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ABSTRACT

The capital structure theory advocates a mix between debt and equity to optimize a firm's value (Modigliani & Miller, 1958). However, Islamic finance recognizes more conservative levels of debt for firms, based not on capital structure, but on debt to total assets or debt to market capitalization. This study is the first attempt to investigate the role of leverage in affecting the returns and the firm's share price volatility in relation to an Islamic finance perspective (IFP). The paper is based on a sample of 320 European companies distributed into different portfolios with high and low debt, high and low assets and focused on ten different countries. Comparative portfolio analysis was used to obtain a number of testable hypotheses, which specify the factors at the level of the firm and at the level of the market, in order to determine optimal financial risk. Specifically, we use the mean variance efficient frontier (MVEF) to confirm, in accordance with the theory, that a portfolio with a higher capital structure has higher volatility and lower returns compared to a portfolio with a lower capital structure. Then, the Shari'ah screening method of improving the firm's stability in the market has been analyzed based on econometric analysis. Dynamic GMM is used in order to correlate the firm's leverage to total assets with its return and volatility in portfolios with high and low capital structure. To ensure the robustness of results, the business cycle effects have been considered after adding the firm and the country characteristics with a view to taking into account the heterogeneity across different firms and different markets. The preliminary results tend to indicate that there are significant correlations between capital structure and both returns and volatility, but not necessarily with high debt to assets given different sizes and growth of firms. The paper suggests that are three main factors which need to be considered by the firms in order to improve their stability in the market: firstly, the level of capital structure but not the debt to total assets as suggested by some scholars using the IFP; secondly, the capitalization or the firm size and finally, the level of the sovereign debt and country dynamics. Although the latter may be beyond the firm's control, it is up to the firm to consider its own market with implications on its leverage policy in relation to the frequency-dependent strategy.

Keywords: Volatility, leverage, dynamic GMM, Wavelet Time–frequency analysis.

1. Introduction

Understanding the level of corporation debt and volatility with a specific focus on contagion under normal economic conditions and under shocks has been a subject of study by many authors in various contexts. According to financial theory, total volatility will increase with the increase of the firm's debt; in general they are correlated positively. Within the capital structure theory, a very high level of debt could rarely be the optimal structure, since a company's risk generally increases as debt increases. However, there is an optimal balance between the ideal debt-to-equity ratio and the firm's cost of capital. Eventually, as the company's capital structure (debt/equity ratio) increases, the cost of debt and the cost of equity will increase. Investors become more concerned about the risk of default and want to be compensated for the higher risk. The risk premium is likely to increase as the risk of bankruptcy could be higher and the risk of loss could be also higher.

Against this background of conventional financial theory of debt management, Islamic finance, in its concepts, advocates less debt for firms and could offer an efficient alternative strategy based on the principle of risk sharing, participation and fair partnership (for example, *musharakah* or *mudarabah* contracts). In Islamic finance, for riskier projects, investors will expect higher profit sharing ratio and also further quality in reporting and transparency. Therefore, considering the nature of the contracts in Islamic finance, good corporate governance is highly regarded since it lowers the agency costs. However, in the operation of the market mechanism, there is a temptation for firms to go for debt, as the tax shield makes the cost of financing, with debt, in most cases, considerably lower than financing with equity. In the absence of the tax deductibility, which is the case of only few countries in the world, the capital structure theory with risk-neutrality assumption, suggests that there is no benefit for borrowing at the firm level. Consequently, based on the assumption (Modigliani and Miller, 1958) that market participants are risk-neutral, firms would be indifferent to the source of capital only if the cost of equity is equal (or less compared) to the cost of the debt.

In this study, we investigate the extent to which the leverage induces volatility level of the firm's share price. Since under shocks, the volatility may differ from its fundamental value (due to market risk and financial risk), assuming a competitive financial market in the context of capital structure theory; therefore, this study also aims to examine whether firms with weak capital and high level of debt ratios (high leverage position) are particularly vulnerable to volatility spillovers.

As the relevant body of literature demonstrates, a number of studies have been undertaken to analyze volatility and contagion across different countries and markets, but few studies have been dedicated to looking into the volatility from the firm's debt perspective. Moreover, only very few have focused on such issues through the Islamic finance principles by applying the stock screening filters (quantitative and qualitative) as a tool to study volatility and its relation with the contagion during the last global financial crisis (GFC). Hence we aim to fill this gap by introducing Shari'ah principles in the stock market and to investigate whether lower leverage, as suggested by Islamic finance, is bringing less volatility and more stability to the markets. There are still open questions about the impact of leverage on volatility; and the controversies are still emerging.

Within the defined aims of this paper, we aim to address the following key questions: (i) Does the return of the firm change with changes in capital structure of the firm?; (ii) Does volatility change with changes in capital structure of the firm?; (iii) How do *Shari'ah* compliant stocks perform in terms of leverage and volatility?; (iv) How do portfolios of *Shari'ah* compliant and conventional stocks compare in terms of risk-return profiles?; and (v) Based on the previous questions, what has been the behaviour of firms and markets during the GFC in 2007-2008?

To investigate the leverage effeect on the volatility and return, this paper has adopted three different methodological approches : (i) *We first applied the Wavelet Transform Coherence technique (WTC) (ii); the Mean Variance Efficient Frontier has been used to* formalize the risk-return profiles of the European firms constructed as high and low debt portfolios profitable with their different profitability outcomes. Then (iii) dynamic panel techniques using vector autoregressive framework by which we have been able to control simultaneously the level of debt effect and the country effects on return and volatility.

It should be noted that the MVEF approach contributes to showing that low debt portfolios are more likely to provide more stability with higher return than the high debt portfolios. Continuous wavelet transform has helped us investigate the lead-lag relationships (in terms of contagion effect) based cross correlation between different variables and helped to identify the variables to be considered in the econometric modeling. Finally, to make our results robust in GMM and in overcoming the heterogeneity across firms, we have used dummy variables linked to the level of debt (measured as total debt over total assets) as suggested by the stock *Shari'ah* screening process. Furthermore, considering the nature of the firms included, the exchange rate has been added to capture the currency effect for the firms originating in countries within and outside the Euro zone.

The remainder of the paper is arranged as follows: section 2 presents the literature review, section 3 discusses the research methodology of the study, section 4 discusses the results, and lastly section 5 provides some reflections on conclusion and policy implications.

2. Literature Review

This section aims to provide a survey of the relevant studies by making reference to conceptual underlying of the study as well as the methodologies and findings of some of the empirical studies.

2.1 Studies on capital structure

Firm's financing related studies based on capital structure have, through time, evolved, and in the process various determinants based on firm characteristics and country specific factors have been generated and included.

In such development, relationship between firm leverage and country specific factors has been studied by many authors; among others, Booth *et al.* (2001), Deesomsak *et al*. (2004), De Jong *et al.* (2008), Driffield and Pal (2008), and Kayo and Kimura *et al*. (2011) can be mentioned. Findings in these studies reveal that not only firm characteristics but also country specific factors do have significant influence on a firm's financing. For example, Booth *et al*. (2001) find that the corporate financing is affected by determinants related to the country specific factors in developed countries with country specific differences that spread across countries. The country specific determinants should not be neglected in the capital structure analysis since they have a sizeable explanatory power (De Jong *et al*., 2008).

Only very recently that debt of the firm has been included in the study of capital structure as one of the variables representing firm specific factors. Therefore, this study intends to fill the gap by analyzing the impact of firm's debt in corporate financing on the volatility and contagion.

2.2. Approach for measuring total volatility and return in the literature

Since this study aims also at measuring the effect of volatility, this section discusses the conceptual base of such measurement. For example, Christie (1982) computes volatility using a regression that has been augmented with the lagged volatility to treat autocorrelation in volatility. The equation for each firm in the form of ($\sigma_t = \alpha + \beta_1 D_{it} + \beta_2 \sigma_{t-1} + \varepsilon_t$) takes into account the level of debt (D_{it}) with the first lag of the standard deviation of the return. In this, Christies constructs D_{it} by dividing face value of debt at the end of the previous available data period by the value of the equity at the beginning of the period, which represents the lagged value of the debt as *de facto*.

In providing a different perspective, Dufee's (1994) model was based on the log difference of the standard deviation as function of the return times a coefficient called λ_0 following the equation ($Log\left(\frac{\sigma_{t+1}}{\sigma_t}\right) = \alpha_0 + \lambda_0 r_t + \varepsilon_{t+1,0}$). The interpretation of this negative coefficient is that a positive r_t corresponds to a decrease in σ_{t+1}. Dufee (1994), therefore, argued that the primary reason for $\lambda_0 < 0$ is that a positive r_t corresponds to an increase in σ_t. However, Christie has decomposed Dufee's econometric model into two equations:

$Log\,(\sigma_t) = \alpha_0 + \lambda_1 r_t + \varepsilon_{t,1}$ as Eq. (1) and ,

$Log\,(\sigma_{t+1}) = \alpha_0 + \lambda_2 r_t + \varepsilon_{t+1,2}$ as Eq. (2)

where λ_0 has been computed as a difference between λ_2 and λ_1 ($\lambda_0 = \lambda_2 - \lambda_1$). This shows that there is no clear relation between the return and volatility (r_t and σ_{t+1}). Christie has found that the covariance between λ_0 and firm leverage is strictly negative and near to one [Cov (λ_0 , Firm Leverage) << ~ -1], while Cheung and Ng found that the covariance between λ_0 and firm size is strictly positive and also near to one [Cov (λ_0 , Firm Size) >> ~ 1]. In giving an empirical meaning, Dufee (1994) found that for the typical firm traded on the American New York Stock Exchanges, λ_1 is strongly positive, while the sign of λ_2 depends on the frequency over which these relations are estimated: it is positive at the daily frequency and negative at the monthly frequency. In both cases $\lambda_2 < \lambda_1$, so $\lambda_0$is negative in Eq. (2).

Black (1976) conducted the first empirical work on the relation between stock returns and volatility. Using a sample of 30 stocks (basically the Dow Jones Industrials), he constructed monthly estimates of stock return volatility over the period 1962-1975 by summing squared daily returns and taking the square root of the result. For each stock *i*, he then estimated

$[\frac{\sigma_{i,t+1}}{\sigma_{i,t}} = \alpha_1 + \lambda_0 \, r_t + \varepsilon_{i,t+1}$].

If there are *N*, days in month *t*, the estimated standard deviation is:

$\sigma_t^2 = \sum_{k=1}^{n} r_{t,k}^2$ (3).

French *et al.* (1987) propose an alternative volatility estimate that adjusts for first-order autocorrelation in returns [$\sigma_t^2 = \sum_{k=1}^{N} r_{t,k}^2 + 2 \sum_{k=1}^{N-1} r_{t,k} \; r_{t,k+1}$], where *N* is the number of days in the period *Q*.

From the Dufee (1994) Model, we can note that λ_0 should be related to the two parameters: the debt and firm size. Because of its 'statiticity', we note that this model is not adapted to the debt dynamic's feature.

Jan Ericsson & al (2007) used a dynamic model taking into account the level of debt [$\Delta\sigma_t = \alpha + \phi_1 \, D_{it} + \phi_2 \sigma_{t-1} + \varepsilon_t$]. In its bi-variate system, the parameters are the same as if the equations were expressed in levels [$\Delta\sigma_{it} = \phi_1 \, \Delta D_{i,t-1} + \phi_2 \Delta\sigma_{t-1} + \Delta\varepsilon_{t2}$]. In its tri-variate system, the change in the return has been added to the model [$\Delta\sigma_{it} = \mu_1 \, \Delta D_{it} + \mu_2 \Delta\sigma_{t-1} + \mu_3 \Delta r_{t-1} + \Delta U_{t2}$].

Engle and Ng and others (1993), reported that conditional volatility of stock returns to be negatively correlated with past returns (see among; Glosten, Jagannathan and Runkle, 1993; and Wu, 2001). Thus, an asymmetric response of equity systematic risk to past stock performance can be transmitted through the variance asymmetry channel.

Vanessa Smith and Takashi Yamagata (2011) model has used the same set variables in the right hand side for return and volatility ($Log(\sigma_{it})$) based on the business cycle, the firm characteristics and the sectors return and volatility by using the value-weight (of the S&P500) for the i^{th} firm of the s^{th} industrial sector. They imposed the restriction that a single firm does not affect the market, business cycle variables or industrial sectors contemporaneously. Their model was limited to the US market and while it integrated the different level of lagged return and volatility, it did not consider a direct impact of the debt level of the firm. To illustrate the contemporaneous firm level effects, they based their model on the Whitelaw (1994), and Brandt and Kang (2004), Pesaran et al. (2004) and Dees et al. (2007), and applied the re-parameterization principle. This allowed them to show the connection to lagged return and lagged volatility of the firm and the sector (lags =1), in the mean models. They added estimates to show the contemporaneous firm level leverage effects, the lagged firm level leverage effects, the contemporaneous and lagged market return effects on firm volatility, respectively.

We consider that this model could help in the way that it is bringing to the model, the vector of business cycle variables. The latter vector (d_{it}) will be added to the retained econometric model. We extend the methodology of Vanessa Smith and Takashi Yamagata (2011) by combining it with the latest model taking into account the change in debt. (Whitelaw (1994), and Brandt and Kang (2004), Pesaran et al. (2004) and Dees et al. (2007)).

Jie Cai & Zhe Zhang (2011) have used the Capital Asset Pricing Model (CAPM) based on the Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model (three-factor plus the momentum factor). They have examined whether the observed negative relation between leverage changes and stock returns reflects these stocks' different cross-sectional loadings on systematic risk factors. They run the time–series regression taking into account the monthly portfolio returns, the risk-free rate (measured by the one-month T-bill yield), factor returns including the market excess return, returns of the Fama-French size factor (SMB), book-to-market factor (HML), and the momentum factor (UMD). They have obtained the return series of these factors and the one-month T-bill yield from Kenneth French's website. The alphas from the regressions represent the risk-adjusted returns of the portfolios. They expected the alphas to be similar across all the portfolios.

Although the factor models cannot explain the negative relation between changes in leverage ratio and next-quarter stock returns, a firm's capital structure choice may depend on other firm characteristics not captured by these factors. Furthermore, Daniel and Titman (1997) argue that characteristic-based models can better explain the cross-sectional variation of stock returns. It is possible that the negative effect of leverage changes on stock returns can be explained by other firm characteristics. To examine the marginal effect of leverage change on cross-sectional stock returns, they estimate Fama-Macbeth (1973) type cross-sectional regressions of monthly individual stock returns on the change in leverage ratio of the most recent fiscal quarter, among other control variables. Their model has used the leverage change (during the most recent fiscal quarter leverage ratio at the beginning of the previous quarter) and a control vector taking into account: the market value of equity, book-to-market ratio, past one-month return, past one-year stock returns and the previous quarter's ROE.

Fama and French (1992), among others, find significant explanatory power of size and book-to-market ratio on stock returns. The log market value of equity at the end of the last month and the book-to-market ratio at the end of the previous quarter as control variables have been included. To follow Fama and French stock beta estimated with past 60-month return data has been also included. In addition, they include the past one-month return to control for the short-term reversal (Jegadeesh, 1990) and past one-year stock returns to control for the momentum effect (Jegadeesh and Titman, 1993). They further include the previous quarter's ROE to control for the effect of earnings on stock returns. They found that the average coefficient for the change in the leverage ratio is negative and statistically significant at the 1% level. The level of leverage ratio at the beginning of the previous quarter (LV_{t-1}) has been included in the regression in order to control the time–invariant effect of leverage documented by Lemmon et al. (2008). But the results have shown that quarter leverage level is not related to stock returns. Intuitively, the information contained in the level of the leverage ratio should already be incorporated into the stock price in an efficient market and the market only reacts to the innovation in the leverage ratio.

We conclude that model of Vanessa Smith and Takashi Yamagata (2011) should be used by combining it with the models used by Whitelaw (1994), and Brandt and Kang (2004), Pesaran et al. (2004) and Dees et al. (2007)) in order to take into account the change in debt used also by Jie Cai & Zhe Zhang (2011).

2.3. Approach for measuring Contagion

The important feature of the approach to be used is to measure causality in the frequency domain by discriminating contagion and interdependence and taking into account two factors: a permanent or long-run term and a transitory or short-run term.

Stronger linkages between the two returns could be due either to a higher co-movement between the permanent components of the returns, or to a higher co-movement between their short-run components. There will be contagion only in the latter case; contagion is therefore measured by a stronger linkage among the short-run components of the two returns after a crisis. In the former case, as the shift in cross-market linkages is permanent, what is measured is not shift-contagion but a higher integration of markets. Simply computing correlations, even causality measures, without distinguishing between short- and long-run components will therefore only provide spurious measures of contagion.

3. Methodology and data collection

3.1. The econometric models for return and volatility

- The relationship between the Capital structure and the firm's level of debt:

  Based on the capital structure theory, the econometric models are using the capital structure ratio (debt over equity), while the Shariah stock screening is using the level of debt (debt over total assets or the debt over capitalization). Therefore we need to find the estimates between the two parameters using the GMM techniques applied to our time series as follows:

$$\mathbf{Dit} = \alpha_{dit} + \lambda d\ \mathbf{Dit-1} + + \beta d1\ \boldsymbol{LV_t} + \beta d2\ DMY + \beta d3\ DMY \times \mathbf{Dit-1} + \varepsilon_{it} \quad \mathbf{(1.1)}$$

  Where DMY is the dummy variable catching the threshold level of debt's effect as follows:

  If debt over total assets <= 0.33 then DMY = 1, otherwise, DMY = 0

  The dummy variable is also used to catch the interaction effect between the level of debt and the capital structure.

- The firm return equation:

We extend the methodology of **Vanessa Smith and Takashi Yamagata (2011) and combine Whitelaw** (1994), Brandt and Kang (2004), Pesaran et al. (2004) and Dees et al. (2007).

$$r_{it} = \alpha_{it} + \emptyset_{11,i}\, r_{i,t-1} + \emptyset_{12,i}\, log\,(\sigma_{i,t-1}) + \gamma_{11,i}\, \sigma^*_{i,t} + \gamma_{12,i}\, log\,(\sigma^*_t) + \gamma_{11,i1}\, log\,(\sigma^*_{i,t-1}) + \gamma_{12,i1} log\,(\sigma^*_{i,t-1}) + \lambda 1\ \mathbf{Dit-1} + ExRate + D2GDP + \beta 1\ DMY + \beta 2\ DMY \times \mathbf{Dit-1} + \varepsilon_{it} \quad \mathbf{(2.1)}$$

- The firm volatility equation:

$$\ln \sigma_{\mathbf{it}} = \boldsymbol{\varphi_0} + \boldsymbol{\varphi_1} r_{\mathbf{i,t}} + \boldsymbol{\varphi_2} r_{\mathbf{i,t-1}} + \boldsymbol{\varphi_3} \ln \sigma_{\mathbf{i,t-1}} + \psi_{\mathbf{1}} r^*_{\mathbf{i,t}} + \psi_{\mathbf{2}} \ln \sigma^*_{\mathbf{i,t}} + \psi_{\mathbf{3}} r^*_{\mathbf{i,t-1}} + \psi_{\mathbf{4}} \ln \sigma^*_{\mathbf{i,t-1}} + \lambda 2\ \mathbf{Dit-1} + ExRate + D2GDP + \beta 3\ DMY + \beta 4\ DMY \times \mathbf{Dit-1} + \upsilon_{\boldsymbol{\sigma}\ \mathbf{it}} \quad \mathbf{(3.1)}$$

The debt vector ($\mathbf{D_{it-1}}$) is added to the retained econometric model. We conclude that this model could help in the way that it is bringing to the model, the vector of the debt variable.

At this stage we are now able to discuss the implications of the level of debt over the two components: return and total volatility.

In our case, we are more interested in the cross countries analysis that is why we contain our study to use the same return and the volatility of the stock index of the country itself rather than the sector index. So, the variables with star will represent the stock market of each studied country. We will replace the sector of the firm by the European stock index since we look to capture volatility through all sectors, across different countries and, in further step, based on Shariah stock screening.

The macroeconomic and financial market variables considered are those typically used in studies that examine the relation of business cycle variables with the stock market such as **Chen et al. (1986), Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989), Fama (1990), Schwert (1989) and Glosten et al. (1993).**

Our methodology will compute the estimates based on the system Generalized Method of Moments (GMM) technique, suggested by **Arellano and Bond** (1991). GMM estimator is designed for situations with “small T, large N” panel data, meaning few time periods and many individual firms (**Roodman**, 2006). This econometric methodology makes use of lagged instruments of the endogenous variables for each time period to tackle possible endogeneity and joint determination of the explanatory variables in the panel.

The consistency of the GMM system hinges crucially on whether the lagged values of the explanatory variables are a valid set of instruments, and whether it is not serially correlated. The study undertakes the Difference **Sargan** test to establish the validity of the instrument set. A first order serial correlation test is performed to test whether the error term suffers from serial correlation. We should note that the two step GMM results tend to give asymptotically more efficient estimates than that of one step. The bias in the two step standard errors are corrected by Windmeijer's (2005) correction procedure.

In fact the construction of two step GMM is different from one step Baltagi's (2005) and Hayashi (2010). One step is equivalent to 2SLS (Cameron and Trivedi, 2005 - chapter 21). Two step uses the consistent variance co-variance matrix from first step GMM. The construction of two and one step GMM are different (both one and two step use different weighting matrices). It is likely that estimates will be different. By the way, both one and two step are consistent, but the latter is more asymptotically efficient. Earlier researchers used to make inference from one step standard errors since two step standard errors were biased downwards. But recently due to Windmeijer's (2005) correction procedure researchers prefer to use two steps.

The consistency of the GMM estimator depends on the soundness of the instruments. To address this issue, two specification tests suggested by Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) are employed. The first specification test is the **Sargan test (or Hansen J-test)** for over-identifying restrictions, where the null hypothesis is the independence of the instruments and the error terms. The second specification test is the tests of serial correlations for the error terms, where the null hypothesis is that there is no serial correlation.

Other advanced techniques will be used to analyze in debt the contagion effect such as Wavelet or mean variance efficient frontier.

3.2 Empirical data

The empirical data consists of 10 major European countries with stock indices including Germany, United Kingdom, France, etc .(See Appendix 1).

We also consider 1000 corporations distributed over these ten countries, so it will be 100 largest Firms per country. Some sectors have been excluded (such Banks, insurance, Tobacco, Financial Services, etc.: see appendix 10) in order to make samples at the country's level able to contain statistically significant number of Shariah stock companies.

The chosen firms' sector are based on the classification of Shariah stock screening to make easier the second step of volatility analysis. So, financial and insurance industry firms have been excluded from our sample.

Firm Quarterly data will be extracted from Datastream (and/or Bloomberg) based on the Market Capitalisation and Islamic Dow Jones Filters.

All parameter will be in ratio form in order to work in percentage and proportions.

The time interval is from quarter 1, 2001 to quarter 1, 2013, including 49 quarterly data with mean closing prices for the studied companies.

The time series of examined corporations (1000) and considered countries (10) will be split into two groups based on the top big capitalization (or total assets). At the end of each fiscal quarter, we calculate for each firm the change in leverage during the quarter. We calculate leverage as the ratio between the book value of total liabilities and the book value of total assets.

3.3 Data selection for the econometric Models

The table in appendix 1 (Breakdown of retained firms in relation to their countries) contains the aggregated information regarding the number of firms that are found based on a large number of firms (6823 firms as initial total sample). The initial sample, was filtered by excluding the missing values of the parameters (such as: total Equity =0, Total Assets=0 or Market Capitalisation = 0). Then from the filtered sample, we split it up to High Debt (D2TASSETS > 0.33) and Low Debt (D2TASSETS <= 0.33) using the ratio as follows:

$$D2TASSETS = Total\,Debts / Total\,Assets$$

The issue, in the case of high debt firms, is that the sample is very small for three countries: France, Netherland and Poland (see table below)

Country Name	Time span >= 9 years	Time span >= 5 years
France (FR)	8	20
Netherland (NL)	5	10
Poland (PL)	0	9

Even for the time span equal to 5 years, we have got only 9 firms for Poland and 10 for Netherlands. This issue is caused because, we need to find firms that have Debt to total assets more that 33% (*D2TASSETS > 0.33 called here the debt ratio threshold*) in a consecutive manner. In other words, the cumulative debt to total assets for a firm should be in sequence, carrying out the debt ratio which is more than 33% during 9 years (or 5 years) – and this by using Total Debt of the current year over Total Assets for the same year (for the fourth quarters of one year). This may imply that the debt ratio for a quarter could be higher lower than 33% while the mean of the same ration for the same year could higher than the threshold.

By working on the yearly basis, we have to deal with the issue of duplicated data. In fact, only few firms could have a successive quarters, during all the studied period, above (or below) the debt ratio threshold. But the majority has the debt ratio swinging up and down around the threshold.

Before using the year basis criteria, we have tried the quarter basis logic, the resulted samples were smaller than what we have got using the annual basis criteria.

In other hand, there is no problem to get a good sample for the low debt firms (D2TASSETS <= 0.33). The smallest sample has 19 firms for Spain during 9 years.

So, one of the two scenarios should be considered:

1- Take the 10 countries with what we have got: small or big number of firms, this will make unbalanced samples between countries (could be for 5 or 9 years).

2- or reduce the number of countries to the bigger samples by excluding Poland and NL. In this, case we will work only on 8 countries.

In all cases, the econometric models will commingle both high and low debt portfolios and to distinguish between the two, a Dummy variable will be used for this purpose.

3.4 List of variables used in the econometric Models

In the GMM specification, we need to determine whether a variable is "predetermined but not strictly exogenous". Therefore, we have classified the variables into the three following categories:

1- The category one is the case of the variables that are strictly exogenous,

2- The category two is the case of the variables that are endogenous,

3- The category three is the case of the Variables that are predetermined but not strictly exogenous.

The table below gives the list of used variable:

Variable Id	Name and category of the variable	Var. Name	Level Name
1	ɸ = Debt/Equity = Debt-to-Equity ratio (As capital Structure) - Predetermined but not strictly exogenous	CapStruct LDt−1	Firm specific factors
2	ROE, Predetermined but not strictly exogenous	ROE t−1	
3	S & P stock index return for Europe - Strictly exogenous	SPEURO_R	Country specific factors
4	S & P stock index Volatility for Europe - Strictly exogenous	SPEURO_S	
5	Sovereign Debt/GDP, is strictly exogenous	d2gdp	
6	Local Currency over the US Dollar, is strictly exogenous	FOREX_Q	

Since the Market Cap is not available for 3 countries (Spain, Poland, Switzerland), we will use the weight for each firm based on the total asset of the sample.

However, the inflation will not be taken into account because the Cross-correlation between Inflation and the return portfolio is very low (see the results based on wavelet coherence)

4. Results and interpretation

4.1. Applying the WTC (Wavelet Transform Coherence) technique

In this section, we are using the continuous wavelet transform based on pairs between variables to investigate the cross-correlation between the return (and volatility) in relation to different variables such as: the level the capital structure, the level of the debt, etc. . This will allow us, to analyze the lead-lag relationship between the studied variables from two perspectives simultaneously - from frequency and time point of view. We are using below the wavelet coherence as our aim is to extract time-frequency features and in particular to capture localized intermittent periodicities.

- While space does not permit a detailed examination of every country and all kind of portfolios, this section highlights one important case of Low Debt Portfolio in the UK
  - ***WTC for return and volatility Debt to equity, inflation, Sovereign debt versus M2, IP, Inflation,MSCI, exchange rate and Libor***

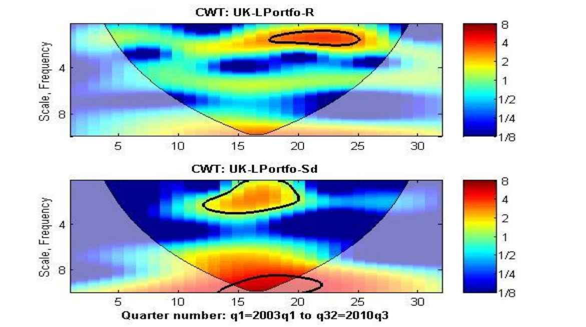

Figure 1.a – CWT: Return alone and Std alone

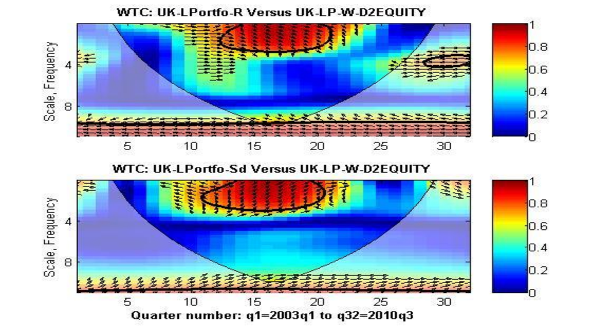

Figure 1.b - WTC: Return/Std – W-Debt2 Equity

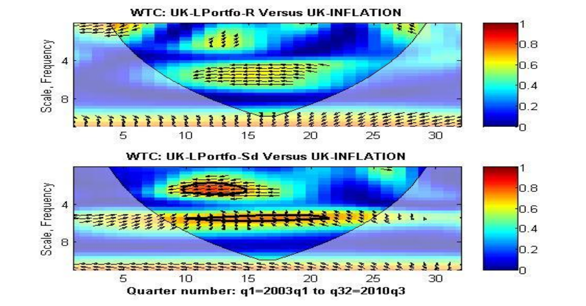

Figure 1.c - WTC: Return/Std – UK-Inflation

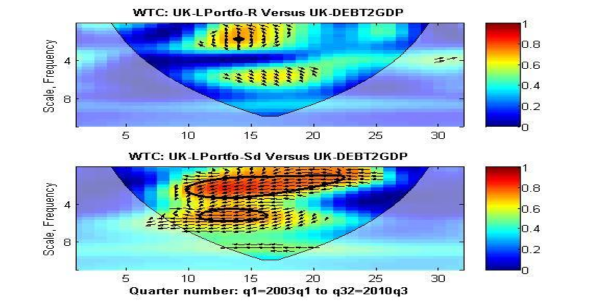

Figure 1.d - WTC: Return/Std – Sov. Debt

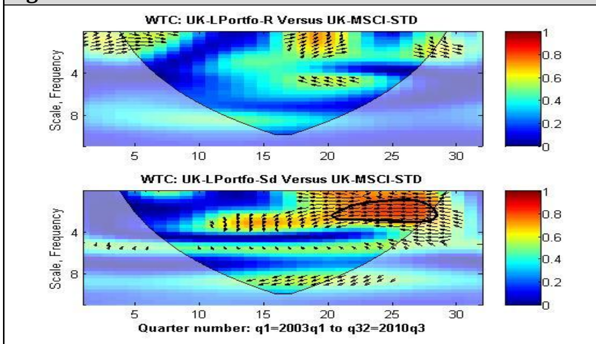

Figure 1.e - WTC: Return/Std – MSCI-std

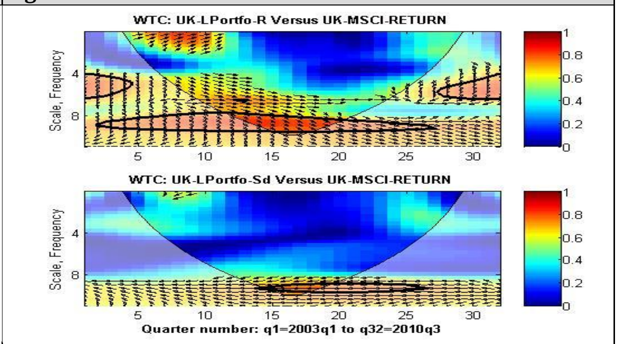

Figure 1.f - WTC: Return/Std – MSCI-Return

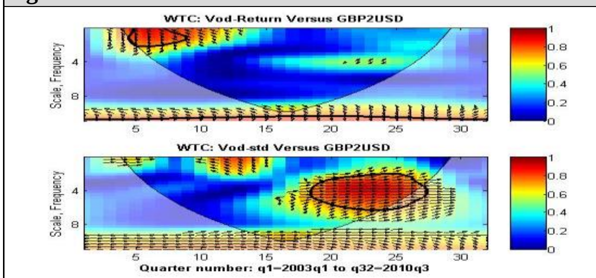

Figure 1.g - WTC: Return/Std – GBP_USD

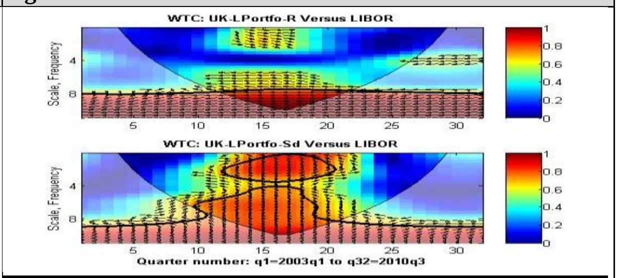

Figure 1.h - WTC: Return/Std – LIBOR

- ***WTC for return and volatility versus M2, IP, S&P, Sharpe Ratio Europe***

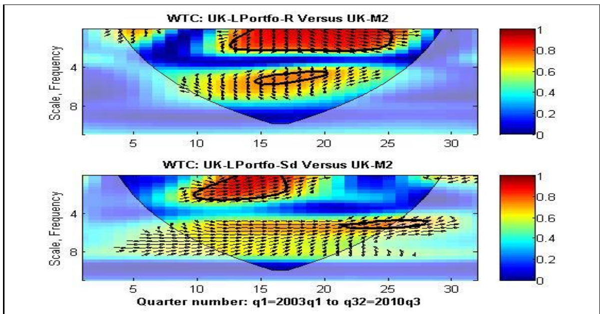

Figure 2.a – WTC: Return/Std – UK-M2

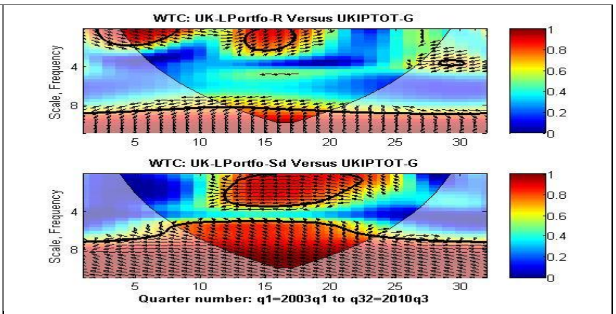

Figure 2.b - WTC: Return/Std – UK-IP

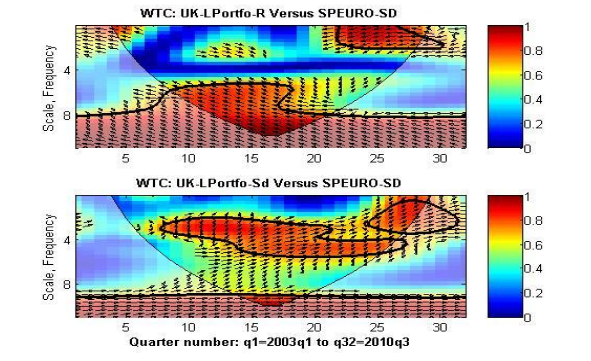

Figure 2.e - WTC: Return/Std S&P -Sd

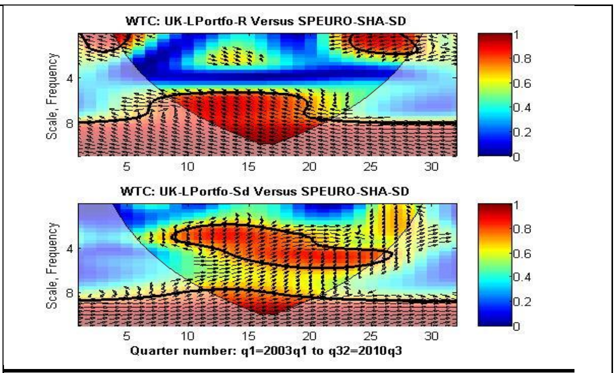

Figure 2.f - WTC: Return/Std – S&P –Sd - Shariah

- ***WTC for return and volatility (Std) versus S&P Shariah and Sharpe Ratio***

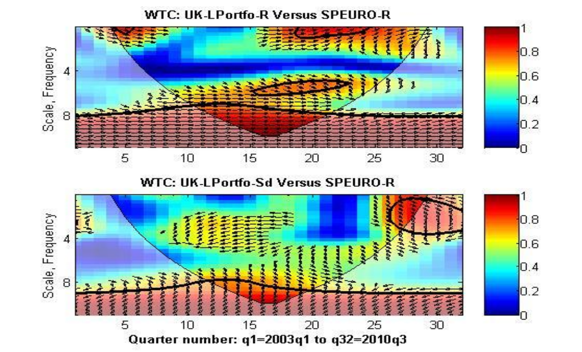

Figure 3.a – WTC: Return/Std S&P -Return

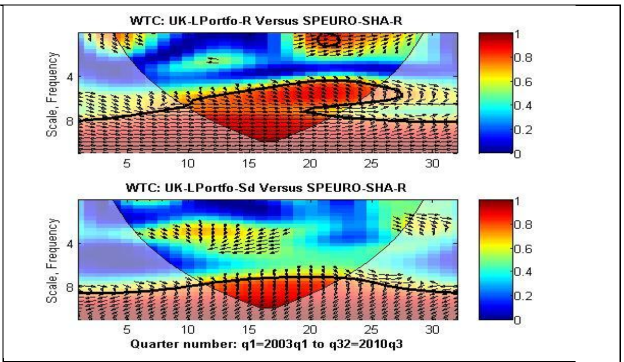

Figure 3.b WTC: Return/Std – S&P –R - Shariah

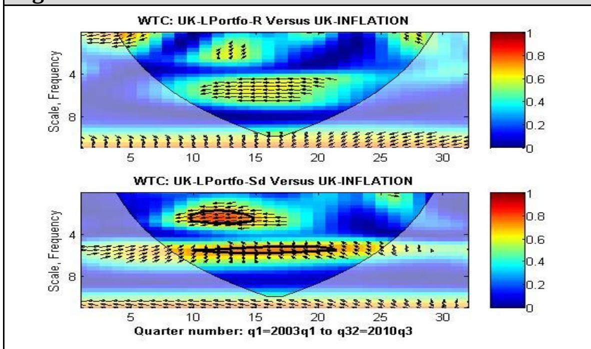

Figure 3.c - WTC: Return/Std – UK-Inflation

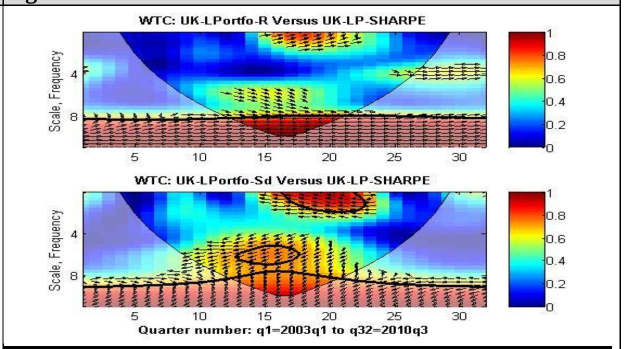

Figure 3.d - WTC: Return/Std – Sharpe Ratio

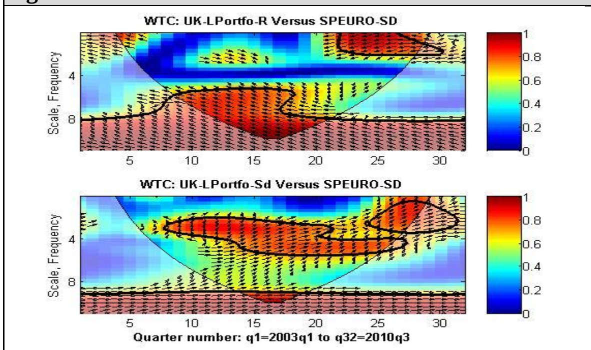

Figure 3.e - WTC: Return/Std S&P -Sd

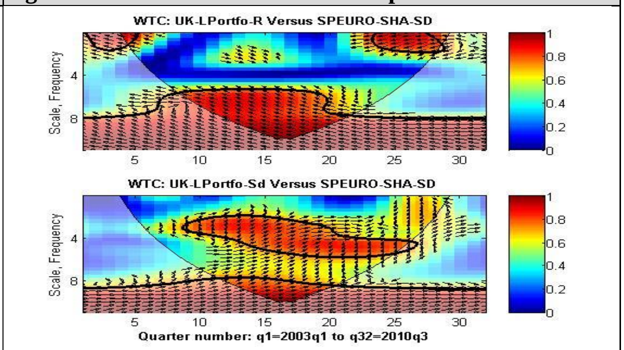

Figure 3.f - WTC: Return/Std – S&P –Sd - Shariah

In the figure above we should mention that:

- The 5% significance level against red noise is shown as a thick contour (black parabolic).
- The relative phase relationship is shown as pointing arrows:
  - Right: in-phase; - Down: X leading Y by 90°;

- Left: anti-phase; - Up: Y leading X by 90°.

The WTC, applied to pairs of indices, is delivering information about the co-movement at different time scales and in particular showing the impact at some specific events. Continuous wavelet transform, including cross-wavelet coherency, is applied to decompose the daily returns and investigate correlations, co-movement, and lead-lag relationship in time-frequency space. Specifically, in this study we start examining the case of UK firms (a portfolio of 18 UK firms) in terms of co-movement between its return and other parameters supposed to be related to it, as well as the correlation between the same parameters and the standard deviation of the same portfolio. Then, we go for analyzing two types of portfolios: High debt and low debt portfolio.

We can see from the figure 1 above, virtually a clear indication of the degree of cross-correlations for both the return and volatility with the other analyzed parameters supporting the idea of and co-movement and contagion in return and volatility. (See above, Figure 1.a to Figure 1.f).

- *Case of the Portfolio Return/Volatility and the capital structure ratio (Debt/Equity):*

In Figure 1.a, the WTC plot, for Portfolio Return/Volatility and the leverage, reveals two areas of high correlations in a specific period of time and different frequency-bands. Both the scale and positions of the components demonstrate good agreement at the two pairs. We can see that the arrows are pointing up (for the bigger area) and slanting towards the right showing a shift of lead-lag interactions between the two pairs.

We can also notice that the leverage was leading the return and the volatility during the GFC. The main feature than we can capture from this is that the lead-lag relationship is not highly heterogeneous. Furthermore, the Portfolio Return/Volatility seems to be lagging behind the leverage around the scale 4 and for the data points around the quarters 10 to 16.

We can say that in the short term and in response to the global economic shock, according to which, the return and volatility of Portfolio were adjusting to both macroeconomic variables and the firm level of capital structure, pointing out certain dependence of the *Return/Volatility on the level of leverage.*

- *Case of the Portfolio Return/Volatility and the Libor*:

For the return and the Libor, in Figure 1.f, the modulus of the wavelet cross spectrum clearly demonstrates a strong component around scale 2 to 6. The magnitude of the component was generally strong over time. The Portfolio Return/Volatility is more likely to be non-sensitive outside the period of the GFC. But it became clearly lagging behind the Libor during the GFC period. It shows also, a high negative correlation zone indicating a clear co-movement between the Portfolio Volatility and the LIBOR. This zone is precisely delimited between frequency-bands near 0 and near the scale 8 and during the time between 15 and 28 quarters (2008 and 2010). We can see that the LIBOR was leading the Portfolio Volatility and in less measure the return. This shows that the LIBOR was clearly driving the investor's policy in the UK market. As suggested by asset pricing theory, any positive change in the LIBOR was followed by a negative change in the Portfolio Return/Volatility and vice-versa.

4.2. Applying the Mean Variance Efficient Frontier (MVEF)

Mean-variance theory formalizes the risk-reward intuition and provides the necessary framework for other advances in the understanding of the investment management including a passive investing technique. A logical first step in the formal analysis of portfolios selection is intuitively based on the choice of an optimal combination of risk and return which suits the need of the investors. At the same equal expected return, an investor, in terms of portfolio, will prefer the one with less variance to another with higher variance. An efficient portfolio has to satisfy the condition under which the investors, holding a portfolio, will get the minimum of volatility with the maximum of expected return. The rate of return of the portfolio is: $r_{it} = \sum_{i=1}^{p}\left(w_{it}\, r_{i,t}\right)$ and $\sum_{i=1}^{p}(w_{it}) = 1$, where w_{it} is the fraction of the portfolio value invested in asset i and p the portfolio size.

The variance of the portfolio is a function of the weights, variances and co-variances and can be expressed as a product of matrices: $\sigma_p^2 = w'.V.w$, where $\boldsymbol{V}$ is the variance-covariance matrix (variances along diagonal and co-variances off the diagonal).

Matlab based matrix computing has been used to compute the mean variance efficient frontier for each studied portfolio. So, In order to analyze the Portfolio quarterly volatility and return, we have used expected return and covariance matrices from return time series.

For each asset the expected return used in the model is the average return for that asset over the past 20 quarters. This assumes that the return figure is the correct long run expected rate of return for each asset. In the same way that the expected return is computed as the mean return for each asset over the past 20 quarters, the variance-covariance matrix is also calculated based on the asset returns over the same period of time.

Our models show that relying on historical data, the mean-variance model can show whether a portfolio with low debt firms has more profitable outcomes (in term of volatility and return) than a portfolio with high level of debt.

4.2.1. Case of firms from UK Market

In this section, we have decided to study the case the UK market knowing that this analysis should be (in the next section) generalized for the whole portfolio containing the 8 countries. Our analysis is based on the mean-variance framework, with a portfolio seeking the lowest risk for a given return target for 4 types of portfolios. The four portfolios are constructed according to the following strategies:

- *Strategy* (i): Taking into the portfolio all the high debt firms. Total 42 firms;
- *Strategy* (ii): This portfolio is formed by taking from the previous portfolio of 42 firms the top 18 firms having big capitalisation;
- *Strategy* (iii): This portfolio is formed by taking from the first portfolio of 42 firms the top 18 firms having small capitalisation.
- *Strategy* (iv): This portfolio of 36 firms is formed by combining the 18 firms having High debt & Small Cap with the 18 firms having low debt.

Matrices, with the adequate size ([18,18], [36,36] and [42,42] for different portfolios), for the following parameters have been considered: Matrix Return of the portfolio [i,j], weight firm matrix [i,j] of the portfolio, Sigma and return matrices [i,j]). In particular, the *portopt* function runs the Markowitz algorithm using the mean return and covariance of the assets while the function *portstats* (from the Financial Toolbox) is used to calculate portfolio risk and return given the following inputs: returns, covariance matrix, and weights.

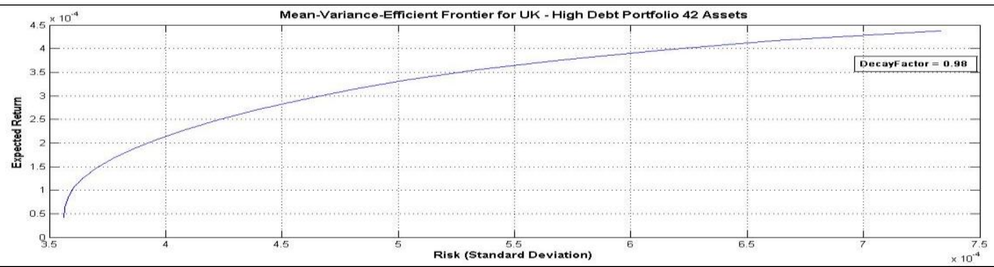

Figure 4.a – ***MVEF***: Risk-Return profile for UK –High debt All Cap Portfolio – 42 Firms

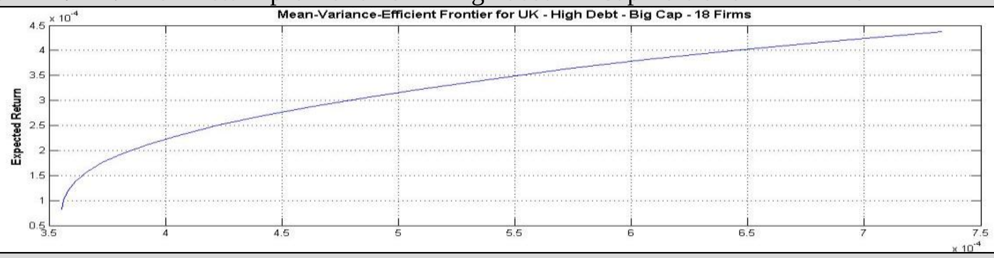

Figure 4.b – ***MVEF***: Risk-Return profile for UK –High debt & Big Cap Portfolio – 18 Firms

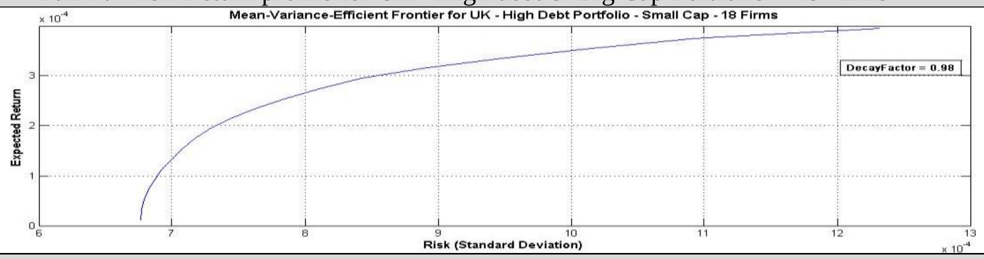

Figure 4.c - ***MVEF***: Risk-Return profile for UK – High debt & Big Cap Portfolio – 18 Firms

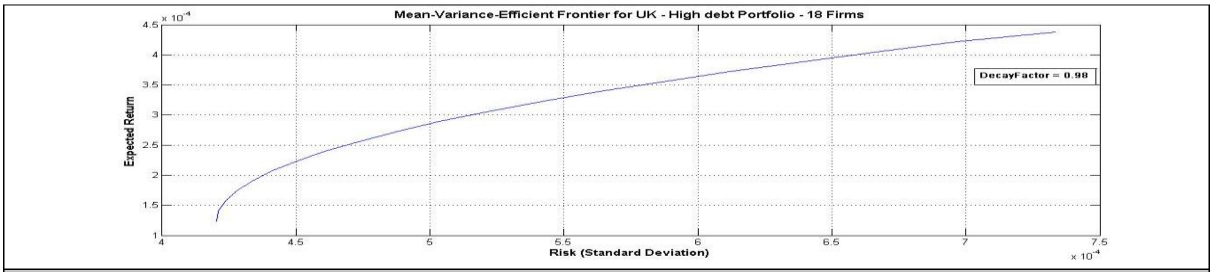

Figure 4.d - ***MVEF***: Risk-Return profile for UK – Low & High debt Specific combination Portfolio

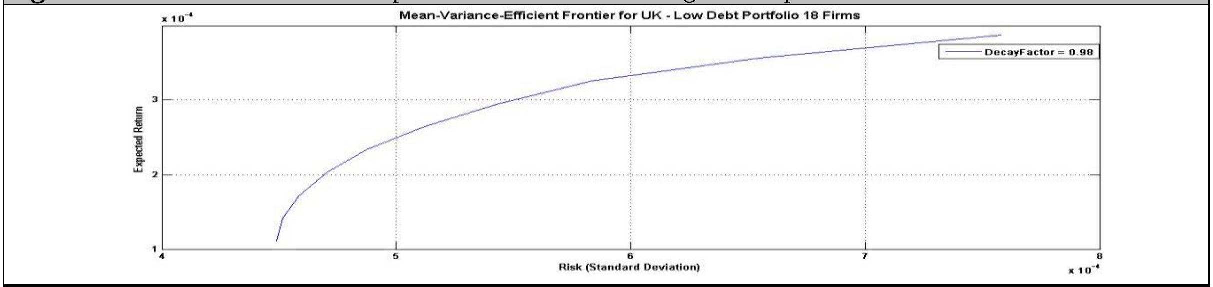

Figure 4.e - ***MVEF***: Risk-Return profile for UK – Low debt Portfolio – 18 Firms

Figure 4 shows that the volatility for high debt big capitalization portfolio is much more higher (sigma starting from 7) than the portfolio with low debt firms (sigma starting ending around 7), knowing the fact that the in the latter portfolio since the firms are low debt so most of them should be small capitalization.

However, comparing the mixed portfolio of high debt (with 42 firms: big and small capitalization) to the portfolio with low debt firms (18 firms), the latter shows higher volatility than the mixed portfolio. This could be simply explained by the diversification effect than by the level of debt effect.

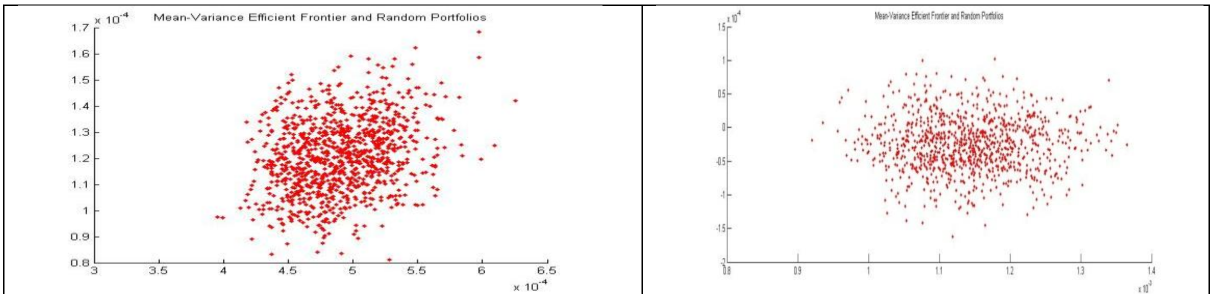

Figure 5.a – ***MVEF***: **Risk-Return profile for UK – Low / High debt Portfolio based on random Weights**

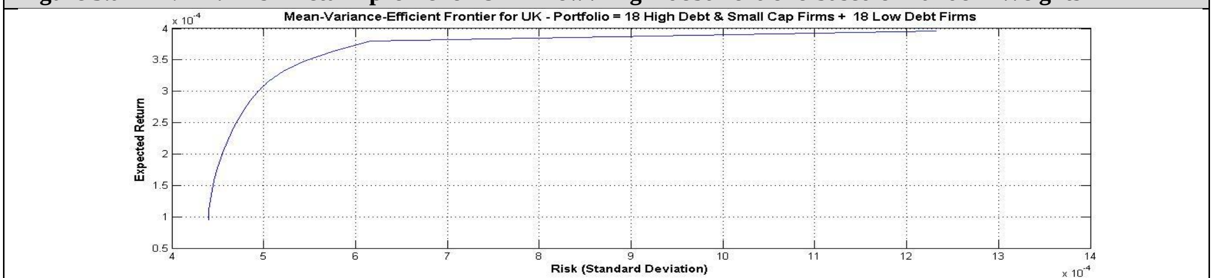

Figure 5.b - ***MVEF***: **Risk-Return profile for UK – combined Portfolios, High debt & small cap + Low debt**

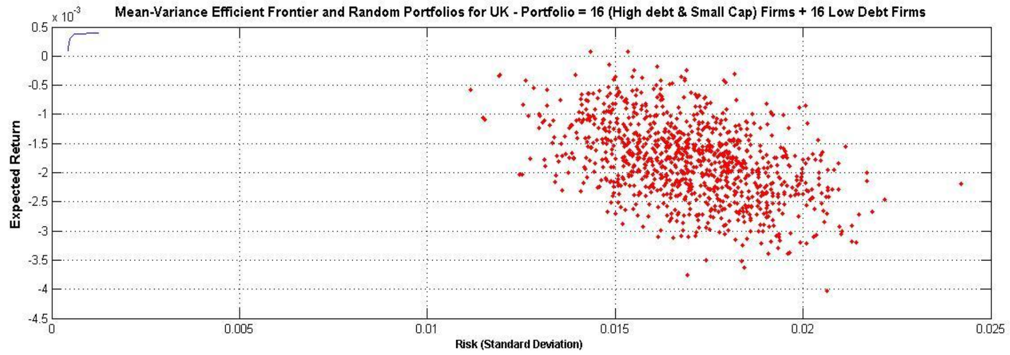

Figure 5.c ***MVEF*****: Risk-Return profile for UK –High debt & Small Cap Portfolio, 36 Firms, random Weights**

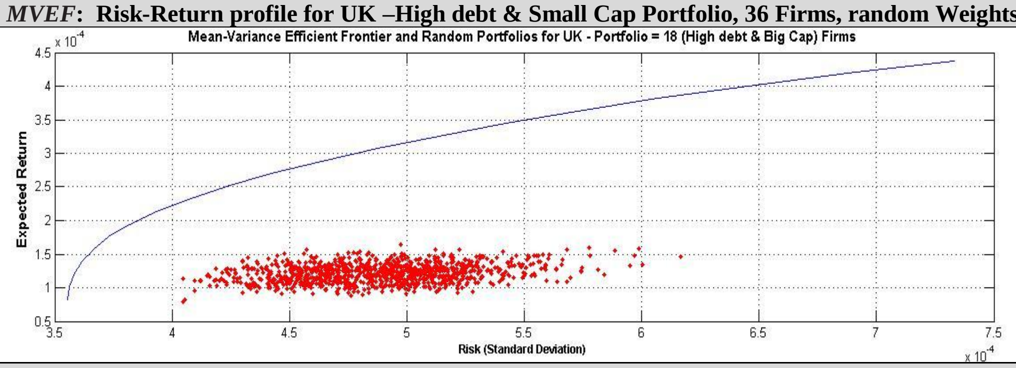

Figure 5.d ***MVEF*****: Risk-Return profile for UK – Low debt & Big Cap Portfolio – Random weights, 18 firms**

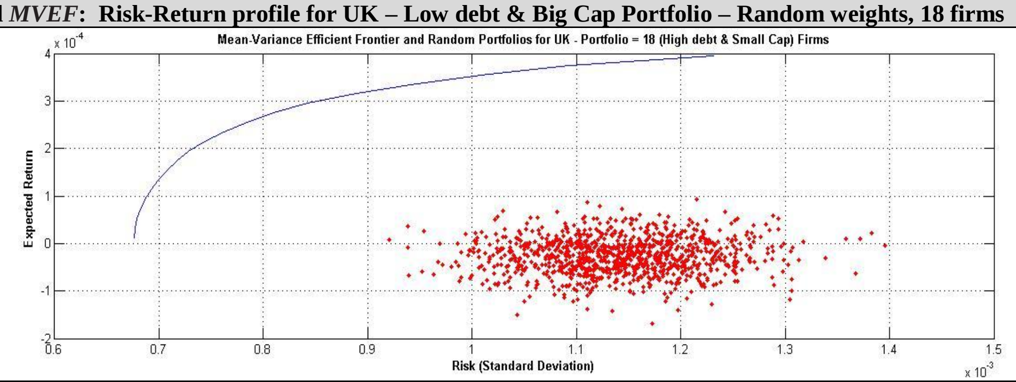

Figure 5.e - ***MVEF*****: Risk-Return profile for UK, combined portfolio: 18 HD & Small Cap + 18 LD & Big Cap firms**

The second test is based on random weights rather than using the initial weight computed as the firm capitalization to the total capitalization of the portfolio.

We started by computing the risk-return profile for the three strategies. Our findings show that the strategy four is providing better return profile by reducing the level of total volatility of the formed portfolio. Hassan et al. (2003) have combined different regions to show the benefit of diversification through regions. In our analysis, we are using the same idea by combining high debt and low debt portfolios and showing that the risk profile is better when we combine the High debt with low debt portfolio. This shows that low debt portfolio when added to high debt and small capitalization portfolio is shifting the total volatility to lower values and increasing the portfolio return (See figure 5.c).

4.2.2. Case of Combined portfolios of 320 European countries: 160 Low Debt and 160 High debt

In this section we have considered three portfolios: (i) 320 firms as a combined portfolio of low and high debt portfolios detailed in (ii) and (iii). (ii) a portfolio of 160 firms with Low Debt, (iii) a portfolio of 160 firms with high Debt.

Figure 6.a show that during the GFC-2008, the combined 320 firms portfolio of high and low debt has very large variations volatility coupled with negative returns compared to the 160 firms portfolio of low debt for same period (see Figure 7.a). This shows that the diversification was not helping during the period of GFC-2008 and the low debt is offering more protection in terms of volatility.

However, the quarter 3, 2008 (Q6) is showing more dispersion in the low debt portfolio (ii) in terms of volatility without offering any noticeable better return than the combined portfolio while the high debt portfolio (iii) is giving less volatility than the two previous one. This could be explained that outside the period of the GFC-2008, portfolio with high debt could offer less volatility than ones with low debt.

In most cases in terms of the 20 studied quarters, low debt portfolios are showing less dispersion of volatility and outperforming the high debt ones, while the combined portfolio is showing less volatility than the two other portfolios. We cannot conclude whether this result is due to the low debt effect or to the diversification effect. Additional analysis should be conducted in future studies in order to elucidate this issue.

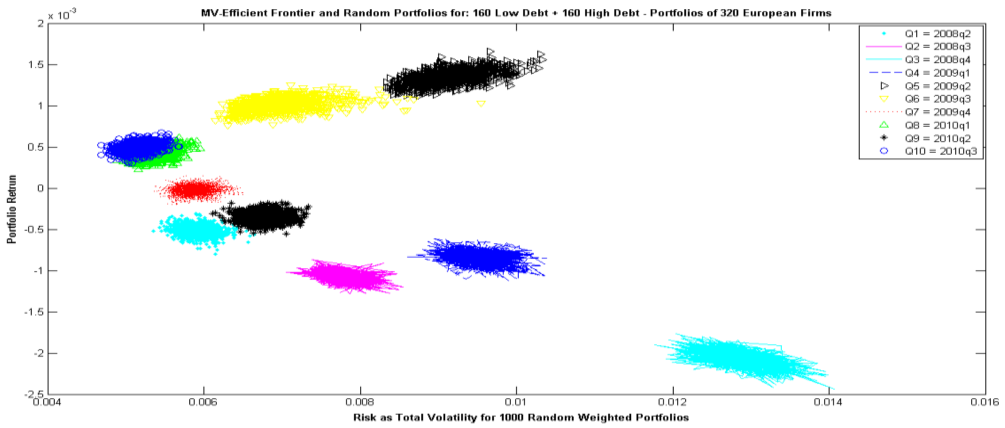

Figure 6.a – Risk-Return profile & Random Weight – combined 320 firms Portfolios 1 to 10

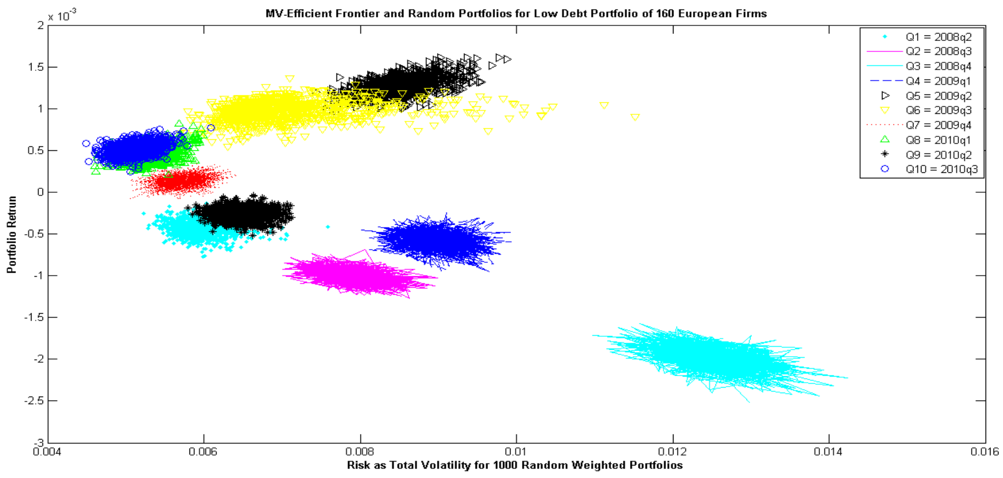

Figure 6.b - Risk-Return profile and Random Weight – Low debt 160 Firms – Portfolios 1 to 10

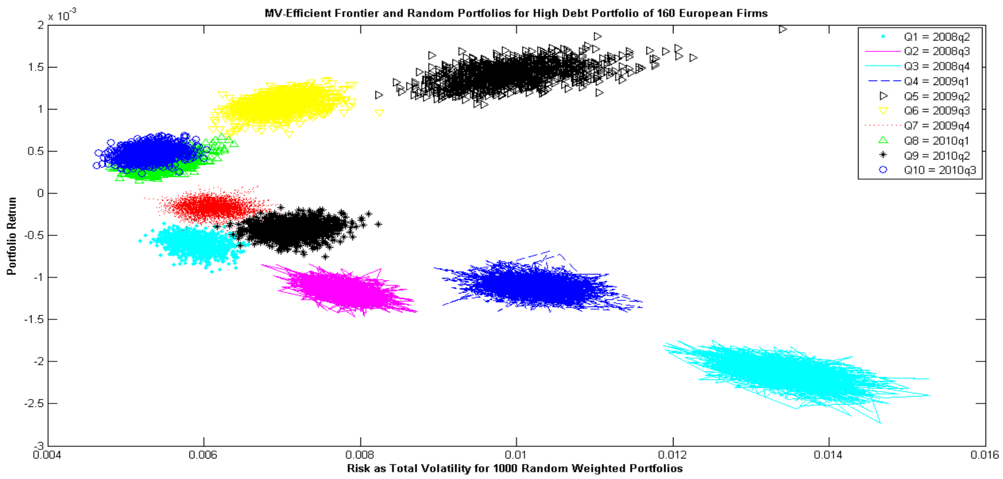

Figure 6.c - Risk-Return profile and Random Weight – High debt 160 Firms – Portfolios 1 to 10

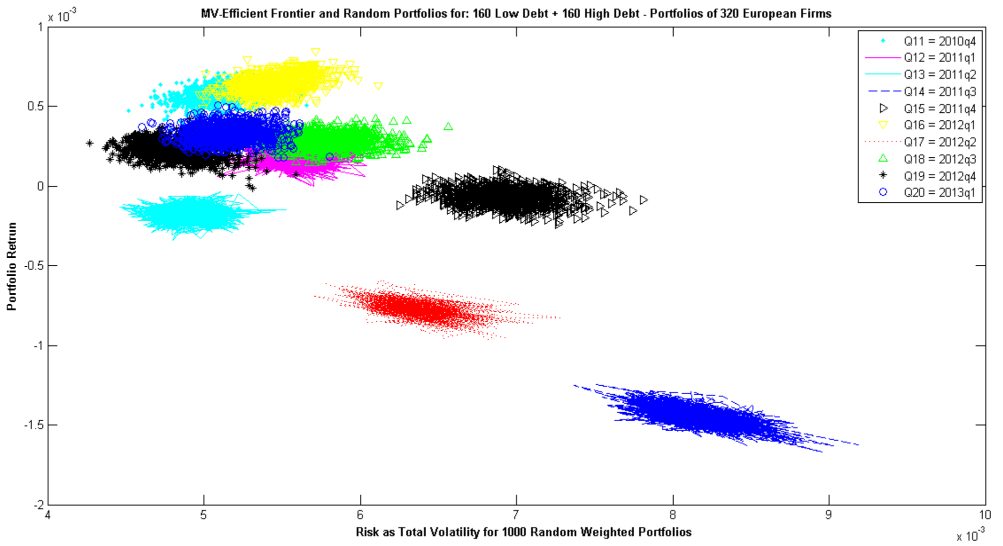

Figure 7.a – Risk-Return profile & Random Weight – combined 320 firms Portfolios 11 to 20

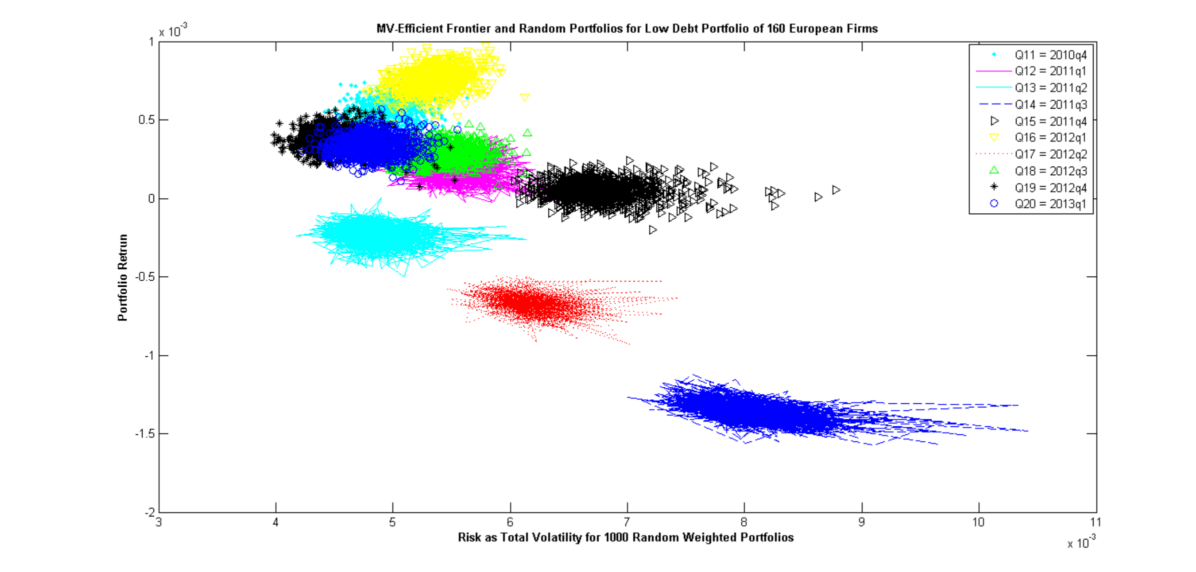

Figure 7.b – Risk-Return profile and Random Weight –Low debt 160 Firms – Portfolios 11 to 20

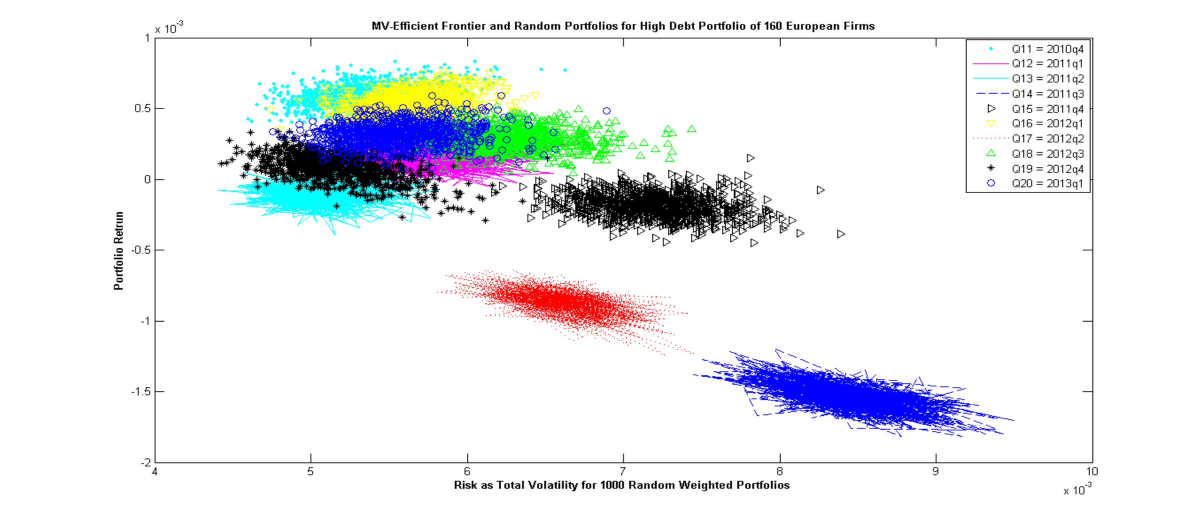

Figure 7.d - Risk-Return profile and Random Weight – High debt 160 Firms – Portfolios 16 to 20

4.3. Applying the GMM techniques (difference and system)

In this section we report the estimation results based on the econometric models. We start by discussing the relationship between the Capital Structure and the Level of Debt, using the estimation results of the GMM model (1.1). Next we consider the long-run debt effects based on models (2.1) and (3.1). The estimation results of the long-run effects of the country and stock index variables follow thereafter.

4.3.1. Volatility feedback and leverage effects

The two following techniques have been used: (i) Difference GMM, (ii) System GMM. Before deciding which results can be supported by theories and intuitions, we have doing some "experiments" by taking different "definitions" of a variable and/or add or drop variables to test the "robustness" of results. By using latest STATA software version, first we have tested the difference GMM then, we have applied Windmeijer-corrected standard errors to take care of one weakness of GMM. For taking care of the second weakness (i.e. instrument proliferations, Roodman 2009b), after that, we have also used the "collapse" sub-option for the xtabond2 command in STATA. This would reduce the number of instruments so that the number of instruments is lower than the "size" of the sample. Finally, to make sure that the instruments are optimum, we have checked the diagnostics for consistency and serial correlation. Finally, the **Arellano and Bond tests** (AR1) and (AR2) have been applied to examine the absence of first and second order serial correlation in the differenced residuals. The failure to reject the null hypothesis for Sargan test (or Hansen J-test) and for AR2 test indicates that the instruments used are valid **(Yalta and Yalta, 2012).**

- ***4.3.2. Relation between the capital structure and the level of debt***

Before presenting the results related to the return and total volatility, we should look to the relation between the capital structure (debt over equity) and the level of debt (debt over total Assets). The table below provides the Dynamic panel data estimators using GMM for the Capital Structure and the level of Debt.

	One-step		One-step No Inter. Dummy		One-step Robust		2-step No Robust		2-step + Robust	
Capstruct	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
L1.Capstruct	.7618389	28.28	.6434402	22.63	.7618389	1.70	1.111336	4069.64	1.111336	3.34
inter_dmy_d2ta	4.880805	8.27	/	/	4.880805	1.48	-.1682117	-108.20	-.1682117	-0.50
dmy_d2ta	-6.219226	-9.11	-15.02704	-15.65	-6.219226	-1.69	.7490163	64.26	.7490163	0.81
d2ta	4.407929	10.29	15.51318	16.63	4.407929	1.15	1.34188	65.63	1.34188	0.66
_cons	/	/	/	/	/	/	-.9356271	-91.58	-.9356271	-1.19
AR(1)	z = -19.64	P> z = 0.000	z= -17.84	P> z = 0.018	z = -2.27	P> z = 0.023	z = -1.87	P> z = 0.061	z = -1.63	P> z =0.102
AR(2)	z = -4.85	P > z = 0.000	z = -7.77	P > z = 0.386	z = -0.59	P > z = 0.552	z = -0.54	P > z = 0.592	z = -0.54	P > z = 0.592
Sargan test of overid	chi2=4247.04	P> chi2 = 0.00	chi2=4072.71	P> chi2 = 0.00	chi2= 4247.0	P> chi2 = 0.00	chi2= 2956.1	P> chi2 = 0.00	chi2=2956.1	P> chi2 = 0.000
Hansen test of overid	/	/	chi2 =135.54	P> chi2 = 0.003	chi2 = 216.49	P > z = 0.000	chi2 = 190.0	P> chi2 = 0.00	chi2 =190.1	P> chi2 = 0.000
GMM Sargan/Hansen [1]	chi2=3761.41	P> chi2 = 0.00	chi2 = 72.76	P> chi2= 0.00	chi2= 102.08	P> chi2 = 0.108	chi2 =50.31	P> chi2 = 0.021	chi2 = 50.31	P> chi2 = 0.021
GMM Diff. (H0= exo.) [2]	chi2= 485.63	P> chi2 = 0.00	chi2 = 62.79	P> chi2= 0.001	chi2= 114.41	P> chi2 = 0.000	chi2= 139.8	P> chi2 = 0.000	chi2 = 139.77	P> chi2 = 0.000
iv Sargan Ex. G. [3]	chi2=1378.77	P> chi2 = 0.00	chi2= 131.44	P> chi2 = 0.00	chi2= 113.77	P> chi2 = 0.000	chi2= 114.9	P> chi2 = 0.00	chi2= 114.85	P> chi2 = 0.000
iv Difference (H0: Exo.)	chi2=2868.27	P> chi2 = 0.00	chi2= 4.10	P> chi2 = 0.128	chi2= 102.72	P> chi2 = 0.000	chi2= 75.23	P> chi2 = 0.00	chi2= 75.23	P> chi2 = 0.000

- All the estimators are computed with 95% Confidence Interval [p < 0.05]

Difference-in-Hansen tests of exogeneity of instrument subsets:

[1] GMM instruments for levels - Hansen test excluding group
[2] GMM instruments for levels - Difference (null H = exogenous)
[3] iv(lnsigma_q nreturn_q L.ncapstruct inter_dmy_d2ta) - Hansen test excluding group
[4] iv(lnsigma_q nreturn_q L.ncapstruct inter_dmy_d2ta) - Difference (null H = exogenous)

Table 1: Dynamic panel data estimators using GMM for the Capital Structure and the level of Debt

Before going further we should mention that the Capital structure is impacted by both its lagged value and the level of the debt (Debt over total assets). Both estimates are statistically significant (see table 1 for: one-step with and without the interactive dummy variable; two-step not robust). The estimate value related to the level of the debt is equal to 4.4 in the case of one-step (first column in table 1) and 1.34 in the case of one-step (fifth column in table 1)

- ***4.3.3. Case of the return***

The table below provides the dynamic panel data estimators using GMM for the RETURN versus Capital Structure. Table 2 shows the long-run effect of the financial and macro-economic variables on firm return. The results show the S&P European stock index return to have a very strong long-run effect on the firm return and the lagged firm's return has also a significant impact on the firm return.

	One-step No Collapse		One-step Robust No Collapse		One-step + Collapse		2-step robust No Collapse		2-step robust + Collapse		2-step Robust No Collapse-EQ	
Return_q	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
L1.Return_q	-.3549162	-21.45	-.3549162	-11.87	-1.239899	-10.00	.2563027	6.64	1.289672	1.51	.1377948	3.94
L1.LOG(Sigma_q)	.0009805	12.46	.0009805	5.18	.0047886	8.81	-.0014964	-15.96	-.0025199	-0.68	-.0002613	1.51
L1.Capstruct	4.17e-06	0.91	4.17e-06	0.76	-.0001426	-1.63	.00002	4.06	.000367	3.06	.0000592	3.70
inter_dmy_d2ta	-.0006837	-7.39	-.0006837	-3.56	-.0054868	-2.62	-.0002481	-2.05	-.0160137	-2.44	-.0016284	-3.87
dmy_d2ta	.0009225	6.01	.0009225	3.37	.0092621	2.54	.0007166	3.38	.0287822	3.52	.0027105	6.05
L1.nroe	6.44e-08	0.52	6.44e-08	0.43	-6.26e-06	-2.13	1.70e-07	1.52	4.16e-06	0.71	8.49e-07	3.69
d2gdp_q	-1.73e-06	-2.90	-1.73e-06	-1.36	-.0000198	-2.06	1.14e-06	0.88	5.95e-06	0.17	1.18e-06	0.57
forex_q	-.0000151	-2.01	-.0000151	-0.62	-.000055	-0.41	.0000387	2.51	.0000288	0.06	9.43e-06	0.31
speuro_r	1.17045	39.99	1.17045	25.99	2.114845	22.22	.8127178	16.90	.9004915	2.80	.824638	18.38
LOG(speuro_s)	.0001431	2.50	.0001431	1.93	.0004828	1.90	.0000492	0.55	.0006079	0.70	-.0003507	-3.78
L1. LOG(speuro_s)	-.0009851	-13.16	-.0009851	-6.97	-9.19	-9.19	.0014121	15.54	.0035014	1.16	.0005056	4.02
_cons	/	/	/	/	/	/	.0000116	0.02	-.0037006	-0.71	-.0016757	-3.70
AR(1)	z = -20.92	P>z = 0.000	z= -9.45	P>z = 0.000	z = -9.50	P>z = 0.000	z = -9.50	P>z =0.000	z = -2.34	P>z = 0.019	z = -9.08	P>z = 0.000
AR(2)	z = -11.20	P > z = 0.000	z= -6.45	P > z = 0.000	z = -8.57	P > z = 0.000	z = 0.48	P > z = 0.628	z = -0.19	P>z = 0.847	P>z = 0.792	P>z = 0.792
Sargan test of overid	chi2=5995.58	P>chi2 = 0.00	chi2=5995.58	P>chi2 = 0.00	chi2=1.60	P>chi2 = 0.206	chi2=5282.59	P>chi2 = 0.000	chi2= 79.85	P>chi2 = 0.00	chi2= 4973.22	P>chi2 = 0.00
Hansen test of overid	/	/	chi2= 307.61	P>chi2 = 0.001	/	/	chi2 = 302.93	P>chi2 = 0.002	chi2 = 37.84	P>chi2 = 0.00	chi2 = 37.84	P>chi2 = 0.002
GMM Hansen Ex. G. [1]	chi2=5540.14	P>chi2 =0.00	chi2 = 276.82	P>chi2= 0.00	chi2=1.60	P>chi2 = 0.206	chi2 = 258.65	P>chi2 = 0.00	chi2 = 12.28	P>chi2 = 0.00	chi2(116) = 269.82	P>chi2= 0.00
GMM Diff. (H0= exo.) [2]	chi2=455.43	P>chi2 = 0.00	chi2 = 30.79	P>chi2= 1.00	chi2=364.33	P>chi2 = 0.000	chi2= 44.29	P>chi2 = 1.00	chi2 = 25.57	P>chi2 = 0.002	chi2(120) = 35.67	P>chi2= 1.00
iv Hansen Ex. G. [3]	chi2=1305.31	P>chi2 = 0.00	chi2= 301.07	P>chi2 = 0.001	chi2= 11.93	P>chi2 = 0.103	chi2= 297.55	P>chi2 = 0.003	chi2= 4.33	P>chi2 = 0.741	chi2(233) = 299.12	P>chi2= 0.002
iv Difference (H0: Exo.) [4]	chi2=4690.27	P>chi2 = 0.00	chi2= 6.54	P>chi2 = 0.088	chi2=353.99	P>chi2 = 0.000	chi2= 5.38	P>chi2 = 0.146	chi2= 33.51	P>chi2 = 0.00	chi2(3) = 6.37	P>chi2= 0.095

- All the estimators are computed with 95% Confidence Interval [p < 0.05]

Table 2: Dynamic panel data estimators using GMM for the RETURN versus Capital Structure

We find a significant negative impact of both the lagged standard deviation of the return and the lagged volatility of the S&P European stock market returns. Hikes in lagged volatility of the two parameters, have a significant and detrimental effect on the stock market of the European countries.

Also, the Capital structure, combined with the interactive dummy variable, is affecting stock returns negatively. Again, this is in line with the theory. In the same time, the results show a negative effect of the exchange rate (domestic currency against US dollar) on stock returns (for the one-step, first column in the table 2, even if it is not the retained model). Decreases in the exchange rate (revaluation of domestic currency) depress aggregate stock prices by lowering expected earnings.

- ***4.3.4. Case of the volatility***

The table below provides the dynamic panel data estimators using GMM for the total volatility versus Capital Structure.

To investigate the effect of the level of debt over the volatility, Table 3 reports the GMM both and difference estimates of the debt effect and lagged coefficient on the volatilities of the firms both high and low debt. The results suggest that volatility effects exist due to both: firm level and market effects, and that the market lagged volatility has the stronger impact over all others, then market volatility effect (contemporaneous and lagged one both are negatively correlated), then the market return (contemporaneous is negatively correlated and lagged one positively correlated) and at the end the capital structure, the exchange rate and the lagged return of the firm. This is quite intuitive if we consider that it is the European market risk which is more difficult to avoid in the absence of international diversification (out of European market).

However, the sovereign debt seems not to have any statistical significant effect on the volatility which easily to understand in the way that a quarterly change in the sovereign debt will not affect the volatility in the stock market. Intuitively the lagged idiosyncratic risk of a specific stock is expected to have a greater bearing on its own current volatility.

A noteworthy finding is the large negative contemporaneous and lagged market volatility effects which are strongly significant. The lagged firm level volatility feedback effect is also negative and highly significant.

Turning to the lagged debt effects, the correlation is negative and the interactive dummy variable is also negative and therefore is increasing the value of the estimate in the absolute value. This result is in line with the theory.

- ***4.3.5. Robustness analysis for the volatility and return models***

Finally to check the robustness of our results, we have conducted many tests and we presented the 4th more relevant ones (see table 1, 2 and 3). We have used 340 firms and eight countries based on the data availability. For the **Arellano and Bond tests** (AR1) and (AR2), the failure to reject the null hypothesis for Sargan test (or Hansen J-test) and for AR2 test indicates that the instruments used are valid **(Yalta and Yalta, 2012).** That is the case of the "one-step robust with collapse sub-option" for the volatility model, "two-step robust with collapse sub-option" for the return model and "one-step robust with no interactive dummy variable" for the relationship between the capital structure and the level of debt based total assets.

	One-step No Collapse		One-step Robust No Collapse		One-step Robust + Collapse		2-step robust No Collapse		2-step robust + Collapse		2-step Robust No Collapse-EQ	
LOG(Sigma_q)	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
L1.LOG(Sigma_q)	.8008967	29.51	.8008967	34.37	.6682714	7.18	1.086611	46.42	1.322356	14.08	1.208775	30.94
Return_q	.780716	0.17	.780716	0.12	-25.89792	-1.75	11.395	1.92	18.6651	1.57	.5885887	0.10
L1.Return_q	-18.6581	-2.15	-18.6581	-2.56	-75.3234	-2.58	-48.53055	-4.19	-93.42752	-2.73	-70.11006	-5.33
L1.Capstruct	.0013377	0.86	.0013377	1.34	.0402376	2.60	-.0074181	-2.91	.0018068	0.15	-.0057735	-2.27
inter_dmy_d2ta	.1158912	3.69	.1158912	3.41	-.9076758	-2.83	.2748859	3.66	-.0647905	-0.29	.0887697	1.87
dmy_d2ta	-.1204311	-2.32	-.1204311	-2.60	1.74042	3.12	-.4643724	-5.72	.1892719	0.56	-.1480992	-2.25
L1.nroe	.0000214	0.52	.0000214	0.63	.0008828	1.69	-.0000895	-1.87	.0001619	0.44	-.0000534	-1.31
d2gdp_q	4.25e-06	0.02	4.25e-06	0.03	-.0019471	-1.09	-.0005741	-1.26	-.0009038	-0.54	-.0005035	-1.80
forex_q	.0060237	2.37	.0060237	2.76	.0141442	0.56	-.000328	-0.06	.0232057	0.81	-.0026282	-0.78
speuro_r	-50.12633	-4.47	-50.12633	-4.52	114.6696	3.71	-87.32672	-6.48	-93.382	-2.52	-46.35793	-3.21
L1.speuro_r	62.62221	6.11	62.62221	6.55	55.27098	1.48	49.321	3.67	4.690721	0.11	38.10033	2.71
LOG(speuro_s)	.3980467	21.27	.3980467	18.15	.8675884	21.29	.4597258	16.46	.4399839	4.59	.4248109	13.79
L1. LOG(speuro_s)	-.2144113	-8.37	-.2144113	-9.04	-.3956941	-5.68	-.4874131	-16.75	-.7433225	-10.55	-.6457832	-20.68
_cons	/	/	/	/	/	/	.4652242	3.21	-.182872	-0.63	-.0811504	-0.75
AR(1)	z = -19.75	P>z = 0.000	z= -10.86	P>z = 0.000	z = -10.39	P>z = 0.000	z = -10.89	P>z =0.000	z = -9.04	P>z = 0.000	z = -10.78	P>z = 0.000
AR(2)	z = 5.46	P>z = 0.000	z = 4.39	P>z = 0.000	z = -0.22	P>z = 0.825	z = 4.51	P>z = 0.000	z = 4.03	P>z = 0.000	P>z = 4.74	P>z = 0.000
Sargan test of overid	chi2=1482.57	P>chi2 = 0.00	chi2=1482.57	P>chi2 = 0.00	chi2=98.57	P>chi2 = 0.00	chi2=1816.99	P>chi2 = 0.000	chi2= 263.90	P>chi2 = 0.00	chi2=1126.36	P>chi2 = 0.00
Hansen test of overid	/	/	chi2= 298.06	P>chi2 = 0.002	/	/	chi2 = 298.91	P>chi2 = 0.003	chi2 = 133.4[illegible]	P>chi2 = 0.00	chi2 = 295.08	P>chi2 = 0.005
GMM Hansen Ex. G. [1]	chi2=468.18	P>chi2 = 0.00	chi2 = 256.86	P>chi2= 0.00	chi2=2.59	P>chi2 = 0.108	chi2 = 264.59	P>chi2 = 0.00	chi2 = 0.56	P>chi2 = 0.455	chi2(116) = 258.21	P>chi2= 0.00
GMM Diff. (H0= exo.) [2]	chi2= 1014.38	P>chi2 = 0.00	chi2 = 41.21	P>chi2= 1.00	chi2=95.98	P>chi2 = 0.000	chi2= 34.33	P>chi2 = 1.00	chi2 = 132.8[illegible]	P>chi2 = 0.002	chi2(120) = 36.88	P>chi2= 1.00
iv Hansen Ex. G. [3]	chi2=671.94	P>chi2 = 0.00	chi2= 292.64	P>chi2 =0.002	chi2= 60.74	P>chi2 = 0.000	chi2= 288.65	P>chi2 = 0.007	chi2= 45.72	P>chi2 = 0.000	chi2(233) = 284.79	P>chi2= 0.009
iv Difference (H0: Exo.) [4]	chi2=810.63	P>chi2 = 0.00	chi2= 5.43	P>chi2 =0.246	chi2= 37.83	P>chi2 = 0.000	chi2= 10.26	P>chi2 = 0.036	chi2= 87.73	P>chi2 = 0.000	chi2(3) = 10.30	P>chi2= 0.036

- All the estimators are computed with 95% Confidence Interval [p < 0.05]

Table 3: Dynamic panel data estimators using GMM for the SIGMA – Total Volatility vs Capital Structure

Furthermore, since and the time series observations are relatively large, the autoregressive parameter is below 0.8, for the volatility and the relationship between the capital structure and the level of debt based total assets. This suggests that the 'System GMM' is not necessarily superior to the 'Standard GMM' (Blundell and Bond, 1998, Moshirian and Wu, 2012) which is in line with our finding. However, that is not the case for the return model since the coefficient of autoregressive parameter is above 0.8 (= 1.289) for 'System GMM'-robust with collapse sub-option". Overall, our statistical results are qualitatively similar for most of the experiments suggesting that the qualitative nature of the above reported findings is robust even for the less valid instruments.

5. Concluding remarks and implications

This paper has examined the leverage effect on the return and the volatility at the firm level by considering both firm level and country level. From more than 6000 European firms, 340 have been chosen based on the availability of the data in the European market.

We adopt a panel GMM framework which allows us to control simultaneously for country effect and firm characteristic effects taking into account the heterogeneity across firms.

We also supported our analysis by investigating the lead/lag relationship between macro-economic and micro-economic variables in relation to the return and the volatility by using the cross-correlation wavelet coherence technique. We corroborated our study by analyzing the risk-profile portfolio in the UK market using the mean variance efficient frontier.

Our finding shows a detrimental negative effect of the level of the debt for small capitalization for the portfolio with high level of debt compared to the portfolios with low level of debt.

Also, under shocks, the firm's debt level has a negative impact on the return and the volatility in the case of the UK market. Interestingly, the inflation has less impact on the volatility and a limited impact on the return. Most parameters have undergone the transmitted shocks due to the GFC (2008).

The results of GMM analysis, tend to show strong evidence of a large negative effect of S&P European stock market volatility (both contemporaneous and lagged), while the sovereign debt, which is not significant, has no negative impact on the return and the volatility at the level of the firm. Overall, our findings are broadly consistent with the theory within the capital structure of firm, in which financial flexibility, in the form of level of debt, plays an important role in the stability of the share price and its volatility.

Our approach based on the mean variance efficient frontier and lead/lag relationships can be extended to the analysis of stock market listed firms for all the studied countries while GMM analysis could be extended to more heterogeneous countries rather than focusing solely on eight European countries. It would also be of interest to examine the other Shariah screening criteria within the same approach and by adding other macro-economic variables at the level of the country. Future research could add to the analysis of systematic risk (beta) with its both components: Financial risk and business risk.

Policy implications in terms of Investment

Two potential policy implications:

1. At the regulator level, the regulator may have to issue standards about reducing the debt level in the listed companies in regard to its detrimental negative impact on the business viability.
2. At the investor level, debt has a tax benefit to the firm while firm's risk is borne only by the stockholders (Hamada, 1992). Higher leverage increases the volatility and decreases the return. This makes equity investment in the firm riskier. Investors may not participate in any new recapitalization of a listed firm if the latter would not be able to reduce its leverage. This may open a new way to the partnership based Musharakah to take place within the compliant firms in the stock market.

- Investors may have to consider their investment strategy to invest in Shariah companies since these firms are not heavily involved in high leverage as the risk-return profile of these portfolios provide less volatility and high return. This may be also attractive for the non-Muslim investors.

Appendix 1

a) List of chosen Countries ranked according to their 2011 GDP

2011 Rank	Country	Currency	2007	2008	2009	2010	2011
—	World[2]		55,678	61,166	57,760	63,075	69,660
—	Europe		20,103	22,246	19,282	19,920	—
—	European Union[2]		16,994	18,342	16,360	16,259	17,578
1	Germany	Euro	3,333	3,651	3,338	3,315	3,557
2	France	Euro	2,598	2,865	2,656	2,582	2,776
3	United Kingdom	**Pound**	2,812	2,679	2,178	2,247	2,418
4	Italy	Euro	2,119	2,307	2,118	2,055	2,199
5	Spain	Euro	1,444	1,601	1,467	1,409	1,494
6	Netherlands	Euro	783	877	796	783	840
7	Switzerland	**Swiss F.**	434	502	491	523	636
8	Sweden	**S. krona**	462	487	406	455	538
9	Poland	**P. Zloty**	425	529	430	468	514
10	Belgium	Euro	459	506	472	465	513
11	Norway	**NOK**	387	446	378	414	484
12	Austria	Euro	372	416	382	376	419

b) List and Status of all sectors

List of sectors (Excluded and Included)	Status
Banks, Beverages, Equity Investment Instruments, Equity Warrants, Financial Services, Fixed Line Telecommunications, Food and Drug Retailers, Food Producers, Leisure Goods, Life Insurance, Media, Non-Equity Investment Instruments, Nonlife Insurance, Other Equities, Other Warrants, Real Estate Investment and Services, Real Estate Investment Trusts, Suspended Equities, Tobacco, Travel and Leisure, Unclassified, Unquoted equities.	Excluded
Aerospace and Defence, Alternative Energy, Automobiles and Parts, Chemicals, Construction and Materials, Electricity, Electronic and Electrical Equipment, Fixed Line Telecommunications, Forestry and Paper, Gas, Water and Multi-utilities, General Industrials, General Retailers, Health Care Equipment and Services, Household Goods and Home Construction, Industrial Engineering, Industrial Metals and Mining, Industrial Transportation, Mining, Mobile Telecommunications, Oil and Gas Producers, Oil Equipment and Services, Personal Goods, Pharmaceuticals and Biotechnology, Software and Computer Services, Support Services, Technology Hardware and Equipment.	Included

c) Breakdown of retained firms in relation to their countries

				High DEBT			Low DEBT				Combined portfolios	
INITIAL TOTAL SAMPLE		Filtred Sample		>=9 Y	>= 5 Y	< 5 Y	>=9 Y	>= 5 Y	< 5 Y		>=9 Y	>= 5 Y
AUSTRIA	132	116	AU	11	32	31	27	57	40	AU	38	89
FRANCE	856	74	FR	8	19	23	34	49	18	FR	42	68
GERMANY	1172	455	GM	35	90	126	177	279	108	GM	212	369
ITALY	364	99	IT	25	51	25	31	55	29	IT	56	106
NETHERLAND	219	98	NL	5	10	50	51	82	7	NL	56	92
POLAND	637	68	PL	0	9	17	33	61	6	PL	33	70
SPAIN	216	75	SP	16	44	16	19	35	28	SP	35	79
SWEDEN	804	102	SD	11	26	25	46	63	22	SD	57	89
SWITZERLAND	412	120	SW	5	19	24	64	97	19	SW	69	116
UK	2011	142	UK	10	22	41	76	114	16	UK	86	136
	6823	**ALL Countries**		**126**	**322**		**558**	**892**			**684**	**1214**

- Aggregated information regarding the number of retained European firms

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