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To Debt or Not to Debt: Are Islamic Banks Less Risky than Conventional Banks?

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Highlights

1. The aim of this paper is to compare estimates of market risk for Islamic and conventional bank over for the period 2000-2013 across pre-financial crisis, during financial crisis and post financial crisis periods. To the best of our knowledge this is the first attempt to compare and contrast the market risk of Islamic banks with conventional banks.

2. We use estimates of Value-at-Risk (VaR) and Expected Shortfall (ES) which incorporates losses beyond VaR as market risk measures for both univariate and multivariate portfolios.

3. Univariate analysis finds no discernible differences between Islamic and conventional banks. However, dynamic correlations obtained via a multivariate setting shows Islamic banks to be less riskier for both sets of conventional banks; and especially so during the recent global financial crisis.

4. The policy implications are: (i) that the inclusion of Islamic banks within asset portfolios may mitigate potential risk; (ii) that the Basel committee should consider the ES measure

of risk for Islamic banks in preference to the current VaR methodology, which over-estimates the market risk of Islamic banks.

Abstract

We empirically analyze the market risk profiles of Islamic banks with two sets of conventional banks taken from the same geographical locations as Islamic banks and from a random global sample respectively for the period 2000-2013. Moreover, we divided our sample period into pre-financial crisis, during financial and post financial crisis. Estimates of Value-at-Risk (VaR) and Expected Shortfall (ES) which incorporates losses beyond VaR are used as market risk measures for both univariate and multivariate portfolios. Our key input is the share price by market capitalization of publicly traded banks of similar size in Islamic and non-Islamic countries. Univariate analysis finds no discernible differences between Islamic and conventional banks. However, dynamic correlations obtained via a multivariate setting shows Islamic banks to be less riskier for both sets of conventional banks; and especially so during the recent global financial crisis. The policy implications are: (i) that the inclusion of Islamic banks within asset portfolios may mitigate potential risk; (ii) that the Basel committee should consider the ES measure of risk for Islamic banks in preference to the current VaR methodology, which over-estimates the market risk of Islamic banks.

JEL classification: C53, C58, G01, G21
Keywords: Islamic finance, Value at risk, Expected shortfall, Capital structure

1. Introduction

By 2015 the Islamic finance industry had reached a gross value of USD 1.88 trillion having maintained double-digit growth rates despite sustained low energy prices, geopolitical conflicts and economic uncertainty in major economies (IFSB 2016; EY 2016). In practice, Islamic finance utilizes its own, unique business model, which arguably has little in common with conventional finance.[1] Yet still they operate alongside in the majority of countries. As a result of the growth in the industry, the number of Islamic Financial Institutions (IFIs) across countries has increased with more being listed in stock exchanges globally.

[1] For example, Islamic banks use profit-and-loss sharing (PLS) instruments (e.g., *Mudarabah*) that do not guarantee a pre-determined profit to depositors and do not force borrowers to repay a pre-determined amount. Islamic fund managers face business type (e.g., pork and alcohol industries are prohibited) and financial constraints (e.g., proportion of debt a firm has) when creating or rebalancing their investment portfolios.

The empirical work comparing Islamic and conventional finance has typically focused on studying issues pertaining to stability. A significant portion of this work is focused on studies between Islamic and conventional[2] banks with respect to stability (Čihák and Hesse, 2010; Pappas et al., 2016; Ashraf et al., 2016a; Ashraf et al., 2016b), efficiency (Johnes et al., 2014; Saeed and Izzeldin, 2014), loan default rates (Baele et al., 2014), business model (Beck et al., 2013), credit risk (Abedifar et al., 2013) and accounting practices (Elnahass et al., 2014; Abdelsalam et al., 2016). There is little empirical evidence concerning the market risk profile of Islamic financial institutions with regards to their conventional counterparts. The aim of this paper is to compare estimates of market risk for the two bank types over different market regimes.

The Global Financial Crisis (GFC) of 2007-2010 presents an ideal environment to compare the market risk profiles of Islamic and conventional banks. During the GFC, major conventional financial institutions either went bust or had to be rescued through multi-billion state-aided rescue packages, such as the Troubled Asset Relief Program (TARP) in the US. A major factor in the fragility of the conventional financial system is the level of debt as aided by the increasing availability of securitization products. Islamic financial institutions are known for their low leverage and avoidance of complex financial instruments, such as financial derivatives and debt securitization. Such differences have been claimed (see for example, Čihák and Hesse, 2010; Pappas et al., 2016) to induce a higher financial stability to Islamic banks relative to their conventional peers.

Market risk is not driven by the fundamentals, as it is derived from share price fluctuations, which are formed by interactions amongst different types of agents. Hence, we do not know as at prior how the market risk of Islamic banks will fare relative to conventional banks nor how the GFC would affect banks' market risk profiles. On the one hand, these institutions may have higher market risk due to (i) lack of experience in managing market risk, (ii) lack of sophisticated

[2] We follow Elnahass et al. (2014), Johnes et al. (2014) and use the term "conventional" to refer to commercial banks that are not involved in Islamic banking products.

market risk management instruments, and (iii) the restricted access to the interbank market for liquidity as these markets have interest-bearing elements. On the other hand, they may exhibit lower market risk based on their significantly higher equity to debt ratios compared with those observed for conventional financial institutions. If this is so, then Islamic financial institutions will have competitive advantage in terms of their market risk exposure. Finally, they may be of equal risk to the conventional financial institutions, as it has been argued that IFIs are too similar to the conventional ones, since the profit sharing ratios and the fee margins charged show very high correlations with standard interest rate proxies, such as LIBOR rates (Khan, 2010).

The closest study to ours is that of Abedifar et al. (2013) that investigates credit risk. As credit risk is not readily defined, the authors use three alternative proxies to measure them; hence, the interpretation is not always definite. By contrast, with market risk there are precise definitions that are accepted by academics, industry-specialist and regulators; therefore, any measurement error related to the use of proxies is avoided.

We contribute to the recent literature in a number of ways. First, we investigate the market risk of Islamic and conventional financial institutions over 2000-2013. We use the Value at Risk[3] (VaR) and the Expected Shortfall (ES) measures in both univariate and multivariate settings; thereby incorporating correlation between assets. Market conditions are accounted for by three sub-periods namely pre-crisis, crisis and post-crisis. Second, we examine the capital structure of Islamic and conventional banks and whether any differences manifested therein would explain differences in the market risk.

Our key findings are summarized as follows. Univariately, we find that the market risk profile of Islamic banks is no different, on average, than that of conventional banks. This holds true across all examined periods/regimes. However, once we allow for dynamic correlation between the banks we find that Islamic banks exhibit lower market risk under both the VaR and

[3] VaR is used by regulators under Basel II and Basel III to assess the market risk of banks.

the ES specifications; a finding more pronounced during the crisis period. Allowing for dynamic correlations between the assets brings out the benefit of Islamic investments as they are less interconnected to the market (El Alaoui et al., 2015; Visser, 2015). Our analysis shows that the capital structure of Islamic banks is distinctive in that Islamic banks operate with lower leverage across the different sub-periods.

The remainder of the paper is structured as follows. Section 2 provides a summary of the relevant literature. Section 3 presents the methodology followed for the VaR and ES estimations. In Section 4, we discuss our data. Results are presented and discussed in Section 5. In Section 6, we perform regressions on the capital structure equation across the different sub-periods of analysis. The final section concludes.

2. Literature Review

Comparative studies find that Islamic banks are more efficient and less exposed to credit risk than their conventional counterparts (Johnes et al., 2014; Abedifar et al., 2013). Some of these qualities of Islamic banks may be attributed to their superior asset quality, as verified through the studies of Hasan and Dridi (2010) and Pappas et al. (2016) in terms of financial ratios such as Loan Loss reserves/Gross Loans and Impaired Loans. This finding is further reinforced by Baele et al. (2014), who track the default rates of 150,000 separate loans from 2006 to 2008. They find that the default rate on Islamic loans is less than half the default rate of conventional bank loans. Ashraf et al. (2016b) suggests that the adoption of IFSB's new regulatory measures, specifically the net stable funding ratio, will further enhance the financial stability of Islamic banks. Gheeraert (2014) approaches Islamic banking from the perspective of its overall impact on banking sector development. The author finds empirical evidence suggesting that the introduction of Islamic banking spurred the overall development of the banking sector because new Islamic banks complement the existing conventional banks.

In many countries, Islamic banks co-exist with conventional banks, and there is pressure to apply conventional regulations to Islamic banks. Moreover, as stated by Abdullah et al. (2011), there is no separate regulatory[4] scheme to govern the operations of Islamic banks. It is common for Islamic banks to operate under the laws governing conventional banks. This approach has led to an interesting dilemma for Islamic banks. On one hand, the adoption of international standards is critical because it enhances credibility and fuels the growth of Islamic banks. On the other hand, subjecting Islamic banks to the same regulatory framework overlooks the nature and types of risks pertaining to these banks. Recent studies have also compared Islamic and conventional banks based on their risk profiles while considering them complementary banking systems within the overall financial system.

Within the Islamic banking literature, there are very few empirical studies that have specifically focused on risk measurement and quantification in Islamic banks and their comparisons with conventional banks. Ashraf et al. (2016a) provides insight into the relationship between the ownership structure and financial fragility of banks from the GCC region and find banks with higher ownership concentration exhibit higher financial fragility. Abdullah et al. (2011) assess key issues in the measurement and monitoring of operational risk in Malaysian Islamic banks. Wiyono and Rahmayuni (2012) explore the variables that affect the relationship between the levels of risk faced by Islamic banks and their relative profitability. Boumediene (2011) explores the credit risk dynamics between Islamic and conventional banks using distance-to-default and default probabilities and finds that Islamic banks have lower credit risk than conventional banks. Wiyono and Rahmayuni (2012) state that, with the exception of Malaysia, central banks have no other mechanism for providing liquidity to banks other than through the

[4] There are currently two regulatory bodies for Islamic finance, IFSB and AAOIFI. However, not all Muslim countries adhere to the standards of one of these bodies and may be following their central bank. For example AAOIFI accounting standards are only mandatory requirements in the jurisdictions of Bahrain, Jordan, Oman, Qatar, Qatar Financial Centre, Sudan and Syria. We would like to thank the reviewer for clarifying this matter for us.

basis of interest lending, which makes Islamic banks more susceptible to liquidity risk, unlike conventional banks, which can tap into a central bank liquidity facility during periods of liquidity shortages. The limited number of Shariah-compliant financial instruments is another reason why Islamic banks may be at an inherent disadvantage to conventional banks.

Our study complements these studies by focusing specifically on the market risk of Islamic banks. By following the methodology used by regulators under the Basel regimes, we directly compare market risk between Islamic and conventional banks. To the best of our knowledge, ours is the first study to make such a comparison.

3. Methodology

Our empirical analysis adopts both a univariate and multivariate VaR specifications which we detail below. We start by defining and discussing the characteristics of Value at Risk (VaR) and the expected shortfall (ES) risk measures. We then discuss, in some depth, the methodology used to estimate these two risk measures in a univariate and then in a multivariate setting. Finally we propose statistical tests for determining the accuracy of the VaR and ES measures.

Since its introduction in the 1980s, VaR has been established as a popular measure of market risk together with its related extension, the expected shortfall. VaR[5] is the single most widely accepted measure of market risk among risk practitioners, as it is simple to calculate and benefits from a simple, intuitive interpretation.

To calculate market risk, we follow the risk measure of Dowd et al. (2008) and define M_{φ} as follows:

$$M_{\varphi} = \int_0^1 \varphi(p)\, q_p dp \qquad (1)$$

[5] VaR has its detractors. For example during the LTCM crisis of 1998, VaR's performance was criticized for its failings.

where q_p is the p loss quintile, $\varphi(p)$ is a weighting function defined over the full range of cumulative probabilities $p \in [0,1]$ and M_φ is the class of quantile-based risk measures.

VaR and ES constitute two well-known members of this class. The VaR at confidence level α is defined as follows:

$$VaR_a = q_a \tag{2}$$

Furthermore, each individual risk measure is characterised by its individual weighting function $\varphi(p)$. The weighting function for VaR is a Dirac delta function that gives the outcome $(p = \alpha)$ an infinite weight and zero weight for every other outcome.

The ES at confidence level α is the average of the worst $1 - \alpha$ losses, which is defined as follows:

$$ES_a = \frac{1}{1-a}\int_a^1 q_p dp \tag{3}$$

The weighting function for ES gives all tail quantiles the same weight of $1/1 - a$ and the non-tail quantiles zero weight.

3.1. Univariate VaR

For the univariate VaR models, we define an asset's return process at time *t* as follows:

$$R_t = \sigma_t \varepsilon_t \tag{4}$$

where σ_t is the conditional volatility, Ψ_{t-1} represents the information available at time $t - 1$ and $\varepsilon_t | \Psi_{t-1} \sim N(0,1)$.

The simplest VaR model assumes that the conditional variance follows the industry standard RiskMetrics (RM), where the conditional variance is specified by equation (5).

$$\sigma_t^2 = (1-\lambda)\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 \tag{5}$$

where λ is set to 0.94[6] for daily data, and the returns are generated from a normal distribution. This is our first univariate method.

An alternative specification of the conditional volatility is the GARCH(1,1) model (Bollerslev, 1986), in which the conditional variance evolves as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

For the second univariate method we use Monte Carlo simulation to produce a series of hypothetical returns based on GARCH(1,1) innovations from day $t+1$ to $t+K$. Based on these hypothetical single day returns, we calculate the hypothetical K-day return for each Monte Carlo path. However, to generate the random variable in our simulation, we make use of standardized residuals based on the asset returns. Combining the two gives the Filtered Historical Simulation (FHS), of Barone-Adesi et al. (1999). Collecting the N hypothetical K-day returns in a set $\{\hat{R}_{i,t+1:t+K}\}_{i=1}^{N}$ allows us to calculate the K-day VaR as follows:

$$VaR_a = q_a\{\hat{R}_{i,t+1:t+K}\}_{i=1}^{N} \tag{7}$$

3.2. Multivariate VaR Models

The multivariate VaR assumes that a portfolio comprises N assets. Typically, the portfolio variance is defined as follows:

$$\sigma_{P,t}^2 = \mathbf{w}'\mathbf{V}\mathbf{w} \text{ with } \boldsymbol{V}_t = \boldsymbol{D}_t'\boldsymbol{R}_t\boldsymbol{D}_t \tag{8}$$

where $\mathbf{w}$ is the weights matrix, $\mathbf{V}$ is the variance-covariance matrix of the asset returns, $\boldsymbol{D}_t$ is a matrix of time varying volatility and $\boldsymbol{R}_t$ is a matrix of time-varying correlations that may be modelled using Engle's (2002) Dynamic Conditional Correlation (DCC) process, whereby the conditional correlation can be denoted as follows:

[6] RiskMetrics uses a lambda value of 0.94 for daily data (RiskMetrics, 1996).

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{9}$$

where $q_{ij,t}$ is an auxiliary variable that drives the correlation dynamics. For the auxiliary $q_{ij,t}$ variable, we assume an exponential smoothing structure:

$$q_{ij,t} = \lambda q_{ij,t-1} + (1-\lambda) z_{i,t-1} z_{j,t-1} \tag{10}$$

where λ may be imposed with typical values in the range $\lambda = 0.94 - 0.98$ for daily financial time series estimated.

In our multivariate DCC-VaR[7] framework, we employ GARCH(1,1) conditional variance modelling. In our setup, we assume that the auxiliary $q_{ij,t}$ variable is driven by the exponential smoothing structure, where λ=0.94.[8] In all cases, we have assumed that the portfolio is equally weighted.

3.3. Backtesting VaR Models

Based on a time series of past ex-ante VaR forecasts and past ex-post returns, we define the hit sequence of VaR exceedances as follows:

$$I_{t+1} = \begin{cases} 1 \text{ if } R_{i,t+1} < -VaR_{t+1}^{a} \\ 0 \text{ if } R_{i,t+1} > -VaR_{t+1}^{a} \end{cases} \tag{11}$$

Based on equation (11), we construct a sequence $\{I_{t+1}\}_{t=1}^{T}$ across T days. The forecast of VaR exceedance should be $100\alpha\%$ every day. Thus, the hit sequence of exceedance should be completely unpredictable and thus distributed independently over time as a Bernoulli variable.

[7] In an earlier version of the paper, we also considered a factor model approach to explain the share price returns. We were able to do this, as we were using much larger banks in our global sample and were able to isolate the bank specific factors. In the current version of the paper, all our banks are much smaller, and thus it is likely that all the banks will be driven by the same set of factors. We have therefore not included the factor models approach in this version of the paper.

[8] As a robustness check, we try different λ values in the $\lambda = 0.92 - 0.98$ range; however, the results of this robustness check do not challenge our main story.

The unconditional coverage test checks whether the percentage of violations is significantly different from the corresponding VaR level $1 - \alpha$. To estimate the required statistics, we follow the method of Christoffersen (1998) and Dias (2013) for calculating the likelihood ratio LR_{uc}[9].

The unconditional coverage test confirms whether the number of violations is as expected for a given level of α for the VaR. As financial returns exhibit volatility clustering, VaR violations are likely to cluster over time. A clustered volatility event arises from events that affect many financial institutions simultaneously, which makes it necessary to test the hypothesis of independence of VaR violations. Christoffersen (1998) tests for this independence of VaR using the likelihood function LR_{ind}. Finally, Christoffersen (1998) simultaneously tests whether the number of violations is correct and whether the VaR violations are independent based on the likelihood function LR_{cc} .

3.4. Expected Shortfall Estimation

The ES for a random variable Y at a point of the distribution q is defined as $ES(q) \equiv E(Y|Y < q)$. We first forecast the condition variance $\left(\sigma_{t+j}^2\right)$ over the period $t + j$ $(j = 1,2, \dots, K)$. Based on this result, the return $R_{t+j} = \sigma_{t+j}\varepsilon_{t+j}$ is generated, and finally, the returns are averaged from the cut-off point to estimate the ES:

$$ES_{t+j|t}(q) = E\left(R_{t+j}|R_{t+j} < q\right) \tag{12}$$

To assess the performance of the ES, we split the data sample into an estimation sample and a holdout forecast evaluation period. The total sample is denoted as $T = 3652$, and the first R $(R = 500)$ observations are used as initial conditions and for initial model estimations. We use the last $P (P = 3152)$ observations as a holdout evaluation period. Under a rolling forecasting scheme, the estimation is always based on a sample of size R. The first estimation window is $t =$

[9] For further details regarding the three likelihood functions, we refer the reader to Christoffersen (1998).

$1, \ldots, R$, and forecasts are generated for $t = R + 1$. The second estimation window is $t = 2, \ldots R + 1$, and forecasts are generated for $t = R + 2$. The last estimation window is $t = T - R, \ldots, T - 1$, and forecasts are generated for $t = T$.

Hence, we recursively evaluate $ES_{t+j|t}(q)$ for one step ahead, and we let q take alternative values. Following Zhu and Galbraith (2011), we set the threshold (loss) returns q between -0.6% and -1.2% to gauge the sensitivity of the expected shortfall measures for the two types of banks. The target is the one-step-ahead expected shortfall; therefore, the predictive performance is assessed on an out-of-sample basis. For each date, assuming that the model is correctly specified, we expect the average of the observed R_{t+j} values $R_{N+1}, \ldots, R_{N+K}$ less than q to be approximately equal to the $ES_{t+j|t}(q)$ predicted by the model. If $ES_j(q)$ is higher than a model's average predictive ES, $ES_j^M(q)$, then the model tends to overestimate the risk, which is measured by mean error (ME), where $ME_j(q) = ES_j^M(q) - ES_j(q)$. Thus, a negative value is an indicator of overestimation of risk. An alternative metric that we implement in this study to measure predictive out-of-sample performance is the mean absolute error (MAE), given as:

$$MAE_j(q) = \frac{1}{\sum_{t=N}^{Tj} 1\{R_{t+j} < q\}} \sum_{t=N}^{T-j} \left| ES_{t+j}(q) - ES_j(q) \right| \tag{13}$$

4. Data

The 14-year period from January 3, 2000, to December 31, 2013 (whole period), is split into three sub-periods[10] around the Global Financial Crisis. The pre-crisis period starts on January 3, 2000, and ends on June 30, 2007. The period covering the financial crisis, starts on July 1, 2007,

[10] The period cut-off is arbitrary and follows the cut-off considered in the majority of studies, including the study by Breitenfellner and Wagner (2012), who take the Lehman bankruptcy as the start of the global financial crisis. We start our analysis period in January 2000 and conclude it in December 2013 to ensure a sufficiently long yet relevant period of analysis based on data availability.

and concluded on June 30, 2009. Finally, the post-crisis period starts on July 1, 2009, and concludes on December 31, 2013. The period splits are in line with those considered in other studies, including Breitenfellner and Wagner (2012).

Our portfolio of Islamic banks includes 65[11] banks with daily share price information on Bloomberg over the period under study.

For the conventional banks we construct two separate portfolios. The first, which we call CBI (Conventional Banks in Islamic countries), contains 65 conventional banks of similar market capitalization to the Islamic banks and from the same countries where the Islamic banks are based. The second, which we call CBO (Conventional Banks in Other countries), contains 65 conventional banks of similar market capitalization to the Islamic banks but taken randomly from a global sample of banks and which strictly excludes banks which are in the CBI portfolio. Table 1 shows a breakdown of the sample by country and average market capitalization.

[Table 1 around here]

Table 2 provides summary statistics of the daily stock returns for the banks across the whole period and for each of the three sub-periods. Returns for both bank types exhibit the common stylised facts of skewness and excess kurtosis. For both bank types, returns exhibit autocorrelation, particularly in the non-crisis periods. The average daily return decreases across all conventional and Islamic bank samples from the pre-crisis to the crisis period and increases from the crisis to the post-crisis period. All bank stock returns exhibit asymmetry across the whole period and the sub-periods. During the crisis period, skewness is negative across all three samples, indicating that, as expected, during times of financial turbulence, upon the recovery of

[11] Initially we had a sample of 85 Islamic banks. However, we were only able to obtain 65 conventional banks in these same Islamic countries and as such we reduced our sample to 65 Islamic and conventional banks.

the stock market, share prices do not recover their original value. We observe excess kurtosis across all three samples and over the whole period and the three sub-periods. During the crisis period, we observe that the kurtosis of Islamic banks is greater than that of conventional banks, indicating that Islamic bank share prices reacted adversely if not more so during the financial crisis compared with conventional bank share prices. Based on these results, we conclude that returns are not normally distributed for conventional or Islamic banks. Thus, in summary, we find that conventional bank returns are as expected based on previous studies. However, more interestingly, we also find that the returns of the Islamic banks do not show any apparent difference from those of conventional banks, which to a certain extent suggests that the market risk of conventional and Islamic banks would behave in a similar manner.

[Table 2 around here]

For the capital structure model the explanatory variables are the market-to-book ratio (*MTB*), measured as the relative value of the company compared with its market value; Profitability (*Profit*), measured as the pre-tax income; Ln(Size), measured as the natural logarithm of total assets; collateral lagged by one year (*Collateral*), measured as the portion of cash; marketable securities and short-term investments pledged as collateral for short-term and long-term borrowing; a dummy variable that is coded as 1 for quarters when dividends were paid (*Dividends*); and *Ln(Risk),* which is measured as the natural logarithm of (the annualised standard deviation of daily stock price returns × (market value of equity / market value of the bank)) for each bank *i* and quarter *t*. The dependent variable leverage (*L*) is defined as one minus the equity over assets in market value and as such includes both debt and non-debt liabilities, including deposits. Unlike debt, leverage has the advantage of being well defined. In addition, leverage increases the sensitivity of equity to bank performance. The explanatory variables are calculated following the definitions provided by Gropp and Heider (2010).

[Table 3 around here]

5. Market risk estimates

In this section, we present the results of the VaR and ES risk measure estimates. We first assume that there is no covariance structure between the individual banks in each of our three portfolios. Given this we only need to consider the diagonal elements of the variance-covariance matrix. The implication is that we can aggregate the VaR and ES market risk measures. We refer to this method as the univariate approach.

Note that assuming zero correlation is a strong assumption, especially as correlation increases during times of financial turbulence. Therefore, we relax the assumption of zero covariance, which leads to the multivariate case in which the VaR and ES risk measures can no longer be summed.

5.1. Univariate VaR and ES

Based on the time series of the daily returns for conventional and Islamic banks, we estimate one-day-ahead VaR estimates using a rolling window of 500 days. The Basel Committee on Banking Supervision (1996) has set a level of 99% VaR over a one-day period. If this VaR is an accurate representation, only 1% of the returns should produce VaR violations. This approach is based on equation (11), and we expect to observe one exceedance every 100 days.

In Table 4[12], we present the average VaR estimated using the industry standard RiskMetrics (RM) and the simulation based Filtered Historical Simulation approach (FHS) Panel A for three separate portfolios. “IB” comprises the average VaR for Islamic banks, “CBI” comprises the average VaR of conventional banks in Islamic countries and “CBO” comprises the average VaR of conventional banks in other countries. The p^{CBI} and p^{CBO} are p-values based on the t-tests between the Islamic banks and conventional banks in Islamic countries and Islamic banks and conventional banks in other countries respectively.

[Table 4 around here]

Panel A shows that for the whole period there is no significant difference in the average VaR between Islamic and conventional banks. A plausible reason for this may be that investors perceive shares of Islamic and conventional financial institutions as complementary to each other. Moreover, this applies equally to all of the three individual sub-periods. In summary regardless of the period and the method, the differences in VaR between Islamic and conventional banks, irrespective of where they are based is not significant. However, this VaR figure is an average snapshot and is obtained at a single-quantile level. To explore these issues further, we perform back testing.

In Panel B, we present the percentage of violations, LR_{uc}, LR_{ind} and LR_{cc}, and the statistical significance from the unconditional coverage test, the independence test and the combined coverage test, respectively. Additionally, we report the percentage of VaR violations for RM and FHS and for all three portfolios. We find that regardless of the methodology employed, both conventional and Islamic banks' violation are greater than 1% indicating that

[12]We also implement the non-parametric historical simulation and bootstrapped historical simulation. As the results were the same, we have not included them in this paper, but they are available on request from the authors.

VaR is inadequate at the portfolio level. Moving from the pre-crisis to the crisis period, the number of violations for Islamic banks decreases, but increases for conventional banks. This result is observed regardless of whether they are from Islamic countries or from the random sample of global banks. A similar trend is observed during the post-crisis period.

In Table 5, Panel A, we present the ES results estimated based on the RM and FHS methods for the whole period and the three sub-periods. We note that the ES is the average of all losses after the 1% level, whereas VaR is simply the loss at 1% level. Our findings are consistent with that of Table 4. We find that regardless of the period, methodology, and the portfolio of conventional banks used, differences between ES of Islamic banks and conventional banks are not significant.

[Table 5 about here]

Panel B reports the MAE for the expected shortfall measures based on the RM and FHS methods. Across the models, a lower mean absolute error (MAE) indicates a better model, whereas across bank types, a lower MAE indicates that the risk is more predictable in the respective banking system. Based on the RM and FHS method, the main inference from Panel B indicates that the MAE is lower for Islamic banks than either of the two conventional bank portfolios. An exception is during the post-crisis period where MAE is higher for Islamic banks than for conventional banks. During the crisis period, the MAE for the Islamic banks increases in the same way as that of conventional banks. This result signifies that during the crisis period, the ES measure shows that risk exhibits lower forecastability for both the conventional and Islamic banks.

The inference drawn from VaR estimation suggests that Islamic banks have similar market risk profiles to conventional banks for the whole period. However, the finding that during the crisis period, the number of VaR violations increases for both Islamic and conventional banks indicates that at times of severe market stress, Islamic and conventional banks behave in the same way. The results of the expected shortfall analysis suggest that there are no differences in the market risk profiles of the two bank types. Hence, the two methods lead to the same conclusions. The focus of VaR is on the cut-off point, which means that under stable market conditions, Islamic banks are less risky than conventional banks. The expected shortfall focuses on the left-most tail of the return distribution and we conclude that during a financial crisis, there is no difference between two types of banks with regard to market risk.[13] In our analysis thus far, we have assumed zero correlation, between the banks in our portfolio. We now proceed to relax this assumption.

5.2. Multivariate VaR and ES

Thus far, we have examined VaR and ES from a univariate angle, assuming that no covariance exists between the assets; we were thus able to aggregate the VaR and ES across all the banks. We now drop this assumption. As a first step, we model the covariance between assets using dynamic conditional correlation (DCC) of Engle (2002), where the covariances are updated on a daily basis. This daily updated variance-covariance matrix is then used to calculate the daily portfolio standard deviation. Furthermore, to calculate the daily VaR we use the Cornish-Fisher approximation[14]. This approximation has the advantages that it allows for skewness and excess kurtosis and it provides an approximation to the VaR from a wide range of conditionally non-normal distributions. The estimated VaR can then be used as the cut-off point to calculate ES.

[13] To take into account that Basel II was mandatorily adopted by Islamic banks from 2007 onwards, we re-estimate VaR and ES calculations for two separate periods between 2000-2006 and 2007-2013. We found no change in our results. This result is expected, as the announcement would have been made well in advance of the date when it became mandatory for Islamic banks to adopt Basel II and this information would have slowly diffused into the traded share prices.

[14] The Cornish-Fisher approximation is given as:

$$CF_p^{-1} = \Phi_p^{-1} + \frac{\zeta_1}{6}\left[\left(\Phi_p^{-1}\right)^2 - 1\right] + \frac{\zeta_2}{6}\left[\left(\Phi_p^{-1}\right)^3 - 3\Phi_p^{-1}\right] - \frac{\zeta_1^2}{36}\left[2\left(\Phi_p^{-1}\right)^3 - 5\Phi_p^{-1}\right]$$

where ζ_1 and ζ_2 are the skewness and excess kurtosis of the standardised returns and Φ_p^{-1} denotes the inverse of the density function at the p confidence level.

$$VaR_{t+1}^{p} = -\sigma_{PF,t+1} CF_p^{-1} \tag{14}$$

where $\sigma_{PF,t+1}$ is the estimated standard deviation on day $t + 1$ and CF_p^{-1} is the Cornish-Fisher approximation.

With respect to VaR measure of market risk, we find that the differences between the VaRs of the portfolio of Islamic banks and each of those pertaining to the two portfolios of conventional banks are not significant. However, significant differences manifest themselves better at the sub-samples level. Most importantly, in the crisis period, the VaR for the Islamic banks is significantly lower than both CBIs and CBOs. This would indicate that at times of severe market stress, Islamic banks are seen as a safe haven, because of their lower debt and higher liquidity. In the pre and post-crisis sub-periods there are also significant differences between the Islamic banks and the CBOs only. This could be due to the fact that during normal times, Islamic banks are potentially seen as less developed, and hence more risky, than similar sized conventional banks in developed countries. These results are presented in Panel A of Table 6.

Panel B of Table 6 shows that irrespective of the period, the ES of the portfolio of Islamic banks is always significantly lower than either of the two portfolios of conventional banks. In particular, during the crisis the ES of conventional banks in Islamic countries (CBI) was twice that of Islamic banks and the ES of conventional banks in other countries (CBO) was 50% more than that of Islamic banks.

[Table 6 about here]

Our results confirm the findings from Panel A, that Islamic banks are less risky than conventional banks during the financial crisis. However, the ES is a more encompassing measure of risk than the VaR as it incorporates losses beyond the cut-off point. More importantly the ES measure demonstrates convincingly that irrespective of the source of conventional bank portfolio, Islamic banks are significantly less risker than conventional banks for the whole period. This casts doubt on the current use of VaR to estimate the risk of Islamic banks and hence its inadequacy. Thus our findings are consistent with theory that Islamic banks are less risky than conventional banks. This may be in part attributed to their stronger financial profile coupled with an abstinence from risk as entailed from their higher liquidity and capitalisation ratios. In summary, our findings corroborate the theory that Islamic finance investments are less risky, findings which has been verified for Islamic banks (Čihák and Hesse, 2010; Pappas et al., 2016) and using Islamic equity indices (Alexakis et al., 2016; El Alaoui et al., 2015 and El Khamlichi et al., 2014).

In sum, the multivariate approach demonstrates convincingly that once correlations among assets are taken into account, the portfolio of Islamic banks exhibits lower market risk than similar-sized conventional banks. Furthermore, our findings suggest that regulators should not solely rely on VaR as measure of market risk for Islamic banks, but place proper attention to the ES too. In Figure 1 we graphically summarize our main findings.

[Figure 1 about here]

6. Capital Structure

In the previous section we concluded that, on average, the market risk profiles of Islamic and conventional banks are distinguishable, however when non-zero correlations between assets are allowed for, differences emerge. A plausible reason for the observed differences in market risk may be linked to the business model that Islamic banks utilise. This unique business model includes not only financial products that are structured on an equity share premise but also limitations for the leverage (i.e., debt) levels of an Islamic bank and its investments.

Below we examine whether the business model of Islamic banks may be, in part, responsible for their lower market risk. We use a standard capital structure model, following

Rajan and Zingales (1995) and Gropp and Heider (2010), which posits that the capital structure (i.e., leverage) of banks may be explained by a limited set of variables, such as bank size, collateral, profits, market-to-book ratio, dividends and risk. The negative relationship between leverage and risk is of particular importance, as it implies that riskier banks would want to increase their equity buffers.[15]

Following Gropp and Heider[16,17] (2010), we consider the following standard capital structure panel data fixed effect regression

$$L_{it} = \beta_0 + \beta_1 MTB_{it-1} + \beta_2 Profit_{it-1} + \beta_3 Ln(Size_{it-1}) + \beta_4 Collateral_{it-1} + \beta_5 Dividends_{it-1} + \beta_6 Ln(Risk_{it-1}) + \beta_7 IB \times MTB_{it-1} + \beta_8 IB \times Profit_{it-1} + \beta_9 IB \times Ln(Size_{it-1}) + \beta_{10} IB \times Collateral_{it-1} + \beta_{11} IB \times Dividends_{it-1} + \beta_{12} IB \times Ln(Risk_{it-1}) + \beta_{13} IB + \mu_{it} \quad (15)$$

where *IB* takes the value 1 for Islamic banks and the other variables are explained in Section 4. The *IB* variable and its interaction terms allow for Islamic banks to have unique intercept and slope coefficients.

[Table 7 about here]

[15] Modified versions of the Basel accord (for example, by the US regulator) grant regulators the discretional ability to ask risky banks for higher capitalisation. However, our wording here implies that banks withholding more equity to account for their increased risk do so at their own discretion, which is in line with key studies (Calomiris and Wilson, 2004; Flannery and Rangan, 2008) that fail to find a connection between regulatory pressure and the leverage/risk relationship.

[16] Other researchers use the same specification to tackle endogeneity. For example, Rajan and Zingales (1995) on page 1452 write, "we lag the explanatory variables one period to reduce the problem of endogeneity".

[17] As an additional robustness test to control for possible endogeneity, we use the two-step system GMM approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998), which is used in the banking context in Mollah and Zaman (2015), among others. System GMM allows for the use of orthogonal transformations of the past values of the endogenous (or potentially endogenous) variables as instruments. The first difference of the variables is used in a matching equation with lagged values entering the right-hand side, and GMM is used in the estimation. The technique further eliminates unobserved heterogeneity and omitted variable bias. This approach allows us to treat all variables as potentially endogenous. We find insignificant second-order autocorrelation - AR(2) and the Hansen J-statistics of instrument validity show that the GMM is a valid representation. Overall, and as expected, the system GMM results corroborate our findings based on panel regression techniques. Results based on GMM are available from the authors upon request.

Table 7 reports the results of the capital structure regression estimation for the whole, pre-crisis, crisis and post-crisis periods. Besides the usual statistical significance tests, we report, in the $\Delta(IB - CB)$ columns, the results of statistical significance of the difference in the coefficients of the conventional and the Islamic banks.

Our results show that the capital structure of Islamic banks is markedly different to that of conventional banks. Most importantly, the statistical significance of the IB dummy shows that these banks operate with lower leverage under all examined periods, ceteris paribus. Hence, Islamic banks' lower leverage could potentially explain the lower market risk, as verified by our earlier results.

Furthermore, the sensitivities of Islamic and conventional financial institutions to key explanatory variables proposed by the capital structure model are significantly different in the majority of occasions. [18] Hence, the capital structure model that has been designed for conventional financial institutions may not be fully applicable to IFIs. In summary, our results do not support the studies of Khan (2010) and Chong and Liu (2009), based on which IFIs should have similar risk and capital structure to conventional financial institutions. In contrast, our findings suggest that IFIs are substantially different from conventional financial institutions.

7. Conclusion

The growing importance of Islamic banking has resulted in an ever-increasing literature that compares Islamic to conventional banking from a variety of perspectives. To date, no study has compared the market risk, as measured by VaR and ES, of Islamic and conventional banks. Ours is the first study to do so over an extensive period including the financial crisis of 2007. Our study complements other researchers such as those of Abedifar et al. (2013), Beck et al. (2013)

[18] An implicit assumption here is that since the capital structure model is tailored for conventional banks, it can only pick up differences with respect to those variables contained in it. However, a capital structure model for Islamic banks could potentially include variables more attuned to their unique business model. We leave this question open for future research.

and Pappas et al. (2016) in examining risks associated with Islamic banking and provide evidence of the stability of Islamic banking as an alternative to conventional banking.

Using daily returns of both Islamic and conventional banks over the 2000-2013 period, we calculate the market risk as defined by VaR and ES. These measures of market risk are used by regulators and are intuitively simple to understand and are estimated based on daily stock price data. In contrast to studies that focus on similar risk measures (e.g., Abedifar et al., 2013 for credit risk), this study shows that market risk is not dependent on accounting data, which may be available only quarterly, and is precisely defined based on a single interpretation.

In aggregating our risk measures, we find that the univariate VaRs and ESs of both Islamic and conventional banks are indistinguishable from each other for the whole period, irrespective of the methodology used for calculation and portfolio of conventional banks used for comparison. However, the number of exceedances of both Islamic and conventional banks increases during the crisis period, indicating that market stress affects conventional and Islamic banks equally. Using the multivariate approach incorporating dynamic conditional correlation, we find that the VaR of Islamic banks is significantly lower than that of portfolio of conventional banks during the financial crisis. Furthermore this finding is robust to different portfolio of conventional banks. More importantly we find that based on the ES measure of market risk Islamic banks are less risky than conventional banks. This finding is robust to time period and the portfolio of conventional banks used for comparison. We conclude that at times of financial crisis Islamic banks are less risky than conventional banks.

One of the key differences observed between Islamic banks and conventional banks is the supposedly fundamental difference in their capital structure, which prohibits the use of debt instruments for Islamic banks. We test this proposition using a series of panel data regressions on the capital structure equation over the whole period and the sub-periods of analysis. We find that the capital structure of Islamic banks is significantly different from that of conventional banks.

Crucially we show that Islamic banks operate with lower leverage for the whole period and the sub-periods. This is consistent with existing theory of Islamic banks and is in contrast to the claims of Khan (2010) and Chong and Liu (2009).

Our study has a number of implications. First, portfolio managers should incorporate Islamic banks into their portfolios as a way of reducing risk, particularly so during a financial crisis. Second, based on the market risk as measured by VaR, Islamic banks should be treated differently from conventional banks and that ES measure of market risk should be used for Islamic banks. Third, existing capital structure models for conventional banks is inadequate for Islamic banks and researchers should develop new capital structure models that explicitly incorporates low level of debt of Islamic banks.

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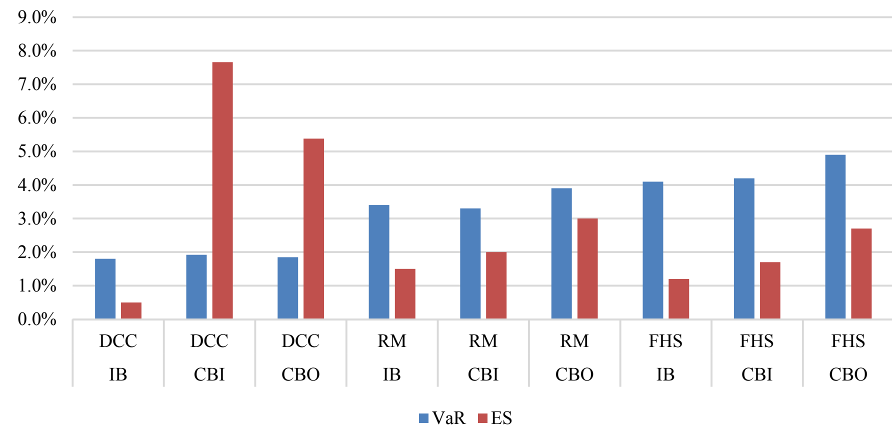
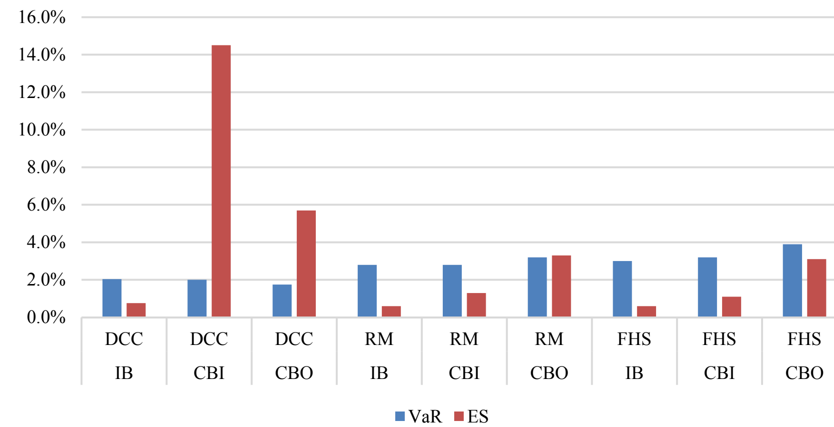
Figure 1. Value at Risk (VaR) and Expected Shortfall (ES) estimates.

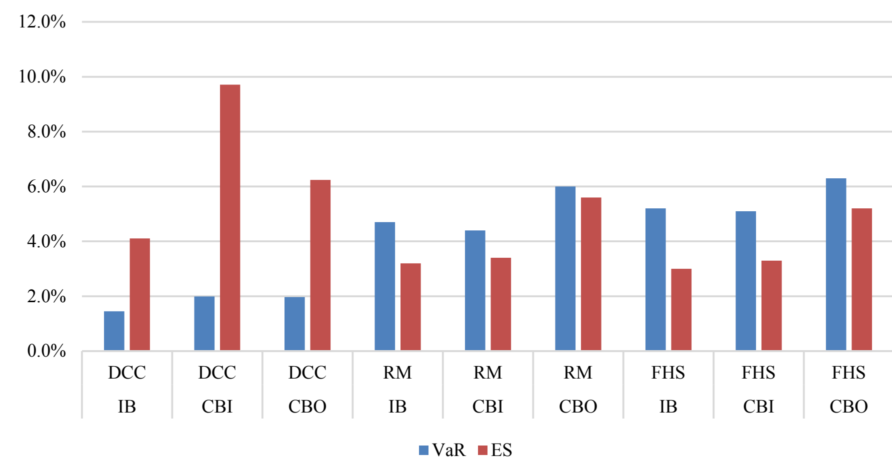
Panel A: Whole period



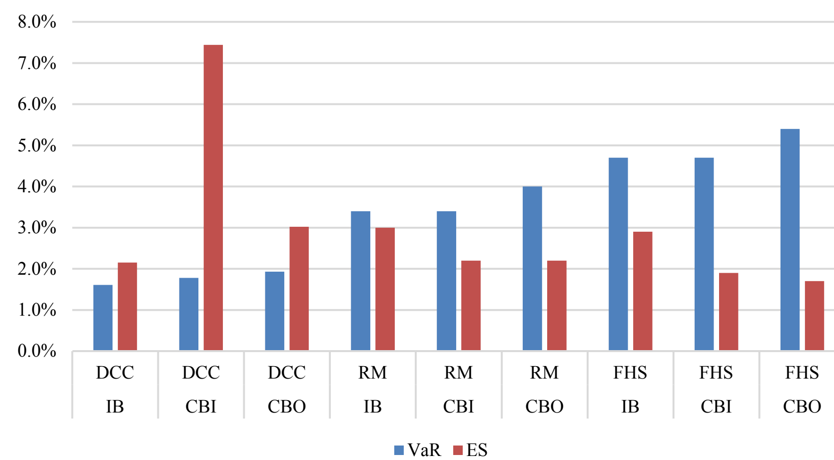
Panel B: Pre-crisis period



Panel C: Crisis period



Panel D: Post-crisis period



Notes: DCC denotes the Dynamic Conditional Correlation (multivariate) estimation model. RM and FHS denote the RiskMetrics and Filtered Historical Simulation (univariate) estimation models. IB denotes Islamic banks, CBI denotes Conventional banks in Islamic countries, CBO denotes Conventional banks in Other countries. Whole period covers January 3, 2000, to December 31, 2013; Pre-crisis period covers January 3, 2000, to June 30, 2007; Crisis period covers July 1, 2007, to June 30, 2009; and Post-crisis period covers July 1, 2009, to December 31, 2013.

Table 1. Sample breakdown by country and bank type

	Islamic banks			Conventional banks (CBI)			Conventional banks (CBO)		
Country	Banks	%	Market Cap	Banks	%	Market Cap	Banks	%	Market Cap
Bahrain	6	9.23	104.66	6	9.23	100.54			
Bangladesh	7	10.77	82.46	7	10.77	72.78	2	3.077	109.09
China	2	3.08	630.97	2	3.08	627.51	2	3.077	566.6
Egypt	3	4.62	92.07	3	4.62	90.76			
Indonesia	7	10.77	1181.37	7	10.77	929.94			
Jordan	2	3.08	82.3	2	3.08	69.7			
Kuwait	6	9.23	1452.77	6	9.23	462.7			
Malaysia	1	1.54	307	1	1.54	316.74	1	1.538	1605.21
Oman	5	7.69	277.31	5	7.69	133.4			
Pakistan	3	4.62	34.37	3	4.62	32.66	1	1.538	675.67
Palestine	2	3.08	14.38	2	3.08	13.7			
Qatar	3	4.62	1264.16	3	4.62	1554.37			
Saudi Arabia	4	6.15	2773.65	4	6.15	2195.78			
South Africa	1	1.54	3170.68	1	1.54	2526.93			
Sri Lanka	1	1.54	31.62	1	1.54	33.46	2	3.077	135.55
Taiwan	2	3.08	2170.59	2	3.08	2474.41			
Turkey	1	1.54	348.57	1	1.54	262.37			
UAE	9	13.85	855.7	9	13.85	841.38			
US							24	36.923	194.25
Other							33	50.769	1013.76
Total	**65**	**100**	**803.07**	**65**	**100**	**645.61**	**65**	**100**	**803.36**

Notes: Market Capitalization is measured in millions of USD in 2000. CBI denotes Conventional banks in Islamic countries. CBO denotes Conventional banks in Other countries.

Table 2. Summary statistics for all banks, conventional banks and Islamic banks

	Mean	**Std dev.**	**Skewness**	**Excess Kurtosis**	**Q(10)**
			Panel A: Islamic banks (IB)		
Whole	0.1024	0.0254	0.8912	3.6713	357.8050***
Pre-crisis	0.0746	0.0167	1.0602	4.1610	198.8943***
Crisis	-0.2088	0.0273	-0.1110	4.9118	38.1668***
Post-crisis	0.0723	0.0256	0.3541	2.9463	108.9015***
			Panel B: Conventional Banks in Islamic countries (CBI)		
Whole	0.1119	0.0276	1.2435	9.6005	352.2853***
Pre-crisis	0.0891	0.0145	1.1881	5.1355	198.6164***
Crisis	-0.2021	0.0163	-0.0223	2.6175	36.5391***
Post-crisis	0.0879	0.0325	0.7385	5.0361	107.3705***
			Panel C: Conventional Banks in Other countries (CBO)		
Whole	0.0551	0.0424	0.5314	3.2023	356.6432***
Pre-crisis	0.0507	0.0305	0.7254	3.8323	197.8663***
Crisis	0.0465	0.0124	-0.1025	2.4662	35.5208***
Post-crisis	0.0557	0.0200	0.1528	3.7185	104.8548***

Notes: Summary statistics of daily returns for Islamic banks (Panel A), Conventional banks in Islamic countries (Panel B), Conventional banks in Other countries (Panel C). Whole period covers January 3, 2000, to December 31, 2013; Pre-crisis period covers January 3, 2000, to June 30, 2007; Crisis period covers July 1, 2007, to June 30, 2009; and Post-crisis period covers July 1, 2009, to December 31, 2013. Q (10) denotes the average Ljung-Box test statistic for autocorrelation of the bank stock returns up to the 10^{th} lag. ***, **, * denote statistical significance at the 1, 5 and 10% level respectively.

Table 3. Summary statistics for the capital structure variables

	Leverage	MTB	Profits	Ln(Size)	Collateral	Dividend	Ln(Risk)
Panel A: Islamic banks							
Mean	0.799	2.119	58.056	8.283	9105.034	0.348	-1.607
Median	0.861	1.488	21.165	8.410	2023.092	0.000	-1.644
Min	0.001	0.292	-606.953	0.828	0.045	0.000	-5.306
Max	0.998	33.872	1983.233	11.556	124851.100	1.000	1.220
SD	0.190	2.489	114.374	1.823	18255.410	0.476	0.957
Skewness	-2.358	5.726	4.861	-1.009	3.138	0.638	-0.081
Kurtosis	8.112	50.281	58.074	5.034	13.118	1.407	3.144
Observations	1841	1822	1849	1841	1837	1681	1760
Panel B: Conventional banks in Islamic countries							
Mean	0.697	2.004	32.891	7.645	5801.102	0.184	-1.516
Median	0.813	1.534	15.157	7.776	1168.513	0.000	-1.566
Min	0.008	-1.418	-8233.113	3.701	0.045	0.000	-5.777
Max	1.043	51.181	2316.242	11.940	166093.100	1.000	1.990
SD	0.245	2.291	224.059	1.649	15729.830	0.387	0.958
Skewness	-1.064	10.994	-27.290	-0.066	6.124	1.633	0.176
Kurtosis	2.948	188.655	998.288	2.411	48.618	3.666	3.300
Observations	1906	1893	1907	1906	1922	3640	1711
Panel C: Conventional bank in Other countries							
Mean	0.904	1.340	2.064	7.874	10256.890	0.282	-1.261
Median	0.908	1.233	5.852	7.882	2390.336	0.000	-1.367
Min	0.268	-0.042	-4560.398	3.655	0.305	0.000	-7.015
Max	1.210	6.581	963.495	12.529	385325.700	1.000	2.851
SD	0.057	0.699	313.581	1.594	29079.670	0.450	0.950
Skewness	-4.619	1.405	-13.413	0.156	7.774	0.967	0.139
Kurtosis	58.654	7.908	195.641	2.414	76.846	1.934	4.977
Observations	2047	2019	2069	2047	2055	3640	1912

Notes: Summary statistics for the variables in the capital structure model. Dividend is a binary variable. Observations are on a firm-quarter basis.

Table 4. Univariate Value-at-Risk (VaR) results

	IB	CBI	CBO	p^{CBI}	p^{CBO}	IB	CBI	CBO	p^{CBI}	p^{CBO}
Panel A: VaR Estimates										
	RiskMetrics (RM)					Filtered Historical Simulation (FHS)				
Whole	0.034	0.033	0.039	0.511	0.289	0.041	0.042	0.049	0.624	0.265
Pre-crisis	0.028	0.028	0.032	0.485	0.367	0.030	0.032	0.039	0.625	0.354
Crisis	0.047	0.044	0.060	0.395	0.171	0.052	0.051	0.063	0.669	0.191
Post-crisis	0.034	0.034	0.040	0.587	0.226	0.047	0.047	0.054	0.606	0.171
Panel B: VaR Backtesting										
Whole period										
% Violations	6.10	4.31	3.09			5.56	3.79	1.86		
LR_{uc}	1397	735	616			392	710	234		
LR_{ind}	392	266	217			408	318	56		
LR_{cc}	1789	1001	833			800	1028	290		
Pre-crisis period										
% Violations	9.64	4.29	1.99			9.62	4.09	3.35		
LR_{uc}	581	363	236			585	353	675		
LR_{ind}	92	88	61			88	117	174		
LR_{cc}	673	451	297			673	470	849		
Crisis period										
% Violations	4.90	4.20	3.26			4.38	3.80	2.77		
LR_{uc}	1629	896	645			1643	883	646		
LR_{ind}	320	236	172			331	272	198		
LR_{cc}	1949	1132	817			1974	1155	844		
Post-crisis period										
% Violations	3.23	4.36	4.37			2.17	3.47	3.71		
LR_{uc}	1744	913	979			1730	882	1053		
LR_{ind}	504	342	309			528	394	301		
LR_{cc}	2248	1255	1288			2258	1276	1354		

Notes: VaR represents the average VaR for each portfolio at the 99% level over a one-day period. In Panel B, %Violations represents the actual number of violations of each portfolio. p^{CBI} and p^{CBO} denote the p-value for the t-tests between the samples of Islamic banks and conventional banks in Islamic countries, and Islamic banks and conventional banks in Other countries. LR_{uc}, LR_{ind} and LR_{cc} are the test statistics, and the corresponding p-values are obtained from the χ_1^2 test. Whole period covers January 3, 2000, to December 31, 2013; Pre-crisis period covers January 3, 2000, to June 30, 2007; Crisis period covers July 1, 2007, to June 30, 2009; and Post-crisis period covers July 1, 2009, to December 31, 2013. Note all violation statistics are significant at the 1% level.

Table 5. Univariate Expected Shortfall (ES) results

	IB	CBI	CBO	p^{CBI}	p^{CBO}	IB	CBI	CBO	p^{CBI}	p^{CBO}
Panel A: ES Estimates										
	RiskMetrics (RM)					Filtered Historical Simulation (FHS)				
Whole	0.015	0.020	0.030	0.487	0.380	0.012	0.017	0.027	0.492	0.380
Pre-crisis	0.006	0.013	0.033	0.485	0.410	0.006	0.011	0.031	0.497	0.424
Crisis	0.032	0.034	0.056	0.469	0.356	0.030	0.033	0.052	0.446	0.381
Post-crisis	0.030	0.022	0.022	0.497	0.348	0.029	0.019	0.017	0.501	0.321
Panel B: Out of sample predictive performance (MAE)										
Whole period										
q = -0.6%	1.05	1.38	1.16			0.79	1.10	0.89		
q = -0.8%	1.04	1.38	1.17			0.82	1.13	0.90		
q = -1.0%	1.03	1.37	1.20			0.88	1.20	0.98		
q = -1.2%	1.05	1.38	1.25			0.94	1.28	1.06		
Pre-crisis period										
q = -0.6%	0.39	0.91	0.82			0.34	0.71	0.61		
q = -0.8%	0.38	0.87	0.80			0.33	0.68	0.60		
q = -1.0%	0.36	0.85	0.78			0.31	0.69	0.59		
q = -1.2%	0.37	0.85	0.78			0.31	0.70	0.59		
Crisis period										
q = -0.6%	2.45	2.60	2.12			2.26	2.34	2.04		
q = -0.8%	2.51	2.64	2.28			2.42	2.48	2.26		
q = -1.0%	2.52	2.66	2.45			2.56	2.57	2.47		
q = -1.2%	2.61	2.74	2.65			2.70	2.71	2.66		
Post-crisis period										
q = -0.6%	2.36	1.54	1.28			1.88	1.19	0.78		
q = -0.8%	2.29	1.55	1.27			1.93	1.24	0.88		
q = -1.0%	2.26	1.53	1.29			2.09	1.34	0.99		
q = -1.2%	2.23	1.53	1.31			2.19	1.46	1.12		

Notes: ES represents the average ES for each portfolio at the 99% level over a one-day period. Whole period covers January 3, 2000, to December 31, 2013; Pre-crisis period covers January 3, 2000, to June 30, 2007; Crisis period covers July 1, 2007, to June 30, 2009; and Post-crisis period covers July 1, 2009, to December 31, 2013. Following Zhu and Galbraith (2011), we set threshold (loss) returns at *q* = -1.2%, -1%, -0.8%, -0.6% to ensure that there is a substantial number of points at which losses exceed *q*.

Table 6. Multivariate Value-at-Risk (VaR) and Expected Shortfall (ES) results

	IB	CBI	CBO	p^{CBI}	p^{CBO}
			Panel A: VaR		
Whole	0.0180	0.0192	0.0185	0.119	0.412
Pre-crisis	0.0204	0.0200	0.0175	0.719	0.000
Crisis	0.0145	0.0199	0.0197	0.010	0.002
Post-crisis	0.0161	0.0178	0.0193	0.167	0.001
			Panel B: ES		
Whole	0.0050	0.0766	0.0538	0.000	0.018
Pre-crisis	0.0076	0.1450	0.0570	0.000	0.009
Crisis	0.0411	0.0971	0.0624	0.010	0.009
Post-crisis	0.0215	0.0744	0.0302	0.011	0.078

Notes: VaR represents the average VaR for each portfolio at the 99% level over a one-day period. ES represents the ES for each portfolio at the 99% level over a one-day period. Whole period covers January 3, 2000, to December 31, 2013; Pre-crisis period covers January 3, 2000, to June 30, 2007; Crisis period covers July 1, 2007, to June 30, 2009; and Post-crisis period covers July 1, 2009, to December 31, 2013. p^{CBI} and p^{CBO} denote the p-value for the t-tests between the samples of Islamic banks and conventional banks in Islamic countries, and Islamic banks and conventional banks in Other countries.

Table 7: Capital structure estimation results

	Whole Period	$\Delta(IB-CB)$	Pre-crisis	$\Delta(IB-CB)$	Crisis	$\Delta(IB-CB)$	Post-crisis	$\Delta(IB-CB)$
MTB	-0.0007		-0.0012		-0.0039*		-0.0037	
	(0.0024)		(0.0017)		(0.0024)		(0.0039)	
Profits	-0.0024*		-0.0193**		-0.0009***		-0.0037***	
	(0.0014)		(0.0097)		(0.0002)		(0.0010)	
Ln(Size)	0.0254**		0.0038		0.0143		0.0419***	
	(0.0120)		(0.0143)		(0.0175)		(0.0142)	
Collateral	-0.2381*		0.4747		-0.3475		-0.2436*	
	(0.1302)		(0.3928)		(0.2936)		(0.1342)	
Dividends	-0.0030		-0.0004		-0.0028		0.0022	
	(0.0033)		(0.0041)		(0.0027)		(0.0017)	
Ln(Risk)	0.0014		0.0055		-0.0004		0.0034	
	(0.0032)		(0.0045)		(0.0020)		(0.0027)	
MTB x IB	-0.0505**	5.4300**	-0.0535**	3.9000**	0.0012	0.1700	-0.0847***	8.4800***
	(0.0209)		(0.0263)		(0.0115)		(0.0270)	
Profits x IB	-92.2187**	4.5000**	-210.3698***	27.4400***	-144.7886	0.8500	-35.8511***	6.9900***
	(43.4538)		(40.1565)		(157.3518)		(13.5564)	
Ln(Size) x IB	0.0181	0.0900	0.0342	0.6300	0.0629**	1.3700	0.0832**	0.8700
	(0.0138)		(0.0292)		(0.0284)		(0.0366)	
Collateral x IB	-1.0264***	3.5700**	-2.2357***	10.9000***	-4.3439*	2.5100	-1.2937***	12.8400***
	(0.3512)		(0.4591)		(2.4731)		(0.1786)	
Dividends x IB	0.3120	2.3000	0.5543***	75.0500***	0.4516***	71.6400***	0.2686*	3.4300*
	(0.2077)		(0.0636)		(0.0535)		(0.1439)	
Ln(Risk) x IB	-0.0163	2.0300	-0.0190	2.8600*	-0.2008*	2.9200*	-0.0491***	16.0400***
	(0.0110)		(0.0123)		(0.1172)		(0.0122)	
IB	-0.4661***		-0.8226***		-1.6349***		-1.3646***	
	(0.1523)		(0.2458)		(0.5372)		(0.3543)	
Constant	0.5956***		0.8011***		0.6819***		0.4648***	
	(0.0978)		(0.1055)		(0.1437)		(0.1199)	
Observations	3488		1115		679		1694	
Adjusted R^2	15.08%		19.86%		9.56%		17.68%	

Notes: The table presents estimated coefficients and robust standard errors in parenthesis for equation (15). IB denotes the Islamic banking dummy that takes 1 for Islamic Financial Institutions, zero otherwise. MTB denotes the Market-to-Book ratio. The $\Delta(IB-CB)$ column reports the chi-square (χ^2) test statistic for the difference in the coefficients of the conventional and the Islamic banks. ***, **, * denote statistical significance at the 1, 5 and 10% level respectively.