots the latent country factor estimates, (ν_i), for the shared-frailty Cox PH model that conditions on accounting and macroeconomic information. The bars represent the estimated log frailties obtained in the balance sheet, restricted and generalised models. $\nu_i > 0$ $(\nu_i < 0)$ implies that the latent country factor has an upward (downward) effect on bank failure risk.

Figure 11.Exponentiated frailties for countries / Income Statement.



The figure plots the latent country factor estimates, (ν_i), for the shared-frailty Cox PH model that conditions on accounting and macroeconomic information. The bars represent the estimated log frailties obtained in the income statement, restricted and generalised models. $\nu_i > 0$ $(\nu_i < 0)$ implies that the latent country factor has an upward (downward) effect on bank failure risk.

Figure 12. Exponentiated frailties for countries / Financial Ratios.



The figure plots the latent country factor estimates, (ν_i), for the shared-frailty Cox PH model that conditions on accounting and macroeconomic information. The bars represent the estimated log frailties obtained in the financial ratios, restricted and generalised models. $\nu_i > 0$ $(\nu_i < 0)$ implies that the latent country factor has an upward (downward) effect on bank failure risk.

Table 34. Proportional Hazards Assumption / Balance Sheet.

	Restricted	Semi-Restricted		Generalised	
	All Banks	**Conventional**	**Islamic**	**Conventional**	**Islamic**
Growth of Loans				0.200	–
(p-value)				*(0.002)*	
Loans				–	0.687
(p-value)					*(0.209)*
Growth of Equity	-0.025	-0.028	-0.001	-0.079	–
(p-value)	*(0.857)*	*(0.839)*	*(0.990)*	*(0.707)*	
Liquid Assets	-0.060	-0.036	0.464	-0.081	–
(p-value)	*(0.481)*	*(0.700)*	*(0.454)*	*(0.316)*	
Other Earning Assets (ln)	-0.022	-0.023	-0.417	0.001	0.054
(p-value)	*(0.753)*	*(0.815)*	*(0.262)*	*(0.989)*	*(0.937)*
Assets (ln)	-0.046	-0.057	0.363	-0.068	0.375
(p-value)	*(0.616)*	*(0.592)*	*(0.491)*	*(0.564)*	*(0.531)*
Growth of Assets	0.181	0.174	-0.133	–	-0.046
(p-value)	*(0.033)*	*(0.057)*	*(0.787)*		*(0.943)*
Islamic	-0.068				
(p-value)	*(0.519)*				
Global Test	*(0.319)*	*(0.357)*	*(0.825)*	*(0.016)*	*(0.291)*

Note: Table reports ρ values for the Schoenfeld test of the proportional hazards and p-values in brackets. The Semi-restricted model is tested individually for the two strata (Conventional and Islamic). Null Hypothesis is that the PH holds.

Table 35. Proportional Hazards Assumption / Income Statement.

	Restricted	Semi-Restricted		Generalised	
	All Banks	**Conventional**	**Islamic**	**Conventional**	**Islamic**
Growth of Overheads	0.094	0.049	-0.086	-0.015	-0.249
(p-value)	*(0.682)*	*(0.843)*	*(0.870)*	*(0.949)*	*(0.720)*
Net Income	-0.040	-0.038	-0.584	-0.009	-0.483
(p-value)	*(0.776)*	*(0.710)*	*(0.297)*	*(0.953)*	*(0.463)*
Net Interest Revenue	-0.196	-0.244	0.367	-0.066	–
(p-value)	*(0.035)*	*(0.068)*	*(0.441)*	*(0.735)*	
Other Operating Income	-0.190	-0.164	-0.259	-0.279	-0.522
(p-value)	*(0.073)*	*(0.246)*	*(0.765)*	*(0.151)*	*(0.869)*
Islamic	-0.029				
(p-value)	*(0.786)*				
Global Test	*(0.384)*	*(0.258)*	*(0.802)*	*(0.631)*	*(0.946)*

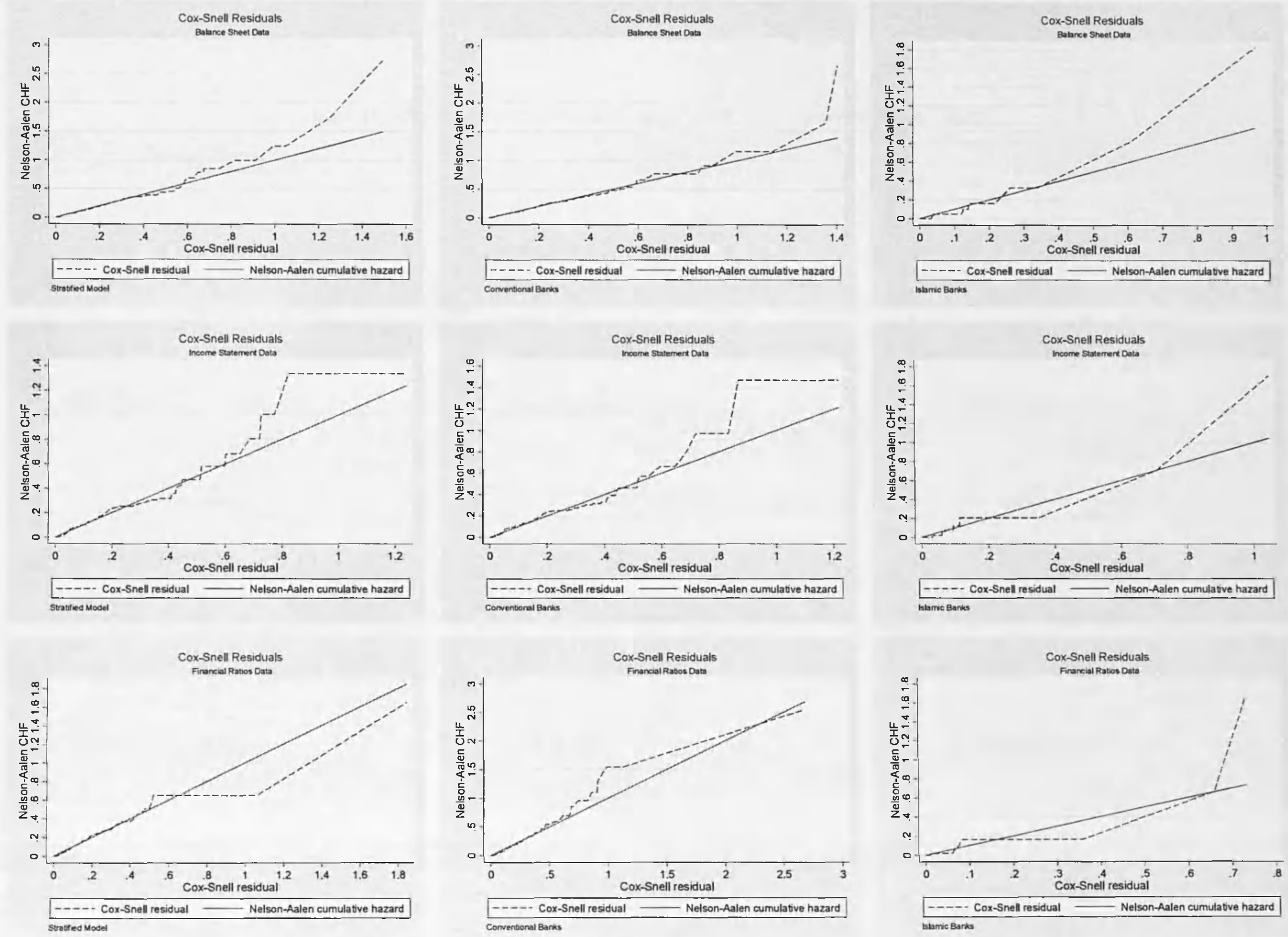
Note: Table reports ρ values for the Schoenfeld test of the proportional hazards and p-values in brackets. The Semi-restricted model is tested individually for the two strata (Conventional and Islamic). Null Hypothesis is that the PH holds.

Table 36. Proportional Hazards Assumption / Financial Ratios.

	Restricted	Semi-Restricted		Generalised	
	All Banks	Conventional	Islamic	Conventional	Islamic
Z score	0.079	0.079	0.641	0.024	0.158
(p-value)	*(0.164)*	*(0.572)*	*(0.661)*	*(0.839)*	*(0.928)*
ROA	0.074	0.080	-0.891	–	-0.502
(p-value)	*(0.697)*	*(0.612)*	*(0.211)*		*(0.437)*
CTI	0.058	0.049	-0.844	-0.030	-0.343
(p-value)	*(0.603)*	*(0.673)*	*(0.111)*	*(0.786)*	*(0.528)*
Net Loans/Assets	0.060	0.014	0.337	–	–
(p-value)	*(0.456)*	*(0.891)*	*(0.580)*		
Equity/Assets				0.104	0.319
(p-value)				*(0.481)*	*(0.618)*
NIM				0.002	0.458
(p-value)				*(0.987)*	*(0.618)*
Income Diversity				0.081	-0.163
(p-value)				*(0.652)*	*(0.776)*
Liquid Assets/Deposits				-0.035	0.023
(p-value)				*(0.626)*	*(0.961)*
Islamic	-0.096				
(p-value)	*(0.340)*				
Global Test	*(0.891)*	*(0.953)*	*(0.337)*	*(0.977)*	*(0.991)*

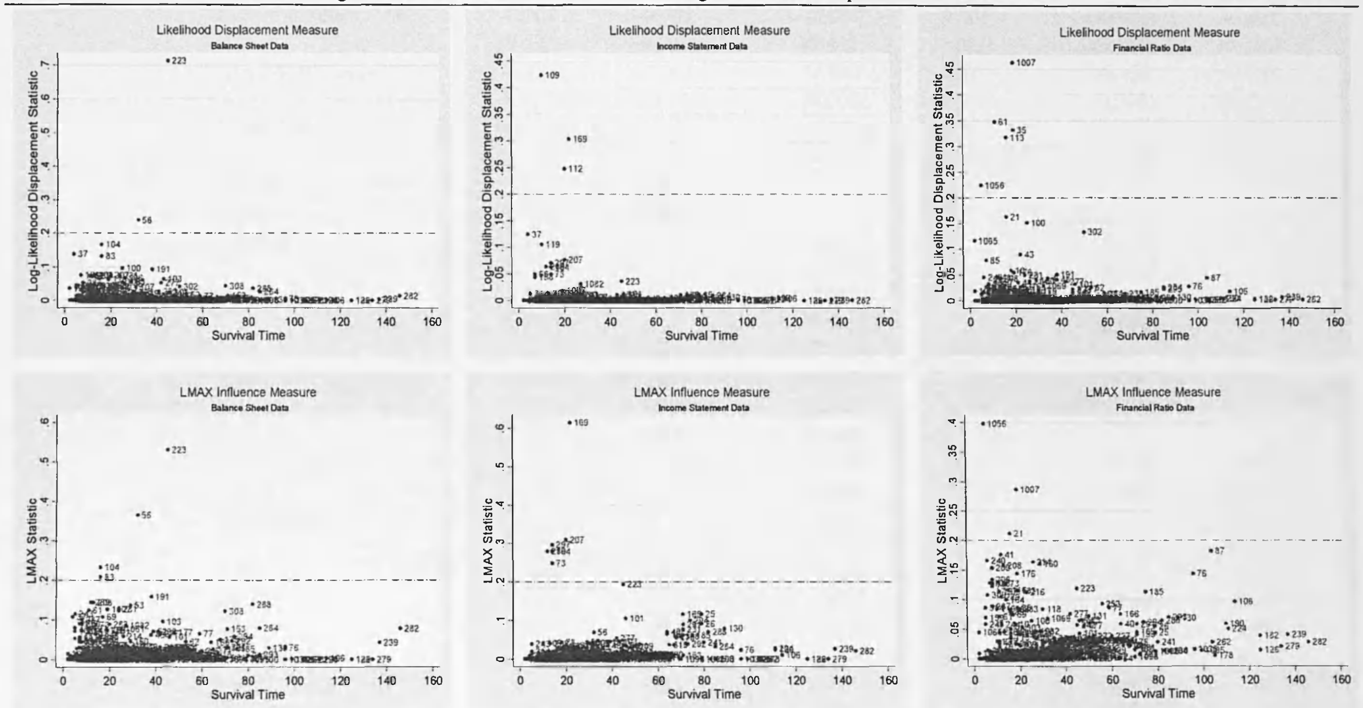
Note: Table reports ρ values for the Schoenfeld test of the proportional hazards and p-values in brackets. The Semi-restricted model is tested individually for the two strata (Conventional and Islamic). Null Hypothesis is that the PH holds.

Figure 13. Cox-Snell Residuals / Semi-Restricted and Generalised Models.



Note: CHF= Cumulative Hazard Function. The closer the two lines, the better the fit.

Figure 14. Influential Points Detection - Log-Likelihood Displacement and LMAX.



Note: All figures refer to the stratified models. The reference line at y=0.2 is arbitrarily drawn to distinguish big influential points.

Table 37. Balance sheet drivers of failure hazard / Full Model.

	Restricted Cox PH model		Semi-Generalized Cox PH model			
	All banks		CBs		IBs	
	Micro+Macro	Micro	Micro+Macro	Micro	Micro+Macro	Micro
Assets	*0.894*	*0.799*	*0.928*	*0.782*	*0.673*	*0.745*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.020)*	*(0.014)*
Other Earning Assets	*-0.597*	*-0.510*	*-0.573*	*-0.440*	*-0.493*	*-0.424*
	(0.000)	*(0.000)*	*(0.001)*	*(0.011)*	*(0.004)*	*(0.021)*
Liquid Assets	*-0.001*	*-0.001*	*-0.001*	*-0.001*	-0.001	-0.001
	(0.003)	*(0.001)*	*(0.002)*	*(0.001)*	(0.137)	(0.185)
Growth of Loans	*-0.923*	*-1.064*	*-1.061*	*-1.240*	-0.156	-0.198
	(0.009)	*(0.003)*	*(0.006)*	*(0.001)*	(0.778)	(0.770)
Growth of Equity	-0.053	*-0.088*	-0.074	*-0.106*	-0.318	-0.395
	(0.152)	*(0.013)*	(0.143)	*(0.019)*	(0.427)	(0.393)
Islamic Bank Dummy	*-1.011*	*-1.079*				
	(0.028)	*(0.018)*				
Growth of Real GDP	*-0.051*		*-0.065*		-0.036	
	(0.033)		*(0.009)*		(0.623)	
Inflation**	*0.012*		*0.009*		*0.035*	
	(0.015)		*(0.079)*		*(0.000)*	
Theta (θ)	1.120	1.419	0.930	1.150		
LR test $\theta = 0$	*25.65*	*41.90*	*22.20*	*36.50*		
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*		
Wald test $\beta = 0$	*61.61*	*44.89*	*52.68*	*38.81*	*61.78*	*10.38*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.065)*
PH test (χ^2)	9.19	5.88	7.28	5.68	4.21	3.49
	(0.326)	(0.436)	(0.400)	(0.339)	(0.756)	(0.625)
AIC	656.22	668.92	575.60	586.15	46.95	49.28
BIC	706.61	707.07	618.35	616.72	78.82	72.68
LogL	-320.11	-328.55	-280.80	-288.07	-16.47	-19.64
Pseudo-R^2	36.29	34.61	36.46	34.82	49.50	39.78
No. of banks	415	415	315	315	100	100
No. of failures	96	96	89	89	7	7
No. of observations	4135	4135	3342	3342	800	800

The table reports estimates of Cox PH models conditional on firm-level balance sheet and country-level variables while controling for latent country factors. Italics denotes significance (p-values in parentheses). LR test is for the null that the latent country factors or shared frailty (H_0: θ =0) are insignificant; the hypothesis cannot be refuted for IBs (p-value 0.236 and 0.196 for Micro+Macro and Micro models, respectively) so the Cox PH model without shared frailty is reported in the last two columns. Wald test is for the joint significance of all variables. PH test is the Schoenfeld residual-based test for the proportional-hazards assumption. AIC (BIC) is Akaike (Bayesian) information criterion. LogL is the log-likelihood. Pseudo-R^2 is the McFadden goodness-of-fit criteria. *, ** and *** on the variable name denote significant difference in the marginal effect for CBs and IBs at the 10%, 5% or 1% levels.

Table 38. Income statement drivers of failure hazard / Full Model.

	Restricted Cox PH model		Semi-Generalized Cox PH model			
	All banks		CBs		IBs	
	Micro+Macro	Micro	Micro+Macro	Micro	Micro+Macro	Micro
Growth of Overheads***	-0.028	-0.064	-0.005	-0.046	*-0.937*	*-1.043*
	(0.718)	(0.360)	(0.905)	(0.592)	*(0.013)*	*(0.001)*
Net Interest Revenue*	*-0.002*	*-0.002*	*-0.002*	*-0.002*	*-0.017*	-0.012
	(0.015)	*(0.004)*	*(0.018)*	*(0.007)*	*(0.096)*	(0.162)
Net Income***	*0.007*	*0.006*	*0.007*	*0.006*	*-0.141*	*-0.144*
	(0.003)	*(0.014)*	*(0.002)*	*(0.012)*	*(0.000)*	*(0.000)*
Islamic Bank Dummy	-0.531	-0.625				
	(0.251)	(0.164)				
Growth of Real GDP	*-0.063*		*-0.074*		-0.016	
	(0.008)		*(0.002)*		(0.884)	
Inflation*	*0.019*		*0.017*		*0.035*	
	(0.000)		*(0.001)*		*(0.001)*	
Sector Concentration*	*-1.829*		*-2.076*		0.269	
	(0.000)		*(0.000)*		(0.859)	
Theta (θ)	1.803	2.175	0.975	1.645		
LR test $\theta = 0$	*44.61*	*55.37*	*16.91*	*47.27*		
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*		
Wald test $\beta = 0$	*24.90*	*16.06*	*42.98*	*13.74*	*61.02*	*35.27*
	(0.000)	*(0.003)*	*(0.000)*	*(0.003)*	*(0.000)*	*(0.000)*
PH test (χ^2)	5.53	0.82	3.47	1.37	1.33	0.47
	(0.596)	(0.935)	(0.748)	(0.713)	(0.970)	(0.926)
AIC	633.06	659.99	550.12	577.71	40.43	40.52
BIC	677.10	685.62	586.72	596.03	67.71	54.54
LogL	-309.53	-326.17	-269.06	-285.85	-14.22	-17.26
Pseudo-R^2	38.40	35.09	39.12	35.32	56.40	47.08
No. of banks	419	419	315	315	104	104
No. of failures	91	91	84	84	7	7
No. of observations	4107	4107	3315	3315	792	792

The table reports estimates of Cox PH models conditional on firm-level income statement and country-level variables while controling for latent country factors. Italics denotes significance (p-values in parentheses). LR test is for the null that the latent country factors or shared frailty (H_0: θ =0) are insignificant; the hypothesis cannot be refuted for IBs (p-value 0.500 and 0.252 for Micro+Macro and Micro models, respectively) so the Cox PH model without shared frailty is reported in the last two columns. Wald test is for the joint significance of all variables. PH test is the Schoenfeld residual-based test for the proportional-hazards assumption. AIC (BIC) is Akaike (Bayesian) information criterion. LogL is the log-likelihood. Pseudo-R^2 is the McFadden goodness-of-fit criteria. *, ** and *** on the variable name denote significant difference in the marginal effect for CBs and IBs at the 10%, 5% or 1% levels.

Table 39. Financial ratio drivers of failure hazard / Full Model.

	Restricted Cox PH model		Semi-Generalized Cox PH model			
	All banks		CBs		IBs	
	Micro+Macro	Micro	Micro+Macro	Micro	Micro+Macro	Micro
Cost/Income*	*0.003*	*0.003*	*0.004*	*0.003*	*0.017*	0.014
	(0.006)	*(0.003)*	*(0.002)*	*(0.004)*	*(0.092)*	(0.113)
Liquid Assets/Deposits	-0.003	-0.001	-0.002	-0.001	*-0.006*	-0.012
	(0.392)	(0.666)	(0.542)	(0.826)	*(0.012)*	(0.300)
Equity/Assets**	-0.006	-0.014	*-0.026*	*-0.035*	*0.073*	*0.046*
	(0.572)	(0.192)	*(0.064)*	*(0.005)*	*(0.000)*	*(0.000)*
Net Interest Margin***	0.011	0.011	*0.064*	*0.075*	-0.447	-0.242
	(0.231)	(0.165)	*(0.021)*	*(0.004)*	(0.276)	(0.218)
Islamic Bank Dummy	*-0.872*	*-0.989*				
	(0.097)	*(0.054)*				
Growth of Real GDP	*-0.066*		*-0.075*		0.017	
	(0.009)		*(0.005)*		(0.903)	
Inflation**	*0.017*		*0.012*		*0.059*	
	(0.001)		*(0.033)*		*(0.000)*	
Sector Concentration***	*-1.547*		*-1.760*		*2.605*	
	(0.002)		*(0.001)*		*(0.058)*	
Theta (θ)	1.206	1.558	0.738	1.084		
LR test $\theta = 0$	*24.30*	*46.39*	*33.26*	*32.63*		
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*		
Wald test $\beta = 0$	*41.28*	*15.57*	*44.14*	*22.84*	*66.30*	*31.92*
	(0.000)	*(0.008)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
PH test (χ^2)	2.77	0.98	3.55	2.06	3.54	0.10
	(0.948)	(0.964)	(0.830)	(0.725)	(0.832)	(0.999)
AIC	629.37	651.48	580.33	580.92	29.80	33.90
BIC	679.66	683.05	605.39	605.35	61.35	52.44
LogL	-306.69	-320.74	-274.34	-286.46	-7.90	-12.95
Pseudo-R^2	38.96	36.17	37.92	35.18	75.78	60.29
No. of banks	416	416	314	314	100	100
No. of failures	87	87	82	82	7	7
No. of observations	4082	4082	3321	3321	761	761

The table reports estimates of Cox PH models conditional on firm-level financial ratio and country-level variables while controling for latent country factors. Italics denotes significance (p-values in parentheses). LR test is for the null that the latent country factors or shared frailty (H_0: θ =0) are insignificant; the hypothesis cannot be refuted for IBs (p-value 0.500 and 0.500 for Micro+Macro and Micro models, respectively) so the Cox PH model without shared frailty is reported in the last two columns. Wald test is for the joint significance of all variables. PH test is the Schoenfeld residual-based test for the proportional-hazards assumption. AIC (BIC) is Akaike (Bayesian) information criterion. LogL is the log-likelihood. Pseudo-R^2 is the McFadden goodness-of-fit criteria. *, ** and *** on the variable name denote significant difference in the marginal effect for CBs and IBs at the 10%, 5% or 1% levels.

Table 40. Full-variable Cox PH model estimates.

	Restricted Cox PH model (all banks)			
	Micro+Macro		Micro	
	Coefficient	p-value	Coefficient	p-value
Assets	*0.707*	*(0.000)****	*0.697*	*(0.000)****
Other Earning Assets	*-0.490*	*(0.000)****	*-0.418*	*(0.003)****
Liquid Assets	*-0.001*	*(0.023)***	*-0.001*	*(0.018)***
Growth of Loans	*-0.768*	*(0.096)**	*-1.055*	*(0.039)***
Growth of Equity	-0.041	*(0.166)*	*-0.087*	*(0.003)****
Growth of Overheads	-0.009	*(0.857)*	-0.032	*(0.606)*
Net Interest Revenue	0.000	*(0.900)*	0.001	*(0.349)*
Net Income	0.000	*(0.828)*	0.000	*(0.992)*
Equity/Assets	0.007	*(0.541)*	-0.003	*(0.825)*
Net Interest Margin	0.010	*(0.119)*	*0.011*	*(0.029)***
Cost/Income	*0.002*	*(0.031)***	0.002	*(0.206)*
Liquid Assets/Deposits	0.001	*(0.561)*	0.002	*(0.250)*
Islamic Dummy	*-1.018*	*(0.004)****	*-1.501*	*(0.003)****
Growth of Real GDP	*-0.078*	*(0.000)****		
Inflation	*0.016*	*(0.008)****		
Sector Concentration	*-1.183*	*(0.035)***		
Wald test $\beta = 0$	*126.9*		*68.8*	
	(0.000)		*(0.000)*	
PH test (χ^2)	10.06		17.87	
	(0.863)		*(0.162)*	
AIC	581.15		617.58	
BIC	681.56		699.49	
LogL	-274.58		-295.79	
Pseudo-R^2	45.35		41.13	
No. of banks	413		413	
No. of failures	87		87	
No. of observations	4062		4062	

The table reports estimates of a Cox PH model without shared frailty. The covariates are from all blocks of the accounting statement. Significance p-values for each coefficient are reported in a separate column, and for the tests in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% significance levels.

3.8 Appendix

Table A1. Estimation output for inflation forecasting models.

Country	Albania	Bahrain	Bangladesh	Brunei	Egypt	Indonesia	Iran	Jordan	Kuwait	Malaysia
Constant	32.200	−0.319	11.098	3.876	10.124	74.285	19.977	5.440	8.281	3.375
(p-value)	*(0.329)*	*(0.902)*	*(0.010)*	*(0.509)*	*(0.000)*	*(0.128)*	*(0.000)*	*(0.034)*	*(0.178)*	*(0.004)*
AR(1)	0.447	0.261	0.225	0.137	0.552	0.272	0.483	–	0.072	0.207
(p-value)	*(0.107)*	*(0.260)*	*(0.199)*	*(0.564)*	*(0.001)*	*(0.119)*	*(0.001)*		*(0.693)*	*(0.209)*
AR(2)	–	–	–	–	–	–	–	0.299	–	–
(p-value)								*(0.197)*		
R^2	0.202	0.104	0.051	0.018	0.320	0.0741	0.231	0.101	0.005	0.048
AIC	11.332	6.822	8.701	9.135	6.473	13.511	8.025	6.817	9.799	6.165
LM(2)	*(0.736)*	*(0.300)*	*(0.663)*	*(0.948)*	*(0.142)*	*(0.915)*	*(0.391)*	*(0.369)*	*(0.915)*	*(0.471)*
Observations	14	14	34	20	34	34	29	18	32	34

Note: Selection of ARMA terms has been done with respect to minimise the AIC. Estimated coefficients and p-values in brackets.
AIC=Akaike Information Criterion; R^2=Coefficient of Determination; LM(2)=Breusch-Godfrey Serial Correlation LM test for 2 lags.

Table A2. Estimation output for inflation forecasting models.

Country	Mauritania	Pakistan	Palestine	Qatar	Saudi Arabia	Sudan	Tunisia	Turkey	UAE	Yemen
Constant	8.315	8.955	0.050	8.327	9.999	3.703	6.977	2.605	2.667	28.924
(p-value)	*(0.000)*	*(0.001)*	*(0.114)*	*(0.312)*	*(0.123)*	*(0.047)*	*(0.000)*	*(0.000)*	*(0.058)*	*(0.079)*
AR(1)	0.330	0.702	0.173	0.314	–	−0.675	0.259	–	0.109	–
(p-value)	*(0.067)*	*(0.000)*	*(0.408)*	*(0.584)*		*(0.000)*	*(0.121)*		*(0.004)*	
AR(2)	–	–	–	–	0.076	–	–	–	–	–
(p-value)					*(0.716)*					
MA(1)	–	–	–	–	–	–	–	−0.343	0.339	0.752
(p-value)								*(0.040)*	*(0.150)*	*(0.082)*
MA(2)	–	–	–	–	–	–	–	−0.620	–	–
(p-value)								*(0.001)*		
R^2	0.114	0.488	0.029	0.052	0.005	0.350	0.075	0.340	0.531	0.259
AIC	6.632	5.758	−1.235	8.341	9.637	8.596	5.992	8.144	5.715	8.424
LM(2)	*(0.940)*	*(0.251)*	*(0.170)*	*(0.471)*	*(0.981)*	*(0.391)*	*(0.819)*	*(0.229)*	*(0.691)*	*(0.112)*
Observations	30	34	25	8	25	34	33	34	21	5

Note: Selection of ARMA terms has been done with respect to minimise the AIC. Estimated coefficients and p-values in brackets.
AIC=Akaike Information Criterion; R^2=Coefficient of Determination; LM(2)=Breusch-Godfrey Serial Correlation LM test for 2 lags.

Table A3. Credit Rating Scores.

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Albania	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	B+
Bahrain	–	–	–	–	–	–	–	A	A	A	A	A	A	A	A	A
Bangladesh	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	BB-
Brunei	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Egypt	–	–	A-	A-	A-	A-	BBB+	BBB	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-
Indonesia	A+	A+	A-	B+	B-	B	B-	B-	B+	BB	BB	BB+	BB+	BB+	BB+	BB+
Iran	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Jordan	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB-	BBB	BBB	BBB	BBB	BBB	BBB	BBB	BBB-
Kuwait	–	–	A+	A+	A+	A+	A+	A+	A+	A+	A+	A+	AA-	–	–	–
Malaysia	AA+	AA+	AA+	AA-	A-	A	A	A	A+	A+	A+	A+	A+	A+	A+	A+
Mauritania	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pakistan	B+	B+	B-	CCC	B	B	B	BB-	BB-	BB	BB	BB	BB	BB-	B-	B-
Palestine	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Qatar	BBB	BBB	BBB	BBB	BBB+	BBB+	A-	A	A+	A+	A+	A+	AA-	AA-	AA-	AA
Saudi Arabia	–	–	–	–	–	–	–	–	A+	A+	A+	A+	AA-	AA-	AA-	AA-
Sudan	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Tunisia	–	–	A	A	A	A	A	A	A	A	A	A	A	A	A-	BBB+
Turkey	B+	B+	B	B	B	B+	B+	B-	B-	B+	BB	BB	BB	BB	BB	BB+
UAE	–	–	–	–	–	–	–	–	–	–	–	–	AA	–	–	–
Yemen	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Source: S&P. When more than one ratings were available for each year we take the average. "-" For these countries rating was not available

Table A4(a). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
1	AB Bank Ltd	Bangladesh	CB	1982	n/a	13
2	Abu Dhabi Commercial Bank	UAE	CB	1985	n/a	10
3	Affin Bank	Malaysia	CB	1975	n/a	20
4	Agrani Bank Limited	Bangladesh	CB	1972	2007	23
5	Ahli Bank QSC	Qatar	CB	1983	n/a	12
6	Ahli United Bank (Bahrain) B.S.C.	Bahrain	CB	1977	2004	18
7	Ahli United Bank (Egypt) SAE	Egypt	CB	1978	n/a	17
8	Ahli United Bank BSC	Bahrain	CB	1977	n/a	22
9	Ahli United Bank KSC	Kuwait	CB	1971	n/a	24
10	Ak Uluslararasi Bankasi AS	Turkey	CB	1985	2004	13
11	Akbank T.A.S.	Turkey	CB	1948	n/a	51
12	Aktif Yatirim Bankasi AS	Turkey	CB	1999	n/a	5
13	Al Ahli Bank of Kuwait (KSC)	Kuwait	CB	1967	n/a	28
14	Al Masraf-Arab Bank for Investment & Foreign Trade	UAE	CB	1976	n/a	19
15	Al Watany Bank of Egypt	Egypt	CB	1980	n/a	15
16	Al-Arafah Islami Bank Ltd.	Bangladesh	CB	1994	n/a	1
17	Alliance Bank Malaysia Berhad	Malaysia	CB	1982	n/a	13
18	Allied Bank Limited	Pakistan	CB	1942	n/a	53
19	AmBank (M) Berhad	Malaysia	CB	2001	n/a	1
20	Amen Bank	Tunisia	CB	1967	n/a	28
21	American Express Bank Ltd - Pakistan Branches	Pakistan	CB	1990	2007	13
22	Anadolubank A.S.	Turkey	CB	1997	n/a	4
23	ANZ Panin Bank	Indonesia	CB	1990	n/a	5
24	Arab African International Bank	Egypt	CB	1964	n/a	31
25	Arab Bank Group	Jordan	CB	1930	n/a	65
26	Arab Bank Plc	Jordan	CB	1930	n/a	65
27	Arab Banking Corporation (Jordan)	Jordan	CB	1990	n/a	5
28	Arab Banking Corporation - Egypt	Egypt	CB	1982	n/a	13
29	Arab Banking Corporation - Tunisie	Tunisia	CB	2000	n/a	1
30	Arab Banking Corporation BSC	Bahrain	CB	1980	n/a	15
31	Arab International Bank	Egypt	CB	1974	n/a	21
32	Arab National Bank	Saudi Arabia	CB	1980	n/a	15
33	Arab Tunisian Bank	Tunisia	CB	1982	n/a	13
34	Askari Bank Limited	Pakistan	CB	1992	n/a	3
35	Atlas Bank Limited	Pakistan	CB	1990	2010	14

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(b). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
36	Attijari Bank	Tunisia	CB	1968	n/a	27
37	Awal Bank	Bahrain	CB	2004	2009	4
38	Bahraini Saudi Bank (The) BSC	Bahrain	CB	1983	n/a	12
39	Baiduri Bank	Brunei	CB	1994	n/a	1
40	Ban Hin Lee Bank Berhad - BHL Bank	Malaysia	CB	1935	2000	60
41	Banca Italo Albanese/ Banka Italo Shqiptare-Italian-Albanian Bank	Albania	CB CB	1993	2007	4
42	Bangkok Bank Berhad	Malaysia	CB	1994	n/a	1
43	Bangladesh Commerce Bank Ltd	Bangladesh	CB	1987	n/a	8
44	Bangladesh Small Industries & Commerce Bank Ltd-BASIC Bank Ltd	Bangladesh	CB	1988	n/a	7
45	Bank Al Habib	Pakistan	CB	1991	n/a	4
46	Bank Al-Jazira	Saudi Arabia	CB	1975	n/a	20
47	Bank Alfalah Limited	Pakistan	CB	1992	n/a	3
48	Bank Artha Graha	Indonesia	CB	1967	2006	28
49	Bank Artha Graha Internasional Tbk	Indonesia	CB	1973	n/a	22
50	Bank Asia Limited	Indonesia	CB	1991	n/a	8
51	Bank Asia Pacific - ASPAC Bank	Indonesia	CB	1957	1997	38
52	Bank Audi SAE	Egypt	CB	1948	n/a	47
53	Bank Bahari	Egypt	CB	1967	1997	28
54	Bank BIRA - Bank Indonesia Raya	Indonesia	CB	1951	n/a	44
55	Bank Bumi Arta	Indonesia	CB	1967	n/a	28
56	Bank Bumiputra Malaysia Berhad	Malaysia	CB	1965	1998	30
57	Bank Central Asia	Indonesia	CB	1957	n/a	38
58	Bank Central Dagang	Indonesia	CB	1969	n/a	26
59	Bank Chinatrust Indonesia	Indonesia	CB	1995	n/a	1
60	Bank Commonwealth	Indonesia	CB	1995	n/a	1
61	Bank Credit Lyonnais Indonesia	Indonesia	CB	1989	2001	6
62	Bank Danamon Indonesia Tbk	Indonesia	CB	1956	n/a	39
63	Bank DBS Indonesia	Indonesia	CB	1989	n/a	8
64	Bank Duta	Indonesia	CB	1966	n/a	29
65	Bank Ekonomi Rahardja	Indonesia	CB	1990	n/a	5
66	Bank Ekspres A.S.	Turkey	CB	1992	n/a	5
67	Bank First Indonesian Finance and Investments Corporation-Bank Ficorinvest	Indonesia	CB	1973	1997	22
68	Bank Haga	Indonesia	CB	1989	2008	6
69	Bank Hagakita	Indonesia	CB	1989	2007	6
70	Bank ICB Bumiputera	Indonesia	CB	1990	n/a	8

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(c). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
71	Bank Internasional Indonesia Tbk	Indonesia	CB	1959	n/a	36
72	Bank Jabar PT	Indonesia	CB	1961	n/a	42
73	Bank Kapital T.A.S.	Turkey	CB	1985	2000	14
74	Bank KEB Indonesia PT	Indonesia	CB	1990	n/a	5
75	Bank Keppel Tat Lee Buana	Indonesia	CB	1990	2002	5
76	Bank Kesawan	Indonesia	CB	1913	n/a	82
77	Bank Lippo Tbk.	Indonesia	CB	1948	n/a	47
78	Bank Mandiri (Persero) Tbk	Indonesia	CB	1991	n/a	8
79	Bank Mashill Utama	Indonesia	CB	1989	1998	6
80	Bank Mega TBK	Indonesia	CB	1969	n/a	30
81	Bank Modern	Indonesia	CB	1989	1997	7
82	Bank Mutiara Tbk	Indonesia	CB	1990	n/a	5
83	Bank Nasional	Indonesia	CB	1980	1997	16
84	Bank Negara Indonesia (Persero) - Bank BNI	Indonesia	CB	1946	n/a	49
85	Bank Nusa Internasional	Indonesia	CB	1989	1997	6
86	Bank Nusantara Parahyangan	Indonesia	CB	1972	n/a	26
87	Bank OCBC NISP Tbk	Indonesia	CB	1905	n/a	90
88	Bank of Alexandria	Egypt	CB	1957	n/a	38
89	Bank of America Malaysia Berhad	Malaysia	CB	1994	n/a	1
90	Bank of Commerce & Development 'Al Tegaryoon'	Egypt	CB	1980	2002	15
91	Bank of Jordan Plc	Jordan	CB	1960	n/a	35
92	Bank of Khyber	Jordan	CB	1991	n/a	4
93	Bank of Nova Scotia Berhad	Malaysia	CB	1973	n/a	22
94	Bank of Palestine Plc	Palestine	CB	1960	n/a	35
95	Bank of Punjab	Pakistan	CB	1989	n/a	6
96	Bank of Sharjah	UAE	CB	1973	n/a	22
97	Bank of Tokyo-Mitsubishi UFJ (Malaysia) Berhad	Malaysia	CB	1959	n/a	36
98	Panin Bank-Bank Pan Indonesia Tbk PT	Indonesia	CB	1971	n/a	24
99	Bank Papan Sejahtera	Indonesia	CB	1980	1997	16
100	Bank Paribas - BBD Indonesia	Indonesia	CB	1974	2001	21
101	Bank Pembangunan Indonesia (Persero) - BAPINDO	Indonesia	CB	1951	1998	44
102	Bank Permata Tbk	Indonesia	CB	1954	n/a	41
103	Bank Prima Express	Indonesia	CB	1956	2000	39
104	Bank Putra Surya Perkasa	Indonesia	CB	1980	1997	15
105	Bank Rabobank International Indonesia	Indonesia	CB	1990	n/a	6

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(d). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
106	Bank Rakyat Indonesia (Persero) Tbk	Indonesia	CB	1895	n/a	100
107	Bank Rama	Indonesia	CB	1967	1999	28
108	Bank Sahid Gajah Perkasa	Indonesia	CB	1990	1998	5
109	Bank Sakura Swadharma	Indonesia	CB	1989	2000	6
110	Bank Sinarmas	Indonesia	CB	1989	1997	6
111	Bank Subentra	Indonesia	CB	1989	1997	6
112	Bank Sumitomo Mitsui Indonesia	Indonesia	CB	1989	n/a	7
113	Bank Surya	Indonesia	CB	1980	1997	15
114	Bank Tabungan Negara (Persero)	Indonesia	CB	1950	n/a	45
115	Bank Tiara Asia	Indonesia	CB	1989	1998	6
116	Bank UFJ Indonesia	Indonesia	CB	1989	2005	9
117	Bank Umum Nasional	Indonesia	CB	1952	1997	43
118	Bank Umum Servitia	Indonesia	CB	1967	1998	28
119	Bank Universal	Indonesia	CB	1990	2001	5
120	Bank UOB Buana	Indonesia	CB	1956	n/a	39
121	Bank Utama (Malaysia) Berhad	Malaysia	CB	1976	2003	19
122	Banka e Tiranes Sha-Tirana Bank SA	Albania	CB	1996	n/a	3
123	Banka Societe Generale Albania Sh.A	Albania	CB	2003	n/a	1
124	C Bank-Bankpozitif Kredi ve Kalkinma Bankasi AS	Turkey	CB	1999	n/a	3
125	Banque de l'Habitat	Tunisia	CB	1989	n/a	6
126	Banque de Tunisie	Tunisia	CB	1884	n/a	111
127	Banque du Caire SAE	Egypt	CB	1952	n/a	43
128	Banque Internationale Arabe de Tunisie	Tunisia	CB	1976	n/a	19
129	Banque Mauritanienne pour le Commerce International	Mauritania	CB	1974	n/a	21
130	Banque Misr SAE	Egypt	CB	1920	n/a	75
131	Banque Nationale Agricole	Tunisia	CB	1959	n/a	36
132	Banque Nationale de Mauritanie	Mauritania	CB	1989	n/a	6
133	Banque Saudi Fransi	Saudi Arabia	CB	1977	n/a	18
134	Barclays Bank - Egypt S.A.E.	Egypt	CB	1975	n/a	20
135	BBK B.S.C.	Bahrain	CB	1971	n/a	24
136	BLOM Bank Egypt SAE	Egypt	CB	1977	n/a	18
137	BNP Paribas Egypt (SAE)	Egypt	CB	1977	n/a	18
138	BRAC Bank Limited	Bangladesh	CB	2000	n/a	1
139	BSN Commercial Bank (Malaysia) Berhad	Malaysia	CB	1975	2000	20
140	Burgan Bank SAK	Kuwait	CB	1975	n/a	20
141	Cairo Amman Bank	Jordan	CB	1960	n/a	35

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(e). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
142	Capital Bank of Jordan	Jordan	CB	1994	n/a	1
143	CIMB Bank Berhad	Malaysia	CB	1971	n/a	24
144	Citibank Berhad	Malaysia	CB	1959	n/a	36
145	City Bank Ltd	Bangladesh	CB	1983	n/a	12
146	Commercial Bank International P.S.C.	UAE	CB	1991	n/a	4
147	Commercial Bank of Bahrain B.S.C.	Bahrain	CB	1984	2001	11
148	Commercial Bank of Dubai P.S.C.	UAE	CB	1969	n/a	26
149	Commercial Bank of Kuwait SAK (The)	Kuwait	CB	1960	n/a	35
150	Commercial Bank of Qatar (The) QSC	Qatar	CB	1975	n/a	20
151	Commercial International Bank (Egypt) S.A.E.	Egypt	CB	1975	n/a	20
152	Credit Agricole Egypt	Egypt	CB	1977	n/a	18
153	Denizbank A.S.	Turkey	CB	1938	n/a	61
154	Deutsche Bank (Malaysia) Bhd.	Malaysia	CB	1968	n/a	27
155	Dhaka Bank Limited	Bangladesh	CB	1985	n/a	10
156	Doha Bank	Qatar	CB	1979	n/a	16
157	Dutch-Bangla Bank Limited	Bangladesh	CB	1995	n/a	1
158	Eastern Bank Limited	Bangladesh	CB	1992	n/a	3
159	Ege Giyim Sanayicileri Bankasi A.S. - EGS Bank	Turkey	CB	1994	2000	1
160	Egyptian American Bank	Egypt	CB	1976	2006	19
161	Egyptian Gulf Bank	Egypt	CB	1981	n/a	14
162	Emirates Bank International PJSC	UAE	CB	1977	n/a	18
163	EON Bank Berhad	Malaysia	CB	1963	n/a	32
164	Eon Finance Berhad	Malaysia	CB	1989	2004	6
165	Esbank Eskisehir Bankasi T.A.S.	Turkey	CB	1927	1999	68
166	Etibank AS	Turkey	CB	1935	2000	60
167	Export Import Bank of Bangladesh Limited	Bangladesh	CB	1960	n/a	39
168	Faysal Bank Ltd	Pakistan	CB	1994	n/a	1
169	Finansbank A.S.	Turkey	CB	1987	n/a	12
170	First Gulf Bank	UAE	CB	1979	n/a	16
171	Fortis Bank AS	Turkey	CB	1964	n/a	35
172	GSD Yatirim Bankasi AS	Turkey	CB	1998	n/a	1
173	Gulf Bank KSC (The)	Kuwait	CB	1960	n/a	35
174	Gulf International Bank BSC	Bahrain	CB	1975	n/a	20
175	Habib Bank Limited	Pakistan	CB	1941	n/a	54
176	Hanil Tamara Bank	Indonesia	CB	1980	2000	15
177	Hock Hua Bank Bhd	Malaysia	CB	1951	2000	44

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(f). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
177	Hock Hua Bank Bhd	Malaysia	CB	1951	2000	44
178	Hong Leong Bank Berhad	Malaysia	CB	1905	n/a	90
179	Housing Bank for Trade & Finance (The)	Jordan	CB	1974	n/a	21
180	HSBC Bank A.S.	Turkey	CB	1990	n/a	10
181	HSBC Bank Egypt S A E	Egypt	CB	1982	n/a	13
182	HSBC Bank Malaysia Berhad	Malaysia	CB	1884	n/a	111
183	IBJ Indonesia Bank	Indonesia	CB	1980	2000	15
184	International Finance Investment and Commerce Bank Limited-IFIC Bank Limited	Bangladesh	CB	1983	n/a	12
185	Iktisat Bankasi Turk A.S.	Turkey	CB	1924	2000	71
186	Indonesia Dai-Ichi Kangyo Bank	Indonesia	CB	1991	2000	4
187	Indonesia Eximbank	Indonesia	CB	1998	n/a	1
188	Indus Bank Limited	Pakistan	CB	1992	n/a	3
189	ING Bank A.S.	Turkey	CB	1984	n/a	11
190	Interbank A.S.	Turkey	CB	1888	2000	107
191	International Bank Malaysia Bhd	Malaysia	CB	1961	2000	34
192	International Bank of Qatar Q.S.C.	Qatar	CB	2000	n/a	1
193	International Bank of Yemen YSC	Yemen	CB	1979	n/a	16
194	Intesa Sanpaolo Bank Albania	Albania	CB	1998	n/a	1
195	Invest Bank P.S.C.	UAE	CB	1975	n/a	20
196	Islami Bank Bangladesh Limited	Bangladesh	CB	1983	n/a	12
197	Islamic Development Bank of Brunei Bhd	Brunei	CB	1994	2006	1
198	Jamuna Bank Ltd	Bangladesh	CB	2000	n/a	1
199	Janata Bank Limited	Bangladesh	CB	1972	n/a	23
200	JayaBank International	Indonesia	CB	1989	1998	6
201	Jordan Ahli Bank Plc	Jordan	CB	1955	n/a	40
202	Jordan Commercial Bank	Jordan	CB	1977	n/a	18
203	Jordan Kuwait Bank	Jordan	CB	1976	n/a	19
204	JP Morgan Chase Bank Berhad	Malaysia	CB	1994	n/a	1
205	KASB Bank Limited	Pakistan	CB	1994	n/a	1
206	Kentbank A.S.	Turkey	CB	1992	2001	3
207	Kocbank A.S.	Turkey	CB	1985	2006	13
208	Korfezbank	Turkey	CB	1987	2001	8
209	Malayan Banking Berhad - Maybank	Malaysia	CB	1960	n/a	35
210	Mashreqbank	UAE	CB	1967	n/a	28
211	MCB Bank Limited	Pakistan	CB	1947	n/a	48
212	Mercantile Bank Limited	Bangladesh	CB	1998	n/a	1

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(g). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
213	MIBank-MISR International Bank SAE	Egypt	CB	1978	2006	17
214	Misr America International Bank	Egypt	CB	1977	2004	18
215	Misr Exterior Bank S.A.E.	Egypt	CB	1970	2001	25
216	Mohandes Bank	Egypt	CB	1979	2005	16
217	Mutual Trust Bank	Bangladesh	CB	1999	n/a	1
218	Mybank Ltd	Pakistan	CB	1962	n/a	33
219	National Bank for Development	Egypt	CB	1980	n/a	15
220	National Bank Limited	Bangladesh	CB	1983	n/a	12
221	National Bank of Abu Dhabi	UAE	CB	1968	n/a	27
222	National Bank of Bahrain	Bahrain	CB	1957	n/a	38
223	National Bank of Dubai Public Joint Stock Company	UAE	CB	1963	2009	32
224	National Bank of Egypt	Egypt	CB	1898	n/a	97
225	National Bank of Fujairah	UAE	CB	1982	n/a	13
226	National Bank of Kuwait S.A.K.	Kuwait	CB	1952	n/a	43
227	National Bank of Pakistan	Pakistan	CB	1949	n/a	46
228	RAKBANK-National Bank of Ras Al-Khaimah (P.S.C.) (The)	UAE	CB	1976	n/a	19
229	National Bank of Umm Al-Qaiwain	UAE	CB	1982	n/a	13
230	National Bank of Yemen	Yemen	CB	1970	n/a	25
231	National Commercial Bank (The)	Saudi Arabia	CB	1938	n/a	57
232	National Credit and Commerce Bank Ltd.	Bangladesh	CB	1993	n/a	2
233	Nile Bank (The)	Egypt	CB	1960	2002	36
234	North Africa International Bank - NAIB	Tunisia	CB	1984	n/a	11
235	OCBC Bank (Malaysia) Berhad	Malaysia	CB	1994	n/a	1
236	Omdurman National Bank	Sudan	CB	1993	n/a	2
237	One Bank Limited	Pakistan	CB	1998	n/a	1
238	Oriental Bank Berhad	Malaysia	CB	1931	2000	64
239	Ottoman Bank-Osmanli Bankasi A.S.	Turkey	CB	1863	2001	132
240	Overseas Union Bank (Malaysia) Berhad	Malaysia	CB	1994	2001	1
241	Pacific Bank Berhad	Malaysia	CB	1919	2000	76
242	Pamukbank T.A.S.	Turkey	CB	1955	2001	40
243	PhileoAllied Bank (Malaysia) Berhad	Malaysia	CB	1994	2000	1
244	PICIC Commercial Bank Limited	Pakistan	CB	1994	2007	1
245	Piraeus Bank Egypt SAE	Egypt	CB	1978	n/a	18
246	Premier Bank Ltd (The)	Bangladesh	CB	1998	n/a	1
247	Prime Bank Limited	Bangladesh	CB	1994	n/a	1
248	PT Bank Bukopin	Indonesia	CB	1970	n/a	25

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(h). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
249	PT Bank CIMB Niaga Tbk	Indonesia	CB	1955	n/a	40
250	PT Bank Mayapada Internasional TBK	Indonesia	CB	1990	n/a	5
251	PT Bank Mizuho Indonesia	Indonesia	CB	1989	n/a	6
252	PT Bank OCBC Indonesia	Indonesia	CB	1996	n/a	1
253	PT Bank Resona Perdania	Indonesia	CB	1953	n/a	42
254	PT Bank Swadesi Tbk	Indonesia	CB	1989	n/a	6
255	PT Bank UOB Indonesia	Indonesia	CB	1989	2010	6
256	Pubali Bank Limited	Bangladesh	CB	1959	n/a	36
257	Public Bank Berhad	Malaysia	CB	1965	n/a	30
258	Qatar Development Bank Q.S.C.C.	Qatar	CB	1996	n/a	1
259	Qatar National Bank	Qatar	CB	1964	n/a	31
260	RHB Bank Berhad	Malaysia	CB	1965	n/a	30
261	Riyad Bank	Saudi Arabia	CB	1957	n/a	38
262	Royal Bank of Scotland Berhad (The)	Malaysia	CB	1905	n/a	91
263	Royal Bank of Scotland Ltd (The)	Pakistan	CB	1991	n/a	4
264	Rupali Bank Limited	Bangladesh	CB	1972	n/a	23
265	Sabah Bank Berhad	Malaysia	CB	1979	n/a	16
266	Samba Financial Group	Saudi Arabia	CB	1980	n/a	15
267	Saudi British Bank (The)	Saudi Arabia	CB	1978	n/a	17
268	Saudi Hollandi Bank	Saudi Arabia	CB	1976	n/a	19
269	Saudi Investment Bank (The)	Saudi Arabia	CB	1976	n/a	19
270	Sekerbank T.A.S.	Turkey	CB	1953	n/a	42
271	Silkbank Limited	Pakistan	CB	1995	n/a	1
272	Société Arabe Internationale de Banque	Egypt	CB	1976	n/a	19
273	Société Tunisienne de Banque	Tunisia	CB	1957	n/a	38
274	Sonali Bank Limited	Bangladesh	CB	1972	n/a	23
275	Soneri Bank Limited	Pakistan	CB	1991	n/a	4
276	Southeast Bank Limited	Bangladesh	CB	1994	n/a	1
277	Southern Bank Berhad	Malaysia	CB	1963	2006	32
278	Standard Bank Limited	Bangladesh	CB	1998	n/a	1
279	Standard Chartered Bank Malaysia Berhad	Malaysia	CB	1875	n/a	120
280	Suez Canal Bank	Egypt	CB	1978	n/a	17
281	T- Bank-Turkland Bank AS	Turkey	CB	1985	n/a	14
282	T.C. Ziraat Bankasi A.S.	Turkey	CB	1863	n/a	132
283	Tamara Bank	Indonesia	CB	1977	1998	18
284	Tarisbank - Milli Aydin Bankasi	Turkey	CB	1913	1999	82

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(i). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
285	Tekstil Bankasi A.S.-Tekstilbank	Turkey	CB	1986	n/a	13
286	Tokai Lippo Bank	Indonesia	CB	1989	2001	6
287	Toprakbank	Turkey	CB	1992	2001	3
288	Turk Ekonomi Bankasi A.S.	Turkey	CB	1927	n/a	72
289	Turkiye Emlak Bankasi A.S.	Turkey	CB	1988	2001	9
290	Turkiye Garanti Bankasi A.S.	Turkey	CB	1946	n/a	53
291	Turkiye Halk Bankasi A.S.	Turkey	CB	1938	n/a	61
292	Turkiye Imar Bankasi	Turkey	CB	1928	2003	67
293	Turkiye is Bankasi A.S. - ISBANK	Turkey	CB	1924	n/a	77
294	Turkiye Tütüncüler Bankasi Yasarbank A.S.	Turkey	CB	1924	1991	71
295	Turkiye Vakiflar Bankasi TAO	Turkey	CB	1954	n/a	43
296	Union Bancaire pour le Commerce et l'Industrie SA UBCI	Turkey	CB	1961	n/a	34
297	Union Bank Limited	Turkey	CB	1991	1996	4
298	Union Internationale de Banques	Tunisia	CB	1963	n/a	32
299	Union National Bank	UAE	CB	1983	n/a	13
300	Union National Bank - Egypt SAE	Egypt	CB	1981	n/a	14
301	United Arab Bank PJSC	UAE	CB	1975	n/a	20
302	United Bank Ltd.	Pakistan	CB	1959	n/a	36
303	United Bank of Egypt	Egypt	CB	1981	2003	15
304	United Commercial Bank Ltd	Bangladesh	CB	1983	n/a	12
305	United Overseas Bank (Malaysia) Bhd.	Malaysia	CB	1993	n/a	2
306	United Saudi Bank	Saudi Arabia	CB	1983	n/a	12
307	Uttara Bank Limited	Bangladesh	CB	1965	n/a	30
308	Wah Tat Bank Berhad	Malaysia	CB	1929	2000	66
309	Watani Bank for Trade & Investment	Yemen	CB	1997	2004	1
310	Workers' National Bank	Sudan	CB	1987	n/a	13
311	Yapi Ve Kredi Bankasi A.S.	Turkey	CB	1944	n/a	55
312	Yemen Commercial Bank	Yemen	CB	1993	n/a	2
313	Yemen Kuwait Bank for Trade and Investment	Yemen	CB	1979	n/a	16
314	Yurt Ticaret ve Kredi Bankasi A.S.-Yurtbank	Turkey	CB	1993	1999	2
315	Zarai Taraqiati Bank Limited	Pakistan	CB	1961	n/a	35
316	A'ayan leasing and investment co	Kuwait	IB	1999	n/a	3
317	ABC Islamic Bank (E.C.)	Bahrain	IB	1985	n/a	20
318	Abu Dhabi Islamic Bank - Public Joint Stock Co.	UAE	IB	1997	n/a	1
319	Affin Islamic Bank Berhad	Malaysia	IB	2005	n/a	1
320	Agricultural Bank of Iran-Bank Keshavarzi	Iran	IB	1908	n/a	88

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(j). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
321	Ajman Bank	UAE	IB	2007	n/a	1
322	Al Amin Bank	Bahrain	IB	1987	2007	13
323	Al Baraka Bank Egypt SAE	Egypt	IB	1980	n/a	15
324	Al Baraka Bank Sudan	Sudan	IB	1984	n/a	17
325	Al Hilal Bank PJSC	UAE	IB	2007	n/a	1
326	Al Rajhi Bank-Al Rajhi Banking & Investment Corporation	Saudi Arabia	IB	1988	n/a	7
327	Al Rajhi Banking & Investment Corporation (Malaysia) Berhad	Malaysia	IB	2005	n/a	1
328	Al Salam Bank	Sudan	IB	2005	n/a	1
329	Al-Salam Bank-Bahrain B.S.C.	Sudan	IB	2005	n/a	1
330	Albaraka Bank Tunisia	Tunisia	IB	1983	n/a	11
331	Albaraka Banking Group B.S.C.	Bahrain	IB	2002	n/a	1
332	Albaraka Islamic Bank BSC	Bahrain	IB	1984	n/a	10
333	Albaraka Islamic Bank BSC (EC) - Pakistan Branches	Pakistan	IB	2002	n/a	1
334	Albaraka Türk Katilim Bankasi AS-Albaraka Turk Participation Bank	Turkey	IB	1984	n/a	17
335	Alinma Bank	Saudi Arabia	IB	2007	n/a	1
336	Alliance Islamic Bank Berhad	Malaysia	IB	1994	n/a	14
337	AmIslamic Bank Berhad	Malaysia	IB	1976	n/a	30
338	Amlak Finance PJSC	UAE	IB	2000	n/a	4
339	Arab Islamic Bank	Palestine	IB	1995	n/a	8
340	Arcapita Bank B.S.C.	Bahrain	IB	1996	n/a	1
341	Aref Investment Group	Kuwait	IB	1975	n/a	31
342	Asian Finance Bank Berhad	Malaysia	IB	2005	n/a	1
343	Bank Asya-Asya Katilim Bankasi AS	Turkey	IB	1996	n/a	5
345	Bahrain Islamic Bank B.S.C.	Bahrain	IB	1979	n/a	16
346	BAMIS-Banque Al Wava Mauritanienne Islamique	Mauritania	IB	1985	n/a	13
347	Bank AlBilad	Saudi Arabia	IB	2004	n/a	1
348	Bank Islam Brunei Darussalam Berhad	Brunei	IB	2005	n/a	1
349	Bank Islam Malaysia Berhad	Malaysia	IB	1983	n/a	12
350	Bank Muamalat Malaysia Berhad	Malaysia	IB	1998	n/a	1
351	Bank of Khartoum	Sudan	IB	1913	n/a	84
352	Bank Syariah Mandiri	Indonesia	IB	1999	n/a	1
353	BankIslami Pakistan Limited	Pakistan	IB	2003	n/a	1
354	Boubyan Bank KSC	Kuwait	IB	2004	n/a	1
355	Capivest	Bahrain	IB	2003	n/a	2
356	CIMB Islamic Bank Berhad	Malaysia	IB	2003	n/a	2

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(k). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
357	Citi Islamic Investment Bank	Bahrain	IB	1996	n/a	9
358	Dubai Bank	UAE	IB	2001	n/a	1
359	Dubai Islamic Bank plc	UAE	IB	1975	n/a	20
360	Emirates Islamic Bank PJSC	UAE	IB	1976	n/a	19
361	EONCAP Islamic Bank Berhad	Malaysia	IB	2005	n/a	1
362	Faisal Islamic Bank (Sudan)	Sudan	IB	1978	n/a	27
363	Faisal Islamic Bank of Egypt	Egypt	IB	1977	n/a	18
364	First Finance Company (Q.S.C.)	Qatar	IB	2004	n/a	1
365	First Habib Modaraba	Pakistan	IB	1985	n/a	18
366	First Investment Company K.S.C.C.	Kuwait	IB	1997	n/a	6
367	First National Bank Modaraba	Pakistan	IB	2003	n/a	2
368	Global Banking Corporation BSC	Bahrain	IB	2006	n/a	1
369	Gulf Finance House BSC	Bahrain	IB	1999	n/a	1
370	Hong Leong Islamic Bank Berhad	Malaysia	IB	2005	n/a	1
371	Ihlas Finans Kurumu A.S.	Turkey	IB	1994	2001	1
372	IIB-International Investment Bank B.S.C.	Bahrain	IB	2003	n/a	2
373	International Investor Company, K.S.C. (The)	Kuwait	IB	1992	n/a	3
374	Investment Dar Co (The)	Kuwait	IB	1994	n/a	7
375	Investors Bank BSC	Bahrain	IB	1997	n/a	6
376	Islamic Bank of Brunei bhd.	Brunei	IB	1980	2006	17
377	Islamic Bank of Yemen for Finance & Investment	Yemen	IB	1995	n/a	3
378	Islamic Co-operative Development Bank	Sudan	IB	1982	n/a	14
379	Islamic International Arab Bank	Jordan	IB	1997	n/a	1
380	Islamic Investment Company of the Gulf (Bahrain)	Bahrain	IB	1997	2000	1
381	Jordan Islamic Bank	Jordan	IB	1978	n/a	17
382	Khaleeji Commercial Bank	Bahrain	IB	2003	n/a	1
383	Kuwait Turkish Participation Bank Inc- Kuveyt Turk Katilim Bankasi A.S.	Turkey	IB	1989	n/a	10
384	Kuwait Finance House	Bahrain	IB	1977	n/a	25
385	Kuwait Finance House	Kuwait	IB	1977	n/a	18
386	Kuwait Finance House (Malaysia) Berhad	Malaysia	IB	2005	n/a	1
387	Kuwait International Bank	Kuwait	IB	1973	n/a	22
388	Masraf Al Rayan (Q.S.C.)	Qatar	IB	2005	n/a	1
389	Maybank Islamic Berhad	Malaysia	IB	2007	n/a	1
390	Meezan Bank Limited	Pakistan	IB	1997	n/a	3
391	Qatar International Islamic Bank	Qatar	IB	1990	n/a	5
392	Qatar Islamic Bank SAQ	Qatar	IB	1982	n/a	13

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Table A4(1). Bank Names, Countries, Bank Types, Establishment Year and Duration.

No	Bank Name	Country	Type	Establ Year	Failure Year	Duration
393	RHB Islamic Bank Berhad	Malaysia	IB	2004	n/a	1
394	Saba Islamic Bank	Yemen	IB	1997	n/a	5
395	Seera Investment Bank BSC	Bahrain	IB	2006	n/a	1
396	Shahjalal Islami Bank Ltd	Bangladesh	IB	2000	n/a	1
397	Shamil Bank of Bahrain B.S.C.	Bahrain	IB	1982	2010	13
398	Shamil Bank of Yemen & Bahrain	Yemen	IB	2001	n/a	1
399	Sharjah Islamic Bank	UAE	IB	1975	n/a	20
400	Standard Chartered Modaraba	Pakistan	IB	1987	n/a	18
401	Sudanese Islamic Bank	Sudan	IB	1977	n/a	23
402	Tadamon Islamic Bank	Sudan	IB	1981	n/a	14
403	Tadhamon International Islamic Bank	Yemen	IB	1995	n/a	1
404	Tamweel PJSC	UAE	IB	1975	n/a	28
405	Islamic Development Bank of Brunei Bhd	Brunei	IB	1994	n/a	1
406	United bank of Albania	Albania	IB	2000	2004	1
407	The oriental bank	Bangladesh	IB	1987	2004	8
408	Bank Maskan	Iran	IB	1938	n/a	59
409	Bank Mellat	Iran	IB	1980	n/a	15
410	Bank Melli Iran	Iran	IB	1928	n/a	69
411	Bank of Industry and Mine	Iran	IB	1979	n/a	19
412	Bank Pasargad	Iran	IB	2004	n/a	1
413	Bank Refah	Iran	IB	1960	n/a	37
414	Bank Saderat Iran	Iran	IB	1952	n/a	43
415	Bank Sepah	Iran	IB	1925	n/a	70
416	Bank Tejarat	Iran	IB	1979	n/a	16
417	EN Bank-Eghtesad Novin Bank PJSC	Iran	IB	2000	n/a	1
418	Export Development Bank of Iran	Iran	IB	1991	n/a	5
419	Karafarin Bank	Iran	IB	1979	n/a	20
420	Parsian Bank	Iran	IB	2000	n/a	1
421	Saman Bank	Iran	IB	1999	n/a	1

Note: Duration refers to the 1st year in the period. For instance:
AB Bank is first observed in 1995; hence Duration=1995-1982

Chapter 4
Financial Markets Synchronization and Contagion

Abstract

In this chapter we examine the synchronization of the 2007 financial crisis upon the stock markets of 55 countries over the 2001-2011 period. The GCC are compared against other country groups, consisting of developed and developing countries, in terms of duration and intensity of the crisis. We adopt a DCC-GARCH framework with Markov-Switching (MS) models. The DCC framework enables us to investigate for financial contagion evidence in the largest sample of countries so far. The contribution of the MS model is an endogenous identification of the country-specific crisis transition dates, which relaxes the assumption that all countries were affected at the same time. Our main findings can be summarized as follows. We find variation in the crisis transition dates and intensity scores of the examined countries. Our results are supportive of financial contagion for both developed and developing countries due to the 2007 financial crisis. The developed markets are hit sooner and more fiercely than the developing markets. Industrialized economies weathered the crisis better. Two case studies of EU-27 and the GCC are provided. The EU-27 shows evidence of varying integration with the New Members being affected at a significant lag. The GCC financial sector shows significant evidence of financial contagion. Yet it shows minimal synchronization with global financial markets as evidenced by one of the lowest crisis intensity measures. The timely and efficient policy response of the GCC cou-

pled with the better capitalized and more liquid banking system has insulated the region from the adverse effects of the global turmoil.

4.1 Introduction

The co-movement of financial markets widely affects investors' decisions, policy implications and economic growth. Early studies have documented the benefits of international diversification in terms of risk reduction due to the low correlations that exist among equity markets (Grubel 1968; Levy and Sarnat 1970; Grubel and Fadner 1971). However, as financial integration increases globally across time the links among financial markets become stronger. Economic shocks can now be transmitted more easily across markets giving rise to financial contagion (Ordóñez 2006). Increased correlations during volatile periods are documented in Lin, Engle and Ito (1994) among others, with the study of correlations being the most widely used method of assessing the degree of financial market synchronization. Financial contagion studies are of special interest as recent financial crises such as, the Mexico peso crisis in 1994, the East-Asian crisis in 1997, the Russian default in 1998, the dot.com bubble in 2001 and the 2007 financial crisis have shown that diversification benefits follow a downward trend across time.

Developing markets have attracted investors' attention as they are less correlated to the global financial markets. Yet during financial crises, the monetary dependence of developing markets upon developed, due to the developing countries receiving of investments, goods and services from developed countries, would erode any diversification benefits as developing countries are affected by financial contagion as well. The decoupling hypothesis relates to such investor benefits arising from low correlations between developing and developed financial markets. Evidence documented in Bekaert (1995), Dooley and Hutchinson (2009), Christoffersen *et al.* (2010) and Syllignakis and Kouretas (2011) among others show decreasing support for the decoupling hypothesis in recent years.

In this chapter we study the synchronization of the 2007 financial crisis by comparing and contrasting developed and developing countries. Special emphasis is given on the GCC, one of the most homogenous[51] groups of countries forming an economic association, and the EU (IMF 2010). The contributions of the chapter are as follows:

Adopting a DCC-GARCH and Markov-Switching model framework enables us to identify which countries were affected earlier or later. Other studies so far have settled for an exogenous date assuming that all countries are affected simultaneously. Dynamic Conditional Correlation (DCC) models have been used in the analysis of co-movements and contagion (Cho and Parhizgari 2008; Yiu *et al.* 2010; Naoui *et al.* 2010). The main advantages of DCC-GARCH models are their ability to capture the time varying nature of volatilities and correlations while being computationally feasible even for a large number of assets. We have adopted a correlation approach to test for contagion effects as this would allow us to study how synchronized the markets are; whereas other approaches (*e.g.* probit) would not be suitable. Markov-Switching Regime models, introduced by Hamilton (1994), provide an appealing framework to accommodate crisis events and non-linearities. Stock markets entering a different regime (affecting volatilities, correlations and business cycles) during crises can be due to their sharing similar economic conditions. Additionally, correct

51 Homogenous in terms of common history, language, culture, resources and economical activity mainly focused in carbonhydrates. In addition, the GCC have pegged currencies to the US dollar.

identification of the current regime has policy and financial applications (*e.g.* Quantitative Easing, Portfolio Management). We find that the financial crisis is experienced by all countries in our sample within a time frame of about 18 months.

Secondly, as simple statistical verification of financial contagion cannot encompass the full extent of the financial crisis upon a country we introduce measures of duration and intensity. A general finding is that developing countries, although they show supportive evidence of financial contagion, experience it later and not as severely as developed countries.

A third contribution is the differentiation of financial contagion into regional and global. We identify country groups (*e.g.* Core EU) that show evidence of regional contagion as the countries therein become more aligned between themselves. By contrast other country groups (*e.g.* GCC) exhibit global contagion as their members show increased correlations with countries outside of their country group too. The finding provides supportive evidence of a two-speed EU integration process which is consistent with the core-periphery framework (Camacho *et al.* 2008). We also find that industrialized countries weathered the crisis better than those with prominent financial sectors.

Similarities and differences between the GCC and the EU in light of the financial crisis are noteworthy. The GCC are a very uniform group, even when compared to the Core EU. However the GCC are affected by the crisis at a year lag compared to the Core EU. Moreover the crisis intensity is much lower than the Core EU and can be compared to that of the most recently accepted member states. In addition the GCC are among the least affected countries and they managed to maintain positive GDP growth amidst the crisis mainly due to two reasons; the revenue diversification projects to reduce the countries' dependence on oil revenue and the financially strong banking sector relative to developing and some developed economies (*i.e.* New Members of the EU). The banking system has benefited by the presence of Islamic banks whose ideals on risk-sharing, linkages to real assets and shunning of conventional debt instruments offers a safer approach compared to what transpired in the US and Europe.

The remainder of the chapter is structured as follows: In section 2 we provide a literature review on financial contagion studies. Section 3 introduces the adopted methodology while section 4 presents the data. Results are presented and discussed in section 5 while section 6 concludes.

4.2 Literature Review

In this section we provide a literature review around the concepts of integration, contagion the studies that have analyzed these concepts and the methodologies used therein. The section is divided in four sub-sections. The first two subsections provide background information on the European Union (EU) and the Gulf Cooperation Council Countries (GCC). Subsection three focuses presents the definitions of contagion, the differences from integration and the implications of the decoupling hypothesis for developing economies in the recent years. The last subsection reviews the econometric methodologies that have been used in the context and their key findings.

4.2.1 The European Union

Since the Treaty of Rome in 1957, the EU has moved forward by implementing measures to foster economic growth and increase integration among all participating countries. Common legislation and common policies are only a few of the measures that have been implemented. In the 21st century the EU has expanded in two stages to include several new members and there are plans to expand even further. Paramount to the integration process was the adoption of the Euro, the common currency by many of the EU-27 countries with more planning to join later. The European Union (EU) sets as a priority the integration and efficient functioning of the financial system in Europe[52]. Financial integration is essential to ensure the effectiveness of any monetary policy in the EU and specifically in the European Monetary Union (EMU) or Eurozone. Financial stability is also enhanced by the promotion of a Single Market, of which financial integration is essential (ECB 2011). Integration leads to highly efficient financial systems that increase opportunities for portfolio diversification, rate of return and enhances risk-sharing. By contrast, integration does not necessarily increase stability. Indeed, high interconnectedness of financial markets allows for cross-border transmission of shocks thus spreading the crisis to other sectors or countries leading to contagion.

In the years leading up to the financial crisis, the capital markets in EU were increasing and becoming more uniform in terms of market size. During 2000 – 2005 capital markets in EU grew by 9% as opposed to 6% for the US while at the same time financial integration indicators (*i.e.* bond yields, CDS spreads, cross-border holding of equities,

52 Financial integration is a priority for the Eurosystem. See mission statement at: *www.ecb.europa.eu*

spread of the overnight EONIA lending rates across countries) suggested that integration is increasing. Therefore, the "experiment" is deemed as successful and the expansion of the EU is the next step. In two expansion phases in 2004 and 2007 the number of EU members leaps from 15 to 27. New members share common elements but have also significant differences among themselves. The level of financial integration varies across countries and is higher the closer the market is to the single monetary policy (ECB 2010). Cyprus has 2 times higher GDP per capita than Poland while the stock markets of the former members of the Soviet Union have very small market capitalization relative to the rest of the EU. Despite the differences many of the New Members opted for a further step of integration by joining the EMU as well. The fact that all these developments took place in a favorable economic climate helped to masquerade the build-up of vulnerabilities and omissions[53]. The drawbacks of integration were also given less attention due to the lack of past evidence relating high calibre economies to costly crises (Ferguson *et al.* 2007).

The financial crisis, especially after the Lehman Brothers collapse, affected EU financial markets to different degrees causing a reversal of the integration tendency in the money markets to retrench within national markets. The tendency was exacerbated for the members of the EMU that having lost the independence of their monetary policy they came across worsening fiscal balances, lack of competitiveness and soaring public debt. As a

53 For example, different markets (capital, retail, labor markets) were integrating at different speeds. The Eurozone also has the inherent flaw of the Inconsistent Trinity under which a country can only have two of the following three at the same time: a) fixed exchange rate; b) free capital movement; c) independent monetary policy. The Eurozone definitely has the two first and the third is arguable. A country cannot print money but given the convergence of the capital markets it could borrow money (bond markets or securitization products) at much lower interest rates than its fundamentals would suggest. In the case of Greece, the extra money in the economy was diverted to consumption rather than productive purposes that could strengthen the country's economy and increase its competitiveness.

result, money markets started pricing differently the perceived risks (a mixture of credit, sovereign, political and liquidity risk) in different parts of the EMU and EU leading to divergence in bond yields and CDS spreads. Actions taken by the EU (ECB accepting bonds of lower credit rating as collateral) to avoid bankruptcy of Greece and potential contagion effects in the EU are of dubious results.

4.2.2 The Gulf Cooperation Council

The superior economic performance of the GCC relative to other developing economies as well as the increased integration they have achieved compared to other Middle Eastern countries is remarkable (UNDP 2002). The GCC states show significant homogeneity among them on various geopolitical, macroeconomic and institutional aspects (IMF 2005). At first the six countries[54] share the same language and history. In terms of monetary convergence, all GCC states have generally low inflation rates compared to other developing countries (IMF 2005). In addition, they all maintain long-standing fixed exchange rates to the US dollar with Kuwait being the only exception after switching to an undisclosed basket of currencies in May 2007. The remarkable exchange rate stability given the liberalized financial sector has led to co-movements in the interest rates and similar sovereign creditworthiness (ECB 2005).

Certainly, the dependence of the countries on energy related exports reduces the likelihood of asymmetric shocks as the countries' dynamics and trade patterns are generally in phase. The GCC has about 42% and 23% of the world's oil and gas reserves. However as

54 Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the UAE

they are not equally spread among the country members, the necessity of the countries to diversify their sources of revenue varies (see table 1).

[Table 1 here]

Bahrain's reserves are depleted and the government has invested in promoting the Kingdom's financial services and banking industry, particularly Islamic finance. In the UAE additional revenue sources are tourism, real estate and transport. Bahrain and the UAE have the lowest dependency on hydrocarbons. By contrast, Saudi Arabia, with about 25% of the world's oil reserves remains geared towards oil related products. Kuwait and Qatar have taken significant steps to diversify into finance and manufacturing respectively. Oman still needs to catch-up with the attempts of revenue diversification.

The GCC is considered an open economy with about 50% of the exports going to Asia, mainly Japan, China and South Korea. In the meantime 2/3 of the imports come from the EU and Asia. Notably there is very limited trade taking place among the GCC members, a result attributed to the similar economic conditions (ECB 2005).

The financial system is mainly bank-based yet profitable, well-capitalised and resilient particularly when compared to neighboring countries (Johnes *et al.* 2012; ECB 2005). However capital markets are classified as small and illiquid according to MSCI, a major provider of financial services[55]. Development of the financial system is taking place with computerised trading infrastructure being introduced and restrictions to investment ceilings for foreign investors being lifted. Bond markets have also been developed both for standard bonds and Islamic type bonds (sukuk) where the GCC is competes with

55 http://www.msci.com/products/indices/country_and_regional/fm/

Malaysia, another financial centre for Islamic finance products. Nevertheless, secondary bond markets are still in infancy.

During the period leading to the financial crisis the stock markets in the region grew almost seven times reaching more than a trillion USD in 2007. Despite the growth in the sector, the GCC still remains relatively isolated from global financial markets yet it appears integrated regionally. It would be expected that countries which are in the process of adopting a common currency would show evidence of financial integration. In that sense co-movements would be observed in their financial indicators and in the financial context, correlation between the stock markets of the region would have been reasonably high. This has been verified by many studies addressing the issue from various perspectives. Assaf (2003) verifies this by finding evidence of interdependence in the GCC markets over the 1997 – 2000 period. Co-integration among subsets of the GCC is verified by Hassan (2003) and Al-Khazali *et al.* (2006). Yet, a study including all six GCC countries fails to find strong evidence of co-movement in all of the markets. It is plausible that some countries are still lagging behind in terms of financial integration which is suggestive of possible risk diversification benefits arising from investments in the region (Marasdeh and Shrestha 2010). In a related context Sipson and Evans (2004) find that the main drivers of the GCC are Saudi Arabia and Kuwait whereas a comparison between the GCC and MENA region, Alkulaib *et al.* (2009) find that the GCC appear as more homogenous and more integrated. Despite the evidence in favour of the regional integration, there are also studies verifying the seclusion of the GCC from the global markets. In particular, Abraham *et al.* (2001) find very low correlations between Bahrain, Kuwait and Saudi Arabia and the USA. Around the same notion is the study of Muhammad (2007) that finds no connection between GCC and European stock markets.

4.2.3 Financial Integration and Contagion

Financial integration is a process of convergence in financial markets, consumption and saving patterns and institutional differences. The process would ensure that identical assets have the same returns, an application of the law of one price, irrespective of geographical location (Pungulescu 2009). Worldwide integration due to globalization is evident by the higher sensitivity of country returns to EU-wide and US shocks (Baele *et al.* 2004). The integration is magnified through the expansion of the EU as well as the monetary convergence with the adoption of a single currency. As a result business cycles appear to be in phase and previously isolated financial markets align themselves to global markets (Adjaoute and Danthine 2004). The EU is the most frequently studies market with studies addressing the integration between New Member states and the rest of Europe (Westermann 2004; Moore 2007) or how the adoption of the common currency has affected the integration process (Hardouvelis *et al.* 2006; Bekaert *et al.* 2010). Integration analyses for groups of countries (like the CEE) or specific countries from the EU-27 are given among others by Moore and Wang (2007), Voronkova (2004) and Syriopoulos (2007). The common denominator in all the case studies is that the newly acquired developing markets have become more synchronized with the rest of EU, a fact that could have negative consequences in times of crises as all countries would respond to the same economic shocks aggravating the effect of the crisis.

Different definitions of contagion exist according to the methodology adopted and the framework used to identify and measure it. For example, contagion can be defined as a rise in the probability of a country experiencing a crisis given that a crisis has occurred in another country, this being a definition that usually relates to exchange rates (Eichgreen *et al.* 1999). Alternatively, contagion definitions can relate to the volatility spillovers among financial markets that arise because of increased uncertainty during turbulent times. The spillovers from one market to another no longer reflect economic fundamentals; thus they allow for a more intensified inter-relation than expected (Rodriguez 2007; Boyer *et al.* 1997). A third definition, perhaps the most widely used, is provided by Forbes and Rigobon (2002) who suggest that following an economic shock in one country, an increase in cross-market linkages is observed. This 'so called shift-contagion' manifests itself as a significant increase in the correlation between market returns (Forbes and Rigobon 2002). Contagion definitions are by no means complete and Pericoli and Sbracia (2003) provide five definitions that have been documented in the literature. Moreover, definitions on contagion are evolving and tend to be reflective of recent developments in econometrics. Hence, the increase in the intensity of jumps in a market which is then transmitted to another market (cross-excitation) is documented in Aït-Sahalia *et al.* (2010).

Contagion starts from a financial crisis to which many countries become aligned to. The reasons for alignement can relate to economic fundamentals, financial linkages or be of behavioral nature. Crises that are based on economic fundamentals comprise changes in interest rates, commodity prices and trade flows. Such shocks could cause financial market co-movements and reversal of capital flows from developed to developing countries or even between countries of the same development level (Calvo *et al.* 1996). In addition, the bad economic fundamentals of a country can be put in the spotlight and investors start worrying about countries exhibiting similar characteristics increasing the likelihood of the crisis spreading to another country (Masson 1999). Thus, for example, when the cause of the recent economic crisis in Greece was traced to the country's chronic fiscal problems concerning its budget deficit and national debt, there was a fear that contagion effects would be felt in other countries with similar characteristics such as Italy and Portugal and both of these countries experienced significant increases in their borrowing costs. Trade flows is also an important factor that can turn a crisis into contagion by affecting the level of exports of a country and thus reducing its revenues (Gelos and Sahay 2001). Reduced demand for the goods and services in a country is likely to hamper the economic fundamentals. Contagion via trade flows is more likely to be relevant for developing economies where the financial markets are not fully developed. Empirical evidence in support of this claim include Krzak (1998) who finds that after the Russian default crisis, the CEE countries were most affected via trade routes. In addition, Forbes (2004) finds that 46 countries with exposure to Russia and East Asia during the respective crises were primarily affected via trade linkages.

Behavioral reasons responsible for contagion comprise investors recalling past bad experiences and subsequently shifts in their confidence on the markets as well as adjustments on their expectations (Mullainathan 2002). Investor perceptions about market prospects can then cause a crisis to be transmitted to another country on the basis of herding behavior (Calvo and Mendoza 1998). Under this scenario, asymmetric information between different types of investors; for example, hedge funds, institutional investors and noise traders, correlates the behavior between the least and most informed, thereby destabilizing the system further (Calvo 1998; Dehove 2003).

As contagion is mainly a financial market phenomenon, countries with active and liquid markets as well as cross-border trading activity, in terms of international portfolio holdings and cross-market hedges, are more prone to it (Calvo, 1998). Bond and stock markets become more and more responsive to common factors increasing systemic risk in the economy. Increased integration with banks being common lenders to several countries and recent developments in financial products such as securitization products (*e.g.* credit default swaps) create new transmission channels allowing the crisis to spread from the turbulent markets to unaffected ones (Kaminsky and Reinhart 2000). Bilateral bank holdings and cross-holdings of equity and bonds have grown by about 40%, 62% and 97% respectively within the EMU since the latters establishment (Kalemli-Ozcan *et al.* 2010; Lane 2006). A study of Brezigar-Masten *et al.* (2010) verifies that investment in asset-backed securities prior to the 2007 financial crisis in the US was aided by increasing financial integration and cross-border investments. In addition, investors readjusting their expectations can lead to portfolio rebalancing and the withdrawal from positions, or markets, that are considered too risky (Kodres and Pritsker 2002). This starts a liquidation procedure which can be intensified by margin calls or regulatory requirements that need to be met (Sbracia and Zaghini 2003). Banks' adjustments of capitalization and leverage ratios especially in a climate of falling stock market prices can have an escalating effect upon contagion as liquidity is restricted and the effects propagated to financially sound sectors of the economy (Davis 2008).

Baele (2005) examined the relationship between integration and vulnerability of stock markets to shocks over the period from 1980 to 2001 in the EU and his results showed evidence of increased integration over the time period under investigation and also revealed an increase in the intensity of contagion across time.

In contrast, developing markets in the Central and Eastern Europe (CEE) along with those in Portugal, Greece and Ireland were found to be less affected by previous crises - the East Asian crisis of 1997, the Russian collapse of 1998, the Brazilian devaluation of 1999 and the dot.com bubble of 2000 - than were the rest of Europe, a fact that was attributed to their lower degree of integration with the EU-15 (Serwa and Bohl 2005). In a similar vein, Gelos and Sahay (2001) reported that the developing CEE markets were less affected by the 1994 Mexican and 1997 East Asian crises than developed markets. The study of Carrieri, Errunza and Hogan (2007) finds that developing markets have not shown any evidence of contagion during the financial crises of the 1997-2000 period.

However as these developing markets progress in their economic and financial integration within the EU, an increasing alignment of their financial markets with the EU-15 is observed (Kocenda *et al.* 2008). In this light, Syriopoulos (2004) documents that CEE markets show stronger linkages with the developed EU than amongst themselves. After the accession of the CEE countries in the EU, cross-country linkages increase even further (Christiansen and Ranaldo 2008). The increased interconnectedness of developing and developed markets will give rise to contagion effects when a crisis hits the economy and developed markets may not be as insulated as they were supposed to be (Grubel 1968; Levy and Sarnat 1970; Grubel and Fadner 1970). Indeed, Eiling and Gerard (2011) conclude that contagion effects have been verified in developing markets during the recent financial crises. In a more recent study, Hesse and Frank (2009) find that developing markets have not been as insulated during the East Asian and Russian crises from the developed markets as during previous crises. They support their arguments by identifying rising correlations between developing and developed markets, a finding verified also by Wälti (2010).

For developed markets, evidence is more clear-cut as many studies find evidence in support of contagion (Longin and Solnik 1995; Bekaert *et al.* 2010).

4.2.4 The Econometrics of Contagion

Empirical research in the field of financial contagion suffers from problems related to small country samples as most studies are confined to the US, EU and the East Asian economies (De Bandt and Hartmann 2000). In addition, defining the crisis periods in an arbitrary way as well as the different definitions of contagion can undermine the validity of the results (Dungey and Tambakis 2003). Modelling of contagion has followed a diversity of econometric approaches including, but not limited to, binary outcome models, correlation analysis of asset returns, multivariate GARCH modelling and extreme value theory.

One of the first approaches in modelling contagion is the estimation of the probability of a country being in crisis, given that another country is already in crisis, while controlling for certain fundamentals such as competitiveness differentials (Forbes 2004). Eichengreen *et al.* (1999), Kaminsky and Reinhart (2000) offer contagion applications within this framework. Thus, for example, within the European Exchange Rate Mechanism (ERM), speculative attacks are likely to propagate to other countries within the mechanism once a country has been the subject of speculative pressures (Eichengreen *et al.* 1996). Probit and Logit models have been used by Carramazza *et al.* (2000) and Van Rijkeghem and Weder (2001). They study the impact of various macroeconomic factors upon their contribution to the likelihood of a developing country to experience a crisis with their focus being on the period encompassing the Mexican, East Asian and Russian crises.

An alternative econometric approach is given within a correlation analysis framework. Tests for "shift contagion" typically boil down to some sort of statistical test for the significance of any observed change between a stable period and a crisis one. Goetzmann and Rouwenhorst (2001) find evidence of rising integration since 1850 especially towards the end of the 20^{th} century. Bekaert and Harvey (2003) conclude that integration is rising between 1960 - 1990 for equity markets. Yet Forbes and Rigobon (2002) argue that gradually rising correlations are sign of integration in financial markets and should not be confused with contagion which is a by-product of financial crises. Two studies relating correlation analysis with contagion identification are those of King and Wadhwani (1990) and Lee and Kwang (1993) who tested for contagion across major stock markets following the 1987 US crash. They found evidence of this as inter-country correlations rose, on average, by 69%. Of course, this methodology is not confined to stock market contagion and it has, for example, been used to uncover contagion between stock and bond markets in the wake of the 1994 Mexican crisis (Calvo *et al.* 1996). Similarly, Baig and Goldfajn (1998) found contagion both between stock and bond markets as well as exchange and interest rates after the 1997 East Asian crisis. Forbes and Rigobon (2002) have criticized this rather simple method of correlation analysis as it does not account for the volatility in the financial markets. They construct a correlation coefficient robust to time-varying volatility levels but its application fails to verify any previous evidence of contagion. One drawback of their measure, as noted by Cho and Parhizgari (2008) is that it treats correlation as time invariant.

Of particular interest are the applications of multivariate GARCH modelling to contagion. The seminal paper of Forbes and Rigobon (2002) only revealed evidence of interdependence among stock markets and not contagion. However, their conclusion can, in part, be explained by their failure to capture the time varying nature of the correlation among stock markets Cho and Parhizgari (2008). Prior to the introduction of DCC-GARCH models by Engle (2002), these were either assumed to be constant or their estimation would suffer from the dimensionality curse, as witnessed by VEC and BEKK models. As a consequence most work has been restricted to a limited number of countries. For instance, Hamao *et al.* (1990) test for contagion between Japan, the UK and the US in the wake of the 1987 US crash while Edwards and Susmel (2003) focused on how the Mexican devaluation of 1994 manifested itself on the bond markets of Argentina and Chile. Due to the difficulties imposed by these models in modelling correlations, many studies were sufficed to test for volatility spillovers and draw conclusions based on these results. Hence, Kanas (1998) and Christiansen (2007) are able to verify significant volatility spillovers among the largest European stock markets and from the US to European bond markets respectively.

DCC-GARCH models were introduced separately by Engle (2002) and Tse and Tsui (2002) with the two approaches differing only in the way the conditional correlation matrix is parameterized. Extensions of DCC-GARCH models can be divided in two categories. First there is the model employed to identify the asymmetric effects on volatility, with the univariate GARCH being superseded by EGARCH, PARCH and TARCH models. The second relates to the estimator itself with the corrected DCC-GARCH model proposed by Aielli (2009) providing an alternative, asymptotically unbiased, estimator. Note though that the bias of the DCC-GARCH estimator is negligible in samples with less than 89 assets (Caporin and McAleer 2010).

Most of the research on financial contagion using multivariate GARCH models has focused on exchange rates (Khalid and Rajaguru 2005), bond markets (Coudert and Gex 2010)or stock markets (Bertero and Mayer 1989; King and Wadhwani 1990). Chiang *et al.* (2007) investigated nine East Asian exchanges from 1990 to 2003 using a DCC-GARCH framework and found evidence of contagion after the 1997 Asian financial crisis, as did Cho and Parhizgari (2008) using a larger sample of 14 countries. Likewise, Yiu *et al.* (2010) and Naoui *et al.* (2010) found evidence of contagion between the US and East Asia for the East Asian, dot.com and financial crises between 1993 and 2010 and during the 2005 to 2010 financial crisis respectively using similar approach. Naoui *et al.* (2010) documents evidence supporting high interdependence between developed and developing financial markets. During the 2007 financial crisis any international diversification benefits have disappeared according to Dooley and Hutchinson (2009) while Frank and Hesse (2009) generalise this finding to other financial crises as well. For the CEE region, Chmielwska (2010) provides supportive evidence of contagion for the stock and bond markets over the period from 2008 to 2010. Syllignakis and Kouretas (2011) verify contagion effects by means of a DCC-GARCH approach for the developing CEE markets over the 1997-2009 period, which encompasses the East Asian, Russian and the 2007 financial crisis. Similarly, Hwang *et al.* (2010) find supportive evidence of contagion for the developed EU stock markets.

One of the major compromises in most of the past studies relates to the identification of the crisis start date and the implicit assumption that all examined countries experience it at the same time. For example, when dating the onset of the recent financial crisis several studies have used the August 1^{st} 2007 which corresponds to the burst of the US housing bubble or other cut-off dates such as the collapse of Lehman Brothers at September 15^{th} 2008 (Hwang *et al.* 2010). Markov regime switching models introduced by Hamilton (1994) offer an endogenous determination of the transition date between regimes whilst, at the same time, accounting for non-linearities. in the shock transmission process. This approach has been documented by, inter alia, Baele (2005), Pelletier (2006) and Billio *et al.* (2005). Baele (2005) highlights the advantages of Markov-switching models in identifying regime changes as opposed to standard GARCH proceedures. The first of these authors examined the volatility spillovers from the US to 13 European stock markets over the period 1980-2001 and found that volatility transmission was intensified during the crisis regime. Similarly, Billio *et al.* (2005) who focuses on contagion effects between the US and European stock markets during the 1997 East Asian crisis and finds non-linear linkages.

Addressing the non-linearities in a contagion framework generated a heterogeneous literature. While several studies have adopted extreme value theory approaches (for example, Longin 1996; Longin and Solnik 2001), others have addressed the issue by using non-linear estimates of correlations (copulas) in tranquil and turmoil times. Longin and Solnik (2001) adopt an extreme value approach and find that correlation between stock markets increases during bear market periods while this is not the case during bull markets.

Copulas offer several advantages over the traditional measures of correlation (*e.g.* Pearson correlation coefficient) as they account for tail asymmetries and dependencies as well as not being restricted on a linear dimension of correlation. Financial contagion is an asymmetric phenomenon as it is more of a concern during downturns of the economy (Ang and Chen 2002). Indeed, Butler and Joaquin (2002) offer an application of correlation analysis during different market conditions (i.e. bull, bear and stable markets). The first application of copulas in the context of financial contagion comes from Patton (2006), who studies contagion in currency markets using copula techniques allowing for Markov-switching regimes. Bartam *et al.* (2007), Jondeau and Rockinger (2006) and Rodriguez (2007) find contagion evidence, in terms of correlation increases, in European markets using different copula methods. In these lines, Serban *et al.* (2007) compared the dependence structure of financial time series and their implications in portfolio management. In particular, they compared a standard BEKK formulation, which assumes linear correlations, to a modified DCC-GARCH model which allows for non-linear correlations. They find that the latter model outperformed the former one which highlights the benefits of addressing non-linearities for portfolio management. Non-linearities in the transmission of economic shocks have also been addressed using a VAR framework by Favero and Giavvazi (2002) for Germany and the rest of Europe whilst Baig and Goldfajn (1999) have utilised the methodology for developing East Asian countries.

Although copulas have benefits over linear correlation measures, their incorporation within a GARCH framework leads to estimation problems (Solnik and Roulet 2000). Hence the econometric literature regarding financial contagion is split mainly in these two strands; the correlation/copula applications and the multivariate GARCH approaches. Despite the variety of techniques used to address the issue, the consistency of the finding, in support of contagion after most of the recent economic crises, is remarkable.

4.3 Methodology

4.3.1 Multivariate Models

The Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982) has been used extensively in modeling volatility of financial time series. The attention it received by the econometric community soon lead to extensions like the well-known generalized variation the GARCH of Bollerslev (1986) which enhances the conditional variance equation of the ARCH so that it is a function of its own past values as well. The integrated GARCH (IGARCH) of Engle *et al.* (1987) eliminates the constant term and forces the estimated coefficients to sum up to one. The IGARCH is applicable in value at risk (VaR) estimation of the RiskMetrics program. The models so far did not differentiate the impact of good or bad news upon the modeling procedure. As negative news tend to have greater impact, the threshold GARCH (TARCH) (Zakoïan 1994; Glosten *et al.* 1993) and exponential GARCH (EGARCH) Nelson (1991) were two models introduced to capture that effect.

An immediate extension of modeling volatilities of the returns is the modeling of co-movements of financial assets with practical applications in portfolio management, risk management and asset allocation. As a consequence, the univariate GARCH family of models had to be extended to a multivariate setup so that covariance and correlation between assets are modeled. Multivariate GARCH (MGARCH) models are also applied in studies of contagion, volatility transmission and spillover effects (Tse and Tsui 2002; Bae *et al.* 2003).

The evolution of MGARCH models faced difficulties as there were many issues to be addressed. At first a multivariate model should be able to capture the full dynamics of a number of assets that is the time evolution of volatilities and correlations. Moreover, it needs to produce estimates of coefficients that are easy to interpret and estimate. At the same time, as the number of assets can get large the model needs to be parsimonious enough so that estimation for all the parameters can be done. As all the models are estimated using maximum likelihood, there can be the case (depending on the model) that the covariance matrix needs to be inverted for every step of the optimization routine. Finally, covariances need to be positive definite by definition, which is not easy in large systems. The time evolution of MGARCH models reveals that not all of the above mentioned prerequisites were ever fully satisfied. In fact, all of the MGARCH models offer a trade-off between them.

The VEC-GARCH model of Bollerslev *et al.* (1988) was the first step from the univariate to the multivariate universe. Every conditional covariance[56] is written as a function of all lagged covariances. Let us define a vector of returns r_t that is conditionally heteroscedastic, hence:

$$r_t = \mathbf{H}_t^{1/2} \eta_t \tag{4.1}$$

where r_t : $N \times 1$ matrix of returns; $\mathbf{H}_t \equiv [h_{ijt}]$: $N \times N$ matrix of conditional covariances; η_t : a vector of the error process. Then the VEC-GARCH is written as:

$$vech(\mathbf{H}_t) = c + \sum_{j=1}^{q} \mathbf{A}_j vech(r_{t-j} r_{t-j}^{\prime}) + \sum_{j=1}^{p} \mathbf{B}_j vech(\mathbf{H}_{t-j}) \tag{4.2}$$

where $vech(\cdot)$: stacks the lower triangular part of the matrix; c : the vector of constants; $\mathbf{A}_j, \mathbf{B}_j$: parameter matrices.

The VEC model that the authors introduced allows for dynamic correlations but the number of parameters to be estimated equals which is large unless N is very small. Assume we estimate a VEC with only two assets and the easiest structure on the lags with $p = q = 1$. This will yield a total of 21 parameters to be estimated. For a slightly larger portfolio of 8 assets and the same structure a total of $2,628$ parameters need to be estimated while for an even larger portfolio of 20 assets and $p = q = 2$ a total of $176,610$ parameters need to be estimated! Of course in reality a company's portfolio could be in excess of 100 assets making obvious the shortcomings of the VEC model.

56 This includes variances as the variance is the covariance of a number with itself.

[Figure 1 here]

Due to the number of parameters to be estimated the diagonal VEC (DVEC) was proposed (Bollerslev *et al.* 1988) which simplifies the VEC by imposing a restriction that the A and B matrices are diagonal. As a result the number of parameters to be estimated drops to $(p+q+1) \times N(N+1)/2$ which gives 9, 108 and $1,050$ parameters to be estimated for the same portfolios. However, the DVEC does not allow for dynamic covariances a rather strong assumption. Assuming correlation remains constant over time is a major drawback in finance applications. The FTSE 100 is a market capitalization weighted equity index of the 102 most prominent companies listed in the UK stock exchange accounting for 84.35% of the market capitalization. Constant correlation would imply that Vodafone and BP, two of the constituents, maintain a constant correlation coefficient with FTSE 100 over the 27 years of the index's existence. This can be verified by a rolling correlation coefficient using a moving window of 365 observations (i.e., 1 year). The correlation changes greatly over time.

[Figure 2 here]

Another drawback of the VEC model is that the covariance matrix needed to be inverted at every observation as part of the likelihood function optimization process. In addition the positive definiteness of the matrices has to be ensured though no general solution exists for this problem (Silvennoinen and Teräsvirta, 2010). To deal with these problems, Engle and Kroner (1995) propose the Baba-Engle-Kraft-Kroner (BEKK) model. The BEKK structure ensures by construction that conditional covariance matrices are positive definite. This is done by decomposing the constant term into a product of two lower-triangular matrices. The model is given by:

$$\mathbf{H}_t = \mathbf{C}\mathbf{C}' + \sum_{j=1}^{q}\sum_{k=1}^{K}\mathbf{A}_{kj}r_{t-j}r'_{t-j}\mathbf{A}_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K}\mathbf{B}_{kj}\mathbf{H}_{t-j}\mathbf{B}'_{kj} \tag{4.3}$$

where $\mathbf{A}, \mathbf{B}, \mathbf{C} :\ N \times N$ parameter matrices. The BEKK succeeds in doing what it was designed for, i.e. to guarantee positive definiteness of the covariance matrix. It is not a model without drawbacks though. The first problem with the BEKK is the interpretation of the estimates as the parameters in A and B do not translate into lagged volatilities or shocks. In addition, it still requires a lot of parameters to be estimated. In fact it requires $(p + q)KN^2 + N(N + 1)/2$ parameters to be estimated, which would be $11, 164$ and $1, 810$ for portfolios of $2, 8$ and 20 assets, and several matrix inversions which render it inferior to the DVEC in terms of computational speed. Therefore two other versions of the BEKK have appeared in the literature, the diagonal BEKK and the scalar BEKK, each one imposing more restrictions. Without going into details, the diagonal BEKK imposes that A and B are diagonal matrices meaning that the estimated covariance parameters are products of the parameters of the variance equations. In addition, the scalar BEKK restricts the diagonal BEKK even further by assuming that A and B are multiplied by two scalars rather than a diagonal matrix. Experience of the BEKK models has shown that many estimated parameters are insignificant leading to additional difficulties in modeling (Tsay 2010).

The conditional covariance matrix $\mathbf{H}_t$ can be expressed as a function of conditional standard deviations and correlations:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{P} \mathbf{D}_t \tag{4.4}$$

where $\mathbf{D}_t = diag\{h_{1t}^{1/2}, ..., h_{Nt}^{1/2}\}$ and $\mathbf{P} = [\rho_{ij}]$. All elements of the $\mathbf{P}$ matrix located on the diagonal $(i = j)$ are equal to 1 whereas the off-diagonal items equal:

$$[H_t]_{ij} = h_{it}^{1/2} \times \rho_{ij} \times h_{it}^{1/2}, \; \forall \, i \neq j \tag{4.5}$$

Returns $\{r_{it}\}$ are modelled as a $GARCH(p, q)$ type process with the conditional variance being:

$$h_t = \omega + \sum_{j=1}^{q} \mathbf{A}_j r_{t-j}^2 + \sum_{j=1}^{p} \mathbf{B}_j h_{t-j} \tag{4.6}$$

Bollerslev (1990) proposed the Constant Conditional Correlation GARCH model which assumes that correlations between the assets are time invariant (CCC-GARCH). The model ensures that the correlation matrix is positive-definite in most situations (Nelson and Cao 1992). In addition the model greatly reduces the number of parameters to be estimated, requiring only $1, 28$ and 190 for portfolios with $2, 8$ and 20 assets. The CCC-GARCH was extended to the DCC-GARCH when the correlation matrix is allowed to depend on time. Hence the conditional standard deviations $(\mathbf{D})$ are obtained from a typical univariate GARCH(p,q) are now used to form the conditional covariance matrix $(\mathbf{H})$:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{P}_t \mathbf{D}_t \tag{4.7}$$

where covariances $(\mathbf{H})$ are expressed as products of standard deviations $(\mathbf{D})$ and correlations $(\mathbf{P})$, both of which are conditional on time. The extension to the constant conditional correlation (CCC) GARCH models, the dynamic conditional correlation (DCC) allows for a correlation specification which is implemented in two stages. In the first stage univariate GARCH models are fitted to the financial series (returns) and the standardized residuals are obtained. These residuals are used in a second stage for the parameter estimation of the correlation. The conditional covariance matrix $(\mathbf{H}_t)$ is generalized by allowing the conditional correlation matrix $(\mathbf{P}_t)$ to be time dependent. The conditional correlation matrix needs to be positive definite at every observation which makes the DCC more complicated than the CCC GARCH. Two parameterizations of the conditional correlation matrix $(\mathbf{P}_t)$ exist, one by Tse and Tsui (2002) and another by Engle (2002). Tse and Tsui (2002) propose the specification for the correlation matrix $(\mathbf{P}_t)$:

$$\mathbf{P}_t = (1 - a - b)\mathbf{S} + a\mathbf{S}_{t-1} + b\mathbf{P}_{t-1} \tag{4.8}$$

where $\mathbf{S}$ is constant positive-definite parameter matrix with ones on the diagonal; a and b are non-negative scalar parameters satisfying the condition $a + b \leqslant 1$ and $\mathbf{S}_{t-1}$ is a sample correlation matrix of the past m standardized residuals $\hat{\varepsilon}_{t-1}, ..., \hat{\varepsilon}_{t-m}$ which can be specified by the user. The higher the value of m the higher the contribution of history to the current value of the conditional correlation.

For the modelling of correlations $(\mathbf{P}_t)$ Engle (2002) starts from a dynamic matrix process:

$$\mathbf{Q}_t = (1 - a - b)\mathbf{S} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + b\mathbf{Q}_{t-1} \tag{4.9}$$

where a and b are scalar parameters so that $a \geqslant 0, b \geqslant 0$ and $a + b \leqslant 1$, $\mathbf{S}$ is the unconditional correlation matrix composed of the standardized residuals ε_t and $\mathbf{Q}$ is positive definite. A rescaling of $\mathbf{Q}$ ensures that the correlation matrix is valid (Silvennoinen and Teräsvirta 2010):

$$\mathbf{P}_t = (\mathbf{I} \odot \mathbf{Q}_t)^{-1/2}\mathbf{Q}_t(\mathbf{I} \odot \mathbf{Q}_t)^{-1/2} \tag{4.10}$$

The major benefit of DCC-GARCH models is that they allow modeling of the correlation, which is assumed to be time variant, in a parsimonious and easy to interpret way. The small number of parameters that need to be estimated $N(N-1)/2 + 2$ makes the model a good choice even when the number of assets is large. It requires two more parameters to be estimated for every portfolio compared to the CCC-GARCH; however the procedure itself is much more time consuming as the correlation matrix needs to be inverted at every iteration. By contrast, the simplifying assumption that a and b are scalars imposes the restrictive assumption that correlation dynamics share the same structure. To avoid this limitation several specifications have been proposed.

Billio and Carporin (2006) impose a BEKK structure on the conditional correlations of the DCC-GARCH formulating the Quadratic Flexible DCC-GARCH (GFDCC). The Q_t matrix is defined as:

$$\mathbf{Q}_t = \mathbf{C}'\mathbf{S}\mathbf{C} + \mathbf{A}'\varepsilon_{t-1}\varepsilon_{t-1}\mathbf{A} + \mathbf{B}'\mathbf{Q}_{t-1}\mathbf{B} \tag{4.11}$$

where the matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}$ are symmetric; $\mathbf{S}$ is the unconditional correlation matrix composed of the standardized residuals ε_t.Stationarity conditions require $\mathbf{C}'\mathbf{S}\mathbf{C}$ to be positive definite. The number of parameters to be estimated is $3N(N+1)/2$ which is unfeasible with increasing asset size and as a remedy the authors suggest grouping of assets according to industry, sector other criteria.

Asymmetric effects were introduced firstly in the DCC - GARCH model by Tsay (2010) who allows the only the estimation of the first stage to be subject to leverage effects and then impose a similar correlation equation as in Tse and Tsui (2002). The volatility equation, similar to an EGARCH model is given below:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \frac{|\varepsilon_{t-1} + \gamma\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{q} b_j h_{t-j} \tag{4.12}$$

Cappiello *et al.* (2006) introduce asymmetries in an asymmetric generalized context (AG-DCC-GARCH). They specify Q_t as:

$$\mathbf{Q}_t = (\mathbf{S} - \mathbf{A}'\mathbf{S}\mathbf{A} - \mathbf{B}'\mathbf{S}\mathbf{B} - \mathbf{G}'\mathbf{S}^{-}\mathbf{G}) + \mathbf{A}'\varepsilon_{t-1}\varepsilon'_{t-1}\mathbf{A} + \mathbf{B}'\mathbf{Q}_{t-1}\mathbf{B} + \mathbf{G}'\varepsilon^{-}_{t-1}\varepsilon^{-}_{t-1}\mathbf{G} \tag{4.13}$$

where $\mathbf{A}, \mathbf{B}, \mathbf{G}$ are $N \times N$ parameter matrices; $\varepsilon^{-} = \mathbf{I}_{\{\varepsilon_t<0\}} \odot \varepsilon_t$, where $\mathbf{I}$ is the indicator function and $\mathbf{S}, \mathbf{S}^{-}$ the unconditional covariance matrixes of ε_t and ε^{-}_t respectively. However these models have more parameters to be estimated than the simple DCC-GARCH which restricts their applicability with large datasets unless restrictions are imposed.

Aielli (2009) proves that the DCC-GARCH estimator is asymptotically biased but the bias is negligible for small number of parameters. For large numbers of assets the DCC has been shown to perform accurately even though in theory the estimator is inconsistent. The consistent alternative of Aielli, the cDCC performs equally well even for large datasets. Caporin and McAleer (2010) compare, among others, the DCC and cDCC up to 89 assets and do not find any significant differences between them.

So far the DCC-GARCH is a way of modeling correlation relying only on past returns. However there have been developments for models that allow the correlation to be controlled by an exogenous variable, observable or latent. The Smooth Transition Conditional Correlation (STCC-GARCH) (Silvennoinen and Teräsvirta 2005) and the Double Smooth Transition Conditional Correlation (DSTCC-GARCH) (Silvennoinen and Teräsvirta 2007) allow the correlation to shift between two extreme states subject to a user selected variable. Pelletier (2006) introduced the Regime Switching Dynamic Correlation (RSDC-GARCH) model which can be classified somewhere between the normal DCC type models and the Smooth Transition ones. For large number of assets, unlike the smooth transition cases, the model can be estimated in two steps. The first step involves the estimation of the parameters of the univariate or multivariate GARCH equations. In the second step with the use of the EM algorithm of Dempster *et al.* (1977) to estimate the switching probabilities. Table 1 presents a summary of the models discussed above.

[Table 2 here]

4.3.2 Markov-Switching Models

Markov-Switching (Hamilton 1994) models (MSMs) are part of the greater family of non-linear models which also includes SETAR (Tong 2005) and LSTAR models (Teräsvirta 1994) among others[57].

Markov-Switching models condition the behavior of a financial time series on the state of the economy (i.e. crisis or non-crisis) while estimating the respective transition probabilities. The resulting model is linear within each regime but the aggregated model is non-linear. In contrast, SETAR/LSTAR models are non-linear throughout. However, these types of models require a user input relating to the sensitivity of the transition process whereas the MSMs rely on the data itself to identify the timing of the shift.

A two-regime switching model[58] is given by:

$$y_t = \mu_0 + \rho y_{y-1} + \varepsilon_t \tag{4.14}$$

$$y_t = \mu_1 + \rho y_{y-1} + \varepsilon_t \tag{4.15}$$

where $\varepsilon_t\tilde{}N[0, \sigma^2]$ and s_t is a variable that follows a Markov-chain and determines the regimes of the economy as follows:

$$\mu_{(s_t)} = \begin{cases} \mu_0 | s_t = 0 : non - crisis \\ \mu_0 | s_t = 1 : crisis \end{cases} \tag{4.16}$$

57 For a more in-depth discussion of these models the reader is directed to Tsay, (2010).

58 A Markov-Switching model can have more than 2 regimes and different models within each regime. More indepth analysis of such models can be found in Teräsvirta and González (2008) and Hamilton (1994).

The s_t variable is the probability of the economy switching to the crisis regime (j) in time $t+1$ given that currently, at time t, is in a non-crisis regime i. Mathematically:

$$P_{j|i} = P[s_{t+1} = j | s_t = i] : i, j = 0, 1 \tag{4.17}$$

Due to the fact that the estimates are probabilities they need to sum to 1. In other words, the economy can either be in crisis or non-crisis regime at any point in time. Mathematically:

$$\sum_{i=0}^{1} P_{j|i} = 1 \tag{4.18}$$

Then the full transition matrix can be given as:

$$P = \begin{pmatrix} & s_t = 0 & s_t = 1 \\ s_{t+1} = 0 & P_{0|0} & P_{0|1} \\ s_{t+1} = 1 & P_{1|0} & P_{1|1} \end{pmatrix} \tag{4.19}$$

Estimation of Markov-Switching models is done via maximum likelihood approach after the likelihood function has been filtered and smoothed (Hamilton 1994; Kim 1994). The algorithm used is the Lawrence and Tits (2001) which is found to be more efficient than the standard EM algorithm of Dempster *et al.* (1977) (Doornik and Hendry 2006).

4.3.3 Duration and Intensity Measures

After a unique crisis transition date has been identified for each country, we calculate the duration of the financial crisis as the number of days spent in the high volatility regime after this time. Our crisis intensity measure is then computed as the ratio of duration to the total number of days after the crisis transition date till the end of our sample (27/09/2011).

The subscript i is used to denote the different countries while T_c is the crisis transition date for each country. Naturally, the intensity measure can only take values between 0 and 1.

$$Intensity_i = \frac{Duration_i}{Total\ Days_i} = \frac{\#Days|t > T_{c,i}}{Total\ Days} \tag{4.20}$$

A high value of this intensity measure indicates that a country takes a relatively long time to revert back to the non-crisis regime. This reflects a market where the impact of the financial crisis has long lasting effects. In contrast, countries with a low intensity measure see their markets recovering more quickly after the shock. Of course, the delimitation between high and low in this setting is arbitrary, although our measure does allow us to gauge the relative intensities of the impact of the financial crisis for our sample countries.

4.3.4 Country Correlation Analysis

As discussed in the previous section, shift contagion is defined as significantly higher bivariate correlations for the financial markets of the sample of countries for the period after the crisis compared to the period before (Forbes and Rigobon 2002). In our study the cut-off point is unique for every country as the crisis transition dates are estimated from the data. We define the crisis period when at least one of the two countries has passed its crisis transition date.

We proceed with our correlation analysis by introducing two new measures; the average intra-group correlation (aIGC) and the average inter-country correlation (aICC). For the aIGC, each country group is considered in isolation. Taking the case of Denmark for example, which is part of the Scandinavian group, the average of two correlations, involving the other two counties in the group, Sweden and Finland, will be reported. In contrast, the aICC analysis considers the correlation of a country vis-à-vis every other country in the sample which involves the average of 55 correlation measures for each country under investigation. This classification allows us to examine separately the effect of contagion within country groups (i.e. regional contagion) as well as allowing us to examine its incidence on a global scale.

As discussed above, one of the downsides of increased integration is the contagion effects that appear once a crisis hits the economy. When markets are segmented then barriers such as capital flows and cross-country investment restrictions prevent, or delay, the spread of a financial crisis to other countries. In contrast, in integrated markets, contagion effects ensure that individual financial markets will be affected shortly after a financial crisis has occurred.

In essence, a higher degree of integration between the financial markets of country X and the rest of the world would mean that more intensified links between the countries in the form of, for example, higher trade volumes and more cross-country investments allow shocks to be transmitted more easily. Moreover, in the wake of a shock, new transmission channels are created between countries that did not previously have close ties. Kaminsky and Reinhart (2000) term this phenomenon "true" contagion while Karolyi (2003) calls it "irrational" contagion. In other words, the stock market in a particular country would respond to global news causing the aICC measure to be higher than the aIGC.

In contrast, lower levels of integration would restrict any contagion to small groups of countries sharing similar characteristics such as their level of development, proximity or trade. Hence the aIGC measure would be higher than the aICC as news in the countries comprising the group is more relevant.

4.4 Data

We use daily data of stock market indices for 55 countries denominated in US $ for the period 01/01/2001 – 27/09/2011, giving a sample of 2,800 observations. All data are taken from Datastream and details on the indices employed are presented in Table 3(a)-(b). We measure industrialization by the percentage value added to GDP by industry and manufacturing activities using the average percentage for the period 2000 – 2009 and as a robustness check we include only the 2009 value. Industrialization data are from the International Monetary Fund (IMF).

[Tables 3(a)-(b) here]

To facilitate discussion we classify the 55 countries into groups. In Europe we identify two main groups, the Old Europe[59] and the Recently Acceded Member States (RAMS) in view of the fact that there have been arguments in the literature about transition economies being less affected by past financial crisis (Gelos and Sahay 2001).

Old Europe is subsequently decomposed into the Core EU (Austria, Belgium, France, Germany, Luxembourg, Netherlands and the UK), the Scandinavian countries (Denmark, Finland and Sweden) and the PIIGS (Portugal, Italy, Ireland, Greece and Spain). The motivation for these groups is partially based on the recent discussion about the lack of competitiveness, fiscal deficit and public debt problems of the southern economies, particularly

59 The Old Europe coincides with the EU-15

Greece, Italy and Portugal. The Scandinavian countries can be viewed as different to the Core EU due to the higher priority these countries attribute to social welfare, the fact that Denmark and Sweden opted not to join the Eurozone and the important trade linkages between them (ECB 2010). In addition, the stock markets of the three Scandinavian countries are part of the NASDAQ OMX exchange company since 1998 for Sweden and since 2003 for Finland and Denmark comprising the NASDAQ OMX Nordic.

The Recently Accepted Member States (RAMS) consists of three sub-groups, the Baltics (Estonia, Latvia and Lithuania), the RAMS I group (Czech Republic, Hungary, Poland and Slovenia) and the RAMS II group (Bulgaria, Cyprus, Malta, Romania and Slovakia). We take the three Baltic countries together (i.e. Estonia, Latvia and Lithuania) because of their proximity, common history and common ownership of their stock markets by the NASDAQ OMX group. The exchanges in the three countries comprise the NASDAQ OMX Baltic. The other two sub-groups are defined according to the starting date of their negotiation talks with the EU which is 1997 and 1999 for RAMS I and RAMS II respectively.

Brazil, Russia, India, China and South Africa constitute the BRICS, a group of newly industrialized, fast-developing countries with sufficient political power to affect regional and global affairs. The first time the term BRIC makes its appearance was in a diplomatic meeting in May 2008 in Yekaterinburg, Russia. South Africa joined in August 2010 and became an official member in December of the same year. Since then the acronym was expanded to BRICS to accommodate the inclusion of South Africa.

The Gulf Cooperation Council or GCC has been introduced in a previous section. Here we highlight that the GCC is considered as an economic and political union with objectives in various sectors such as education (establishment of research centres), economic (stimuli for private sector investments, common currency) and military (common military presence). Consequently in economic terms it can be viewed as similar to the BRICS but the GCC has a more complete form of integration among its members. The UAE are not included in the analysis due to data limitations.

The selection of countries for Africa and Asia is restricted by data availability as stock markets are not existent in many countries. A total of 14 countries is included in this category. We make a distinction between developed and developing countries based on the combination of two criteria; the United Nations (UN) Human Development Index (HDI) and the IMF. Hence a country is considered as developed if it is included in at least one of the two lists. The Africa and Asia Developed countries comprises Hong Kong, Japan, South Korea, Singapore and Taiwan. By contrast the Africa and Asia Developing countries category includes Egypt, Indonesia, Jordan, Lebanon, Malaysia, Morocco, the Philippines, Thailand and Tunisia.

Finally there is a special worldwide group which includes two stock market indices which are used as a proxy for the global economy; these are the S&P 500 and the Euronext 100. The S&P 500 comprises 500 large capitalization and highly liquid common stocks traded in either of the two stock market exchanges in the USA, the New York Stock Exchange (NYSE) and the NASDAQ. The Euronext 100 comprises the 100 largest and most liquid stocks from European stock markets (mainly France, Germany, Portugal, Belgium and the Netherlands). These two indices are considered as representative market benchmarks for the worldwide economy. In addition we include two popular measures of market sentiment, the VIX and the VSTOXX indices. The indices are measures of the implied volatility of S&P 500 and Euronext index options respectively. They reflect the market's expectations over the next 30 days based on the option prices.

4.4.1 Macroeconomic Background

Table 4(a)-(d) summarizes key macroeconomic indicators for the countries under examination. Specifically the table reports country population in 2010 and GDP in constant 2000 USD as measures for size of the economy. Real GDP growth rates averaged over 2001 – 2010 rates specifically for 2009 and 2010 to show the extent of the recession following the financial crisis. GDP per capita in purchasing power parity terms is a proxy for the level of prosperity in a country. Unemployment and inflation rates are standard macroeconomic indicators. Market capitalization of listed firms as a percentage of GDP in 2010 is a measure of the development of a country's financial markets. Industrialization measures the percentage value added to the country's GDP by industry and manufacturing activities. The values reported are averages over the 2001 – 2009 period[60].

[Tables 4(a)-(d) here]

A similar level of prosperity is evidenced in the Old Europe by the similar values of GDP per capita at about 33 thousand USD perhaps with the exception of Luxembourg which is in excess of 71 thousand USD. In 2010 all countries in the Core EU group had

60 Values for 2010 were not available for all countries; hence we used 2001-2009 instead.

recovered from the recession that followed the financial crisis by recording positive, yet small, GDP growth rates. However the members of the Scandinavian group of countries record higher GDP growth on average with Sweden having the highest growth in EU in 2010 at 5.54%. Market capitalization is similar between the Scandinavian and the Core EU groups at about 84% of GDP. In the Core EU group, Luxembourg and the UK have the highest relative stock market capitalization with approximately 183% and 138% of GDP respectively. By contrast, Austria is the least capitalized among the Core EU at about 18% of GDP.

The financial problems in the economies of the five European countries comprising the PIIGS group emerged during the financial crisis and subsequently gave rise to the Euro crisis. With the exception of Spain, which has a market capitalization to GDP ratio of 83%, the other four countries exhibit much lower market capitalization figures (35% on average), the lowest being Italy at 15.51%, than the Core EU and the Scandinavian groups. This is surprising given that the PIIGS are part of the Eurozone which is supposed to be promoting convergence among the countries. In that sense the market capitalization of Sweden and Denmark, both of which are not part of the Eurozone, is much closer to the average capitalization of the Core EU group. In terms of GDP growth Greece, Ireland and Spain in 2010 are still in a contracting phase with figures being −4.47%, −1.04% and −0.14% respectively. There has been an imposition of austerity measures to all of the PIIGS which aim to the countries regaining their competitiveness. As a by-product of the measures rising unemployment has reached 18% in Spain and the living standards have deteriorated with an average GDP per capita at about 27 thousand USD, 18% lower than the Core EU.

In the RAMS stock markets were only re-established in the early 1990s after the collapse of the Soviet Union. Therefore they are still relatively underdeveloped when compared to mature markets in the rest of Europe (Claessens *et al.* 2003). The Polish stock exchange is the most capitalized at about 40% of GDP while the Slovakian market is still a very swallow one with its stock market values at only 4% of GDP. These countries have recovered from the crisis, with the exception of Latvia where the economy is still contracting, albeit at a low rate of 0.34%. Poland, on the other hand, is enjoying significant growth of almost 4 per cent. The other two RAMS, Cyprus and Malta, have above average stock market capitalizations of 24.81% and 19.94% respectively yet both are experiencing contracting economies. Average GDP per capita in this region is about 18 thousand USD, about 45% and 33% lower than that of the Core EU and the PIIGS respectively. Yet there is great variability among the countries in the RAMS category; hence on one end there is Cyprus at GDP per capita of about 25 thousand USD whereas on the bottom end there is Romania with barely 11 thousand USD. Unemployment is much higher compared to the Core EU. The reason for this is the large fall of GDP in 2009 as the three Baltic countries fell into deep recession due to the financial crisis[61].

The newly industrialized countries of the BRICS are all deemed to be at a similar stage of economic development. Currently they account for more than 25% of the world's land area and about 40% of the population. According to the IMF, the BRICS will ac-

61 Estonia -13.9%, Latvia -18.0% and Lithuania -14.7%.

count for 61% of the global growth by 2015. South Africa joined in 2011 when the BRIC countries formed a political organization (SouthAfrica.info 2011). However, at a population under 50 million and a GDP under 190 billion USD it is considerably smaller economy than the other four; hence its participation at the BRICS is often disregarded for economic analysis (Reuters 2011). The crisis has helped the BRICS group of countries to grow even faster and take a bigger share of GDP sooner (Reuters 2008). In 2010, their average GDP growth was at 7.8% while China was growing at 10.3% and South Africa was experiencing a modest growth of 2.8%. Stock markets are highly developed in these countries with market capitalization levels in excess of 67%. Living standards as proxied by the GDP per capita are highest in Brazil and lowest in China at an average GDP of about 10 and 3 thousand USD respectively.

The total population of the GCC is estimated at around 40 million while their combined GDP is around 450 billion USD. The GCC countries show significant variations in terms of population, aggregate output and GDP per capita. Saudi Arabia is the largest by population (26 million) and GDP (249 billion USD) whereas the highest GDP per capita is in Qatar at about 73 thousand USD. Stock market capitalization is in excess of 80% for all countries but Oman (37%). The countries did not experience any recession as their GDP growth retained its positive sign throughout the crisis. Oil dependent and largest economy Saudi Arabia has a GDP growth rate of 3.76% in 2010 whereas Qatari economy was expanding at 8.64%[62].

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62 The UAE was the only exception with a contraction in the economy by 0.70% in 2010 mainly an effect of the Dubai crisis.

The rest of the countries in the analysis represent a less uniform group. Japan and South Korea are the only ones part of the OECD. Hong Kong, Singapore and Taiwan, in addition to Japan and South Korea, are considered as developed countries according to the IMF and the Human Development Index methodology (Human Development Report 2011). Indeed these countries included in the Africa and Asia Developed Countries identify themselves out of the rest as they have an average GDP per capita which is considerably higher than the rest of the group at about 38 thousand USD compared to about 7 thousand USD for the Africa and Asia Developing Countries. Stock market capitalization ranges between 24.12% and 172.64% for both the Developed and the Developing countries without any major differences between the groups. Only exception is Hong Kong where market capitalization is in excess of $1,000\%$, a fact attributed to the state being a major capitalist service economy characterized by low taxation and free trade. In the index of Economic Freedom it's ranked first for fifteen years in a row and also described as the closest the world can get to laissez-faire capitalism (The Economist 2010).

4.4.2 Descriptive Statistics

Table 5(a)-(d) summarizes the descriptive statistics of the daily returns of the examined stock markets while table 6 shows the average return, volatility and VaR for the country groups. Stock market returns have the properties suggested by relevant literature, that is leptokurticity, negative skewness and non-normality. Furthermore, annualized volatility and Value at Risk (VaR) are suggestive of the turbulence in the EU stock markets during the examined period. Volatility is calculated as the standard deviation of the returns and has been annualized using the square root of time rule assuming 252 trading days for every market. Value at Risk estimates the worst possible outcome in the following day at a specified confidence level (here 95%) given the available evolution of prices. For instance, a VaR estimate of -9.33% shows that the worst possible outcome for the next period, at the 95% significance level, is a -9.33% drop. The Jarque-Bera (JB) test verifies that the distribution of returns is not normal, while the Efficient Market Hypothesis (EMH) tests suggest that the weak form of market efficiency, a sign of developed financial markets, does not hold for many of the stock markets under investigation. Though there are many approaches as to how one can test for EMH, we report two of the most commonly used ones. The first is the Lo and MacKinlay (1988) variance ratio test. The null hypothesis is that the returns (r_t) follow a random walk; hence the ratio of the variance of $r_t - r_{t-n}$ to $1/n$ the variance of $r_t - r_{t-1}$ would be close to one (Lock 2007). Rejection of the null hypothesis would imply that the EMH does not hold. The second test is the Runs test which was firstly used by Fama (1965). This test, which is also called Wald-Wolfowitz test, is a non-parametric test on the sequence of observations. The tests calculate how many "runs" of consecutive values above or below the mean appear in the data. Too few runs indicate a tendency for high and low values to cluster; an indication opposed to the EMH. By contrast, many runs ensure that high and low values alternate. The null hypothesis for the Runs test is that of randomness; hence a rejection implies that the EMH does not hold in the particular country.

When both the EMH tests agree that the EMH does not hold (rejection of the null in both cases), we conclude that the weak form of the efficiency market hypothesis does not hold for the stock market in question. In particular, the EMH holds for 9 out of the 15 countries consisting the Old Europe group (Scandinavian, Core EU and PIIGS), a ratio of 60%. For the 12 Recently Accepted Member States (RAMS I, II and Baltics) the EMH holds for 4 out of the 12 countries, a ratio of 33%. The 2 out of 5 countries in the BRICS verify the EMH, a ratio of 40% while only one member of the GCC shows evidence in favour of the EMH. In the Asia and Africa Developed group all countries show support for the EMH whereas in the Asia and Africa Developing group the EMH holds only for Taiwan.

[Tables 5(a) - (d) here]
[Table 6 here]

The Core EU countries group has an average daily return of −0.002%, with the highest and lowest returns being observed in Germany (0.043%) and the Netherlands (−0.029%) respectively. Furthermore, average annualized volatility shows that Germany is the most stable market (8.95%) while the Netherlands are the second most volatile (25.65%). Value at Risk calculations reveal that the German is the safest with a a VaR estimate of −4.29%, while the Luxembourgish is the most risky with a corresponding figure of −16.46%. The Luxembourgish stock market is also the most volatile (30.76%).The apparent riskiness of the stock market in the Grand Duchy is confirmed by the fact that, at the outbreak of the financial crisis between August and October 2008, the Luxembourg index lost about 85% of its value, this was the steepest drop of all European countries[63]. The EMH holds for Austria, France, the Netherlands and the United Kingdom.

63 This can be attributed to Luxembourg being a major international financial centre with many money market funds (including hedge funds) domiciled there, due to the favourable tax and legal environment.

The Scandinavian group of countries recorded an average daily return of -0.009%, with the lowest returns being observed in Finland (-0.028%) which was also the most volatile (28.87%) and the most risky according to the VaR estimate of -11.27%. As a group the Scandinavian countries performed slightly worse than the Core EU. However this is probably driven by Finland which has been hit hard as the region entered into recession. Finland's economy shrank by 8.2% in 2009 as demand for the country's mainly industrial goods fell rapidly. The EMH holds for all three members.

On the south, the PIIGS have experienced the lowest average daily returns in the region of -0.025% with Greece recording the most negative (-0.0517%) and Portugal the least negative (-0.003%). Volatility was highest in Greece (25.77%) and lowest in Portugal (17.27%). Value at Risk figures show that Ireland has been the most risky at -23.70%, with Greece being very close however at -23.65%. At the other end, Portugal has been the safest relatively at a VaR estimate of -7.33%.The EMH holds for Spain and Italy.

While the previous three groups were recording negative returns, the Recently accepted member states were offering a lucrative investment environment. More specifically returns in the Baltics were at an average level of 0.043% coupled with relatively low volatility of about 21.29%. The VaR, at -12.97%, is similar to that of Scandinavian or PIIGS group. Estonia has been the most profitable financial market offering the highest return among the three (0.049%) and the safest in the region with volatility at 19.21% and VaR of -6.48%, comparable to that of more financially developed markets such as the UK. Reasons for this favorable investment climate in Estonia relate to the modern market-based structure of the country's economy with adopted reforms to enhance productivity in the electronics and telecommunication sectors, two of the strongest pillars of the Estonian economy (CIA World Factbook). The country also benefits from an export boom and increased foreign investment after the adoption of the Euro on January 2011. The EMH does not hold for any country in this group.

RAMS I and RAMS II also show positive average daily returns 0.023% and 0.016% respectively while the volatility levels were comparable to that of the Old Europe at 21.79% and 24.29% respectively. The highest returns were recorded in Romania (0.074%) while the most volatile market has been Cyprus (34.76%). The high uncertainty in Cyprus, reflected in the high volatility, relates to the exposure of Cyprus to Greek debt. In 2010 the exposure to Greek households and businesses of the three largest Cypriot commercial banks was about 53% of their assets (FinancialMirror.com 2011). As a consequence, measures imposed on the Greek economy (i.e. a reduction in the face value of Greek government bonds by more than 50%) severely affect Cyprus's economy. Moreover, the country's economy has been downgraded several times in the recent months by credit rating agencies. For all these reasons the investment prospects in the country were bleak. The EMH holds in Czech Republic, Hungary, Poland, Bulgaria and Slovakia.

The average daily return for the BRICS (0.046%) confirms that these fast-developing countries offer large returns to the investors willing to take the necessary risks. The risks in the BRICS at a volatility level of 27.59% and with a VaR of −15.90% are considerable higher than other groups of developing countries such as the RAMS. Brazil, China and South Africa show supportive evidence for the EMH.

The GCC countries have an average daily return of 0.037, which ranks them below the Baltics in terms of performance. The GCC are less volatile however than the Baltics. Indeed with a volatility of 19.76% they are on average one of the safest investment options from the country groups in this analysis. The Value at Risk figures −10.569% also verify this point. The EMH only holds for Bahrain.

Finally the Asia and Africa Developed and Developing groups have average returns, 0.012% and 0.042% respectively, which verify the notion that investments in developing countries have higher returns. By contrast, volatility levels are 26.65% and 18.88% for the groups respectively. In this case it is striking the result that higher returns are not necessarily accompanied by higher risk. The finding is plausibly related to the fact that the financial crisis was more contained within the developed world. The Value at Risk figures of −10.91 and −12.78% respectively are similar in magnitude.

4.4.3 Graphical Analysis

Figures 3(a)-(k) show the evolution of the price indices of the examined stock markets. The graphs are sorted according to the groups defined earlier. The WorldWide graphs in 3(g) define the pattern that is apparent in this time period; that is the burst of the dot-com bubble in the early 21^{st} century where the stock markets were falling till the second half of 2002 and the boom that lead to the financial crisis in 2007, which is currently ongoing for many countries while others have recovered. The pattern is primarily distinguishable in the Old Europe countries. Most markets have been affected severely by both crises. Two exceptions are Austria and Germany. The burst of the dot-com bubble is barely noticeable in the former, a fact plausibly attributed to the lower magnitude of this crisis compared to the 2007 financial crisis as well as the relative importance of the financial markets in the country which is reflected in the much lower stock market capitalization than the Core EU average. Germany on the other hand shows an upward trend for the full period under examination with the 2007 financial crisis being only of minor importance around 2010. The reason is the strength of the German economy, its export capacity and its sound financials. Germany is affected as the financial crisis turned into a Euro crisis where the fiscal problems of the PIIGS were brought to surface and the subsequent bail-out plans organized involved great loan contributions from Germany. The Euro crisis is evident in graph 3(c) where most notably Greece's stock market is in free-fall after 2010 while Italy shows a similar picture.

[Figures 3(a)-(k) here]

The Recently Accepted Member States experienced the 2007 financial crisis and are still recovering from it. Some, like Estonia, with greater success and others, like Bulgaria or Cyprus, with more problems. Another pattern is identified here with the Baltics and the RAMS I groups of countries showing a better performance after the crisis as opposed to the RAMS II group. A plausible reason for this can be traced to the accession date of these countries to the EU as well as the differences in their economies. The 3 years difference in the accession dates has had an important effect as the countries that joined first could tap the resources offered by EU to develop their economies, build infrastructure and make the necessary reforms to enhance competitiveness. Hence when the crisis hit they were at a better position compared to the RAMS II group. In addition, the latter group includes

Bulgaria and Romania, two of the weakest economies in Europe with average GDP per capita of about 1/3 of the Core EU's.

The BRICS, figure 3(h) verify the fact that they are strong economies developing fast as four out of five countries have already reverted back to the levels of the pre-crisis period with China being the only exception. In addition the upward sloping trend leading to the crisis is much steeper than other economies, reflective of the countries' high growth and significant investment opportunities.

The GCC, figure 3(i) are also affected by the financial crisis of 2007 as evident by the sharp fall in their stock market indices. In addition, the Saudi Arabian stock exchange experienced a crash in late 2005 following a slow-down in oil production, an effect which was spread to the neighboring economies, particularly the Qatari.

The last two groups, Asia and Africa Developed and Developing, graphs 3(j) and 3(k) respectively seem to have overcome the crisis. In specific, from the developed countries three out of five have reverted to their pre-crisis levels the only exceptions being Hong Kong and Japan. Five out of the nine developing countries have even surpassed the price levels on the eve of the crisis and they show great financial strength. These are Indonesia, Malaysia, the Philippines, Thailand and Tunisia.

4.5 Results

Table 7(a)-(f) presents the estimation results for the 55 countries using the DCC-AR(1)–GARCH(1,1) model. The AR(1) term is fitted to account for autocorrelation in the logarithmic returns. Tables report the estimated coefficients and the p-values are given in brackets. We have conducted robustness checks for the mean and the variance equations by specifying alternative structures. In particular, following the Box - Jenkings approach, we implemented an automatic ARIMA selection algorithm which cycles among various orders of ARMA(p,q) structure with respect to minimize the Bayesian Information Criterion (BIC). The results confirmed the sole inclusion of an AR(1) term in the majority of times. In some cases the algorithm would settle for a less parsimonious model, with a minor improvement in the BIC over the AR(1) specification. Hence for consistency, we have used an AR(1) specification for the mean equation in all the countries. For the variance equation we have opted for the widely used GARCH(1,1) although different variants were tried (i.e. EGARCH) but without any improvement in terms of goodness-of-fit.

[Tables 7(a)-(f) here]

The Markov-Switching Model has been fitted to the volatility series in each of the 55 countries and the results are presented in figures 4(a)-(l). The main findings are as follows. First, the figures clearly show the high-volatility, turbulent, periods in the beginning of the sample that corresponds to the dot.com bubble. This is followed by a low-volatility and tranquil period. After 2007 the markets revert to a high-volatility regime as they react to the onset of the financial crisis and this regime change is depicted by the solid black lines in the figure. Some markets have experienced additional crises like the Saudi Arabian crash and the impact on neighboring markets is depicted.

[Figures 4(a)-(l) here]

Figure 5 shows the transition dates for all of the sample countries. It is interesting to note the great deviations in the transition dates for the countries which span in a time frame of about 21 months. It is apparent from the graph that some countries like Luxembourg are affected early while others like Brazil are amongst the last to be affected. Earlier work typically relying on monthly and weekly data has failed to find any significant lead/lag relationship among equity markets in the wake of a crisis (Granger and Morgensten 1970; Agmon 1972; Branch 1974). Initially Roll (1988) and then Lau and McInish (1996) are the first studies that investigate the lead/lag structure in equity markets following the financial crisis of 1987 in the US. They conclude that as integration in the financial markets progresses, any lead/lag relationship following a crisis in equity markets around the world would tend to diminish (Lau and McInish 1996).

[Figure 5 here]

Table 8(a)-(c) shows, in the second column, the estimated crisis transition date for the countries in the sample as identified by the Markov-Switching model. The Lead/Lag measure, reported in column 3 shows the deviation in days between the estimated crisis transition date and the "guideline" crisis transition date that has been most commonly used as a guideline in other research; *i.e.* 1/8/2007 (Hwang *et al.* 2010). A negative sign indicates that the crisis transition date for the country under consideration was before the "guideline date" whereas a positive sign shows that the country entered the crisis regime after it. Columns 4 and 5 report the number of days after the crisis transition date that each country spent in the low-volatility (non-crisis) regime and the high volatility (crisis) regime respectively. Column 6 reports the crisis intensity measure which is has been introduced in the methodology section. Table 9 presents these indicators by the country groups as described earlier.

[Tables 8(a)-(c) here]

[Table 9 here]

Our results show that the groups of developed countries (Scandinavian, Core EU, PIIGS, Asia & Africa Developed) are hit earlier by the 2007 financial crisis than the groups of developing countries (RAMS, Baltics, BRICS, GCC, Asia & Africa Developing). We observe that the deviation between the crisis transition dates of United States and the developed European countries has been reduced in the recent financial crisis. Hon and Young find that the lead/lag relationship between US-Europe has decreased from previous crises and after the 9/11 crisis it was estimated to be around 3-6 months (Hon *et al.* 2004). In addition, the intensity of the crisis has been stronger for developed countries than the developing ones. Specifically the average delay for the developed group is about 0.5 months whereas for the developing group is 8.5 months compared to the "guideline date". The intensity values are 55.88% for the developed and 50.68% for the developing countries. However, within the subgroups there are important differences.

The Core EU is the first to be affected, alongside the WorldWide group, showing a minimal lead of about 5 days evidence that the stock markets in these countries were among the first to be affected. The group has the second highest crisis intensity score suggesting that these countries were among the most affected. Focusing on individual countries now, the most interesting finding is that Luxembourg was affected about 5 months earlier than the rest of the Core EU, rendering it the first country to enter the crisis regime globally. Additionally, Luxembourg had the highest crisis intensity score at 78.4% within the group. One rationalization of this is the dependence of the Luxembourgish economy on financial services and, in particular, various types of funds, including hedge funds and the relatively lax regulation. Legal requirements applicable to hedge-funds were reduced further by the inception of a specialized investment fund (SIF) law in February 2007 specifically for "well-informed investors" (KPMG 2011). This law is less restrictive compared to usual regulatory laws for hedge funds as it allows them to be launched and then seek the approval of the regulator. In addition, SIF law places no quantitative or qualitative restrictions on how much the hedge fund can borrow (for comparison, the second less restrictive class of hedge funds only allows till 400% leverage of fund's net assets for market neutral strategies) (Luxembourg for Finance 2009). By contrast Germany, the largest economy in the EU was affected at an approximate lag of 3 months while the crisis intensity was the lowest in the group at 41.9%.

Examining the geographical periphery of the Core EU, that is the PIIGS and the Scandinavian countries, we find that these two country groups were affected at a lag of about 9 days from the "guideline date". There is not significant variability in the crisis transition dates between the countries included in the two groups besides the case of Greece. Greece, entered the crisis regime at a lag of about 5 months after the guideline date. Although the troubled economies of the Eurozone do not show any distinctive behavior relative to the Core EU as far as their crisis transition dates are concerned, there are differences in their crisis intensity scores. As expected, Greece was the most affected, exhibiting an intensity value of 97.9% as the country was in the epicenter of the Euro crisis that followed. Ireland and Spain, two other troubled economies that have been facing similar problems, albeit to a lesser extent, also have high crisis intensity values of 78.7% and 69.0% respectively. The mean intensity for the four PIIGS economies, even when Greece is excluded, is higher than the respective measure of Core EU, albeit by only three percentage points. By contrast, the Scandinavian countries showed an average intensity of 52.8% as opposed to the figure of 70.7% of the PIIGS.

The RAMS I group entered the crisis mode with at a lag of 2 months relative to the "guideline date". However, there is considerable variation among the members of this group as the Czech Republic shows a lag of approximately 5 months. The delay evidenced for the Czech Republic may be related to the relative higher significance of the industry in the country as opposed to financial services. By contrast, Slovenia is affected about 7 months prior to the "guideline date" while . Yet this is likely to be caused by the transitory period for the Slovenian economy which in the beginning of 2007 entered the EMU being the first of the Recently Accepted Member States. Intensity which is at 53.35% shows that the crisis has been less felt in these developing economies as it is lower than the Core EU.

The RAMS II group shows a lag of 5.5 months compared to the "guideline date" and is also affected significantly (at the 10%) later than the RAMS I group. In terms of crisis intensity, the RAMS II group is at 57.35%. However, Cyprus with an intensity score of 85.3% is an outlier due to the very large exposure to Greek debt. In consequence, austerity measures imposed on the Greek economy severely affect Cyprus's economy. Hence the latter has been downgraded several times in the recent months by credit rating agencies. The average intensity for the RAMS II group, excluding Cyprus, is 50.4%, a figure which is lower than that for the RAMS I group. The reason for this may be related to the fact that the countries of the RAMS II group started negotiations with the EU with a delay of 2 years relative to the RAMS I group giving evidence of lower integration of these economies with the rest of the EU.

The Baltics show a lag of 13 months and an intensity score of 52.48%. Within the group, Estonia experienced the crisis about two months sooner than its neighbors Latvia and Lithuania. The relatively high intensity score for Latvia (71.18%) can be attributed to the Latvian crisis that the country experienced.

The BRICS are affected at an 11 month lag while the average crisis intensity is at 47.24%. Compared to the Core EU and the RAMS I group, the crisis intensity of the BRICS is about 13 and 7 percentage points lower respectively. It is plausible that the industrialized economies of the countries within the BRICS group has helped them to weather the crisis. China is affected much sooner than the rest of the BRICS. Specifically it enters the crisis regime about three months before the "guideline date" or about a year before the rest of the BRICS. Till the onset of the crisis China was experiencing a prolonged boom period (see figure 3h). As the boom period continues, investors become increasingly worried that it will come to an end. The self-fulfilling prophecy states that crises occur because of agents expect them (Diamond and Dybvig 1983). In February 2007 the Bureau of Economic Analysis revised its forecast on US GDP growth down to 2.2% from 3.5%. Although major European and US stock markets rebounded to that announcement positively, the situation in Asia was more bleak. On the 27^{th} of February 2007 the Chinese stock market experienced its biggest drop (about 9% in a single day) for over a decade with a major impact on stock markets worldwide. The drop in the Chinese stock market made investors worried about potential losses on a global scale. It is then that the housing bubble in the US, the subprime lending operations and the possibility of the USA entering into recession that enlarge the negative investment climate leading to the climax of the financial crisis (The Economist 2007).

The GCC experienced the financial crisis with the second longest lag, after only the Baltics, of 12.5 months. The high homogeneity of the GCC countries is evidenced by the low variability in the crisis transition dates. The low variability, at about 22 days, is comparable to that of the Baltics (31 days) and the Scandinavian (9 days) countries. At the other end, the BRICS show higher variability in their crisis transition dates of about 7 months. The intensity of the crisis in the GCC was at 51.8%, about 9 and 2 percentage points lower than the Core EU and the RAMS I group. Amongst the countries in the GCC group, Bahrain has significantly higher crisis intensity (67.3%) than the rest (47.9%). The Bahraini financial market is the most developed in the region offering exquisite financial products such as Islamic finance. Even though market capitalization of the Bahraini stock exchange is similar to that of Kuwait and Qatar, Bahrain has been more affected by the financial crisis as its economy was not relying on energy revenue which would have reduced the impact of the crisis.

The last two groups, Asia & Africa Developed and Asia & Africa Developing provide interesting reading. The distinction between developed and developing countries provides evidence that the former experienced the financial crisis earlier than the latter, the difference is also verified statistically at the 1% significance level. Four out of five countries in the Asia & Africa Developed group show a minimal deviation from the guideline date of only 2 days. This finding is in line with previous groups that consist of developed economies

(Scandinavian, Core EU, PIIGS) also showing small deviations from the "guideline date". In terms of crisis intensity, the country group has an average score of 52.0% which is about five percentage points higher than the BRICS and eight percentage points lower than the Core EU. Hong Kong has been the hardest hit by the financial crisis showing an intensity of 64.5% a result attributed to the very prominent financial sector. The country had been severely affected during the 1997 East Asian financial crisis (Lim *et al.* 2008). In this group, Japan is a unique case for two reasons. First it is the only developed market in the sample that becomes affected by the financial crisis at such a big lag (5.5 months) and secondly it has the lowest intensity score (32.9%) among all developed economies.

The deregulation of the Japanese financial system in the 70s allowed companies and individual savers to access the capital markets. As a consequence the country's banking sector was facing increased competition which led to decreasing profit margins. The banks in an attempt to boost their competitiveness resorted to aggressive lending to real estate. The high economic growth and the rising asset prices concealed problems in collateralized loans where the value of the collateral was driven by an asset bubble. In addition, the peculiarities of the Japanese banking system where banks and corporations are bonded through a relationship system involving cross-holdings of shares and representation in the board of directors lead to lax monitoring of lending practises and further expansion in credit as banks' capital expanded (The New York Times 2008). During the 1980s the Nikkei stock market index and real estate prices more than quadrupled. High economic growth and steep rise in asset prices often lead to asset bubbles which are in turn followed by financial crises when the hype can no longer be sustained (Reinhard and Rogoff 2009). The downturn happened during the 90s and it took Japan a decade to recover, what has been known as "the lost decade" (Hayashi and Prescott 2003). When the subprime loans were gaining momentum in the US leading to the 2007 house bubble, Japan did not have great exposure to it because of its recent history. In some sense, Japan has been the most segmented developed market during the last two major financial crises, the dot.com bubble and the 2007 financial crisis (Dekker *et al.* 2001). Japan was hit later when the financial crisis impacted the real economy and its export-driven manufacturing sector started facing difficulties as other countries were entering a recession. Yet Japan has one of the lowest crisis intensity scores of about 32.9% which is attributed to the significant savings amounting to more than 14 trillion USD. The trade surplus that Japan has been enjoying for decades ensured it had adequate money to finance its short term deficits during the peak of the financial crisis. Due to the financial crisis in 2007 the Japanese financial companies were in a much better situation as they wrote off about 8 billion USD compared to a global estimate of around 1 trillion USD (IMF 2009).

The Asia & Africa Developing group experiences the crisis at an average lag of almost 9 months, which ranks it after than the RAMS II group (8 months) and before than the GCC (12.5 months) in terms of the average lag. In terms of crisis intensity, this country group has the lowest value of 41.9%. Many countries in this group have not as developed financial markets compared to the global financial centres and some of the countries have strong industry and manufacturing sectors like Indonesia and Thailand; hence lower intensity scores are expected. Some economies, like the Philippines, have been integrated regionally and, to a smaller extent, internationally before the 1997 East Asian crisis (Yang *et al.* 2003). However the Philippines, Malaysia and Thailand were the hardest hit by the 1997 East Asian crisis (Lim *et al.* 2008). The Philippines have still not recovered fully and they appear to be fairly isolated markets, as shown by the particularly low crisis intensity score of 25.8%, the lowest in our entire sample. The isolation from financial markets of the Philippines is consistent with Dekker *et al.* (2001) among others. A notable exception is Malaysia which shows a minimal lead of 2 days between the crisis transition date and the guideline date, a remarkably different result compared to the rest of its group. The reason is plausibly related to the prominent financial sector of Malaysia, evidenced by the high market capitalization ratio of about 172%.

As a further step to our analysis we investigate the relationship between industrialization and crisis intensity by means of a linear regression. More industrialized countries both developed like Germany and Japan as well as developing such as the Czech Republic and Saudi Arabia have suffered less from the financial crisis. By contrast, countries with prominent financial sectors such as Luxembourg, Bahrain and Hong-Kong recorded higher crisis intensity levels. Table 10 reports the results fo the regression of crisis intensity upon the country's industrialization. The negative and statistically significant coefficient of the explanatory variable verifies our previous claims that more industrialized countries weathered the crisis better.

[Table 10 here]

4.5.1 Correlations

Tables 11 and 12, in the second and third column, show the average Intra Group Correlation (aIGC) and average Inter Country Correlation (aICC) before and after the crisis respectively. In columns 4-5 the median and mean changes of the two correlation indicators are reported for the respective country groups. Columns 6-7 report the standard deviation of the correlation changes in every country group together with a t-test for the statistical significance of the change between the pre and post crisis periods. Results show that the correlations between the countries in the sample increased, to different degrees, after the financial crisis yet not all of them are statistically significant to be classified as contagion according to the the definition of Forbes and Rigobon (2002).

The aIGC indicator is a measure of regional integration. Results[64] show that the Old Europe is the most integrated region (59.2%) followed by the Baltics (26.8%) and the RAMS I (36.5%) group. The low correlation (4.7%) among the countries comprising the RAMS II group is evidence of the little integration compared to other developing country groups such as the RAMS I group at 36.5% or the BRICS at 26.1%. The GCC countries show very little financial integration (6.1%). The result is at odds with the level of homogeneity in these countries, it is nevertheless expected given the low development of financial markets in the region. After the financial crisis the correlations between stock markets in the examined country groups increased as evidenced by the positive median and mean changes[65]. The statistical significance of the change in correlations verifies regional

64 We report correlations before the crisis but the results do not change qualitatively if we focus on the after-crisis correlations instead.

65 The mean change for the RAMS II group is negative. However for this group the change is not statistically

contagion effects. These are significant for the Scandinavian, Core EU, Baltic and RAMS I group in Europe. In addition, the BRICS and the GCC groups also show strong evidence of regional contagion as the change is significant at the 1% and 5% respectively.

The aICC is a more generalized measure of integration among financial markets. Correlation levels are lower than the respective aIGC measure. This is anticipated as the aICC measure is the average correlation of all country pairs. The fact that GCC show the lowest correlation prior to the financial crisis at 6.0%, much lower than the BRICS (24.0%) or the Old Europe (33.3%) provides supportive evidence that the GCC countries are isolated from the global financial markets. Developed markets (31.7%) are more integrated than developing markets (16.9%). The financial crisis leads to rises in the aICC measures for all the groups. Contagion is observed for the majority of them. Specifically, we find contagion at the 1% significance level for the Scandinavian, Core EU, PIIGS and BRICS groups, while the RAMS I and GCC show evidence at the 5% significance level. Finally, the Baltics and the two Asia & Africa groups show evidence in favor of contagion at the 10% significance level.

[Tables 11 - 12 here]

The aIGC measure tracks the increase in correlation within the group members whereas the aICC measures the change in the correlations against all other countries. Hence the comparative analysis of the aIGC and aICC measures identifies whether regional or global contagion has been more significant in every country group. Evidence of regional contagion would verify the claims of financial markets retrenching back into national borders

significant.

after the crisis (ECB 2010). The direct implication of this result is to identify the alignment patterns of stock markets during the financial crisis. For example, the constituent members of the PIIGS witnessed an increase in the average inter-group correlation (aIGC) of 3.4% and an increase in the average inter-country correlation (aICC) of 4.3%. As the aICC is higher than the aIGC it indicates that after the crisis the stock markets in the PIIGS group reacted more strongly to information from stock markets in the other country groups. In other words for this country group the global has been more important than regional contagion. Hence they have been aligned more to stock markets outside of their group (i.e. Core EU). A similar finding also holds for the Scandinavian group of countries where the values are 2.6% and 3.8% for aIGC and aICC respectively. From the New Member states, the RAMS I group shows similar characteristics with 6.3% and 6.7% values for aIGC and aICC respectively.

By contrast, the opposite is observed for the Core EU, where the aIGC (4.8%) measure is lower than the aICC (4.0%) indicating that the crisis has aligned more the financial markets of the countries included in the group. In other words, these stock markets would react more strongly to news and information related to countries inside the group. The same is true for the Baltic and the RAMS II groups with aIGC measures of 7.0% and 10.3% while the aICC measures are 5.1% and 3.0% respectively.

The findings suggest that there is varying degree of integration in the EU-27 which leads to contagion effects of varying duration and intensity for the country members. the Scandinavian, the PIIGS and the RAMS I groups are aligning themselves to the stock markets outside of their respective group. The increased emphasis that is placed on the financial markets outside of the respective group is plausibly attributed to the fact that as the financial crisis unravels the financial markets affected first are part of the Core EU and WorldWide groups. Most of the countries contained in there are well established financial centres, like New York, London and Luxembourg. The Core EU is considered an economic barometer for the EU and any developments would be of vital importance to countries in the PIIGS or the RAMS I groups as they would have direct implications on their economies. For the PIIGS the implications could be related to their weathering of their fiscal problems while for RAMS I they may be more in-line with the availability of financial support that the EU gives for infrastructure developments in the peripheral states.

By contrast to the PIIGS, Scandinavian and RAMS I groups, the Baltics and the RAMS II appear secluded, similar to the Core EU, but the reasons are different. In the Core EU the notion of the seclusion was attributed to the financial development of the countries and them being earlier affected by the crisis. For the Baltics and the RAMS II it is plausibly associated with the lower degree of integration that these countries have acquired with the rest of the EU. This is verified statistically and economically. The lower integration of the two aforementioned groups is evidenced by the lower correlation they have amongst themselves (aIGC) and among other financial markets (aICC) compared to other EU groups.

Specifically the correlation indicators for the Baltics and the RAMS II groups with respect to the Core EU before the crisis are 22 and 44 percent lower for the aIGC indicator and 13 and 20 percent lower for the aICC indicator respectively. Economically, the RAMS II members are the last ones to enter the accession talks with the EU and among the last ones to officially join in early 2007. Therefore the bonds with the EU are expected to be at a much lower level compared to countries which have been members for a longer period and this is likely to be reflected in the financial sector as well. The Baltics on the other hand, despite the fact that they are closer to RAMS I group in terms of accession dates, they show a segmentation from the rest of the EU but this could be related to the low stock market development in the region where market capitalization averages about 10%, the lowest in EU-27. From the three countries only Estonia is part of the Eurozone but is the smallest economy in terms of contribution to the Eurozone's output. Hence these countries are economically smaller and show important dissimilarities to other EU members. A consequence of these differences is that the Latvian financial crisis was contained within the country without the rest of the EU-27 experiencing any externalities as is the case with Greece, which is however part of the Eurozone too.

The remaining groups can be classified into two broad categories according to which of the two indicators is higher. The BRICS and the Asia & Africa Developing groups have 8.3% and 4.8% aIGC respectively while the aICC measure is 7.2% and 4.2% respectively. The findings for these two groups verify that the financial crisis has increased the correlations among the country members of every specific group suggesting that stock markets were reacting primarily to group specific developments and news. The BRICS are among the fastest growing economies with stock markets accounting for a significant part of the economy with an average market capitalization of 118%, higher than that of Core EU's. They were among the least affected from the financial crisis, a fact attributed to their strong productive sector. The countries in the Asia & Africa Developing group show similar results to other groups of developing countries like the Baltics or the BRICS. Hence a seclusion from the global financial markets, by means of lower alignment of reactions is evidenced here as well.

The GCC and the Asia & Africa Developed groups have aIGC of 10.9% and 0.0% while the aICC is at 37.5% and 1.7%. The fact that aIGC is lower than aICC classifies these two groups in the same category as the PIIGS and the RAMS I group in terms of alignment of their stock markets to the global economic environment. The results show that stock markets in the Asia & Africa Developed group were reacting to developments taking place in the global financial centres in Europe and the USA. This is also verified by the high crisis intensity value for the particular group, which at 59.3% ranks third after the PIIGS at 69.0% and the Core EU at 65.8%. By contrast, the GCC have the lowest correlations not only amongst themselves (6.1%) but also with international financial markets (6.0%). The only other group of countries that comes relatively close to this level of seclusion in terms of financial market co-movements is the RAMS II group with 4.7% and 11.9% respectively.

4.5.2 Contagion Channels in EU

In the financial contagion literature the view in support of the decoupling hypothesis has been fading in the recent years (Mollah and Hartman 2012). Evidence has shown that developing countries are affected by financial crises; hence these countries are victims of financial contagion.

Identification of contagion channels has focused upon foreign bank ownership, cross-border exposures and the reliance upon a few "common lenders". The "common lender" has received much attention as evidence has highlighted its relevance in contagion studies since the Mexican crisis (Van Rijkeghem and Weder 1999). In particular, developing countries rely heavily on foreign funds to stimulate economic activity.

Focusing in Europe, it has been documented that most of the New Member states (RAMS I, II and Baltics) are highly dependent on a handful of Western European banking groups either via the local banking sector or via the private sector. Moreover, the exposure of Western European banking groups to the banking sector of the New Members is both concentrated and substantial. Austria, Belgium, Germany and Italy are the most exposed countries to the New Members of the European Union.

In the banking sector, before the financial crisis the asset share of foreign banks in seven[66] out of twelve countries was in excess of 80% of the total assets. The seven largest institutions in the area had a combined exposure of more than 370 billion euros their relative presence in the region is different. Some of these institutions, classified as regional banks, had focused their activities in their home countries and the New Member economies[67]. In addition to these regional banks, large European[68] or even international banking groups have been actively engaging in the New Member countries. In relative, but not necessarily in absolute, terms they have small presence in the region. This could result in vulnerability of the host country transmitted from the home country through the banking system. By contrast, regional banks are likely to transmit contagion both ways (Árvai *et al.* 2009).

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66 Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Romania, Slovakia.

67 Erste, Raiffeisen and OTP Bank.

68 Unicredit, KBC, Société Générale and Intesa SanPaolo

The majority of the New Member countries have experienced a huge credit expansion to the private sector by about 30-50% in real terms during the years leading to the crisis (Árvai *et al.* 2009). Although this growth has had structural and positive development implications, the less positive implications for financial stability had been stressed out (Cottarelli *et al.* 2003). The prominent banking system compared to capital markets in the region further aggravated the over-investment and excessive external borrowing practices. In the PIIGS the practices of current account deficits being re-financed with external borrowing, which has been cheaper since the countries have joined the Euro, have created moral hazard issues. This behavior relied on the implicit guarantee that cross-border liabilities either via government intervention or via international bail-out programs (Sbracia and Zaghini 2001). Government intervention, particularly within the Euro, has been unable to take action as reassessment of country risk led to increased borrowing costs. Furthermore, the refinancing difficulties of a single country can cause a revision of beliefs about similar problems in other countries; hence aggravating potentially existing fundamental problems (Missio and Watzka 2011).

This dependence on foreign funding and the financial links between banking institutions create a mechanism that would transfer a shock from a country to another leading to contagion. A trigger event could start in the host country if, for instance, a reassessment of the credit risk entailed were to happen. Concerns on the fragility of the host country's economy may lead to increased pressure to curtail lending and liquidity in the host country to safeguard operations in the home country. Or vice versa the trigger event may be in the home country due to changes in market conditions, possibly related to regulatory compliance where deleveraging across markets takes place leading to liquidity and lending curtailing in host countries (Árvai *et al.* 2009).

Linking the above with some country specific results in terms of lead/lag crisis relation and intensity we find that the Baltic group of countries is the more segmented. This is also evidenced elsewhere and can be attributed to two facts; first the concentrated exposure (about 60% of their bank-to-bank claims) of Baltics to Sweden and second the minimal economic dependence of the RAMS I and II groups on Sweden. As a result any potential contagion between Sweden and the Baltics is likely to be contained therein feeding to the segmentation of the Baltics.

By contrast, Czech, Poland and to a lower extent Hungary that have more diversified sources of funds are affected earlier and at a lower intensity than Romania and Slovakia whose exposures are more concentrated to a single lender (Árvai *et al.* 2009).

Even developed countries that have large exposure to New Member states have recorded a higher crisis intensity measure compared to the other group members. For instance Austria and Belgium, part of the Core EU group, have exposure of about 70% and 25% of their GDP to New Member countries respectively. This has affected their crisis intensity measures which are among the highest in their group at 74.8% and 73.8% respectively. Sweden has also recorded higher crisis intensity measure of 60.8% compared to the other two Scandinavian countries due to its large exposure in the Baltics.

Yet these two approaches; the decoupling hypothesis and the bank transmission channels fail to receive definite support in our study. We find significant differences between the dispersion of the crisis transition dates for developed and developing countries within the EU. The developed countries experience contagion within 3 months, showing much lower deviation in their crisis transition dates compared to the developing countries that are affected by contagion effects at a lag of 3-13 months. Under the decoupling hypothesis, developing countries would not have been affected at all. By contrast, given the extent of foreign bank penetration and the "common lender" argument one would expect that contagion hit these countries sooner.

4.5.3 The impact of the crisis on the GCC

The GCC are less affected by the initial impact of the financial crisis. As global financial conditions worsen the global productive sector takes its toll on the oil prices which drop sharply. Oil related revenues decline and fiscal positions are adversely affected. Liquidity shortages in the global financial markets impact the GCC as investor confidence is shaken and capital inflows are reduced. The global deleveraging and reversal of capital flows back to developed markets has a negative impact on GCC banks' reserves while short-term interest rates rise sharply (IMF 2010).

Contagion impact and revenue diversification in the GCC

Plunging stock markets lead to a decrease in market capitalization by 41% or about 400$ billion in money terms (IMF 2010). Bahrain is the most affected in the region due to the more prominent inter-linkages of its wholesale banking sector to the global financial markets. The contracting real estate sector has a severe effect on the UAE economy. The announcement of *"DP World"* seeking a standstill on debt repayment for two of its subsidiaries (*"Nakheel"* and *"Limitless"*) puts more pressure in the country's equity markets with volatilities of Abu Dhabi and Dubai stock exchanges reaching record-high levels in the region since the end of 2008. *"Nakheel"* and *"Limitless"* had been engaging in property development before the financial crisis hit the Emirate yet the falling demand for residential and commercial property led them into financial distress. The deteriorating investor sentiment and uncertainty are manifested in higher CDS spreads for sovereign and private equities.

However the effect of the Dubai crisis is isolated within the UAE with other GCC countries only marginally affected (IMF 2010). This can plausibly be linked to the low regional integration of equity markets as well as the significant part that oil revenue constitutes in most of the countries. This allows them to intervene and bail-out troubled business entities as happened with the oil-rich Abu-Dhabi in the case of *"Nakheel"* and *"Limitless"*.

Credit to the private sector falls as banks in response to stricter regulatory constraints reduce lending. Initial public offerings (IPO) amounting for about 11.7$ billion in the first half of 2008, they are cut down completely during the second half. Bond issuance by corporations drops by 40%, a decrease of about 16.5$ billions in money terms, in the same period. Islamic bond issuance falls by 73%, reaching 4.3$ billion as concerns on contract enforceability receive more attention during these bleak economic conditions. The tightening in the credit markets takes its toll on investment projects of 2.5$ trillions in total worth across the GCC, 23% of which were put on hold mainly in the UAE.

Corporate profitability declines from 2008 onwards but rises up again after mid-2009 (Global Investment House 2012). Non-oil GDP growth remains positive at 2.8% in 2009. On the contrary, oil related GDP faces a contraction of 3.8% around the same time frame as

US and Europe, major importers from the GCC, fall deeper into recession. Diversification of revenue income into non-energy related sources is paying off for the GCC which is recording a positive average growth of about 1%.

GCC's reaction to financial contagion

With the first appearance of financial contagion effects, regulatory response has been timely and efficient with a variety of measures taken by local governments as reported in table 13. Coordination in the GCC response has been better compared to the US or Europe and was well received by the financial markets (IMF 2010).

[Table 13 here]

Central banks and governments inject liquidity into the system through purchase-repurchase agreements (repos) and via long-term deposits. Monetary easing in the form of lowering interest rates and relaxing reserve requirements of bank institutions with the central bank is adopted by all countries except Qatar. Measures to boost investor confidence are also taken by the GCC that have been enjoying fiscal surpluses during the years leading to the crisis. First, deposit insurance schemes are put in place in Kuwait, Saudi Arabia and the UAE (IMF 2011a). Second, government managed sovereign wealth funds (SWF) support domestic assets and banks by directing their investments into these sectors, a practice followed in Kuwait, Oman and Qatar (IMF 2012a,b). Third, troubled corporations receive direct subsidies in Kuwait and the UAE (IMF 2012a,d). The affluent and timely government support, backed by the surpluses of the energy sector, helps the GCC to maintain their investment grade credit rating scores (Fitch). To stimulate demand in the GCC and the wider region, Saudi Arabia initiates a 400$ billion investment plan. GCC countries maintain pre-crisis levels of consumption while the positive spillovers of these supportive policies are felt in other economies of the MENA region (IMF 2010).

Besides the actions at the macro level (governments, regulatory bodies) there have been significant steps at the micro level that help to alleviate any financial contagion problems. The strong supervision and regulation of the banking sector as well as the appropriate risk management practices have played a crucial role (IMF 2012c). Banks in the GCC have shown great hindsight as even before the second-half of 2008, when GCC was affected by financial contagion, they had been increasing their loan loss provisions at the expense of lower profitability. The GCC banking system has been found capable of withstanding significant credit and market events before any recapitalization need arises (IMF 2012c). As a result of the policy actions at the micro and macro level, the impact of a few failures is largely contained without any adverse effects in the GCC economy.

Financial institutions under distress are mainly in the more financially developed countries of Bahrain, UAE and Kuwait. In Bahrain, two wholesale banks (*"International Banking Corporation"* and *"Awal Bank"*) file for bankruptcy in the first half 2009. In Kuwait one commercial bank is recapitalized a process financed by 1/3 from the Kuwaiti government and by 2/3 from the shareholders. In addition, *"Global Investment House"* and *"Investment Dar"*, two of the largest investment companies in the country, face difficulties in bond repayments of 3$ billion and 100$ million respectively. Both companies reach restructuring agreements without any further impact on the Kuwaiti economy (IMF 2012a). In the UAE the government acquires two real estate finance companies (*"Amlak*

Finance" and *"Tamweel"*) that faced financial difficulties following the collapse in the real estate market. Spillovers to other financial or non-financial institutions are minimal (IMF 2012d). Islamic banks are affected later than conventional banks, only by mid-2009. However their profitability, although it declines, still remains positive and comparable to that of conventional banks.

Challenges for the GCC

As the financial crisis affected the GCC some problems are brought to surface. However the economic prosperity of the GCC states helped to keep the magnitude of these problems low.

The first problem the crisis highlights is the dependence on foreign funding that stimulated economic growth. The low regional integration of GCC stock markets, the insignificance of institutional investors, the lack of developed secondary debt markets in conjunction to the buy and hold strategy, particularly reinforced by Islamic banks and high net worth individuals, and family owned businesses (these account for 90% of the corporate sector) need to be addressed to further stimulate endogenously generated growth (IMF 2011b, 2010).

Secondly, the violation of regulatory requirements with respect to loan-to-deposit ratios reveals potential problems in the enforceability of regulatory decrees. At the same time it reveals moral hazard issues. Particularly for firms in which the government has some direct or indirect stake, there is the perception that an implicit bail-out guarantee is in place.

Thirdly, the Dubai crisis case reveals maturity mismatching and investment concentration problems (IMF 2012d). Real estate requires a relatively longer investment horizon yet most of the credit that was made available by foreign sources had been on a short term basis. The authorities need to diversify away from hydrocarbon revenues but this must not entail too much focus on a single economic sector.

4.6 Conclusions

The chapter examines the synchronization of the 2007 global financial crisis in the GCC and a wide selection of 47 developed and developing countries. Special focus is given in the GCC in comparison to the developed and developing countries of the EU.

We adopt a DCC-GARCH framework that allows us to estimate the conditional volatilities and correlations of the respective stock markets. The unique crisis transition date for each country is identified by a Markov-Switching model. The novelty of the methodology is that it enables the identification of countries that were affected earlier or later. Financial contagion, defined as in Forbes and Rigobon (2002), is verified statistically for all country groups except the RAMS II group, comprising Bulgaria, Cyprus, Malta, Romania and Slovenia.

Yet the verification of contagion cannot capture the actual impact of the financial crisis upon a country; hence measures of duration and intensity are employed. A general finding is that although developed and developing countries show evidence of financial contagion, developing countries do so later and not as severely. More specifically, in duration terms the Core EU group is the first to be affected while the GCC is the last with an approximate lag of 1 year. An extreme case is Luxembourg, the first country to be affected in March 2007, about 5 months earlier than the commonly assumed crisis starting point in August 2007. The group with the highest intensity is the PIIGS whereas for the GCC the same indicator is amongst the lowest indicating that financial contagion has not hit as severely the region. Extreme cases include Greece at the high end, an expected finding as the country has been the epicenter of the Euro crisis, and the Philippines at the low end. An exception within the GCC is Bahrain with an intensity score much higher than the other countries of the group due to the Kingdom's higher interlinkages with global financial markets and its prominent banking sector.

A drawback of studies with a small number of countries is that they cannot differentiate between global and regional contagion effects. Our large sample and decomposition measures reveal two cases; the first case consists of country groups where the countries therein become more aligned among themselves during the crisis showing evidence of regional contagion or segmentation (e.g. Core EU, Baltics). In the second case the countries in the respective country groups become more aligned to global markets such as the PIIGS and the GCC. The fact that these two groups show evidence of global contagion is plausibly attributed to the bail-out deals and austerity measures decided at the EU level for the former group. In the GCC case it is related to their dependence upon the outside world in terms of foreign investments flowing in, the expansion of the real estate sector – which has been driven by the high demand for property by outsiders, as well as the falling demand for oil as the world was sliding into recession.

Any similarities in the crisis experience between the GCC and the EU have to be traced between the GCC and the RAMS II group as this is the one closest in terms of duration, intensity of the crisis and the fact that both groups experience global contagion. The RAMS II country group includes countries that were the last to join the EU. Hence the finding in support of global contagion is reflective of potential developments at the EU level that would affect their integration course, funding and future prospects within the Union. As a group, the GCC is more uniform even when compared to the Core EU. Yet the GCC show a response to the financial crisis similar to a group (RAMS II) that is far less integrated with the rest of the EU. Therefore the GCC seem to have the best of two worlds, the benefits of integration without the evils of contagion.

We also find that industrialized countries have weathered the crisis better than those where the financial sector has been more prominent. The countries with a prominent financial sector (e.g. Luxembourg, Malaysia, and Hong Kong) have been affected earlier and more intensely with Bahrain and Japan being two special cases. The fact that Bahrain is affected after 1 year is plausibly attributed to the high presence of Islamic banks, investments into infrastructure projects and the prohibition of debt contracts. Among the developed countries, Japan is the last to be affected. This is due to its past experiences at a similar domestic crisis that has made it particularly skeptical about dangerous debt contracts (the lost decade).

The GCC have managed to maintain a positive GDP growth amidst the crisis, a sign that the revenue diversification projects have paid off. In addition, the timely and efficient response of regulators as well as the financial strength of conventional and Islamic banking sectors has helped to alleviate the negative effects of the financial crisis in the region.

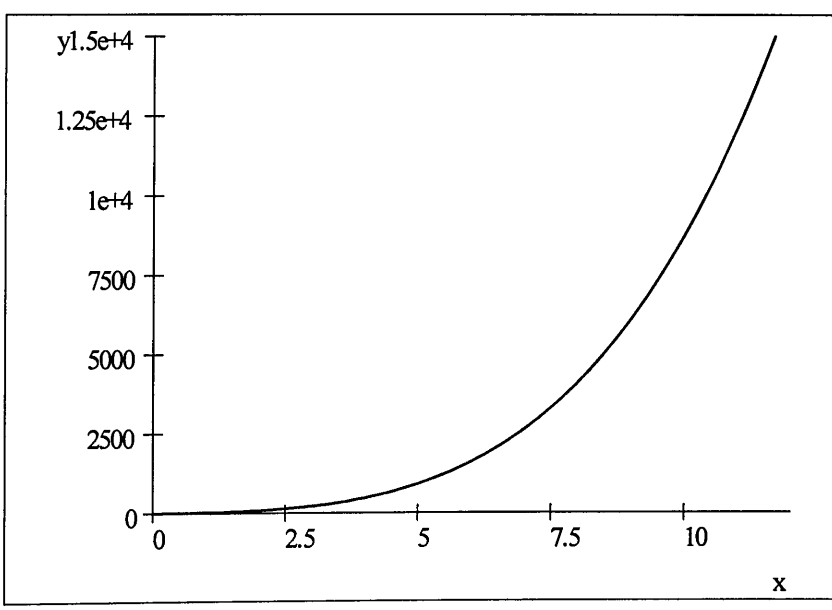
4.7 Table Appendix

Table 1. Hydrocarbon Reserves.

Countries	**Oil** (billion barrels)	**Gas** (billion ft^3)
Bahrain	–	3.0
Kuwait	101.5	62.9
Oman	5.6	34.6
Qatar	27.3	899.3
Saudi Arabia	264.1	267.3
UAE	97.8	227.1
GCC Total	**496.3**	**1494.2**

Source: BP Statistical Review of World Energy, 2009

Figure 1. Estimated Parameters in VEC models.



y-axis: Number of Parameters; x-axis: Number of Assets. VEC Model (p=q=1)

Figure 2. Rolling Correlations of Vodafone and BP against the FTSE100

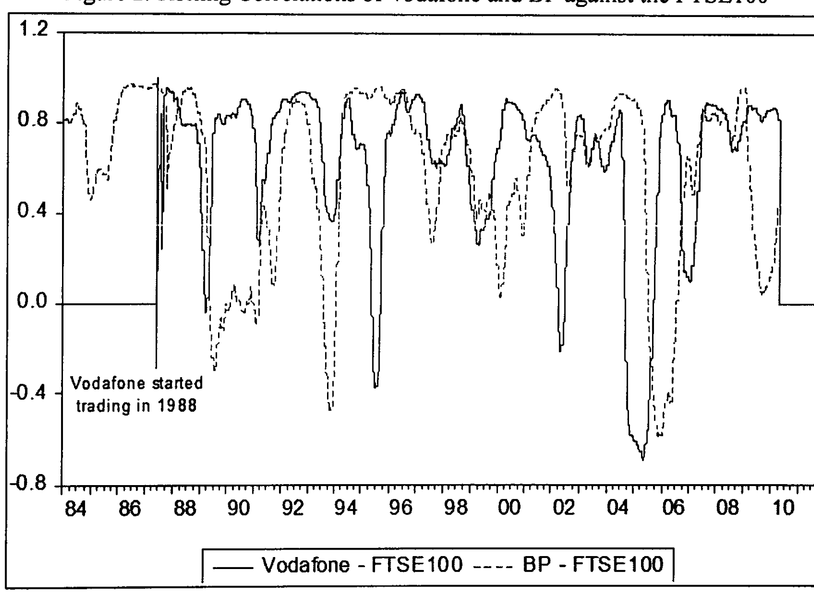


Table 2. Multivariate Model Summary.

Multivariate Models	Notable Extensions	Parameters for 8 asset portfolio[1]	Conditional Correlation	Dimensionality Curse	Estimation Intense	Other Issues	Introduced by
VEC		2,628	Yes	***	***		Bollerslev et al (1988)
DVEC	Scalar VEC	108	No	**	**		Bollerslev et al (1988)
BEKK	Diagonal BEKK	164	Yes	**	***	Interpretation	Engel and Kroner (1995)
	Scalar BEKK					Issues	
CCC		28	No	*	*		Bollerslev et al (1990)
DCC	cDCC-GARCH	30	Yes	*	**		Tse and Tsui (2002)
	STCC-GARCH						Engle (2002)
	RSDC-GARCH						

Notes:[1] Assuming the most basic model where$p = q = 1$ and $k = 1$ (BEKK). More asterisks denote a higher severity of the problem.

Table 3(a). Stock Market Indices per country, symbols and sources.

Countries	Index	Symbol	Source
Group: Scandinavian			
Denmark	OMXC 20	DKKFXIN	Stockholmsborsen
Finland	OMXH	HEXINDX	Stockholmsborsen
Sweden	OMXC 30	SWEDOMX	Stockholmsborsen
Group: Core EU			
Austria	ATX	ATXINDX	Wiener Boerse
Belgium	BEL 20	BGBEL20	BEL
France	CAC 40	FRCAC40	Euronext Paris
Germany	DAX 30	DAXINDX	Deutsche Borse
Luxembourg	SE General	LUXGENI	Luxembourg Stock Exchange
Netherlands	AEX	AMSTEOE	Euronext Amsterdam
UK	FTSE All Share	FTALLSH	United Kingdom
Group: PIIGS			
Portugal	PSI General	POPSIGN	Euronext Lisbon
Italy	FTSE MIB	FTSEMIB	FTSE
Ireland	SE Overall	ISEQUIT	Irish Stock Exchange
Greece	ATHEX Composite	GRAGENL	Athens Stock Exchange
Spain	IBEX 35	IBEX35	Spanish Exchanges
Group: Baltics			
Estonia	OMX Tallin	ESTALSE	Stockholmsborsen
Latvia	OMX Riga	RIGSEIN	Stockholmsborsen
Lithuania	OMX Vilnius	LNVILSE	Stockholmsborsen
Group: RAMS I			
Czech Republic	SE PX	CZPXIDX	Prague Stock Exchange
Hungary	BUX	BUXINDX	Budapest Stock Exchange
Poland	Warsaw General Index	POLWIGI	Warsaw Stock Exchange
Slovenia	DS Market	TOTXRSJ	Datastream
Group: RAMS II			
Bulgaria	SE SOFIX	BSSOFIX	Bulgaria Stock Exchange
Cyprus	FTSE Cyprus SE 20	FTSEC20	FTSE
Malta	SE MSE	MALTAIX	Borza ta' Malta
Romania	BET	RMBETRL	BET Indices
Slovakia	SAX 16	SXSAX16	Bratislava Stock Exchange

Note: All data downloaded from Datastream

Table 3(b). Stock Market Indices per country, symbols and sources.

Countries	Index	Symbol	Source
Group: Worldwide			
Pan-European	Euronext 100	EUNX100	Euronext
	Vstoxx	VSTOXXI	STOXX
US	S&P 500	S&PCOMP	S&P
	Vix	CBOEVIX	CBOE
Group: BRICS			
Brazil	Bovespa	BRBOVES	Sao Paolo Stock Exchange
Russia	RTS Index	RSRTSIN	Red Star Financial
India	BSE 100	IBOMBSE	BSE Ltd
China	Shanghai SE	CHSASHR	Shanghai Stock Exchange
South Africa	FTSE/JSE	JSEOVER	FTSE
Group: GCC			
Bahrain	S&P BMI	IFGDBHL	S&P
Kuwait	KIC General	KWKICGN	Kuwait Investment Company
Oman	Muscat Securities Mkt	OMANMSM	Muscat Securities Market
Qatar	Qatar Exchange Index	QTRMRKT	Qatar Stock Exchange
Saudi Arabia	TASI	TDWTASI	Saudi Arabian Stock Exchange
Group: Asia & Africa Developed			
Hong Kong	Hang Seng	HNGKNGI	Hang Seng Bank
Japan	Nikkei 225	JAPDOWA	Nikkei
Korea (South)	Korea SE Composite	KORCOMP	Korea Stock Exchange
Singapore	Straits Times	SNGPORI	Singapore Stock Exchange
Taiwan	SE Weighted	TAIWGHT	Taiwan Stock Exchange
Group: Asia & Africa Developing			
Egypt	Hermes Financial	EGHFINC	Egypt Stock Exchange
Indonesia	IDX Composite	JAKCOMP	Jakarta Stock Exchange
Jordan	Amman SE	AMMANFM	Amman Stock Exchange
Lebanon	BLOM	LBBLOMI	Beirut Stock Exchange
Malaysia	KLCI	FBMKLCI	FTSE
Morocco	MASI	MASIIDX	Morocco Stock Exchange
Philippines	PSEI	PSECOMP	Philippine Stock Exchange
Thailand	S.E.T.	BNGKSET	Thailand Stock Exchange
Tunisia	Tunindex	TUTUNIN	Tunis Stock Exchange

Note: All data downloaded from Datastream

Table 4(a). Macroeconomic Data.

Country	Poppulation (millions)	GDP (constant 2000) (bil. USD)	GDP Growth 2001-2010 (%)	GDP Growth 2009 (%)	GDP Growth 2010 (%)	GDP/Capita (constant 2000) (USD)	GDP/Capita (constant 2005) (USD,PPP)	Unemployment (%)	Inflation (%)	M.Cap. (%)	Industrialisation 2001-2009 (%)
Group: Scandinavian											
Denmark	5.54	171.23	0.70	-5.21	2.09	55,987	32,608	6.0*	2.30	74.66	40.06
Finland	5.36	145.56	1.87	-8.20	3.12	44,576	31,532	8.2*	1.22	49.48	56.57
Sweden	9.38	1,698.16	2.07	-5.33	5.54	48,832	33,686	8.3*	1.16	126.89	47.52
Group: Core EU											
Austria	8.38	222.63	1.55	-3.89	1.96	26,552	35,266	4.8*	1.81	17.99	49.65
Belgium	10.88	266.51	1.39	-2.75	2.18	24,497	32,824	7.9*	2.19	57.62	41.52
France	64.87	1,484.70	1.14	-2.73	1.48	40,576	29,647	9.1*	1.53	75.25	34.63
Germany	81.70	2,071.24	0.89	-4.72	3.63	40,658	33,498	7.7*	1.14	43.20	51.74
Luxembourg	0.51	27.38	3.09	-3.64	3.52	108,921	71,161	5.1*	2.28	183.55	26.04
Netherlands	16.61	440.12	1.37	-3.92	1.77	47,158	36,915	3.4*	1.27	84.40	38.60
UK	62.22	302.11	1.43	-4.87	1.25	36,099	32,187	7.7*	3.29	138.33	37.76
Group: PIIGS											
Portugal	10.64	124.99	0.67	-2.49	1.33	21,473	21,658	9.5*	1.39	35.88	41.03
Italy	60.48	1,125.08	0.27	-5.22	1.30	33,916	26,753	7.8*	1.54	15.51	46.14
Ireland	4.48	123.81	2.60	-7.58	-1.04	45,497	35,183	11.7*	-0.95	16.54	62.72
Greece	11.32	158.67	2.42	-2.04	-4.47	26,933	24,990	9.5*	4.71	23.83	29.21
Spain	46.08	712.34	2.09	-3.72	-0.14	30,541	26,934	18.0*	1.92	83.25	44.91

Note: All data are 2010, except when *,**,*** which is latest available, 2009,2008 and 2007 respectively.

Source: IMF

Table 4(b). Macroeconomic Data.

Country	Population (millions)	GDP (constant 2000) (bil. USD)	GDP Growth 2001-2010 (%)	GDP Growth 2009 (%)	GDP Growth 2010 (%)	GDP/Capita (constant 2000) (USD)	GDP/Capita (constant 2005) (USD,PPP)	Unemployment (%)	Inflation (%)	M.Cap. (%)	Industrialisation 2001-2009 (%)
Group: Baltics											
Estonia	1.34	77.63	4.10	-13.90	1.78	13,939	16,353	13.7*	2.97	12.10	41.47
Latvia	2.24	11.22	4.07	-17.95	-0.34	10,704	12,938	17.1*	-1.09	5.21	34.86
Lithuania	3.32	17.53	4.62	-14.74	1.33	10,933	15,390	13.7*	1.32	15.59	50.37
Group: RAMS I											
Czech Rep/ic	10.52	19.21	3.23	-4.15	2.32	18,256	22,557	6.7*	1.41	22.41	63.34
Hungary	10.01	57.01	1.82	-6.69	1.17	13,030	16,514	10.0*	4.88	21.25	47.20
Poland	38.18	250.89	3.91	1.65	3.82	12,270	17,336	8.2*	2.71	40.60	48.46
Slovenia	2.05	26.00	2.79	-7.80	1.18	23,266	24,982	5.9*	1.84	19.74	53.32
Group: RAMS II											
Bulgaria	7.54	8.25	4.13	-5.52	0.20	6,325	11,486	6.8*	2.44	15.25	52.32
Cyprus	1.10	12.17*	3.03	-1.02	-1.02*	31,298*	25,803*	5.2*	2.38	19.94*	25.21
Malta	0.41	4.43	1.48	-2.12	-2.12*	19,326*	22,102*	6.9*	1.52	24.81*	58.45
Romania	21.44	56.53	4.44	-8.50	0.95	7,537	10,929	6.9*	6.09	20.04	53.88
Slovakia	5.43	43.78	4.41	-6.20	0.50	16,386	19,244	12.1*	0.96	4.66	59.94

Note: All data are 2010, except when *,**,*** which is latest available, 2009,2008 and 2007 respectively.

Source: IMF

Table 4(c). Macroeconomic Data.

Country	Population (millions)	GDP (constant 2000) (bil. USD)	GDP Growth 2001-2010 (%)	GDP Growth 2009 (%)	GDP Growth 2010 (%)	GDP/Capita (constant 2000) (USD)	GDP/Capita (constant 2005) (USD,PPP)	Unemployment (%)	Inflation (%)	M.Cap. (%)	Industrialisation 2001-2009 (%)
Group: Worldwide											
US	309.05	11,681.22	1.68	-2.67	2.85	47,184	42,642	9.3*	1.64	117.53	36.53
Group: BRICS											
Brazil	194.94	916.13	3.61	-0.64	7.49	10,710	10,056	8.3*	5.04	74.03	44.97
Russia	141.75	414.35	4.88	-7.81	4.03	10,439	14,183	8.2*	6.85	67.88	49.30
India	1,170.94	971.48	7.78	9.10	9.72	1,476	3,240	n/a*	11.99	93.46	42.75
China	1,338.30	3,243.06	10.50	9.20	10.30	4,392	6,810	4.3*	3.31	81.02	78.99
South Africa	49.99	187.23	3.51	-1.68	2.84	7,275	9,476	23.8*	4.27	278.40	49.75
Group: GCC											
Bahrain	1.17*	13.16**	6.48	n/a	6.30**	17,608*	23,755**	n/a	1.95	82.22*	n/a
Kuwait	2.64*	61.44***	7.35	n/a	4.37***	41,364*	49,541***	n/a	4.02	87.64*	55.94
Oman	2.71*	30.35*	4.88	1.10	n/a	17,280*	24,226*	n/a	3.20	36.92*	62.42
Qatar	1.60*	54.21*	13.55	8.64	n/a	61,531*	73,196*	n/a	-2.42	89.36*	n/a
Saudi Arabia	26.81*	249.32*	3.25	0.16	3.76	13,900*	20,103*	5.40*	5.34	85.54*	68.99
UAE	6.93*	117.75*	5.92	-0.70	n/a	33,183*	34,750*	4.00**	0.90	47.61*	n/a

Note: All data are 2010, except when *,**,*** which is latest available, 2009,2008 and 2007 respectively.

Source: IMF

Table 4(d). Macroeconomic Data.

Country	Population	GDP	GDP Growth			GDP/Capita	GDP/Capita	Unemployment	Inflation	M.Cap.	Industrialisation
	(millions)	(constant 2000) (bil. USD)	2001-2010 (%)	2009 (%)	2010 (%)	(constant 2000) (USD)	(constant 2005) (USD,PPP)	(%)	(%)	(%)	2001-2009 (%)
Group: Asia & Africa Developed											
Hong Kong	7.07	251.17	4.09	-2.66	6.97	35,537	41,714	5.20*	2.34	1207.95	11.95
Japan	127.45	5,064.04	0.86	-6.29	5.12	39,733	30,903	5.00*	-0.70	74.57	51.41
Korea	48.88	800.21	4.15	0.32	6.16	16,372	27,027	3.60*	2.93	107.37	64.27
Singapore	5.08	162.40	5.69	-0.77	14.47	31,990	51,969	n/a	2.81	166.18	55.73
Taiwan	23.16	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1.00	n/a	n/a
Group: Asia & Africa Developing											
Egypt	81.12	164.09	5.11	7.16	5.18	2,023	5,676	9.40*	11.27	37.68	54.46
Indonesia	239.87	274.37	5.22	4.58	6.10	1,144	3,880	7.90*	6.96	51.01	74.97
Jordan	6.05	15.32	6.14	2.33	3.11	2,534	5,157	12.90*	5.01	111.93	46.61
Lebanon	4.23	28.52	5.19	8.50	6.99	6,745	12,605	9.00***	3.99	32.14	32.93
Malaysia	28.40	146.94	4.63	-1.71	7.16	5,174	13,186	3.70*	1.71	172.64	76.23
Morocco	31.95	59.80	4.93	4.95	3.30	1,841	4,219	10.00*	0.99	75.83	44.36
Philippines	93.26	129.02	4.78	1.15	7.63	1,383	3,560	7.50*	3.81	78.82	57.37
Thailand	69.12	187.48	4.37	-2.33	7.80	2,712	7,672	1.20*	3.31	87.11	77.84
Tunisia	10.55	30.35	4.56	3.13	3.70	2,877	7,704	14.20**	4.42	24.12	46.48

Note: All data are 2010, except when *,**,*** which is latest available, 2009,2008 and 2007 respectively.

Source: IMF

Table 5(a). Descriptive Statistics.

Country	Mean (%)	Volatility (Annualised %)	Skewness	Excess Kurtosis	JB	Min	Max	Range	VaR 95%	EMH Tests VR(2)	Z
Group: Scandinavian											
Denmark	0.0040	21.51	-0.223	6.10	4,314***	-11.72	9.50	21.22	-8.15	-1.098	-1.079
Finland	-0.0280	28.87	-0.261	5.60	3,695***	-17.17	9.23	26.40	-11.27	-2.710***	-2.690***
Sweden	-0.0026	25.68	0.115	3.60	1,533***	-8.53	9.87	18.39	-7.60	0.120	0.101
Group: EU											
Austria	0.0230	24.14	-0.374	8.10	7,717***	-10.25	12.02	22.27	-9.33	-1.342	-1.322
Belgium	-0.0122	21.58	0.127	6.30	4,556***	-8.32	9.33	17.65	-7.51	-1.776*	-1.757*
France	-0.0226	24.88	0.037	5.30	3,278***	-9.47	10.59	20.07	-8.20	1.207	1.188
Germany	0.0426	8.95	-0.414	11.20	14,598***	-5.00	4.11	9.11	-4.29	-8.018***	-7.997***
Luxembourg	-0.0151	30.76	0.241	54.20	3,422***	-30.05	33.22	63.27	-16.46	-2.157***	-2.138**
Netherlands	-0.0287	25.65	-0.057	5.90	4,027***	-9.59	10.03	19.62	-8.99	-0.807	-0.788
UK	-0.0021	19.87	-0.209	6.20	4,482***	-8.71	8.81	17.52	-7.56	-0.772	-0.753
Group: PIIGS											
Portugal	-0.0027	17.27	-0.222	12.30	17,629***	-10.65	10.11	20.76	-7.33	-4.450***	-4.430***
Italy	-0.0370	23.98	-0.062	6.00	4,204***	-8.60	10.88	19.48	-7.83	0.816	0.796
Ireland	-0.0287	24.19	-0.587	7.50	6,747***	-13.96	9.73	23.70	-10.62	-3.304***	-3.284***
Greece	-0.0517	25.77	0.025	5.40	3,432***	-10.21	13.43	23.65	-8.36	-5.314***	-5.293***
Spain	-0.0027	24.21	0.129	6.30	4,631***	-9.59	13.48	23.07	-8.37	0.670	0.651

Note: *,**,*** denote the 10%, 5% and 1% significance level. Z is the z-statistic for the Runs-test.

Table 5(b). Descriptive Statistics.

Country	Mean (%)	Volatility (Annualised %)	Skewness	Excess Kurtosis	JB	Min	Max	Range	VaR 95%	EMH Tests AR(1)	Z
Group: Baltics											
Estonia	0.0487	19.21	0.116	8.00	7,497***	-7.05	12.09	19.14	-6.48	-7.391***	-7.371***
Latvia	0.0324	25.35	-0.697	14.50	2,459***	-14.71	10.18	24.89	-12.97	1.716*	1.697*
Lithuania	0.0467	19.31	-0.026	19.90	4,634***	-13.52	11.87	25.38	-10.02	-5.984***	-5.964***
Group: RAMS I											
Czech Republic	0.0251	24.30	-0.534	13.30	2,064***	-16.19	12.36	28.55	-12.49	-1.418	-1.399
Hungary	0.0261	26.13	-0.117	6.50	4,927***	-12.65	13.18	25.83	-10.59	-0.008	0.011
Poland	0.0277	21.11	-0.322	3.00	1,074***	-8.29	6.08	14.37	-7.10	0.415	0.396
Slovenia	0.0115	15.60	-0.512	9.60	1,084***	-8.24	7.54	15.78	-7.17	-7.760***	-7.741***
Group: RAMS II											
Bulgaria	0.0424	27.71	-0.604	28.60	9,527***	-20.90	21.07	41.97	-16.69	-5.757***	-5.737***
Cyprus	-0.0667	34.76	0.176	4.40	2,264***	-11.99	16.47	28.46	-10.79	-2.900***	-2.881***
Malta	-0.0026	12.07	0.319	8.10	7,630***	-4.74	6.10	10.83	-4.51	-9.817***	-9.796***
Romania	0.0735	27.82	-0.437	7.20	6,162***	-13.12	11.54	24.66	-11.86	-5.885***	-5.864***
Slovakia	0.0324	19.09	-1.074	19.70	4,577***	-14.81	11.88	26.69	-10.86	-2.552**	-2.533**

Note: *,**,*** denote the 10%, 5% and 1% significance level. Z is the z-statistic for the Runs-test.

Table 5(c). Descriptive Statistics.

Country	Mean (%)	Volatility (Annualised %)	Skewness	Excess Kurtosis	JB	Min	Max	Range	VaR 95%	EMH Tests AR(1)	Z
Group: Worldwide											
US	-0.0049	21.40	-0.195	8.40	8,278***	-9.47	10.96	20.43	-8.99	3.669***	3.649**
Euronext	-0.0190	23.04	-0.005	5.60	3,659***	-8.95	10.32	19.27	-7.74	-0.124	-0.105
VStox	0.0166	89.97	0.926	4.00	2,303***	-24.92	43.71	68.63	-21.01	-0.015	0.004
Vix	0.0125	98.64	0.709	5.00	3,178***	-35.06	49.60	84.66	-31.41	2.342**	2.322**
Group: BRICS											
Brazil	0.0421	29.94	-0.161	4.60	2,502***	-12.10	13.68	25.78	-10.63	0.705	0.493
Russia	0.0839	35.04	-0.488	10.70	13,551***	-21.20	20.20	41.40	-15.90	-3.446***	-3.426*
India	0.0513	26.09	-0.328	7.40	6,375***	-11.94	15.49	27.43	-10.60	-3.145***	-3.125***
China	0.0042	26.07	-0.127	4.30	2,155***	-9.26	9.40	18.66	-8.48	-2.378**	-2.359**
South Africa	0.0483	20.80	-0.108	3.30	1,249***	-7.58	6.83	14.41	-6.98	-1.636	-1.616
Group: GCC											
Bahrain	0.0044	14.58	-1.467	18.10	39,287***	-11.71	5.00	16.71	-8.30	-1.445	-1.425
Kuwait	0.0367	16.33	-0.603	6.09	4,5051***	-7.52	5.88	13.40	-6.29	-4.656***	-4.712***
Oman	0.0371	17.49	-0.746	19.90	46,366***	-11.01	9.90	20.91	-9.17	-7.734***	-7.713***
Qatar	0.0688	23.44	-0.417	7.12	6,006***	-9.36	9.42	18.78	-9.08	-12.327***	-12.227***
Saudi Arabia	0.0357	26.97	-0.566	10.90	13,920***	-11.68	16.40	28.08	-10.59	-4.902***	-4.882***

Note: *,**,*** denote the 10%, 5% and 1% significance level. Z is the z-statistic for the Runs-test.

Table 5(d). Descriptive Statistics.

Country	Mean	Volatility	Skewness	Excess	JB	Min	Max	Range	VaR 95%	EMH Tests	
	(%)	(Annualised %)		Kurtosis						AR(1)	Z
Group: Asia & Africa Developed											
Hong Kong	0.0078	25.06	-0.001	9.20	9,797***	-13.58	13.41	26.99	-10.34	0.522	0.503
Japan	-0.0168	25.04	-0.404	7.40	6,392***	-12.11	13.23	25.35	-10.91	0.827	0.807
Korea (South)	0.0430	25.63	-0.528	5.50	3,706***	-12.80	11.28	24.09	-10.78	-0.802	-0.782
Singapore	0.0103	19.49	-0.259	4.90	2,812***	-8.40	7.28	15.67	-7.55	0.249	0.229
Taiwan	0.0132	23.05	-0.188	2.30	648.02***	-6.91	6.52	13.44	-6.48	-1.753	-1.734*
Group: Asia & Africa Developing											
Egypt	0.0626	25.99	-0.691	11.30	15,184***	-17.20	13.70	30.90	-12.78	-4.884***	-4.865***
Indonesia	0.0767	23.28	-0.712	6.90	5,858***	-10.95	7.62	18.58	-10.43	-3.982***	-3.962***
Jordan	0.0440	18.54	-0.305	5.60	3,708***	-8.85	6.82	15.67	-7.31	-2.337**	-2.288**
Lebanon	0.0272	19.87	0.084	11.29	1,488***	-10.69	8.49	19.18	-9.64	-4.713***	-4.784***
Malaysia	0.0261	13.47	-1.023	11.90	17,040***	-9.98	4.50	14.48	-7.02	-3.055***	-3.035***
Morocco	0.0241	15.32	-0.116	4.50	2,404***	-5.88	5.16	11.04	-5.47	-7.514***	-7.493***
Philippines	0.0337	21.46	0.074	13.60	21,651***	-13.09	16.18	29.27	-9.45	-4.421***	-4.401***
Thailand	0.0446	22.47	-0.815	11.30	15,099***	-16.06	10.58	26.64	-11.68	-0.593	-0.574
Tunisia	0.0426	8.95	-0.414	11.20	14,598***	-5.00	4.11	9.11	-4.28	-8.018***	-7.997***

Note: *,**,*** denote the 10%, 5% and 1% significance level. Z is the z-statistic for the Runs-test.

Table 6. Descriptive Statistics for Country Groups.

Country Groups	Mean (%)	Volatility (Annualised)	VaR 95%
Scandinavian	-0.0089	25.35	-11.27
Core EU	-0.0022	22.26	-16.46
PIIGS	-0.0246	23.08	-10.62
Baltics	0.0426	21.29	-12.97
RAMS I	0.0226	21.79	-12.49
RAMS II	0.0158	24.29	-16.69
Worldwide			
US & Euronext	-0.0120	22.22	-8.99
Vix & VStoxx	0.0146	94.31	-31.41
BRICS	0.0460	27.59	-15.90
GCC	0.0365	19.76	-10.59
Asia & Africa Developed	0.0115	23.65	-10.91
Asia & Africa Developing	0.0424	18.88	-12.78

Note: VaR is not subadditive, hence the worst case is reported here

Figure 3(a). Price Graphs / Scandinavian.

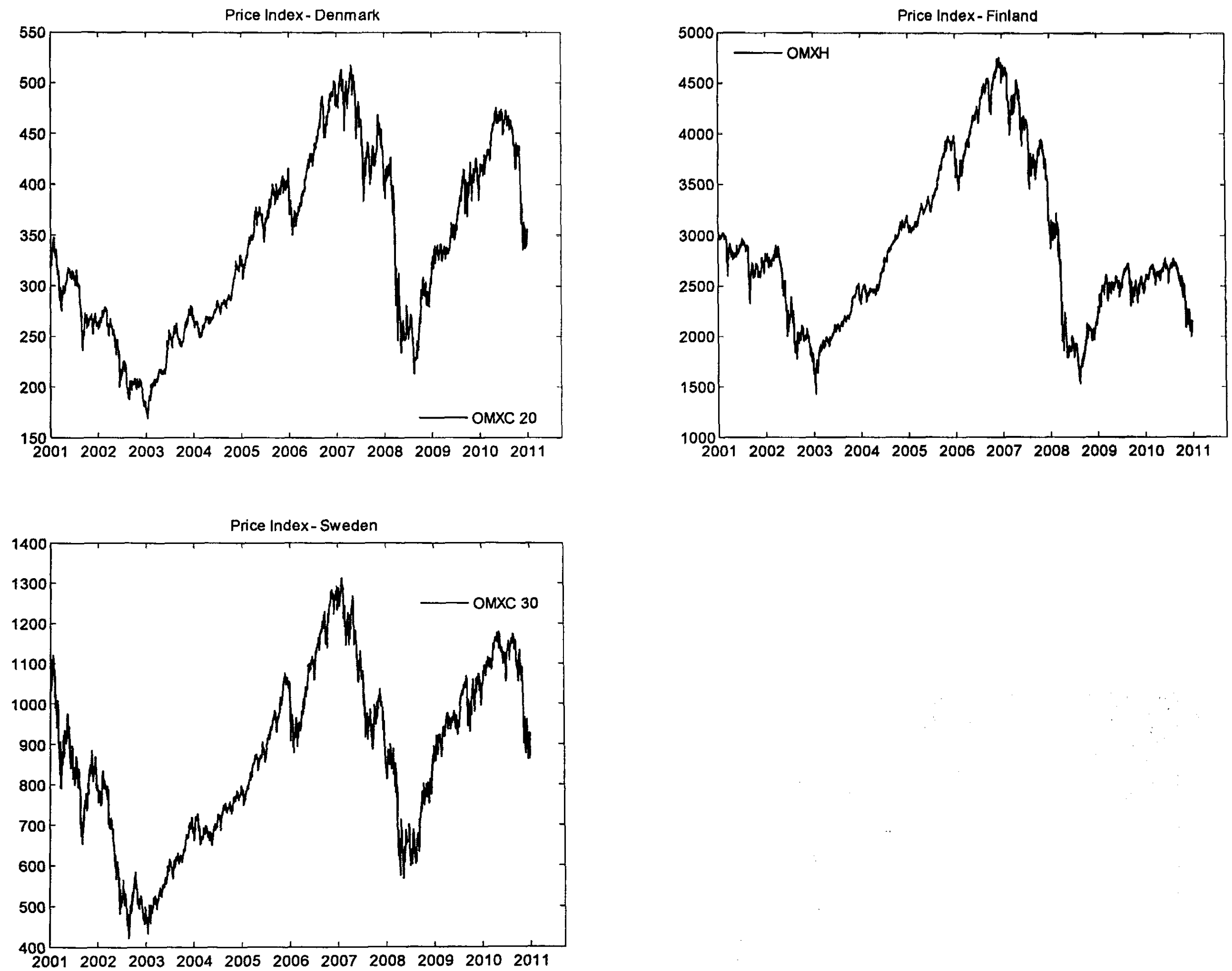


Figure 3(b). Price Graphs / Core EU.

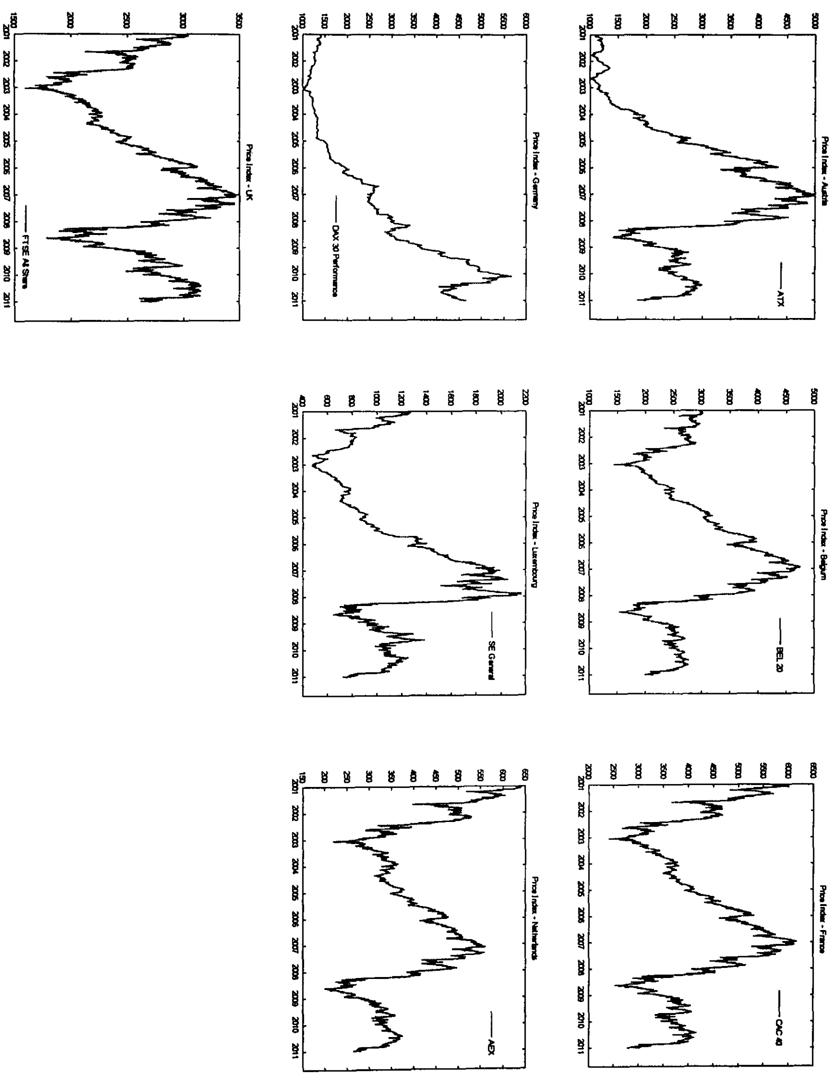


Figure 3(c). Price Graphs / PIIGS.

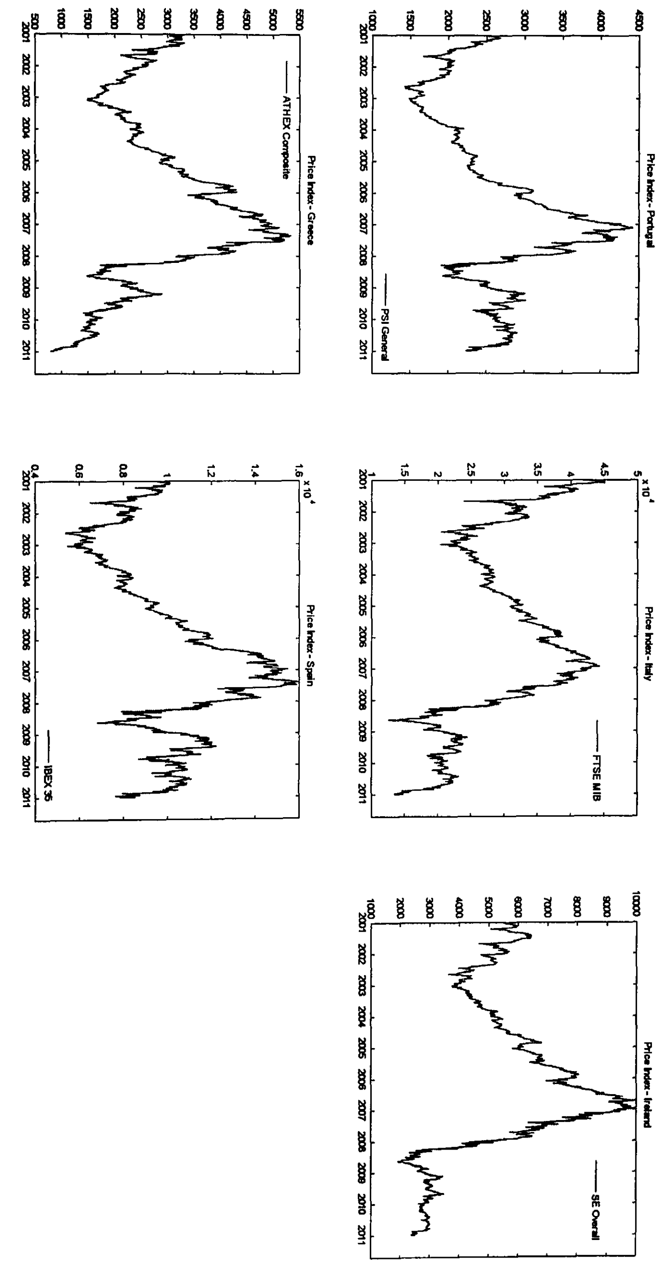


Figure 3(d). Price Graphs / Baltics.

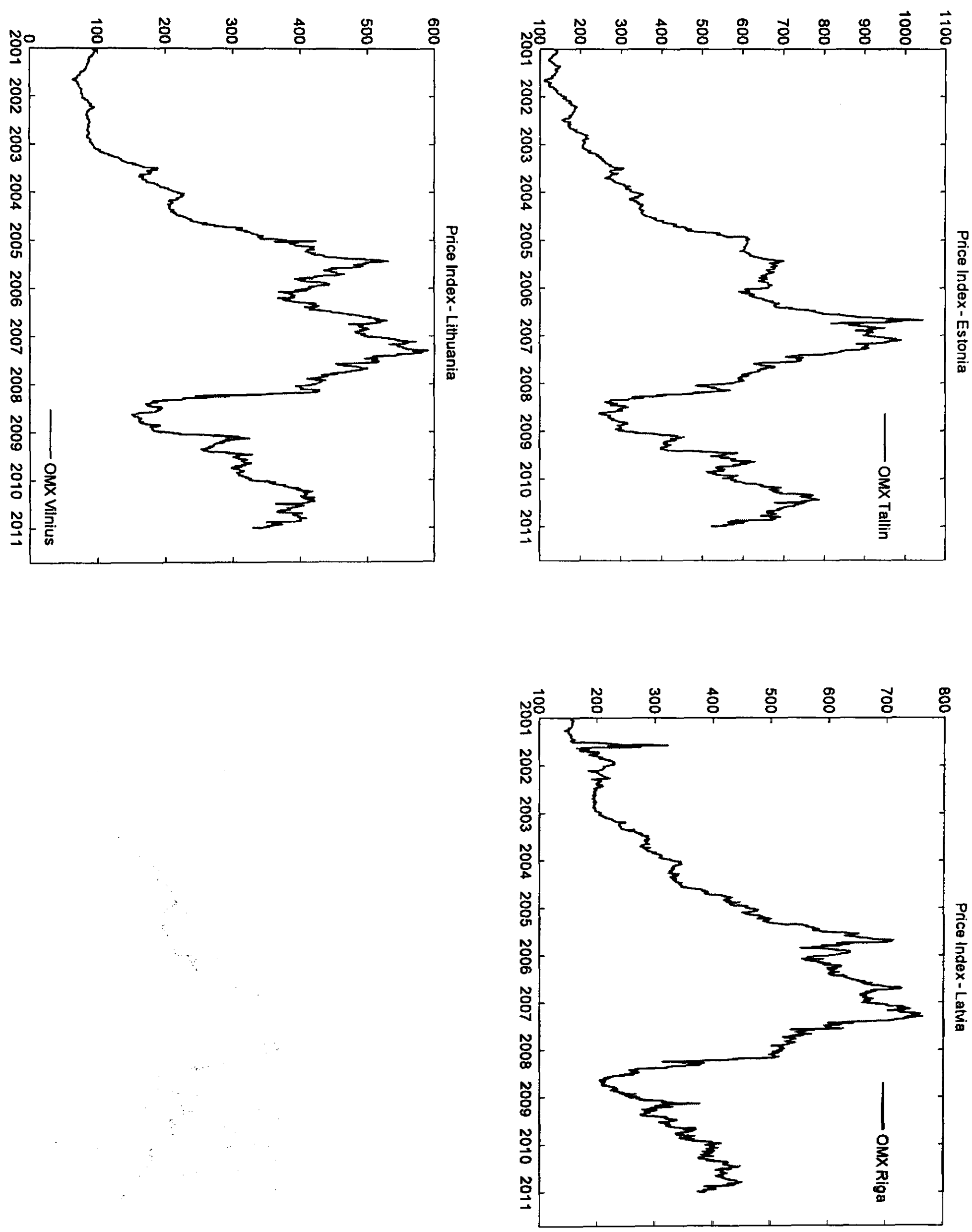


Figure 3(e). Price Graphs / RAMS I.

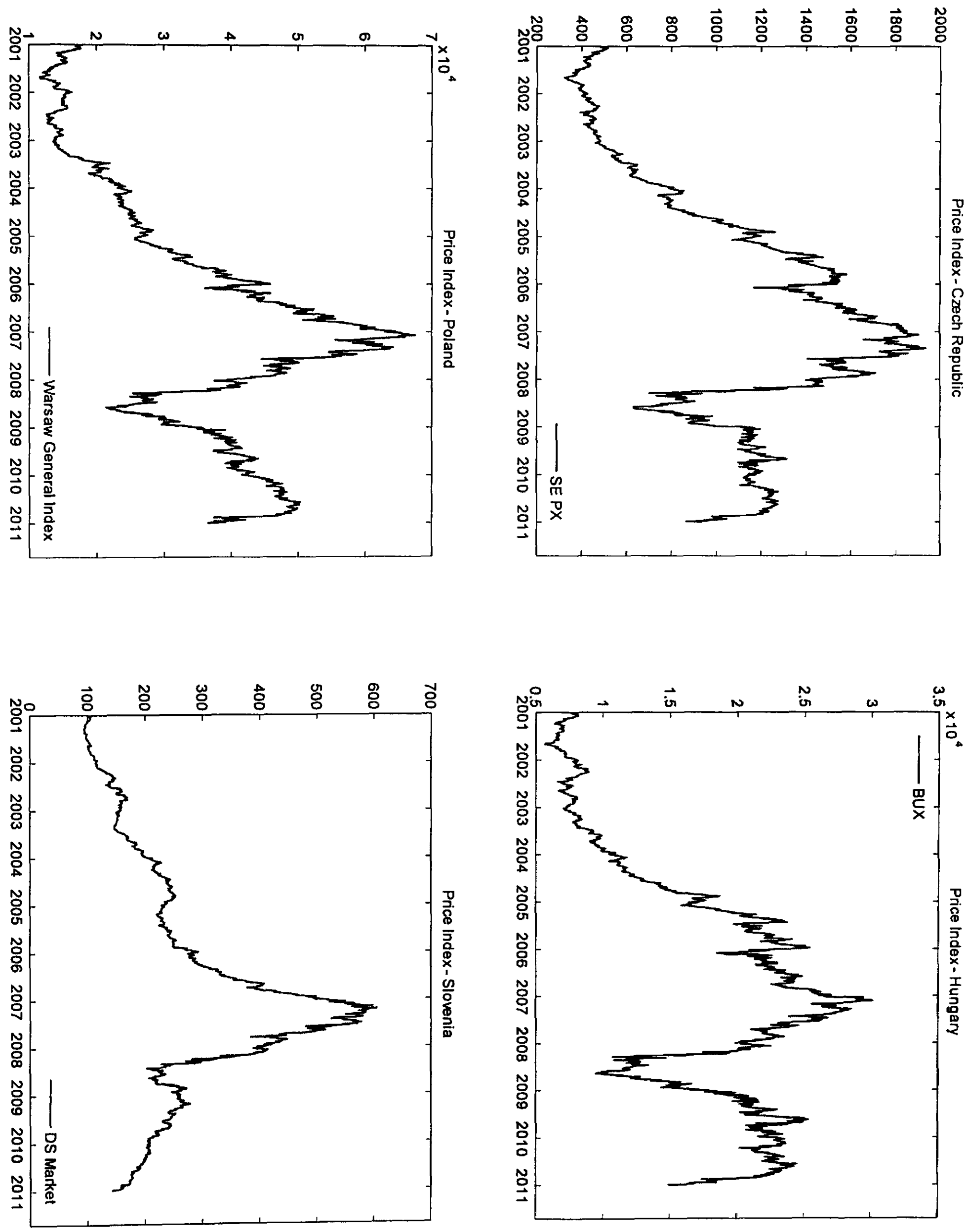


Figure 3(f). Price Graphs / RAMS II.

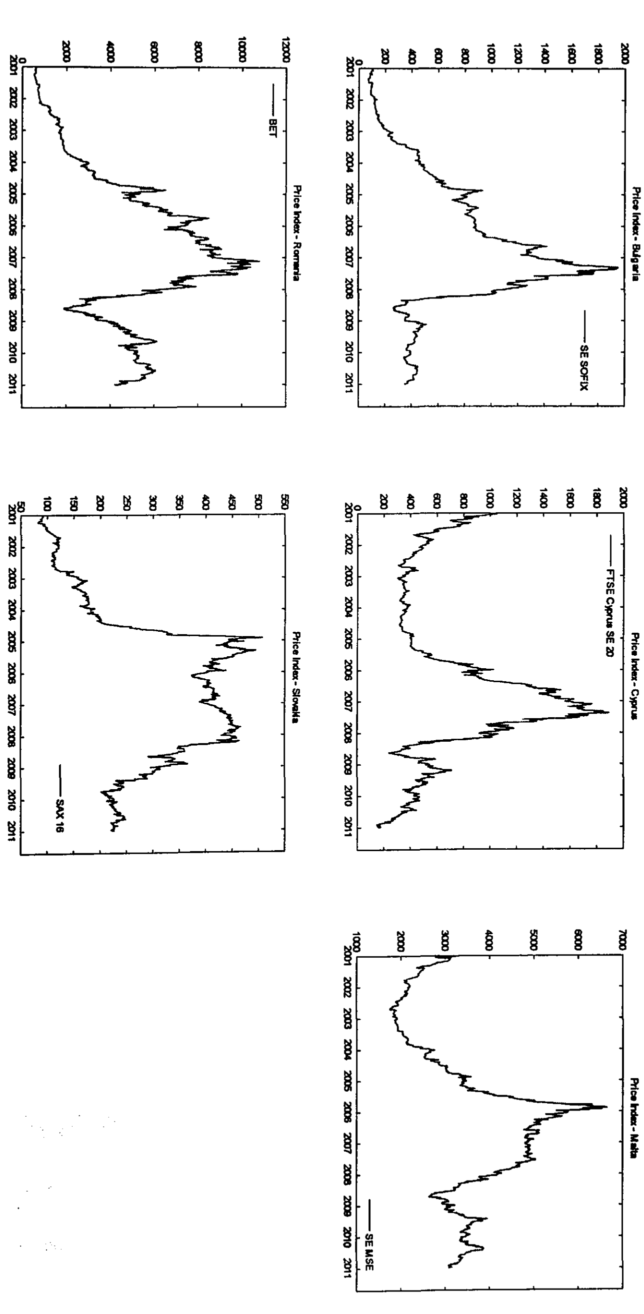


Figure 3(g). Price Graphs / WorldWide.

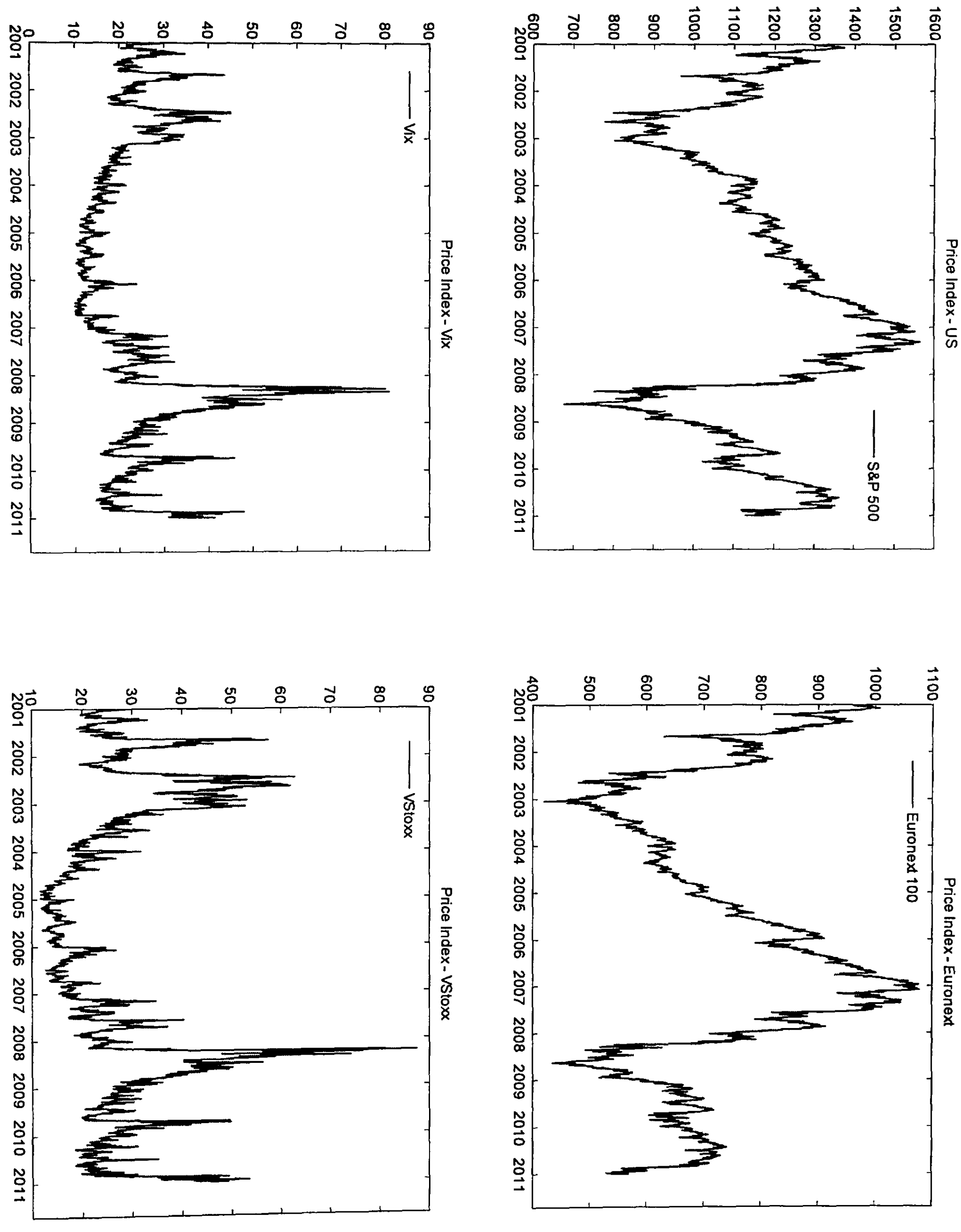


Figure 3(h). Price Graphs / BRICS.

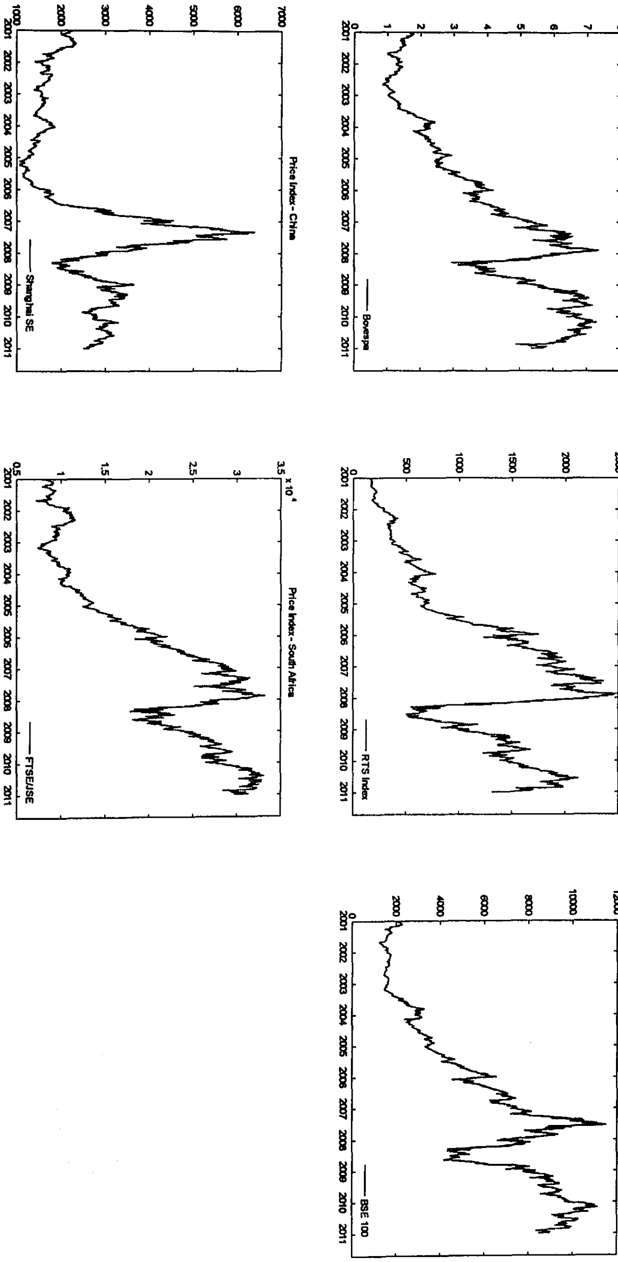
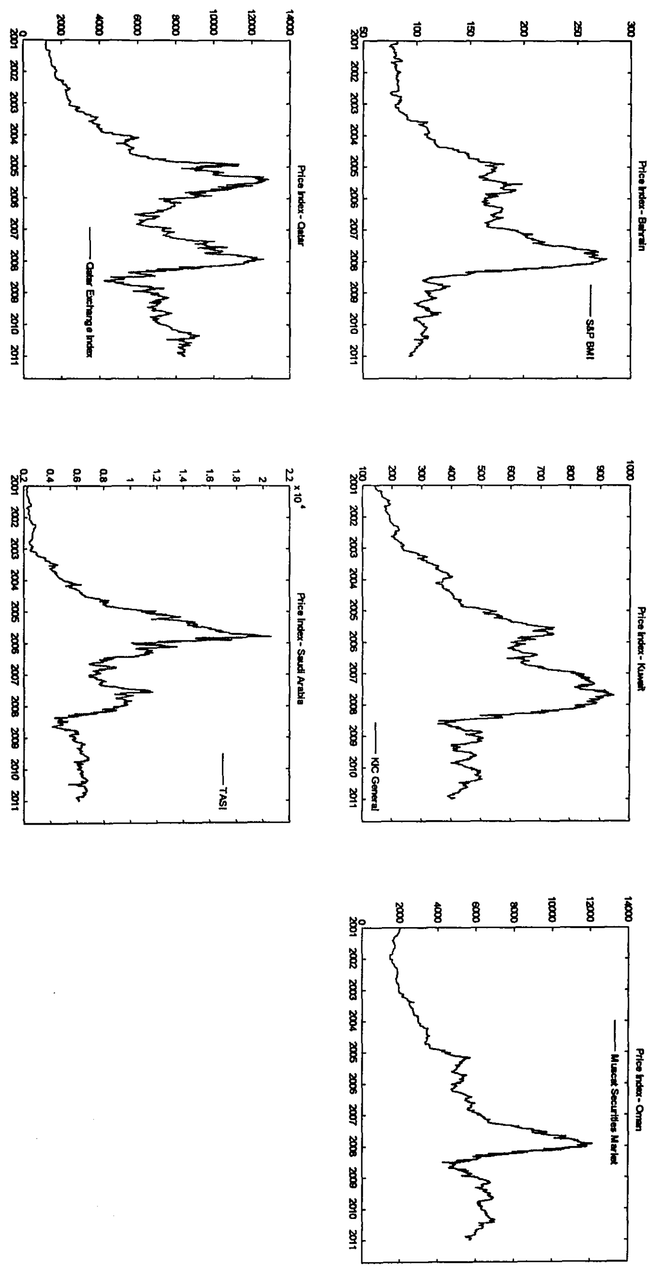


Figure 3(i). Price Graphs / GCC.



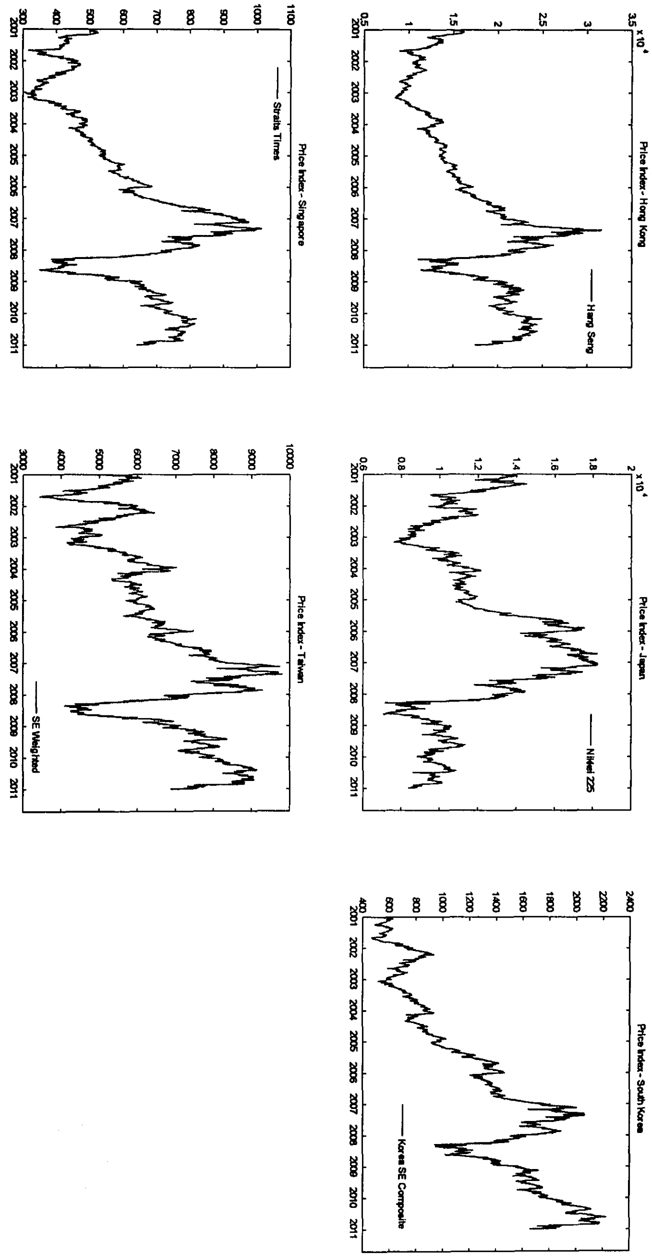


Figure 3(j). Price Graphs / Asia & Africa Developed.

Figure 3(k). Price Graphs / Asia & Africa Developing.

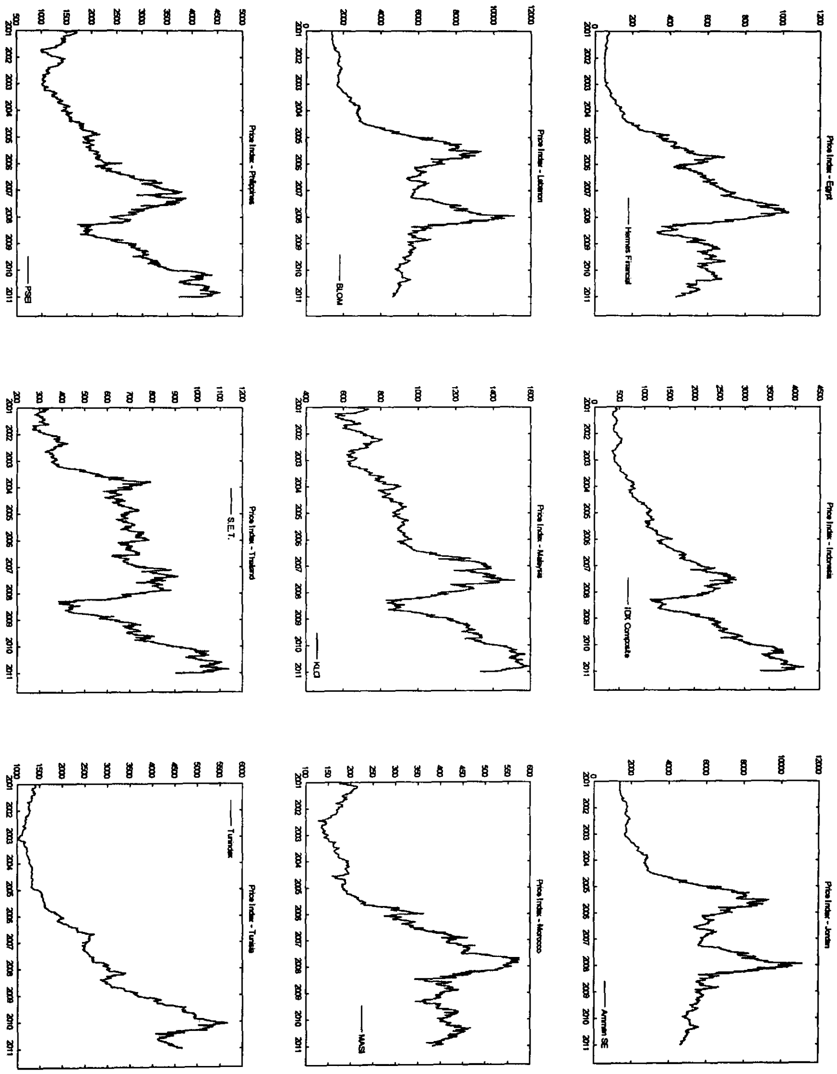


Table 7(a). DCC Garch Models Estimation (Country Groups: Scandinavian, Core EU).

	Scandinavian			Core EU						
	Denmark	**Finland**	**Sweden**	**Austria**	**Belgium**	**France**	**Germany**	**Luxembourg**	**Netherlands**	**UK**
					Mean Equation					
μ	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000
	(0.001)	*(0.035)*	*(0.004)*	*(0.000)*	*(0.000)*	*(0.011)*	*(0.000)*	*(0.005)*	*(0.016)*	*(0.003)*
$AR(1)$	0.023	0.029	-0.022	0.040	0.019	-0.042	0.242	0.013	-0.003	-0.036
	(0.268)	*(0.162)*	*(0.269)*	*(0.059)*	*(0.365)*	*(0.028)*	*(0.000)*	*(0.621)*	*(0.861)*	*(0.068)*
					Variance Equation					
ω	0.030	0.009	0.020	0.025	0.024	0.020	1.078	0.048	0.019	0.012
	(0.009)	*(0.137)*	*(0.006)*	*(0.001)*	*(0.001)*	*(0.003)*	*(0.004)*	*(0.005)*	*(0.001)*	*(0.002)*
α	0.090	0.050	0.085	0.121	0.146	0.104	0.147	0.263	0.115	0.117
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*
β	0.892	0.949	0.909	0.870	0.846	0.891	0.818	0.763	0.880	0.880
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LogLikelihood	8,543	7,752	8,055	8,500	8,758	8,250	11,116	8,026	8,338	8,966
Obs	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799

Note: Table reports estimated coefficients and p-values are given in brackets

Table 7(b). DCC Garch Models Estimation (Country Groups: PIIGS, Baltics).

	PIIGS					Baltics		
	Portugal	**Italy**	**Ireland**	**Greece**	**Spain**	**Estonia**	**Latvia**	**Lithuania**
			Mean Equation					
μ	0.001	0.000	0.001	0.001	0.001	0.000	0.001	0.001
	(0.000)	*(0.092)*	*(0.000)*	*(0.017)*	*(0.001)*	*(0.030)*	*(0.000)*	*(0.000)*
$AR(1)$	0.069	-0.027	0.035	0.061	-0.007	0.197	-0.067	0.151
	(0.001)	*(0.177)*	*(0.096)*	*(0.004)*	*(0.746)*	*(0.000)*	*(0.005)*	*(0.000)*
			Variance Equation					
ω	0.012	0.015	0.028	0.017	0.022	0.016	0.066	0.069
	(0.005)	*(0.006)*	*(0.015)*	*(0.031)*	*(0.006)*	*(0.048)*	*(0.005)*	*(0.060)*
α	0.144	0.102	0.122	0.087	0.112	0.142	0.153	0.200
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
β	0.854	0.895	0.870	0.910	0.882	0.867	0.824	0.764
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LogLikelihood	9,409	8,433	8,412	8,031	8,309	8,870	8,401	9,001
Obs	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799

Note: Table reports estimated coefficients and p-values are given in brackets

Table 7(c). DCC Garch Models Estimation (Country Groups: RAMS I, II).

	RAMS I				RAMS II				
	Czech	**Hungary**	**Poland**	**Slovenia**	**Bulgaria**	**Cyprus**	**Malta**	**Romania**	**Slovakia**
				Mean Equation					
μ	0.001	0.001	0.001	0.000	0.001	0.000	-0.000	0.001	0.000
	(0.000)	*(0.003)*	*(0.001)*	*(0.016)*	*(0.005)*	*(0.384)*	*(0.101)*	*(0.000)*	*(0.197)*
$AR(1)$	0.035	0.013	0.067	0.173	0.126	0.059	0.259	0.113	-0.018
	(0.091)	*(0.524)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.004)*	*(0.000)*	*(0.000)*	*(0.472)*
				Variance Equation					
ω	0.044	0.062	0.016	2.922	0.019	0.033	0.000	0.138	0.006
	(0.000)	*(0.000)*	*(0.007)*	*(0.232)*	*(0.190)*	*(0.021)*	*(0.000)*	*(0.006)*	*(0.780)*
α	0.131	0.097	0.064	0.153	0.181	0.099	0.207	0.202	0.025
	(0.000)	*(0.000)*	*(0.000)*	*(0.054)*	*(0.006)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.520)*
β	0.852	0.879	0.929	0.817	0.846	0.901	0.611	0.761	0.972
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LogLikelihood	8,347	7,902	8,407	9,600	8,270	7,196	10,034	7,869	8,561
Obs	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799

Note: Table reports estimated coefficients and p-values are given in brackets

Table 7(d). DCC Garch Models Estimation (Country Group: WorldWide).

	WorldWide			
	S&P 500	**Euronext 100**	**Vix**	**VStoxx**
		Mean Equation		
μ	0.000	0.001	-0.001	-0.000
	(0.015)	*(0.003)*	*(0.442)*	*(0.710)*
$AR(1)$	-0.064	-0.023	-0.076	-0.031
	(0.001)	*(0.225)*	*(0.000)*	*(0.142)*
		Variance Equation		
ω	0.013	0.018	1.955	1.977
	(0.012)	*(0.002)*	*(0.001)*	*(0.000)*
α	0.080	0.112	0.088	0.082
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
β	0.912	0.883	0.861	0.856
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
LogLikelihood	8,800	8,516	4,011	4,202
Obs	2,799	2,799	2,799	2,799

Note: Table reports estimated coefficients and p-values are given in brackets

Table 7(e). DCC Garch Models Estimation (Country Group: BRICS, GCC).

	BRICS					GCC				
	Brazil	**Russia**	**India**	**China**	**S.Africa**	**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**S.Arabia**
					Mean Equation					
μ	0.001	0.002	0.001	0.000	0.001	0.000	0.001	0.001	-0.004	0.001
	(0.005)	*(0.000)*	*(0.000)*	*(0.671)*	*(0.000)*	*(0.010)*	*(0.001)*	*(0.004)*	*(0.862)*	*(0.000)*
$AR(1)$	-0.003	0.093	0.094	0.001	0.062	0.068	0.293	0.156	0.025	0.065
	(0.862)	*(0.000)*	*(0.000)*	*(0.964)*	*(0.001)*	*(0.003)*	*(0.058)*	*(0.000)*	*(0.948)*	*(0.003)*
					Variance Equation					
ω	0.071	0.116	0.060	0.035	0.029	0.000	0.085	0.063	0.016	0.038
	(0.006)	*(0.000)*	*(0.000)*	*(0.019)*	*(0.000)*	*(0.016)*	*(0.072)*	*(0.049)*	*(0.000)*	*(0.017)*
α	0.071	0.102	0.138	0.076	0.099	0.068	0.044	0.120	0.154	0.147
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.041)*	*(0.000)*	*(0.266)*	*(0.000)*
β	0.908	0.870	0.844	0.914	0.885	0.912	0.899	0.815	-0.008	0.852
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.203)*	*(0.000)*
LogLikelihood	7,434	7,249	8,020	7,817	8,536	9,562	7,976	9,372	2,747	8,279
Obs	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799

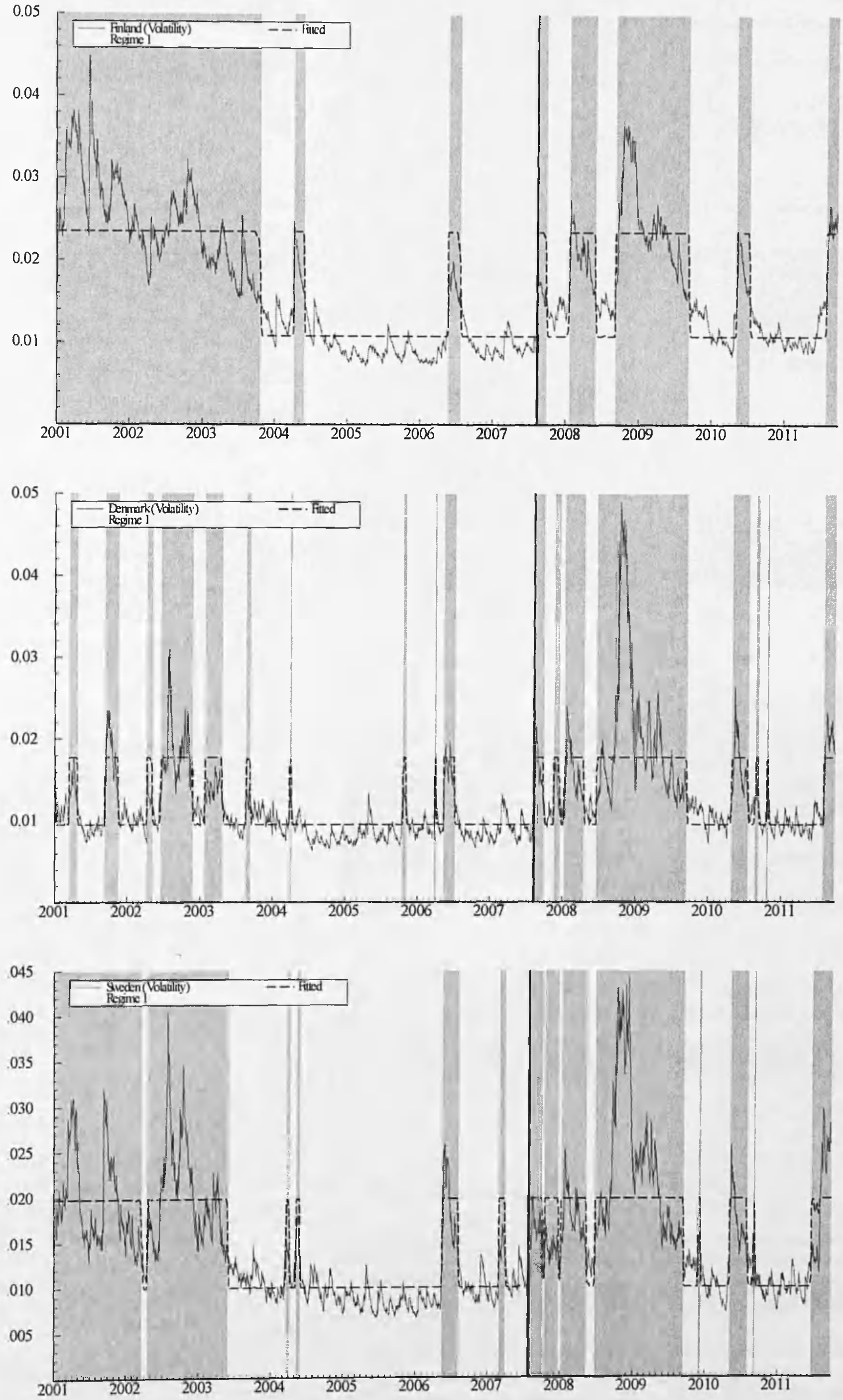
Note: Table reports estimated coefficients and p-values are given in brackets

Table 7(f). DCC Garch Models Estimation (Country Group: Africa & Asia).

	Africa & Asia Developed					Africa & Asia Developing								
	Hong Kong	**Japan**	**Korea**	**Singapore**	**Taiwan**	**Egypt**	**Indonesia**	**Jordan**	**Lebanon**	**Malaysia**	**Morocco**	**Philippines**	**Thailand**	**Tunisia**
							Mean Equation							
μ	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.000	-0.001	0.001	0.000	0.001	0.001	0.000
	(0.034)	*(0.084)*	*(0.000)*	*(0.001)*	*(0.016)*	*(0.000)*	*(0.000)*	*(0.331)*	*(0.101)*	*(0.000)*	*(0.211)*	*(0.013)*	*(0.000)*	*(0.000)*
$AR(1)$	0.022	-0.016	0.023	0.015	0.058	0.162	0.113	0.022	0.130	0.164	0.226	0.152	0.057	0.242
	(0.254)	*(0.412)*	*(0.253)*	*(0.475)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.546)*	*(0.090)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.007)*	*(0.000)*
							Variance Equation							
ω	0.014	0.034	0.023	0.016	0.018	0.118	0.084	0.037	0.024	0.000	0.000	0.101	0.161	0.000
	(0.007)	*(0.002)*	*(0.006)*	*(0.003)*	*(0.012)*	*(0.091)*	*(0.028)*	*(0.452)*	*(0.418)*	*(0.026)*	*(0.136)*	*(0.002)*	*(0.154)*	*(0.004)*
α	0.067	0.105	0.077	0.104	0.067	0.107	0.107	0.131	0.249	0.123	0.146	0.140	0.094	0.147
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.261)*	*(0.002)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.000)*
β	0.928	0.885	0.917	0.889	0.926	0.852	0.856	0.862	0.841	0.863	0.805	0.808	0.822	0.818
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LogLikelihood	8,242	8,057	7,934	8,816	8,176	7,843	8,139	8,705	8,340	9,796	9,371	8,374	8,164	11,116
Obs	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799	2,799

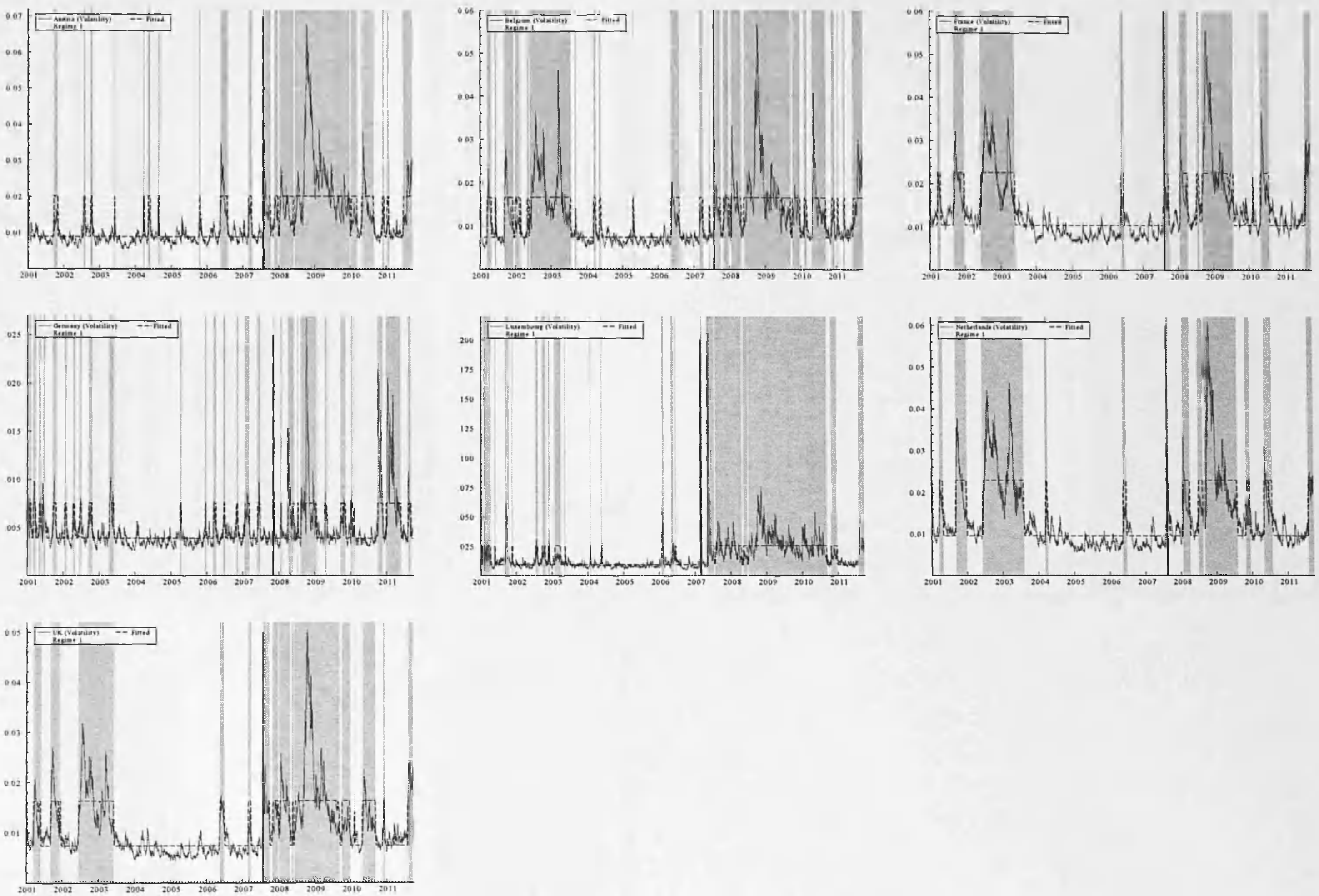
Note: Table reports estimated coefficients and p-values are given in brackets

Figure 4(a). MS Crisis Regime Identification / Scandinavian.



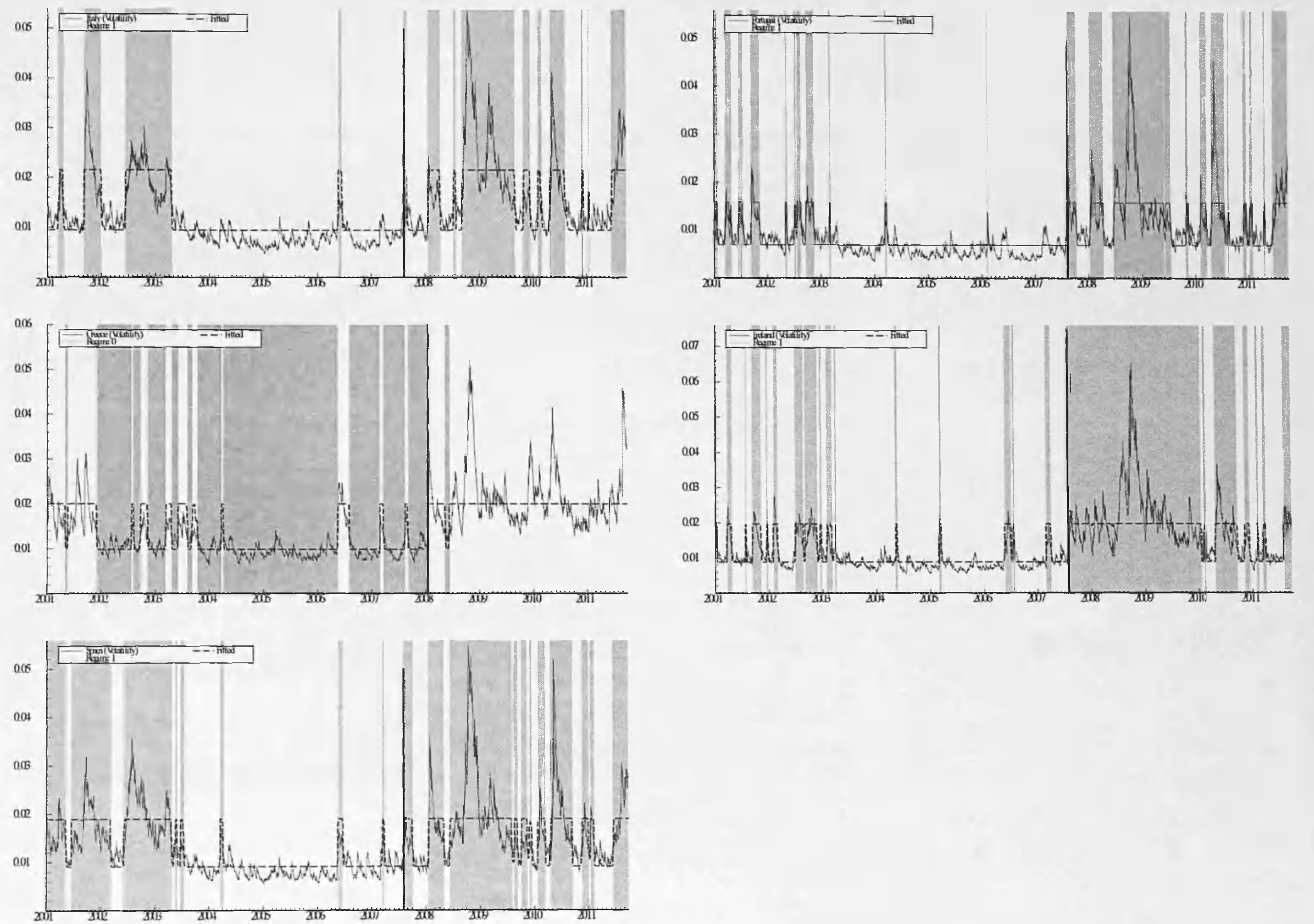
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Finland: 10/08/2007; Denmark: 13/08/2007; Sweden: 27/07/2007

Figure 4(b). MS Crisis Regime Identification / Core EU.



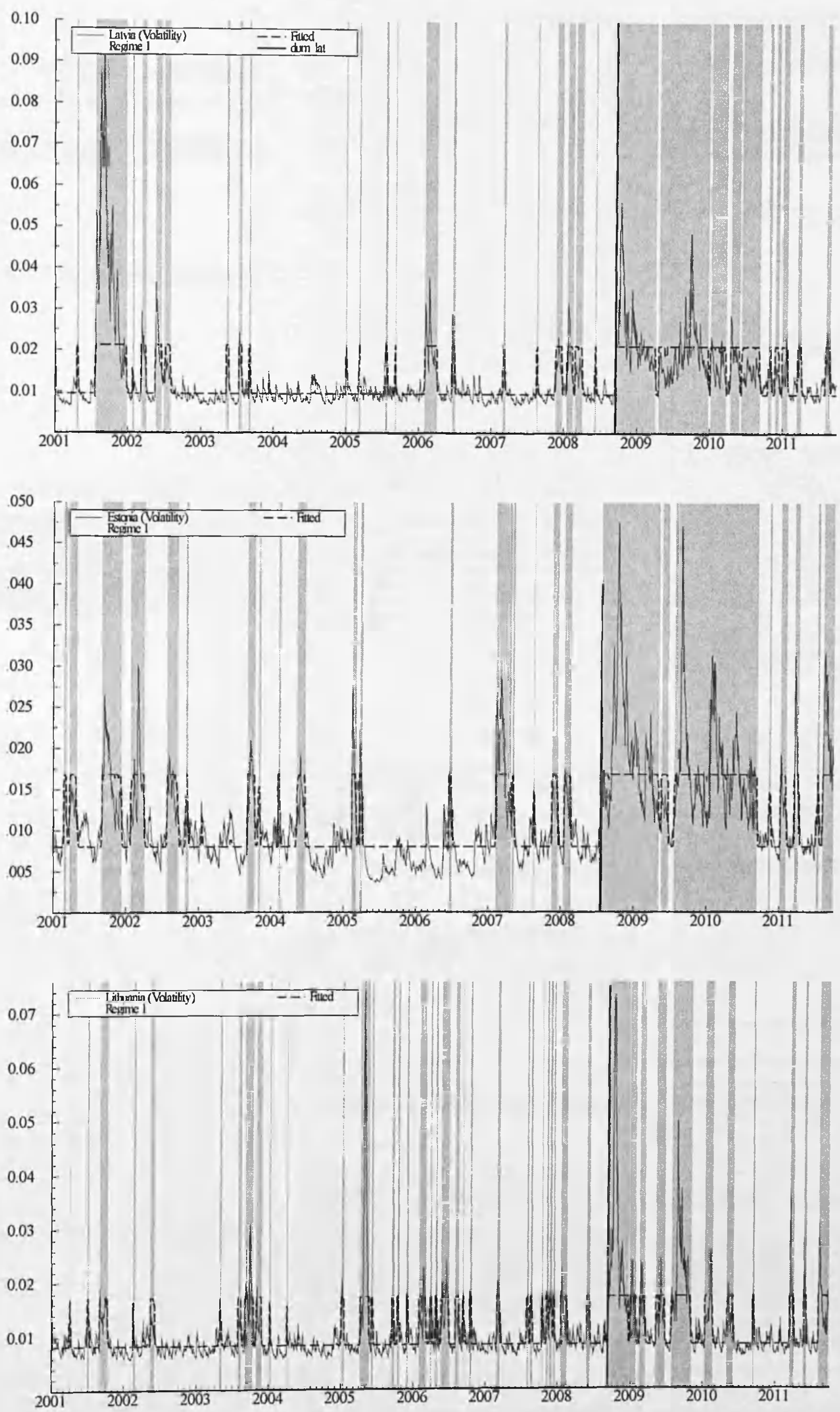
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Austria: 27/07/2007; Belgium: 26/07/2007; France: 09/08/2007; Germany: 06/11/2007; Luxembourg: 01/03/2007 Netherlands: 10/08/2007; UK: 26/07/2007

Figure 4(c). MS Crisis Regime Identification / PIIGS.



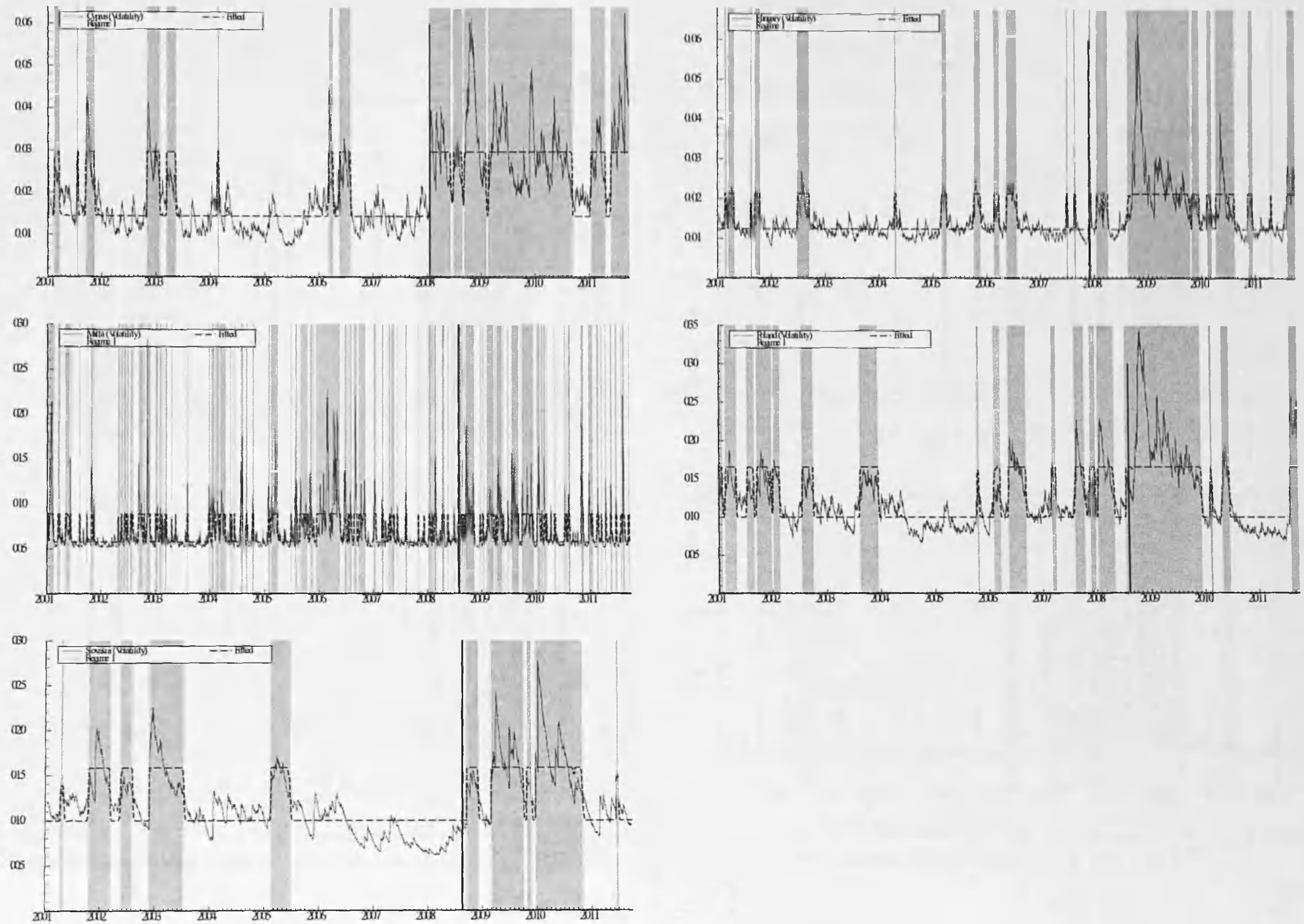
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Italy: 10/08/2007; Portugal: 10/08/2007; Greece: 16/01/2008; Ireland: 27/07/2007; Spain: 02/08/2007

Figure 4(d). MS Crisis Regime Identification / Baltics.



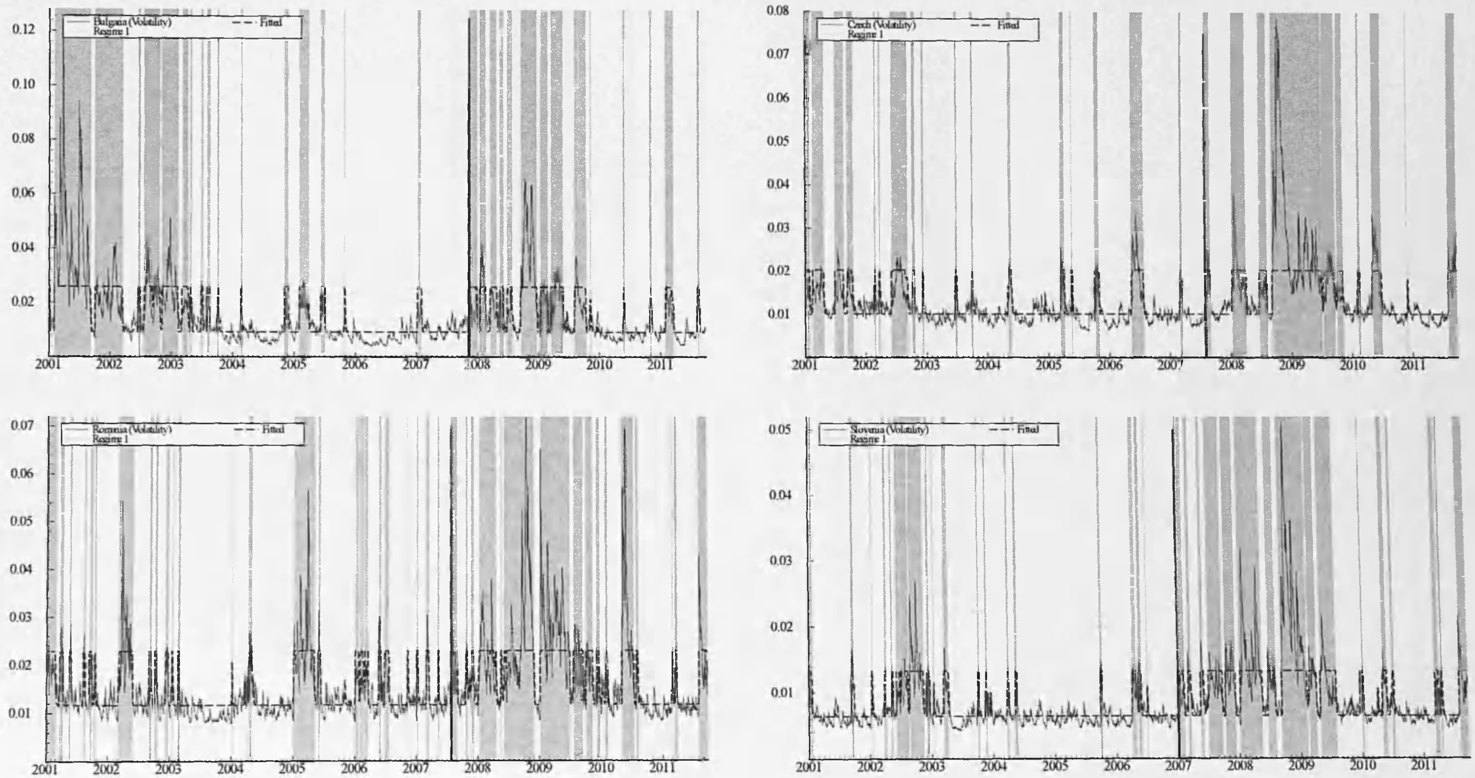
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Finland: 10/08/2007; Denmark: 13/08/2007; Sweden: 27/07/2007

Figure 4(e). MS Crisis Regime Identification / RAMS I.



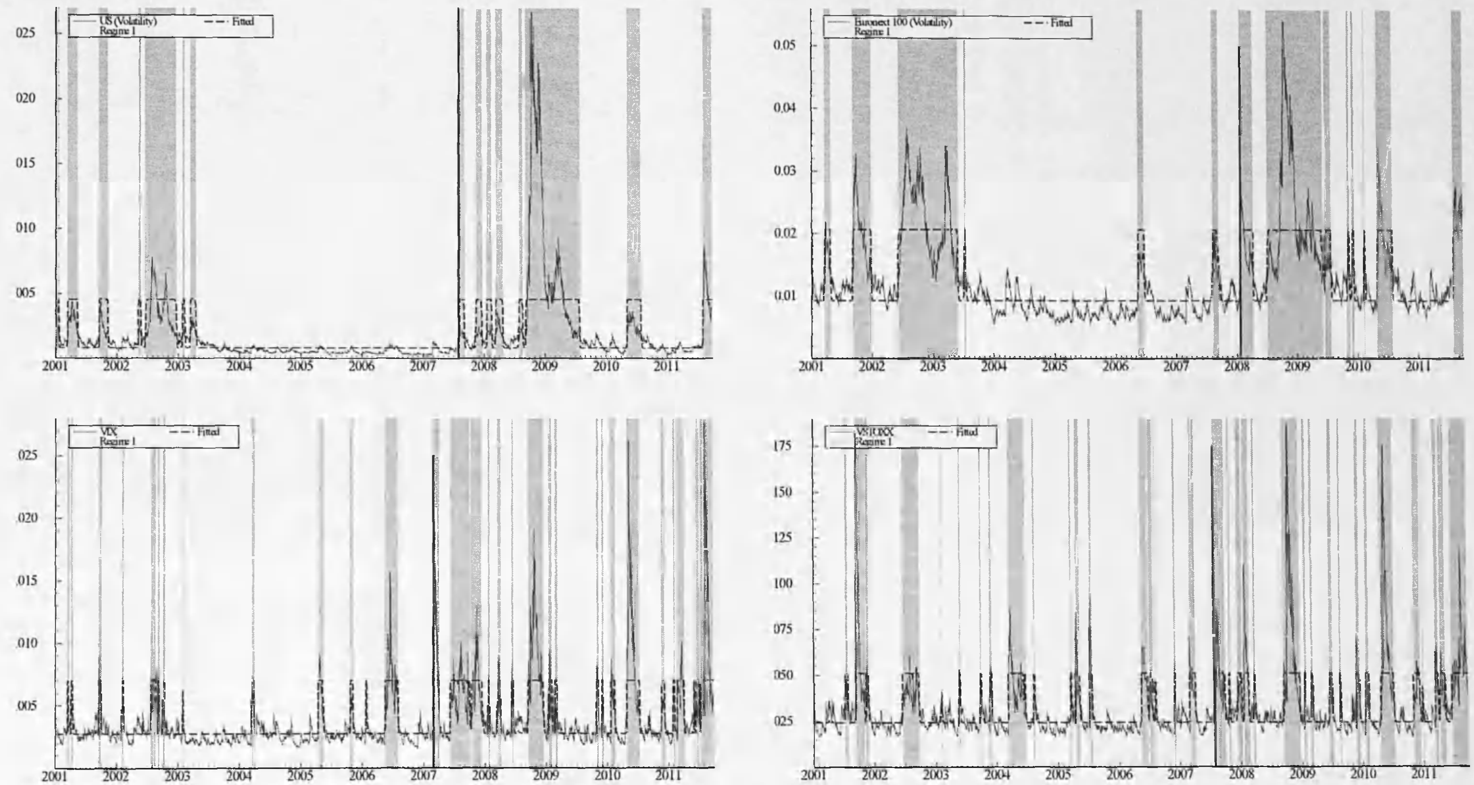
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Cyprus: 17/01/2008; Hungary: 28/11/2007; Malta: 29/07/2008; Poland: 06/08/2007; Slovakia: 18/09/2008

Figure 4(f). MS Crisis Regime Identification / RAMS II.



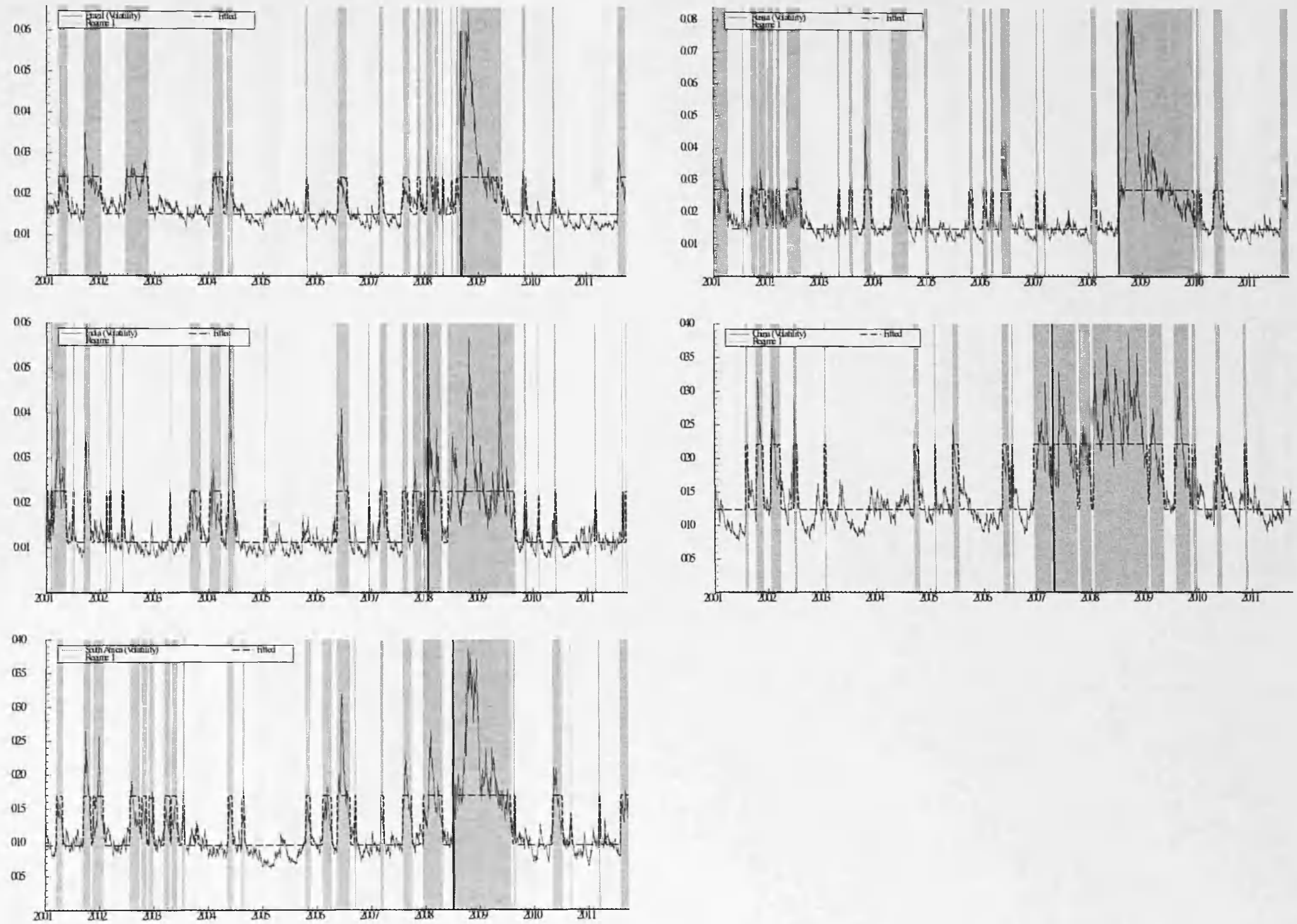
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Bulgaria: 12/11/2007; Czech Republic: 01/08/2007; Romania: 26/07/2008; Slovenia: 04/01/2007

Figure 4(g). MS Crisis Regime Identification / WorldWide.



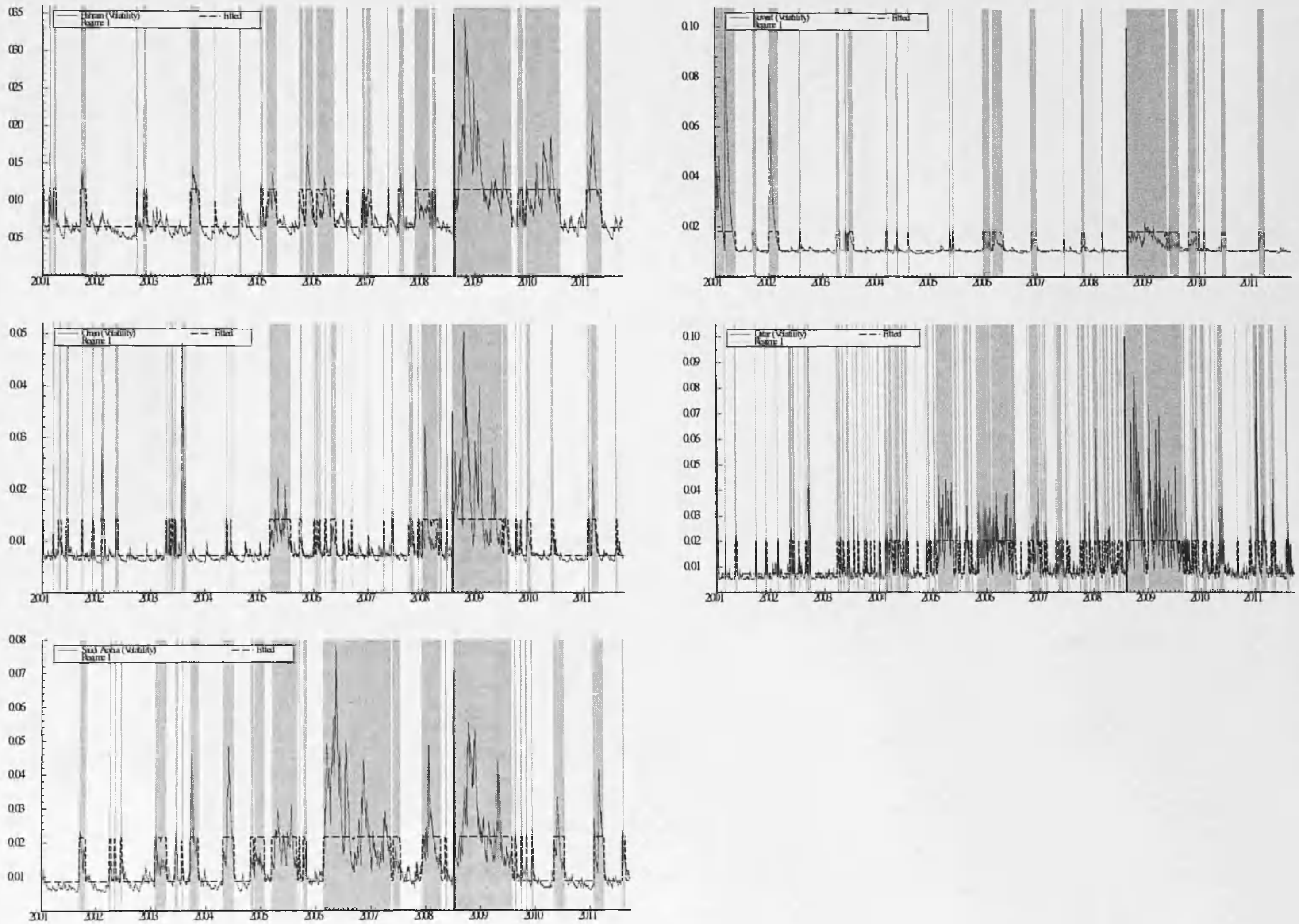
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: US: 12/11/2007; Euronext: 01/08/2007; VIX: 26/07/2008; VSTOXX: 04/01/2007

Figure 4(h). MS Crisis Regime Identification / BRICS.



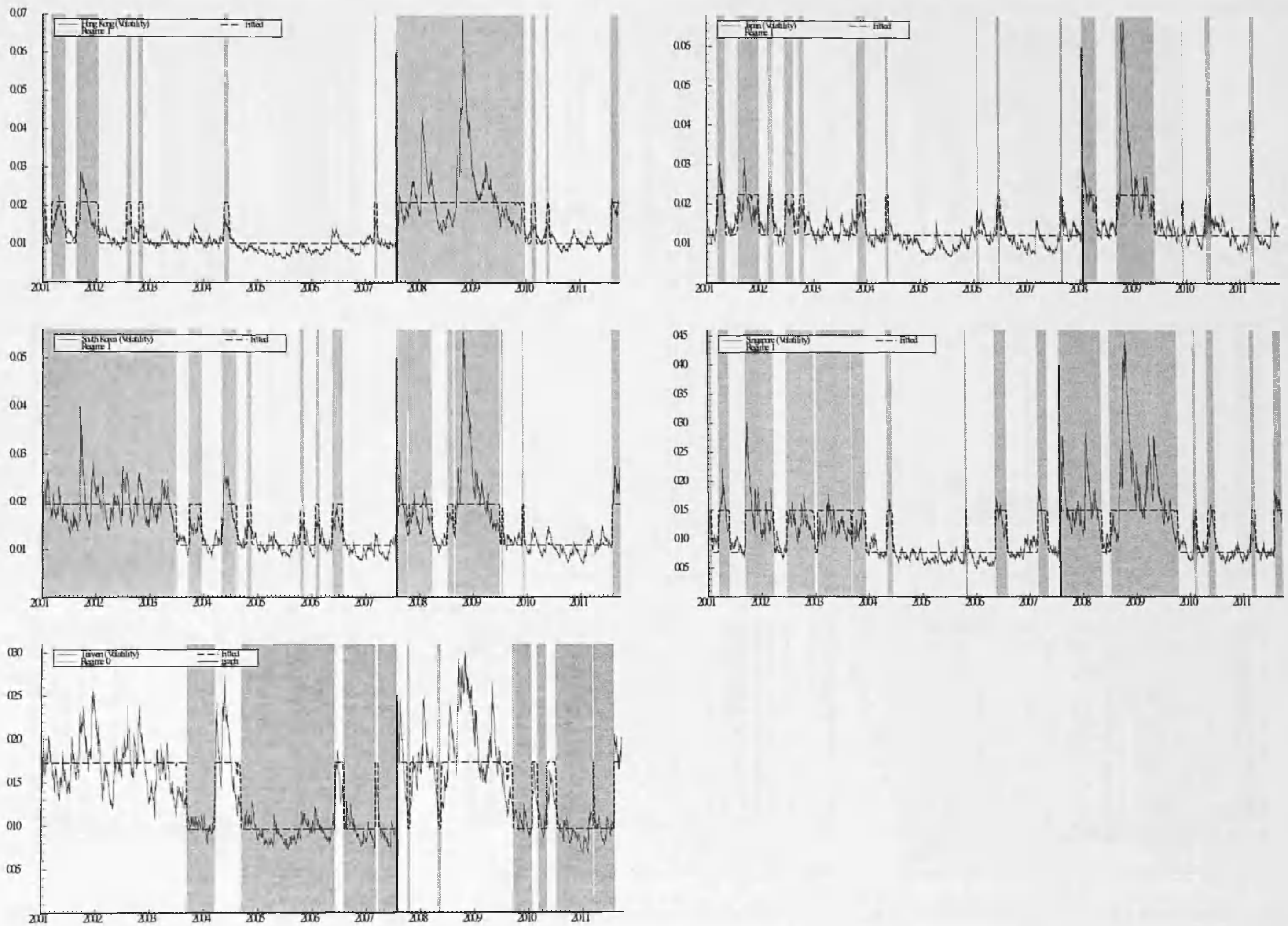
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Brazil: 05/09/2008; Russia: 24/07/2008; India: 21/01/2008; China: 20/04/2007; South Africa: 03/07/2008

Figure 4(i). MS Crisis Regime Identification / GCC.



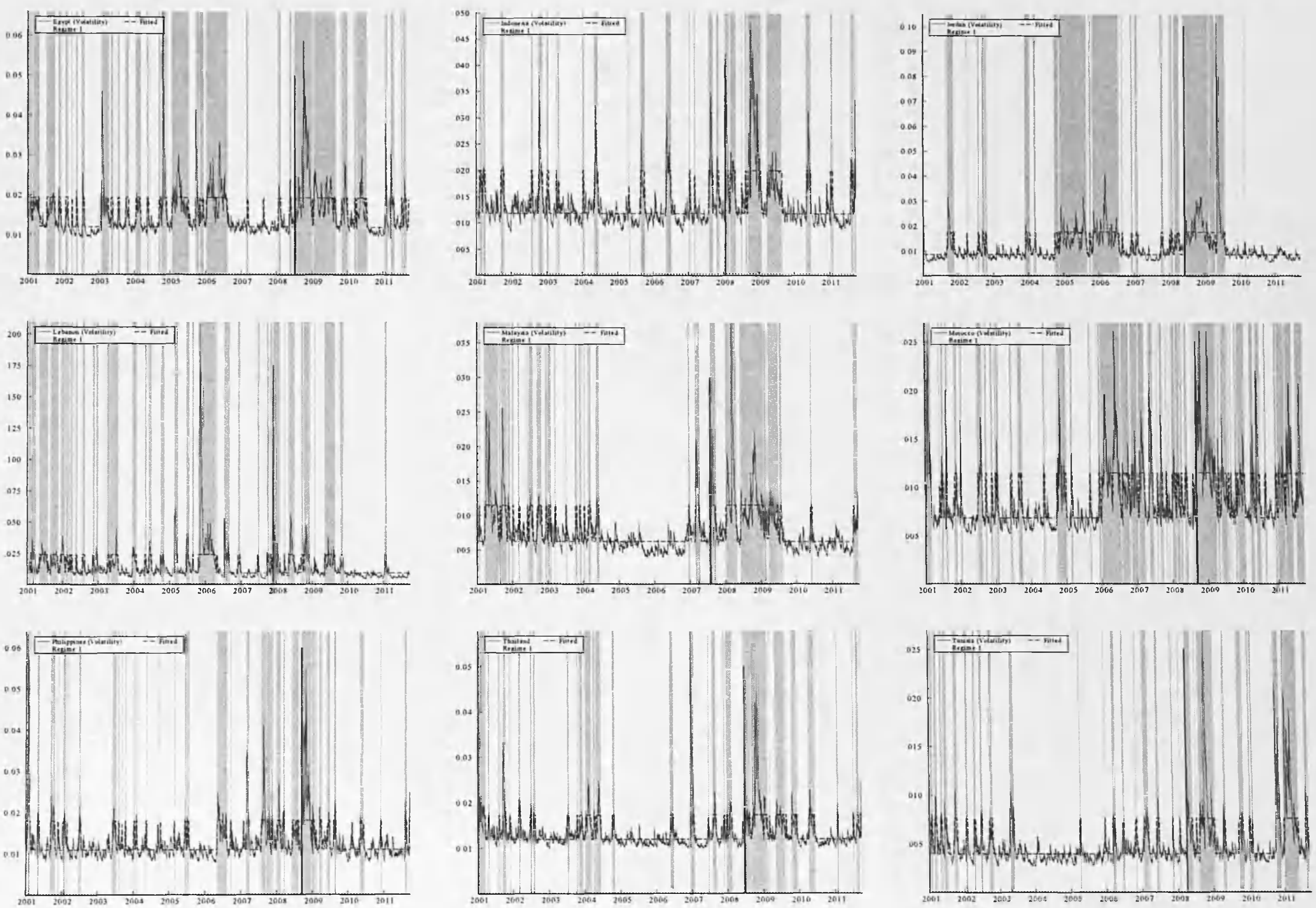
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Bahrain: 12/08/2008; Kuwait: 08/09/2008; Oman: 28/07/2008; Qatar: 11/08/2008; Saudi Arabia: 09/07/2008

Figure 4(j). MS Crisis Regime Identification / Asia & Africa Developed.



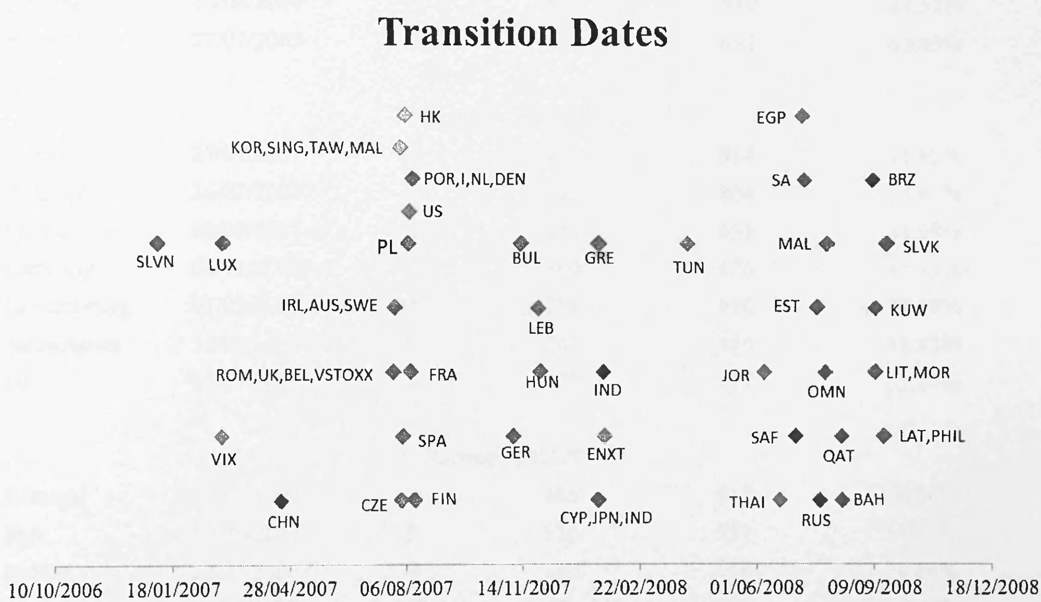
Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Hong Kong: 03/08/2007; Japan: 17/01/2008; South Korea: 30/07/2007; Singapore: 30/07/2007; Taiwan: 30/07/2007

Figure 4(k). MS Crisis Regime Identification / Asia & Africa Developing.



Notes: Identification of the crisis and non-crisis regimes according to Markov-Switching models on the DCC-GARCH Volatility series. The solid black line represents the crisis transition date. Crisis transition dates are: Egypt: 07/07/2008; Indonesia: 17/01/2008; Jordan: 06/06/2008; Lebanon: 26/11/2007; Malaysia: 30/07/2007 Morocco: 09/09/2008; Philippines: 16/09/2008; Thailand: 20/06/2008; Tunisia: 01/04/2008

Figure 5. Crisis Transition Dates.



Notes: Crisis transition dates identified for the countries in the sample. SLVN=Slovenia; LUX=Luxembourg; POR=Portugal I=Italy; NL=Netherlands; DEN=Denmark; PL=Poland; IRL=Ireland; AUS=Austria; SWE=Sweden; ROM=Romania UK=United Kingdom; BEL=Belgium; Fra=France; SPA=Spain; CZE=Czech Republic; FIN=Finland; BUL=Bulgaria HUN=Hungary; GER=Germany; CYP=Cyprus; GRE=Greece; MAL=Malta; EST=Estonia; SLVK=Slovakia; LIT=Lithuania LAT=Latvia; US=United States; ENXT=Euronext 100; BRA=Brazil; RUS=Russia; IND=India; CHN=China SAF=South Africa; HK=Hong Kong; JPN=Japan; KOR=South Korea; SING=Singapore; TAW=Taiwan; EGP= Egypt IND=Indonesia; JOR=Jordan; LEB=Lebanon; MAL=Malaysia; MOR=Morocco; PHIL=Philippines; THAI=Thailand TUN=Tunisia; VIX and VSTOXX Volatility Indices

Table 8(a). Crisis Transition Dates, Duration and Intensity.

Country	Crisis Transition Date	Lead/Lag	Days not in Crisis Regime	Days in Crisis Regime	Crisis Intensity
			Group: Scandinavian		
Denmark	10/08/2007	9	506	572	53.06%
Finland	13/08/2007	12	597	479	44.52%
Sweden	27/07/2007	-5	426	662	60.85%
			Group: Core EU		
Austria	27/07/2007	-5	274	814	74.82%
Belgium	26/07/2007	-6	285	804	73.83%
France	09/08/2007	8	626	453	41.98%
Germany	06/11/2007	97	590	426	41.93%
Luxembourg	01/03/2007	-153	258	936	78.39%
Netherlands	10/08/2007	9	501	480	48.93%
UK	26/07/2007	-6	372	717	65.84%
			Group: PIIGS		
Portugal	10/08/2007	9	465	613	56.86%
Italy	10/08/2007	9	526	552	51.21%
Ireland	27/07/2007	-5	232	856	78.68%
Greece	16/01/2008	168	20	945	97.93%
Spain	02/08/2007	1	336	748	69.00%
			Group: Baltic		
Estonia	21/07/2008	355	832	626	42.94%
Latvia	16/09/2008	412	228	563	71.18%
Lithuania	09/09/2008	405	451	345	43.34%

Note: Transition Dates as identified by the Markov-Switching model on the DCC-GARCH volatility series of the stock market indices. The Lead/Lag column reports the difference between the crisis transition date and the "guideline date" (1/8/07). For example, Denmark experienced the financial crisis in 10/8/2007 (10 days after the "official date"). Days not in Crisis Regime and Days in Crisis Regime identify how many days each country was in "crisis mode" after the transition date.

Table 8(b). Crisis Transition Dates, Duration and Intensity.

Country	Crisis Transition Date	Lead/Lag	Days not in Crisis Regime	Days in Crisis Regime	Crisis Intensity
		Group: RAMS I			
Czech Republic	09/01/2008	161	490	480	49.48%
Hungary	28/11/2007	119	417	583	58.30%
Poland	06/08/2007	5	467	615	56.84%
Slovenia	04/01/2007	-209	632	602	48.78%
		Group: RAMS II			
Bulgaria	12/11/2007	103	604	408	40.32%
Cyprus	17/01/2008	169	142	822	85.27%
Malta	29/07/2008	363	456	370	44.79%
Romania	07/01/2008	159	420	552	56.79%
Slovakia	18/09/2008	414	319	470	59.57%
		Group: WorldWide			
US	07/08/2007	6	633	448	41.44%
Euronext 100	22/01/2008	174	502	459	47.76%
VIX	28/02/2007	-154	695	500	41.84%
VSTOXX	26/07/2007	-6	644	445	40.86%
		Group: BRICS			
Brazil	05/09/2008	401	531	267	33.46%
Russia	24/07/2008	358	354	475	57.30%
India	21/01/2008	173	530	432	44.91%
China	20/04/2007	-103	519	639	55.18%
South Africa	03/07/2008	337	461	383	45.38%

Note: Transition Dates as identified by the Markov-Switching model on the DCC-GARCH volatility series of the stock market indices. The Lead/Lag column reports the difference between the crisis transition date and the "guideline date" (1/8/07). For example, Denmark experienced the financial crisis in 10/8/2007 (10 days after the "official date"). Days not in Crisis Regime and Days in Crisis Regime identify how many days each country was in "crisis mode" after the transition date.

Table 8(c). Crisis Transition Dates, Duration and Intensity.

Country	Crisis Transition Date	Lead/Lag	Days not in Crisis Regime	Days in Crisis Regime	Crisis Intensity
			Group: GCC		
Bahrain	12/08/2008	377	267	549	67.28%
Kuwait	08/09/2008	404	438	359	45.04%
Oman	28/07/2008	362	477	350	42.32%
Qatar	11/08/2008	376	378	439	53.73%
Saudi Arabia	09/07/2008	343	414	426	50.71%
			Group: Asia & Africa Developed		
Hong Kong	03/08/2007	2	384	699	64.54%
Japan	17/01/2008	169	647	317	32.88%
Korea	30/07/2007	-2	614	473	43.51%
Singapore	30/07/2007	-2	435	652	59.98%
Taiwan	30/07/2007	-2	443	644	59.25%
			Group: Asia & Africa Developing		
Egypt	07/07/2008	341	341	501	59.50%
Indonesia	17/01/2008	169	591	373	38.69%
Jordan	06/06/2008	310	575	288	33.37%
Lebanon	26/11/2007	117	715	287	28.64%
Malaysia	30/07/2007	-2	650	437	40.20%
Morocco	09/09/2008	405	279	517	64.95%
Philippines	16/09/2008	412	587	204	25.79%
Thailand	20/06/2008	324	506	347	40.68%
Tunisia	01/04/2008	244	500	411	45.12%

Note: Transition Dates as identified by the Markov-Switching model on the DCC-GARCH volatility series of the stock market indices. The Lead/Lag column reports the difference between the crisis transition date and the "guideline date" (1/8/07). For example, Denmark experienced the financial crisis in 10/8/2007 (10 days after the "official date"). Days not in Crisis Regime and Days in Crisis Regime identify how many days each country was in "crisis mode" after the transition date.

Table 9. Crisis Transition Dates, Duration and Intensity.

Country	Crisis Transition Date			Crisis Intensity	
	Median	Mean	Variability	Median	Mean
Scandinavian	9	5.33	9.07	53.06	52.81
Core EU	−5	−8.00	73.72	65.84	60.82
PIIGS	9	36.40	73.80	69.00	70.74
Baltic	405	390.67	31.09	43.34	52.48
RAMS I	62	19.00	165.67	53.16	53.35
RAMS II	169	241.60	137.63	56.79	57.35
WorldWide	0	5.00	134.12	41.64	42.98
BRICS	337	233.20	206.86	45.38	47.24
GCC	376	372.40	22.39	50.71	51.82
Asia & Africa Developed	−2	33.00	76.05	59.25	52.03
Asia & Africa Developing	310	257.78	139.14	40.20	41.88

Note: Removing Greece from the PIIGS will give 62.9% and 63.9% median and mean intensity respectively. Removing Cyprus from the RAMS II will give 50.8% and 50.4% median and mean intensity respectively. Variability is the SD of the mean lead/lag indicator within a group.

Table 10. Regression Output for industrialization and Crisis Intensity.

Dependent Variable	Crisis Intensity		Crisis Intensity	
	Coefficient	p-value	Coefficient	p-value
Average Industry	-0.422	*(0.006)******		
Industry (2009)			-0.384	*(0.009)******
Constant	0.736	*(0.000)******	0.705	*(0.000)******
Observations	49		49	
$\bar{R}^2$	14.82%		13.55%	
White χ^2	3.989	*(0.136)*	4.265	*(0.118)*

Note: Industry measures the average (over 2000-2009) percentage value added to the country's GDP by industry and manufacturing sectors. Industry 2009 is the percentage value added to the country's GDP by industry and manufacturing sectors in 2009 only. Numbers in brackets show p-values. The White test shows no presence of Heteroscedasticity.

Table 11. Average Intra Group Correlations (aIGC).

Country Groups	Average Correlations		Change in Correlations			
	Before	**After**	**Median**	**Mean**	**SD**	**p-value**
Scandinavian	68.80%	70.50%	2.62%	2.55%	0.87%	0.015**
Core EU	49.26%	50.77%	4.83%	5.20%	4.45%	0.017**
PIIGS	59.35%	60.54%	3.38%	4.25%	6.57%	0.207
Baltic	26.83%	28.63%	7.00%	6.38%	1.42%	0.004***
RAMS I	36.48%	38.53%	6.33%	6.15%	2.43%	0.007***
RAMS II	4.72%	5.25%	10.32%	−24.58%	78.84%	0.517
Worldwide	58.85%	59.76%	2.35%	2.16%	0.95%	0.011**
BRICS	26.11%	28.42%	8.28%	9.87%	4.08%	0.003***
GCC	6.11%	7.13%	10.94%	12.73%	8.17%	0.018**
Asia & Africa Developed	56.75%	57.12%	0.00%	0.69%	0.90%	0.149
Asia & Africa Developing	14.60%	13.61%	4.84%	5.22%	19.78%	0.449

Note: The table reports the average correlations before and after the crisis for every country group separately (i.e.the Scandinavian group only includes the correlations DEN-SWE, DEN-FIN and SWE-FIN). The crisis period is assumed to start when at least one country (of the correlation pairs) is in crisis regime.

Table 12. Average Inter Country Correlations (aICC).

Country Groups	Average Correlations		Change in Correlations			
	Before	**After**	**Median**	**Mean**	**SD**	**p-value**
Scandinavian	34.71%	36.04%	3.83%	4.17%	0.53%	0.001***
Core EU	31.00%	32.20%	4.01%	4.08%	0.82%	0.000***
PIIGS	34.08%	35.37%	3.83%	4.01%	0.76%	0.000***
Baltic	17.47%	18.45%	5.07%	5.43%	3.39%	0.081*
RAMS I	28.43%	29.81%	6.73%	5.36%	3.65%	0.021**
RAMS II	11.98%	13.67%	3.03%	10.84%	14.84%	0.667
Worldwide	31.38%	31.08%	−1.42%	3.58%	9.35%	0.777
BRICS	24.00%	25.57%	7.19%	6.08%	2.40%	0.001***
GCC	6.01%	7.50%	37.51%	23.21%	28.00%	0.030**
Asia & Africa Developed	27.50%	27.93%	1.66%	0.76%	1.58%	0.066*
Asia & Africa Developing	13.75%	14.35%	4.24%	6.12%	6.12%	0.067*

Note: The table reports the average correlations before and after the crisis for every country vis-à-vis every other country in the sample (i.e. 26 pairs of correlations of Denmark are included in the analysis. The crisis period is assumed to start when at least one country (of the correlation pairs) is in crisis regime.

Table 13. Summary of GCC Policy Response.

Country	Deposit Insurance	Central Bank Liquidity Support	Long-Term Government Deposits	Capital Injections	Bank Asset Support	Stock Market Support	Monetary Easing
Bahrain		✓	✓				✓
Kuwait	✓	✓	✓	✓		✓	✓
Oman		✓	✓			✓	✓
Qatar		✓	✓	✓	✓		
Saudi Arabia	✓	✓	✓				✓
UAE	✓	✓	✓	✓			✓

Source: IMF

Chapter 5
Conclusions and Proposals for Further Work

In the last two decades, GCC countries have embarked on a revenue diversification plan to reduce their dependence on non-renewable and highly volatile hydrocarbon income. Among the business sectors that have been expanding, the financial sector has received the greatest attention.

Bahrain has evolved as a financial hub of the GCC and the wider Middle East region while the equally prominent financial sector of the UAE has specialised in the real estate market. Within the financial sector, Islamic banks have enjoyed considerable growth and the GCC has evolved into the largest market for Islamic finance. The arising attention Islamic finance has acquired in the aftermath of the 2007 financial crisis, we undertook comparative studies of Islamic and conventional banking, and of the performance of the GCC financial sector.

After a brief introduction outlining the background of the GCC countries we compare the evolution of cost, revenue, profit and technical efficiency in the two banking systems. Our analysis proceeds by applying a decomposition technique to our efficiency estimates into two components; one attributed to managerial inadequacies and one reflective of the different way of business and financial products that Islamic banks utilise. Moreover, as part of the financial ratio analysis, we apply a bootstrapped version of the equality of means test to correct for any small sample bias. Our results suggest that Islamic banks have higher efficiency in generating revenues and are at least as profit efficient as conventional banks.

Following large investments in human resource development, the cost efficiency gap observed during the first years of the period under study has been closing down. This is attributed to the higher quality of managerial staff employed by Islamic banks, which is verified by the decomposition of DEA efficiency scores and the significantly higher productivity change in Islamic banks over the study period. Nevertheless, the Islamic banking *modus operandi* remains significantly less efficient than the conventional model.

The third chapter investigates the differences between failure risk in the two bank types. We find that Islamic banks have significantly lower failure risk. We adopt a novel survival time model allowing for unobserved heterogeneity using bank-specific variables pertaining to three blocks of the accounting statment, namely balance sheet, income statement and financial ratios in addition to country-wide macroeconomic indicators. We evidence different marginal effects to the failure risk in the two banking systems. Higher capitalisation decreases failure risk for conventional banks, whereas the opposite is observed for Islamic banks. The importance of liquidity management in Islamic banks is highlighted as their higher liquidity preference gives rise to lower failure risk. Macroeconomic factors have greater significance for Islamic banks with inflation having the highest marginal effect upon failure risk. This is expected as Islamic banks use asset-backed contracts while debt use is shunned. We find evidence of increased likelihood of co-failure (contagion) within the conventional banking sector. Nevertheless this effect is not statistically significant for Islamic banks, a finding related to their "tailored-made" products and practises.

The fourth chapter investigates the financial sector of the GCC during the 2007 financial crisis and compares to other developing and developed financial markets. A DCC-GARCH and Markov-Switching framework allows an endogenous unique identification of the crisis transition date for every country. Our findings show that all countries were hit by the financial crisis within a period of 18 months. Financial contagion is verified statistically for all countries under study yet two additional measures, duration and intensity, show important differences between the countries. Most importantly we show that, while developing countries experience financial contagion, they experience it later and less severely than developed countries. A distinction of financial contagion effects into regional and global provides supportive evidence of a GCC financial sector that is becoming increasingly aligned to global financial markets. The GCC, show some evidence of global contagion arising from their linkages with the outside world in terms of investments, services and demand for real estate. A comparison of the GCC with the EU shows that the GCC have the best of two worlds; the benefits of integration, as they constitute a very homogenous group of countries, without most of the evils of contagion, as they are affected about a year later and less severely. Bahrain, the most financially advanced country in the region, is affected at a higher lag than other countries with prominent financial sectors (e.g. Malaysia, Hong Kong). This is plausibly attributed to the prominence of Islamic banks in Bahrain, their investments into infrastructure projects, prohibition of debt contracts, lower failure risk as well as higher profitability and liquidity indicators.

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