

Systemic risk of Islamic Banks

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Abstract

The main aim of this paper is to investigate the proposition that Islamic banking services support financial stability. We examine this proposition using network modelling for stock market returns based on graphical Gaussian distributions, aimed at capturing the contagion effects that move along countries, combined with a regression modelling approach, aimed at capturing the effect of bank-specific strategies, that depend on the degree of Islamic financial services specialization levels. The integration between the two models will enable us to distinguish the systemic correlations between banks due to common idiosyncratic characteristics, from the systemic correlation that can be attributed to country effects that are common to all banks in a given country. Our proposed models are applied to the MENA region banking sector for the period from 2007 to 2014.

Keywords: Camels regression, Centrality measures, Graphical Gaussian models, Islamic bank specialisation levels.

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1. Introduction

The late global financial crisis that started in 2007 has assured the importance of stability and soundness of financial systems and has highlighted the difference between Islamic and conventional banks in terms of their stability. Even though Islamic banks faced the challenges encountered by their conventional peers, not only they managed to resist credit crunch effects, but also managed to achieve an average growth rate of 20% after 2009.

The high growth rate and the resilience abilities of the Islamic banking model attracted players in the conventional financial sector to exploit its characteristics as a means of financial stability, leading to a range of mixed conventional/islamic specialization levels.

These developments have stimulated research, aimed at comparing Islamic and conventional banks in terms of risks and performances. However, to our knowledge, the available literature does not clearly address the issue of differential effects of different specialization levels in Islamic financial services on bank's performance and risks. In addition, the issue of modelling interconnectedness and systematic risks in systems with Islamic banks has not yet been addressed.

The main applied contribution of this paper is to investigate whether and how different Islamic financial services support performance and stability of financial systems. To achieve this purpose, we use financial network modelling based on graphical Gaussian models, aimed at capturing the contagion effects that move along countries, affected by the differences in Islamic financial specialization levels, combined with a regression modelling approach, aimed at capturing the effects of bank-specific strategies, also affected by Islamic financial specialization levels.

From a methodological viewpoint, we first infer systematic risks between countries, using aggregated market prices. We then check whether the found correlations between countries depend on specific bank types, categorized based on the level of Islamic financial services provided by the banks into: conventional banks (CBs), conventional banks with Islamic windows (CB-Win), conventional

banks with Islamic subsidiaries (CB-Sub), and fully fledged Islamic banks (IBs) that are completely Shariah based in their activities.

We then consider whether, once the systematic country effect is taken into account, there remain differences in the market performance of banks and, if so, whether such differences can be attributed to bank type and/or to the level of bank specific financial indicators. For each bank, we calculate the excess market return by subtracting from the return the country mean level. We then regress the excess return with respect to bank types as well as to financial balance sheet ratios that are selected following the CAMELS approach.

The main methodological contribution of this paper is to provide a statistical model that allows to study, in an integrated way, both idiosyncratic and systematic correlations, between banks and their aggregates at the country level, in a systemic risk perspective. To achieve this aim we propose a statistical model based on two types of models: a graphical Gaussian model between aggregate country returns and, conditionally on it, a regression model for banks, in which their excess returns are made dependent on a set of explanatory variables, that include bank type variables.

Even though in the last years foreign large international conventional banks from Europe, UK and the USA have introduced Islamic Shariah-compliant products within their conventional banking system, the majority of the Islamic banking activities are still settled within the Middle East and North Africa (MENA) region, which includes the Gulf Cooperation Council Countries (GCC). We focus this study on this region, which holds 78.57% of the total global Islamic banking assets, with the GCC countries holding 38.19% of this total (IFSB, 2014).

We believe that the implications of our research results can be beneficial to several institutions. Regulators and central banks will be able to determine Islamic banks contagion effects, and the effects of using Islamic finance services to support financial and economic stability. Conventional banks can have insights about the effect of a chosen level of specialization in Islamic banking activities on the banks risk and performance profile. Finally, fund providers and investors may benefit from the research in acquiring more information to take portfolio

allocation decisions.

To address the above issues, the paper is organized in six sections. The second section includes a literature review on the stability of Islamic banks, in terms
65 of risks and performance. The third section provides the proposed methodology, based on graphical Gaussian models, centrality measures obtained from them, and regression modelling on excess returns. The fourth section provides data and variables description. The fifth section describes the application of the proposed model to the considered MENA data and discussion of the research
70 results. The final section provides some research conclusions.

2. Literature review

An Islamic bank is a financial institution that is engaged in all banking activities at a zero-interest rate according to Islamic Shariah rules (see e.g. Shafique et al., 2012). There are five pillars upon which Islamic banking is
75 based, the first and most important one is the prohibition of interest payment or receipt within borrowing or lending transactions, which is known as *riba*, and is defined as a premium paid by a borrower within a lending transaction. The second is the risk sharing feature represented by profit and loss sharing (PLS) accounts, which is a profit-loss sharing arrangement that implies risk sharing
80 between the provider of funds (depositor or investor) and the user of funds (borrower or entrepreneur). The third pillar refers to the integration of Islamic banking activities with the real economy, as all transactions are to be backed by real tangible assets. The fourth is the prohibition of excessive uncertainty (*gharar*) and risk taking as in gambling (*maysar*), which means that all Islamic
85 contractual agreements must have clear certainty in their clauses. The fifth and final pillar is the prohibition of financing the production and sales of any business activities that are not ethically accepted (*halal* in terms of Islamic Shariah principles).

Islamic banking products differ between countries in terms of being Shariah
90 based or Shariah compliant, and in terms of how Islamic banking is actually

practiced. For example, the absence of interest rates implies that Islamic banks are theoretically more stable than conventional banks. However, in many countries, Islamic banks follow the prevailing market interest rates in pricing their products and services.

95 In a recent speech, the governor of the Malaysian central bank (Aziz, 2008) stated that Islamic banks business features such as being equity-based, along with the mutual risk sharing property, establish a deep connection between financial and industrial opportunities in the economy, which protects Islamic banks from high exposure to excessive leverage and risk taking. However, the
100 same high connection with the real economy as well as the growing integration with the conventional financial system increases Islamic banks exposure to contagion effects, and challenges their stability in a novel way.

The most important stream of research on the stability of Islamic banks compares them with conventional banks in terms of financial risks.

105 In a comparative study of the default risk of Islamic and conventional banks using survival models based on 421 banks from 20 countries, observed between 1995 and 2010, the evidence suggests that Islamic banks have lower failure risk than conventional banks (Pappas et al., 2013). In a study on credit risk conducted in Pakistan from 2006 to 2008, 150,000 loans default rates were compared
110 between Islamic and conventional banks. The researchers found that conventional banks have almost twice the default rate of Islamic banks (Baele et al., 2014).

Another important reference on default estimation is Cihak and Hesse (2010), who focused on comparative estimation of default probability for 19 banking systems, introducing a z-score. They found that the bank size has an important
115 effect: for small size banks, Islamic ones are financially stronger than small conventional banks, whereas for large size banks, conventional ones are stronger than Islamic banks. In a similar study, the evidence has shown that Islamic banks are more stable than conventional banks but the significance of the difference vanishes for large banks (Abedifar et al., 2013). Beck et al. (2013) used
120 a z-score measure, and found a lower distance to insolvency for Islamic banks.

They also highlighted large cross country differences and confirmed a size effect on the stability of the considered banks. Another study who also applied a z-score measures on 16 countries with a matched sample of 34 Islamic and 34
125 conventional banks, found no difference between them, regarding the effect of the crisis (Bourkhis and Nabi, 2013).

In terms of market risk, Boumediene and Caby (2009) applied EGARCH and GARCH asymmetric models on 14 conventional and 14 Islamic banks during the recent crisis, and found that conventional banks show high volatility in their
130 returns during the crisis period, while Islamic banks started from a low level of volatility, but witnessed a substantial increase during the crisis as a result of their link to the real economy. A related analysis investigated the impact of the crisis on the Islamic stock market in Malaysia, using monthly data for the Period from 2000 to 2011. They concluded that profit sharing within Islamic
135 banking can reduce market risk. However, Islamic banks need to develop risk mitigation techniques to be effectively stable in front of future financial crisis (Karim et al., 2012).

Another important stream of research on Islamic banking stability focuses on performance rather than on financial risks.

140 Hasan and Dridi (2011) investigated the late financial crisis effect on the comparative performance of Islamic and conventional banks. They found that Islamic banks contributed to the financial system stability during 2008-2009 in terms of their better credit and asset growth, which allowed them to receive a more favorable risk assessment from external rating agencies.

145 In the same context, Daly et al. (2013) measured the resilience of bank performances during crisis periods, for eight banking systems with both conventional and Islamic models. They found that, at small sizes, Islamic banks are financially stronger and more resilient but that, at large sizes, conventional ones are stronger. Another study on the effect of the financial crisis on the performance of 34 Islamic and 34 conventional banks from 16 countries (Bourkhis and
150 Nabi, 2013) showed that the two banking models have no significant difference, in general. However, Islamic banks outperform conventional ones regarding the

return on assets indicator, and related this to the better cost efficiency of Islamic banks, and to the differences in the used provisioning strategies. The study also
155 points out that Islamic banks have deviated from the original Islamic finance model towards a conventional one, and this has placed their resilience under the pressure of the financial crisis.

The available studies on the stability of Islamic banks focus on their comparison with conventional ones, and do not examine hybrid or mixed business
160 models between the two, which are gaining ground, particularly in non Islamic countries. An exception is the study by Imam and Kpodar (2010), who suggest that Islamic banks can complement, rather than substituting, conventional banks, allowing for the diversification of the banking sector, which may be helpful to the overall financial stability. This is the first motivation of our paper,
165 which is especially aimed at understanding the effect on stability of different specialisations in Islamic banking.

Another important gap in the research literature concerns the understanding of the systemic risks carried by Islamic banks, including mixed and hybrid types. From a general viewpoint, Billio et al. (2015) pointed out that changes in
170 stock market returns of banks may reflect both direct and indirect correlations, with the direct effect being related either to idiosyncratic characteristics of the banks, or to their systematic factors at the country level; and the indirect effects reflecting the systemic correlations between banks and/or countries. This is the second motivation of our paper, which is aimed at understanding the contribution of both systematic and idiosyncratic effects of different banking models on
175 systemic risks and, therefore, on the stability of financial systems.

We emphasize that the study of systemic risk of Islamic banks should be carried out not only in terms of correlations between banks, but also in terms of correlations between countries. This because the literature clearly establishes
180 the presence of cross country differences in terms of Islamic banks governance, Islamic products compliance with Shariah, in addition to the different financial and economic development levels of each country.

The research field of systemic risk has emerged after the recent financial

crisis. Several empirical studies have been carried out to determine the de-
185 gree of contagion between conventional banks and the related financial systems,
relating to the spread of significant events from one unit of the economy to
another. Such studies were performed modelling correlations between market
data (Allen and Gale, 2000; Dasgupta, 2004; Leitner, 2005; Billio et al., 2012;
Diebold and Yilmaz, 2014; Hautsch et al., 2014; Brownlees and Engle, 2011;
190 Barigozzi et al., 2014), accounting data (Cifuentes et al., 2005; Lagunoff and
Schreft, 2001) or direct contagion that results from the failure of interconnected
systematically important financial institutions (Furfine, 2003; Allen and Babus,
2009; Brunnermeier and Oehmke, 2013).

In this paper we follow the previous stream of literature and, in particular,
195 the network approach of Billio et al. (2012) and Barigozzi et al. (2014), to
study how systematic and systemic risk affect the stability of Islamic banks, in
connection with idiosyncratic risks and bank type. We employ both backward-
looking data, from accounting financial statements, and forward-looking data,
from the stock market. The latter is particularly relevant to study systemic
200 effects, which typically manifest their effects in a short time span, and are often
based on expectations.

We remark that our contribution fits the two prevailing views present in the
literature on Islamic banking stability. The first view remarks the deviation of
Islamic banks from their underlying Islamic principles, questioning the benefits
205 of Islamic banking in comparison to the conventional one (see e.g. Kuran, 2004;
Nomani, 2006; Chong and Liu 2009; Khan 2010). We consider this point of
view in the analysis of the systemic country effects. The second view suggests
that the two models are different and may be complementary, once the relative
strengths and weakness are understood (Sundararajan and Errico, 2002; Iqbal
210 and Llewellyn 2002; Sol j., 2008; Ariffin et al. 2009). We consider this point of
view in the analysis of the bank-specific effects.

3. Methodology

The methodological contribution of this paper is a novel graphical model, that allows correlations between the returns of financial institutions to be decomposed into correlations between country means plus correlation between bank-specific returns. This similarly to what is assumed for the asset returns in CAPM models (Sharpe, 1964). Before introducing our proposal we review some background material on graphical Gaussian models and on centrality measures.

3.1. Graphical Gaussian models

Let $g = (V, E)$ be an undirected graph, with vertex set $V = \{1, \dots, n\}$, and edge set $E = V \times V$, a binary matrix, with elements e_{ij} , that describes whether pairs of vertices are (symmetrically) linked between each other ($e_{ij} = 1$), or not ($e_{ij} = 0$). If the vertices V of the graph g are put in correspondence with a vector of random variables $X = X_1, \dots, X_n$, the edge set E induces conditional independence on X via the so-called Markov properties (Lauritzen, 1996). More precisely, the pairwise Markov property determined by the graph g states that, for all $1 \leq i < j \leq n$,

$$e_{ij} = 0 \iff X_i \perp X_j | X_{V \setminus \{i,j\}};$$

that is, the absence of an edge between vertices i and j is equivalent to independence between the random variables X_i and X_j , conditionally on all other variables $X_{V \setminus \{i,j\}}$.

Here we are concerned with quantitative random variables and, therefore, the graphical model we assume is a graphical Gaussian model. Let $X = (X_1, \dots, X_n) \in R^n$ be a random vector distributed according to a multivariate normal distribution $\mathcal{N}(\mu, \Sigma)$, with Σ a non singular matrix. Whittaker (1990) proved that the pairwise Markov property implies that the following equivalence holds, for graphical Gaussian models:

$$X_i \perp X_j | X_{V \setminus \{i,j\}} \iff \rho_{ijV} = 0,$$

where

$$\rho_{ijV} = \frac{-\sigma^{ij}}{\sqrt{\sigma^{ii}\sigma^{jj}}}$$

230 denotes the ij -th partial correlation, that is, the correlation between X_i and X_j conditionally on the remaining variables $X_{V \setminus \{i,j\}}$.

Therefore, in a graphical Gaussian model, the absence of an edge between vertices i and j is equivalent to the partial correlation between X_i and X_j being equal to zero. Thus, given an undirected graph $g = (V, E)$, a graphical Gaussian model can be defined as the family of all N -variate normal distributions
235 $\mathcal{N}(0, \Sigma_g)$ that satisfy the constraints induced by a graph g on the variance-covariance matrix, in terms of zero partial correlations.

Statistical inference for graphical models can be of two kinds: quantitative learning, which means that, given a graphical structure, with the equivalent
240 partial correlation constraints, data is employed to estimate the unknown parameters of the model; and structural learning, which means that the graphical structure itself (or, equivalently, the zero partial correlation constraints) is estimated on the basis of the data.

Here we focus on structural learning, as our aim is to infer from the data the
245 graphical Gaussian model that best describes the relationship network between the financial institutions we consider. The use of graphical Gaussian models in financial networks is recent: see, for example, Barigozzi and Brownlees (2014) and Giudici and Spelta (2015).

To achieve this aim, we now recall the expression of the likelihood of a
250 graphical Gaussian model, on which structural learning will be based.

For a given graph g , consider a sample X of size n from $P = \mathcal{N}(0, \Sigma_g)$, and let S be the corresponding observed variance-covariance matrix. For a subset of vertices $A \subset N$, let Σ_A denote the variance-covariance matrix of the variables in X_A , and define with S_A the corresponding observed submatrix.

255 When the graph g is decomposable the likelihood of a graphical gaussian model specified by P nicely decomposes as follows (see e.g. Dawid and Lauritzen, 1993):

$$p(x|\Sigma, g) = \frac{\prod_{C \in \mathcal{C}} p(x_C|\Sigma_C)}{\prod_{S \in \mathcal{S}} p(x_S|\Sigma_S)},$$

where \mathcal{C} and \mathcal{S} respectively denote the set of cliques and separators of the graph G , and:

$$P(x_C|\Sigma_C) = (2\pi)^{-\frac{n|C|}{2}} |\Sigma_C|^{-n/2} \exp[-1/2 \text{tr}(S_C (\Sigma_C)^{-1})],$$

260 and similarly for $P(x_S|\Sigma_S)$.

Note that the likelihood depends on the parameter Σ and on g , which indicates the set of cliques and separators that factorise the likelihood, and determine which submatrices of Σ to consider.

Structural learning can be achieved replacing Σ with its maximum likelihood
 265 estimator, the observed sample variance covariance matrix S (constrained by g) and comparing graphical Gaussian models in terms of their resulting maximised likelihood, in a likelihood-ratio based statistical test. The best model can be chosen according to a stepwise procedure in which, at each step, models that differ in terms of only one edge can be compared. The procedure can start
 270 from a fully connected model (backward selection) or from an independent model (forward selection) or on a combination of the two. In all cases, the null hypotheses being tested concerns adding/removal of a single edge, which is equivalent to one extra/less non zero partial correlation.

3.2. Centrality measures

275 Once a graphical Gaussian model is selected, a natural request is to summarise it into a systemic risk measure. This request is quite reasonable, not only from a descriptive viewpoint, but also to provide an indicator that can act as an "early warning" predictive monitor.

The main summary measure that has been proposed in financial network
 280 modeling to explain the capacity of an agent to cause systemic risk, that is, a large contagion loss on other agents, is the eigenvector centrality (see e.g. Furfine, 2003 and Billio et al., 2012). The eigenvector centrality measures the

importance of a node in a network by assigning relative scores to all nodes in the network, based on the principle that connections to few high scoring nodes contribute more to the score of the node in question than equal connections to low scoring nodes.

More formally, for the i -th node, the eigenvector centrality is proportional to the sum of the scores of all nodes which are connected to it, as in the following equation:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^N a_{i,j} x_j,$$

where x_j is the score of a node j , $a_{i,j}$ is the (i, j) element of the adjacency matrix of the network, λ is a constant and N is the number of nodes of the network.

In a graphical Gaussian model, the adjacency matrix is the matrix that describes whether, for each pair of vertex, there is or there is not an edge between them in the selected model.

The previous equation can be rewritten for all nodes, more compactly, as:

$$Ax = \lambda x,$$

where A is the adjacency matrix, λ is the eigenvalue of the matrix A , with associated eigenvector x , an N -vector of scores (one for each node).

Note that, in general, there will be many different eigenvalues λ for which a solution to the previous equation exists. However, the additional requirement that all the elements of the eigenvectors be positive (a natural request in our context) implies (by the Perron–Frobenius theorem) that only the eigenvector corresponding to the largest eigenvalue provides the desired centrality measures. Therefore, once a graphical Gaussian model is selected, A is obtained and, therefore, network centrality scores can be obtained from the previous equation, as elements of the eigenvector associated to the largest eigenvalue.

Besides eigenvector centrality, other measures can be used. The most basic measure is node degree, which assumes linearity, and represents the number of nodes that are adjacent to a specified node in a network. Another one is

node strength, which represents the sum of the correlations of a specified node with other nodes connected to it. A third measure is closeness centrality, which represents the average shortest path from a node to all other nodes.

3.3. Proposal

In high dimensional settings, such as those occurring in systemic risk modelling, there is a high chance that model selection algorithms used for structural learning get trapped, spending much time to learn local optimum structures which might not be optimal at a global level. In addition, it may be difficult to extract interpretable information from a learned structure that is large and shows many interrelationships. A possible solution to the above problems is to add more structure to graphical models, and this is what we propose. To ease understanding, and without loss of generality, we will from now on refer the notation to the specific systemic risk problem we face.

Assume that $R_{i,j,t}$ is a random variable representing the return for the i -th bank in the j -th country at time t and that \bar{R}_{jt} is the mean return of all banks present in country j , at time t . The joint distribution of all bank returns can then be factorised, using the country mean variables, as follows:

$$P(R_{11t}, \dots, R_{IJt}) = P(R_{11t}, \dots, R_{IJt} | \bar{R}_{1t}, \dots, \bar{R}_{Jt}) * p(\bar{R}_{1t}, \dots, \bar{R}_{Jt}).$$

According to the previous assumption, we can proceed decomposing the dependence between bank returns into a dependence between country means and a dependence between banks returns, within each country. We assume that both dependence structures can be described by a graphical Gaussian model, as follows.

First, we assume that the vector of all bank returns $R_{i,j,t}$, conditionally on the country means, is distributed as a graphical Gaussian model with mean $\mu_{j,t}$, the country mean. Indeed the (observed) country mean return can be subtracted out, leading to the extra returns $Y_{i,j,t} = R_{i,j,t} - \bar{R}_{j,t}$ be distributed as follows:

$$Y_{i,j,t} \sim N(0, \Sigma_b), t = 1, \dots, n, \quad (1)$$

where Σ_b indicates the (non singular) variance-covariance matrix between bank extra returns. According to the pairwise Markov property, the following then holds, for any pair of banks (i, i') :

$$e_{ii'} = 0 \iff \rho_{ii'V} = 0 :$$

340 a missing edge between two banks is equivalent to a zero partial partial correlation between the corresponding extra-returns.

The zero partial correlation constraints on the matrix Σ_b are to be estimated from the data, in a graphical Gaussian model selection procedure, specific for each country, in accordance with the pairwise Markov property.

345 Second, we assume that the vector of all country mean returns, \bar{R}_{jt} , is also distributed as a graphical Gaussian model, with mean μ_t , the overall mean. The overall mean return can be subtracted out, leading to the extra returns $Z_{j,t} = \bar{R}_{jt} - \bar{R}_t$ distributed as follows:

$$Z_{j,t} \sim N(0, \Sigma_c), t = 1, \dots, n, \quad (2)$$

350 where Σ_c indicate the (non singular) variance-covariance matrix between country mean extra returns. According to the pairwise Markov property the following then holds, for any pair of countries j, j' :

$$e_{jj'} = 0 \iff \rho_{jj'V} = 0.$$

a missing edge between two countries means is equivalent to a zero partial correlation between the corresponding extra-returns.

355 The zero partial correlation constraints on the matrix Σ_c are to be estimated from the data, in a graphical Gaussian model selection procedure based on the country mean returns.

Note that the model we have specified is made up of two components: a graphical model between country mean returns and, conditionally on the mean

returns of each country, a graphical model between excess bank returns of that
 360 country.

We now further extend our proposed model to take into account covariates that may explain the returns and their correlations. In our context, we may consider two types of covariates: bank type variables, and CAMELS based balance sheet indicators.

365 Covariates can be introduced in our model as further conditioning variables.

Mathematically, the introduction of covariates can be done maintaining the hierarchical structure seen before. More formally, we first assume that:

$$Y_{i,j,t} \sim N(X\beta, \Sigma_{b'}), t = 1, \dots, n,$$

where $\Sigma_{b'}$ is such that, for any pair of banks (i, i') :

$$e_{ii'} = 0 \iff \rho_{ii'V} = 0,$$

and X is a data matrix containing explanatory variables with β the correspond-
 370 ing vector of regression coefficients.

Second, we assume that:

$$Z_{j,t} \sim N(W\Gamma, \Sigma_{c'}), t = 1, \dots, n,$$

where $\Sigma_{c'}$ is such that, for any pair of countries (j, j') :

$$e_{jj''} = 0 \iff \rho_{jj''V} = 0,$$

and W is a data matrix containing explanatory variables with Γ the correspond-
 ing vector of regression coefficients.

The two previous graphical models can be selected using the model selection
 375 procedures general methods available for graphical Gaussian models, reviewed beforehand. From an interpretational viewpoint, it is important to consider the specific type of application being considered.

In our application to Islamic bank stability, we assume that country returns may be affected only by the categorical bank type covariate, whereas bank

380 returns may be affected by continuous CAMELS indicators as well as by the
same categorical bank type covariate. We can thus condition country mean
returns on bank type variables, and check whether the correlations between
countries are maintained or changed when different Islamic bank specialisations
are being considered. Or we may condition excess bank returns on CAMELS
385 balance sheet ratios as well as on bank type and check whether the correlations
between banks in a country are due to common management strategies, or to a
common bank type.

Therefore, systemic risks between countries systematic components can be
read from the variance-covariance matrix $\Sigma_{c'}$ between countries, conditional on
390 the levels of the bank type variable. In the application section we will compare
the different graphical structures resulting from $\Sigma_{c'}$, that correspond to the
four different considered bank types. As, in this case, the explanatory variable
is categorical, the regression coefficients are simply the means of the country
returns, for each bank type. The main focus of our application will thus be on
395 the interpretation of the graphical structures, comparing that resulting from Σ_c
with the conditional ones deriving from $\Sigma_{c'}$.

In the case of the idiosyncratic component, instead, the main interest of our
study will be in the interpretation of the regression coefficients β , rather than on
the variance-covariance matrix $\Sigma_{b'}$, as our aim is to study common factors that
400 affect bank stability and, therefore, its transmission. Such common factors may
be financial indicators or bank specialisation types. For our interpretational
purposes, therefore, the model for the idiosyncratic component can equivalently
be seen as a regression model on bank excess returns, and this allows an easier
comparison with literature results that concern the determinants of risks and
405 performances of Islamic banks.

4. Data and variables description

We have selected from Bankscope all publicly traded banks in the MENA
region, from which we discarded those with data limitations, resulting in a total

of 81 listed banks. The banks in the resulting sample belong to 14 different
 410 countries, with corresponding percentage of total assets, along the years, as
 described in Table 1 below.

Table 1 about here.

Table 1: MENA Countries Assets Distribution per Year

Country	2008	2009	2010	2011	2012	2013
AE	21.09	21.62	21.33	20.55	20.35	19.92
SA	16.75	17.78	17.41	17.12	18.02	17.66
IL	17.3	17.51	18.06	17.62	16.72	16.31
KW	11.09	10.9	10.83	10.95	11.04	10.84
QA	6.83	6.52	7.13	8.25	9.54	10.24
IR	2.87	3.78	3.95	4.34	4.67	5.7
BH	5.82	5.55	5.28	5.19	4.91	4.63
MA	5.05	5.24	5.18	5.36	4.01	4.29
LB	4.39	4.55	4.51	4.36	4.19	4.13
JO	2.54	2.2	2.21	2.28	2.21	2.04
OM	2.51	1.6	1.69	1.65	1.92	1.93
EG	1.27	1	1.02	1.05	1.06	1.01
MT	1.52	1.1	0.83	0.74	0.81	0.81
TN	0.97	0.62	0.57	0.56	0.54	0.51

From Table 1 note that the highest proportions of bank assets in our sample
 can be attributed to Arab Emirates, Saudi Arabia, Israel, Kuwait and Qatar.

415 The banks in the sample can also be classified according to four banking
 types: a CBs group, which includes conventional banks that do not provide any
 type of Islamic financial services; a CB-Win group, which includes conventional
 banks that provide Islamic financial services within their operations but do not
 operate a fully Islamic banking subsidiary; a CB-Sub group, which includes con-
 420 ventional banks that provide Islamic financial services and operates an Islamic
 banking subsidiary; an IBs group, which includes fully fledged Islamic banks in
 all its services and subsidiaries. The 81 banks in the sample are distributed be-
 tween 19 CBs, 24 CB-win, 17 CB-sub, 21 IBs, with a more detailed distribution
 by country as shown in Table 2.

425 Table 2 about here.

From Table 2, note that IL represents a pure CBs system, while IR represents
 a pure IBs one. In terms of total assets, at the overall MENA level, the CB
 group represent 23.42% of them, the CB-win group 21.41%, the CB-sub group

Table 2: Distribution of Bank Type per Country

Country	Country code	Gulf countries	CBs	CB-Win	CB-Sub	IBs
Kuwait	KW	Yes	2	3	1	4
United Arab Emirates	AE	Yes	1	4	6	4
Oman	OM	Yes	1	3	-	-
Qatar	QA	Yes	-	3	2	3
Saudi Arabia	SA	Yes	-	6	1	4
Bahrain	BH	Yes	-	2	2	2
Iran	IR	Yes	-	-	-	3
Total Number of Banks = 57			4	21	12	20
Israel	IL	No	6	-	-	-
Morocco	MA	No	3	1	1	-
Lebanon	LB	No	1	-	2	-
Jordan	JO	No	1	-	2	-
Malta	MT	No	2	1	-	-
Tunisia	TN	No	2	-	-	-
Egypt	EG	No	-	1	-	1
Total Number of Banks = 27			15	3	5	1

35.67% and the IBs group 19.49% .

430 In the systematic country level part of the analysis we use a monthly dataset
that represents market data on equities represented by monthly stock market
returns, and extends over 89 months from January 2007 to May 2014. The data
set is then split into two main parts, a period during the crisis, which extends
from January 2007 to December 2009, and a period after the crisis, from January
435 2010 to May 2014.

In the idiosyncratic, bank specific part of the analysis, we use a quarterly
data set that ranges over 22 quarters; the independent variables of this dataset
are represented by quarterly financial ratios that start from the third quarter of
2008 until the fourth quarter of 2013. The aim of this variation in time line is
440 to take the period within which all banking types are affected by the financial
crisis. In addition, stock returns are shifted one quarter ahead with respect to
their balance sheet counterpart, since the latter is expected to affect the market
one quarter after the period in which it is published. Thus, our final period
ranges from the fourth quarter of 2008 until the first quarter of 2014.

445 The quarterly financial indicators are selected in line with the CAMELS
framework that is considered an industry standard, used by regulators world-
wide.

In the CAMELS context, regulators rate banks under six parameters that comprise the acronym of this approach: Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity. In terms of Capital adequacy
450 measures, we use equity to total assets (ETA) and Tier 1 (TR1) ratios. We expect Islamic banks to have a higher level of ETA as suggested in the empirical literature (Abedifar et al., 2013; Beck et al., 2013; Bourkhis and Nabi, 2013; Olson and Zoubi, 2008). TR1 reflects the amount of core capital that a bank
455 is obligated to set aside as a proportion of its risk-weighted assets. We expect Islamic banks to have higher TR1 as suggested by Al-Hares et al. (2013).

In regards to Asset quality measures, we partially approximate credit risk using loan loss reserves to gross loans (LLRG) and loan loss reserves to impaired loans (LLRI) ratios. The LLRG ratio is lower for Islamic banks which points out
460 their lower levels of credit risk compared to conventional ones and thus lower coverage needs (Khediri et al., 2015; Abedifar et al., 2013). Concerning LLRI, Abedifar et al. (2013), show that Islamic banks have lower ratios of impaired loans to gross loans.

As for Management quality, we partially approximate management efficiency
465 with bank size, represented by total assets (TA) that is transformed into the log format to approximate total assets growth rate (L.TA). In general, IBs have maintained stronger asset growth compared to CBs during the crisis (Hasan and Dridi, 2011).

Earnings adequacy measures are represented by net interest margin (NIM)
470 and return on average assets (ROAA) ratios. We expect NIM to have a low indirect effect on IBs in conformity with Abedifar et al. (2013). ROAA was found to be higher for Islamic banks (Olson and Zoubi, 2008; Hassan and Dridi, 2011). This was confirmed by Khediri et al. (2015). In general, Islamic banks are shown to be more profitable than conventional banks (Olson and Zoubi,
475 2008; Abedifar et al., 2013; Beck et al. 2013; Bourkhis and Nabi, 2013).

Liquidity adequacy is approximated using two ratios, net loans to total assets (NLTA) and liquid assets to total deposits and borrowing (LATDB). In terms of Islamic banks liquidity; Ainley (2000) pointed out that Islamic banks assets are

long-term and illiquid. Olson and Zoubi (2008) found that liquidity ratios are
480 not different between Islamic and conventional banks; however, Islamic banks
retain more cash as a percentage of deposits but less as a percentage of assets in
comparison with conventional banks. Khediri et al. (2015) shows that Islamic
banks are more liquid than conventional banks.

Finally, sensitivity measures the degree of banks risk exposure to stressful
485 financial market conditions, mostly represented by market interest rate. It is
approximated with our dependent variable of excess stock market return, sim-
ilarly to what done in Baele et al. (2007). We also remark that Laeven et al.
(2014) measured individual bank's characteristics effects on systemic risk using
banks stock performance.

490 We remark that, in previous studies, it was found that CAMELS ratios can
be used to differentiate between Islamic and conventional banks (Olson and
Zoubi, 2008), and this was confirmed by Khediri et al. (2015). We expand
these studies considering whether different types of Islamic service levels can
affect the dependence of market performances on the CAMELS ratios.

495 We also remark that all explanatory variables in our study are transformed
into their time variation. For the dependent variable Y , this variation is the
return. Formally, if V_t and V_{t-1} are the values of one variable at time t and
 $t-1$, the variation is represented by $W(t) = \frac{V_t - V_{t-1}}{V_{t-1}}$, and can be approximated
using the following:

$$w_t = \log(W_t) = \log \frac{V_t - V_{t-1}}{V_{t-1}}$$

500 **5. Application and results**

5.1. Contagion Network between countries

We first describe the systematic effects of countries on bank performance.
Figure 1 shows the evolution of bank returns, aggregated by countries, for the
period 2007-2014.

505 Figure 1 about here

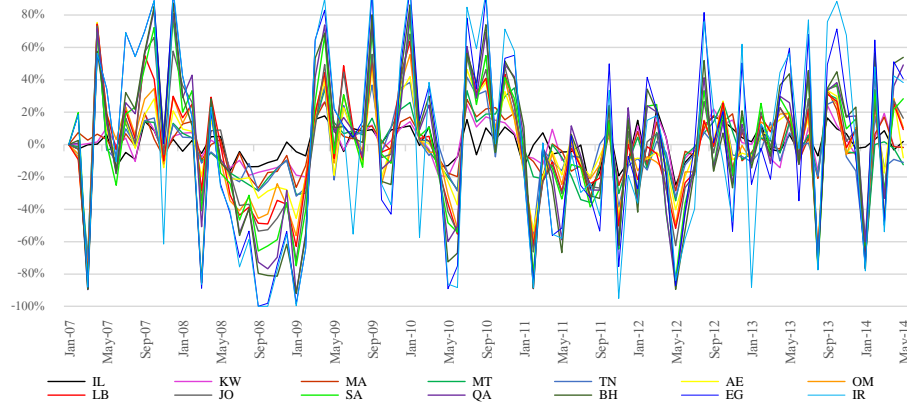


Figure 1: MENA Countries Stock-Market Return Volatility over the period 2007-2014

From Figure 1 note that there is a high volatility of country returns, which seem to be centered around the trend of Israel. Overall, countries with a high portion of Islamic banks, such as Saudi Arabia and Iran, are more volatile than countries with a high portion of conventional banks, such as Tunisia.

510 Having seen the systematic effects of countries, we now consider their impact in terms of systemic risk.

To achieve this aim we present the graphical Gaussian model obtained by analysing the partial correlations between aggregate country returns, for the crisis period (2007-2009) and the post-crisis period (2010-2014). We have chosen
 515 the best model by means of two backward selection procedures that, starting from the fully connected model, progressively test for edge removal using, respectively, a significance level of $\alpha = .05$ and of $\alpha = .01$. Figures 2-5 describe the selected graphical models.

Figures 2-5 about here

520

In all the above Figures, the nodes with the highest number of edges are more linked with respect to the other ones: we can determine the capacity of the corresponding countries as agents for systematic risk using centrality measures, in order to rank countries from the most to the least contagious.

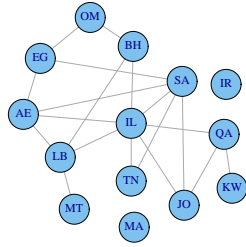


Figure 2: Crisis network at $\alpha = 0.05$

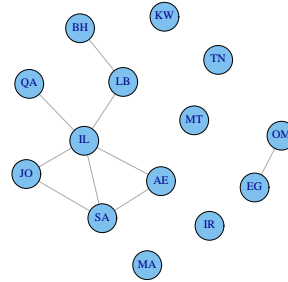


Figure 3: Crisis network at $\alpha = 0.01$

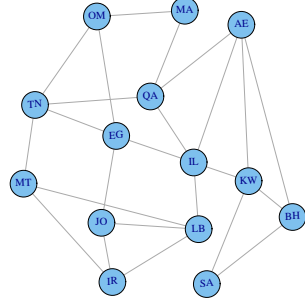


Figure 4: Post-crisis network at $\alpha = 0.05$

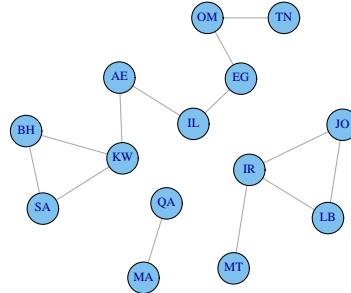


Figure 5: Post-crisis network at $\alpha = 0.01$

525 The centrality measures for the models in Figures 2-5 show that the conventional banking system, represented by IL, has the highest rank for almost all selected models and centrality measures, whereas the Islamic banking system represented by IR ranks lowest during the crisis, but has a moderate increase in its contagion rank in the post-crisis period. These findings reflect the higher
 530 stability of the IBs system during and after the crisis.

We remark, however, that the conclusions that can be drawn from Figure 2-5 may be incomplete, as the model is unconditional on bank types. This may lead to masking and/or confounding of effects. A better model would be a graphical
 535 Gaussian model, conditional on bank types, as described in the methodological section. We now present the results obtained from such a model, for each of the four considered bank types. In all cases, model selection is carried out following the same backward procedures described before.

5.1.1. Contagion Network between countries for the CBs group

We first present, in Figures 6-9, the graphical Gaussian models obtained
 540 analysing the partial correlations between aggregate country returns of CB
 banks alone.

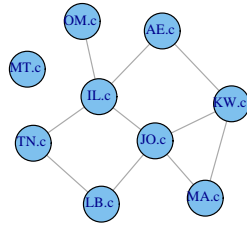


Figure 6: Crisis network at $\alpha = 0.05$

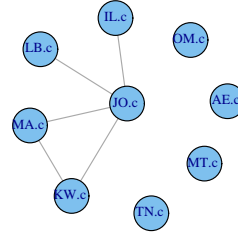


Figure 7: Crisis network at $\alpha = 0.01$

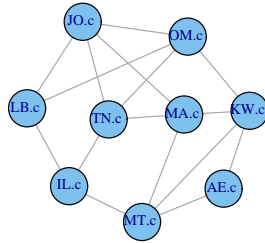


Figure 8: Post-crisis network at $\alpha = 0.05$

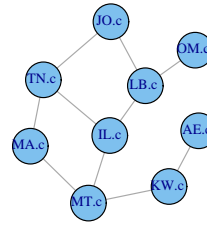


Figure 9: Post-crisis network at $\alpha = 0.01$

Figure 6 and Figure 7 reflect the CBs group countries network during the
 crisis period. On the basis of the model in Figure 6, we can categorize countries
 into four levels, in terms of their closeness measures. At the highest level of 0.10
 545 closeness, we find IL and JO; at the second level of 0.08 we have KW and AE,
 at a level of 0.07 we have MA, TN and LB, at 0.06 we have OM and, finally,
 MT is not ranked as it is disconnected. In terms of the node strength measure,
 JO and IL are followed by KW, then by MA, TN, AE and LB, than by OM
 and, finally, by MT which consistently has a zero value. In terms of eigenvector
 550 centrality measures, JO has the first rank with 0.52, and IL the second, with
 0.44. The eigenvector centrality for KW is 0.41, followed by MA at 0.33, AE
 0.30, LB 0.28, TN 0.25, OM 0.16 and finally MT, with a zero value.

Thus, conditionally on the CB type, JO is ranked at the top contagion level,
 instead of its geographically adjacent country IL, which is the most contagious

555 at the unconditional level. Indeed, JO is not an Oil and Gas production country, and is considered a relatively weak economy. It can thus be influenced by its many connections to other high-influential strong and rich economies, and these moved it to the first contagion rank in the CBs group.

Figure 7 is based on a lower significance level and, therefore, contains less
560 edges. The calculation of the centrality measures on the basis of the model in Figure 7 does not lead to changes in the country ranks, apart from KW that replaces IL in the second rank after JO. Differently from JO, KW is a strong economy and has a large volume of banking assets. However, during the overall study period from 2007 to 2014, KW shows an aggregate market return
565 variability that mirrors pure conventional systems, reflecting a high degree of integration between its Islamic and conventional banking systems.

Figure 8 and Figure 9 describe the CBs group countries selected network after the crisis period from 2010 to 2014. At the 0.05 significance level of Figure 8, the network is highly connected, similarly as in Figure 4. The 0.01 level graph
570 in Figure 9 is more parsimonious and allows an easier interpretation.

The closeness measure based on Figure 9 has four levels, the first level of 0.07 includes IL and MT, the second level of 0.06 includes TN, LB and MA, the third level of 0.05 includes KW and JO and the fourth level of 0.04 includes OM and AE. On the other hand, the node strength measure classifies countries
575 into three levels, with the first level of 0.15 including IL, MT, TN, and LB, the second level of 0.10 including MA, JO and KW and the third level of 0.05 including OM and AE. In terms of the eigenvector centrality measure, the first is IL with 0.48, followed by TN at 0.45, MT 0.39, LB 0.38, MA 0.33, JO 0.32, KW 0.18, OM 0.15 and AE at 0.07.

580 We can conclude from the analysis of the CBs group underlining that there are substantial differences between the crisis and the post-crisis periods, and this indicates the instability of the CBs system within the MENA region. The most systemic country, during and after the crisis, appear to be IL, while JO and KW are so during the crisis but not afterwards.

585 5.1.2. Contagion Network between countries for the CB-WINs group

Figures 10-13 represent the crisis and post crisis period selected graphical Gaussian networks between countries, in terms of their aggregate CB-WINs returns.

Figures 10-13 about here

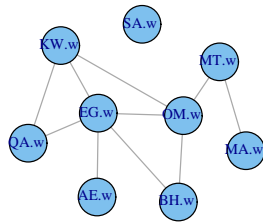


Figure 10: Crisis network at $\alpha = 0.05$

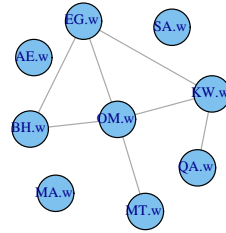


Figure 11: Crisis network at $\alpha = 0.01$

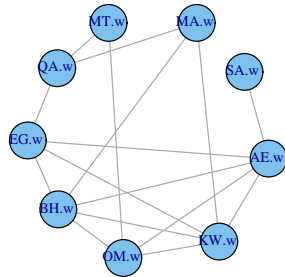


Figure 12: Post-crisis network at $\alpha = 0.05$

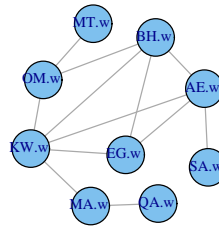


Figure 13: Post-crisis network at $\alpha = 0.01$

590 Figure 10, at the 0.05 significance level, provides a closeness measure that
subdivides the countries into five levels: at the 0.10 scale, two countries are
included, which are EG and OM; in the next level of 0.08, KW and BH are
selected, followed by MT and QA at the 0.07 level, AE at 0.06, MA at 0.05,
whereas SA is disconnected and thus not ranked. With regards to the node
595 strength measure, EG keeps the first rank at 0.25, OM still ranks second at
0.20, KW at 0.15, MT, QA and BH at the 0.10 level, AE and MA at the 0.05
level, and SA has a zero value. As for the eigenvector centrality, EG continues to
keep the first rank at 0.56, OM also continues to be second with a 0.48 measure,
KW 0.43, MT 0.33, QA 0.32, BH 0.18, MA 0.17 and QA 0.05, and, finally, SA
600 with a zero value. In Figure 11, OM is ranked the first, followed by EG, KW,

BH, MT and QA. The same ranking is kept for node strength and eigenvector centrality, while MA and AE become disconnected along with SA. In summary, during the crisis period, OM and EG are the most systemic CB-Win systems.

For the post-crisis period, Figure 12, at the 0.05 significance level, provides the same order of ranking for the three centrality measures, with the first rank given to KW, followed by BH, AE, EG, OM, MA, QA, MT and SA in the last rank. Figure 13, at the 0.01 significance level, provides almost the same ranking, with the first rank given to KW, followed by BH, AE, EG, OM, MA, SA, MT and, finally, QA.

Differently from what happens for the CBs group, the systemic rank of countries do not change considerably between the two periods. The use of an Islamic window within the conventional banking system seems to help in having a more stable network.

5.1.3. Contagion Network between countries for the CB-Sub group

Figures 14-17 represent the crisis and post crisis period selected graphical Gaussian networks between countries, in terms of their aggregate CB-Subs returns.

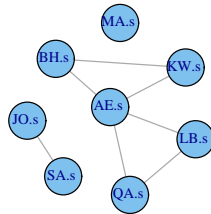


Figure 14: Crisis network at $\alpha = 0.05$

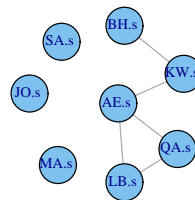


Figure 15: Crisis network at $\alpha = 0.01$

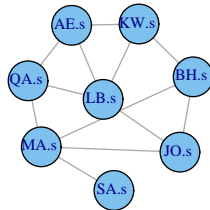


Figure 16: Post-crisis network at $\alpha = 0.05$

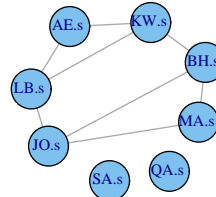


Figure 17: Post-crisis network at $\alpha = 0.01$

Figures 14 and 15 represent the crisis period network for the CB-Sub group countries. In Figure 14, at the 0.05 significance level, we have one main clique, in which the closeness measure subdivides the countries into two levels: at the 0.25 scale, only AE is included; the next level of 0.17 contains KW, LB, QA and BH. The same ranking is kept in terms of node strength and eigenvector centrality. Figure 15, at the 0.01 level, confirms the previous findings, in terms of the closeness measure. On the other hand, node strength and eigenvector centrality provide some small changes and indicate an upward shift for KW.

In the post crisis period, Figure 16 provides a closeness measure with four levels, in which MA is ranked first at 0.10 level; LB, JO, QA, and BH are assigned a value of 0.09, KW and AE are at 0.08, and the last rank at 0.06 is assigned to SA. In terms of the node strength measure, the model maintains the same order of ranking. Instead, the eigenvector centrality measure assigns the first rank of 0.45 to LB, followed by QA, AE and MA at 0.37, KW and JO at 0.36, BH at 0.34 and a value of 0.11 is assigned to SA. Figure 17 had the same ranking order across closeness, node strength and eigenvector centrality measures starting from KW, followed by LB, JO, BH, MA and AE. Finally, both SA and QA are disconnected.

Overall, the CB-Subs models shows that the countries with a higher concentration of CB-Subs (such as JO, LB) are more instable than those with a lesser concentration, presumably because they have exceeded the optimal specialisation threshold.

5.1.4. Contagion Network between countries by IBs group

Figures 18-21 represent the crisis and post crisis period selected graphical Gaussian networks between countries, in terms of their aggregate IBs returns.

From Figures 18 and 19 notice that, in spite of the change in the significance level from 0.05 to 0.01, the two resulting network models are identical in their graphical representation and centrality measures outcomes, indicating stability of the results. Both models include three separated cliques, the larger one includes BH, SA and IR; the second one includes QA and AE; the last one

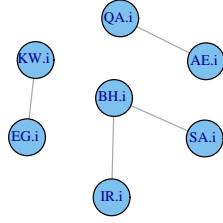


Figure 18: Crisis network at $\alpha = 0.05$

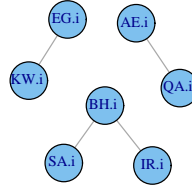


Figure 19: Crisis network at $\alpha = 0.01$

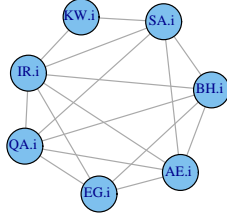


Figure 20: Post-crisis network at $\alpha = 0.05$

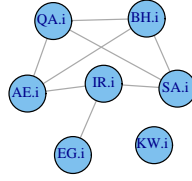


Figure 21: Post-crisis network at $\alpha = 0.01$

includes KW and EG. The ranking with all the three centrality measures sets BH first, followed by SA and IR.

650 The post-crisis period network models are displayed in Figures 20 and 21. At the 0.05 significance level, Figure 20 provides the same ranking for the included countries within the IBs group across the closeness, node strength and eigenvector centrality measures. The countries are ordered, starting from IR in the first rank, followed by AE, QA, BH, SA, EG and KW. From Figure 21, the results rank AE along with SA and IR first at 0.14 level, QA and BH at the 0.13 closeness level, then EG at 0.09 in the last level. In terms of node strength, QA, BH AE, SA and IR had the same level of 0.19, while EG is ranked at 0.06 level, KW is disconnected and not ranked. In terms of the eigenvector centrality measure, QA followed by BH had the same result of 0.48, next is AE and SA 660 at the 0.45 level, IR has 0.35 and EG 0.12.

In summary, the results confirm that IBs are less systemic during the crisis, being less connected than the other networks. They become affected after the crisis although they remain more stable in rankings than CBs, CB-win and CB-Sub models. A partial exception can be found in the behaviour of KW whose rank does change. This can be explained referring to Figure 1, which shows that 665

the KW market return volatility follows the pure conventional system of IL. We also recall that KW ranks second in terms of total CBs assets, after IL and this gives a further indication towards its resemblance to conventional systems.

5.2. Regression analysis results

670 In this subsection we investigate the stability of Islamic banks by focusing on banks idiosyncratic characteristics through the use of CAMELS financial indicators.

Conditionally on the countries systematic effects, whose relationships have been examined in the last subsection, we build a regression model that considers, 675 as a response variable, the excess return of a bank from its country average. As explanatory variables we consider the CAMELS indicators described in the previous section, along with the bank type that may interact with them.

As specified in Section 3, we use quarterly data that ranges from the third quarter of 2008 until the fourth quarter of 2013. The excess stock market return 680 is lagged one quarter since it is expected to capture the effect of the balance sheet indicators one period after their release.

We present four different regression models, each of which is highly significant, in terms of the corresponding F statistic.

In the first model, we examine only the differential effect of the four different 685 bank types, by means of specific dummy variables. In the second model, we consider only the effect of balance sheet ratios. The third model includes both bank types and balance sheet indicators as explanatory variables. The results of these three regression models are described in Table 3, where we report only significant effects.

690 Table 3 about here

Model 1 results reveal that CBs and CB-Win banks have lower positive contribution to excess stock market returns than CB-Sub, with the effect of the IB type being reflected in the intercept. Indeed, the increase in Islamic banking activities level is non-linear in terms of excess returns, as the movement from 695 CBs towards CB-Win lowers the coefficient, but the movement from CB-Win to

Table 3: Linear regression results for Model 1, 2 and 3

		Dependent variable: Sensitivity (S): Quarterly Excess Stock Market Return		
Independent Variables:		model 1	model 2	model 3
Bank Type	dummy CB	0.072 [0.022]**		0.081 [0.023]***
	dummy CB-Win	0.055 [0.021]**		0.046 [0.021]*
	dummy CB-Sub	0.183 [0.023]***		0.142 [0.025]***
Capital Adequacy	(C) TR1		-0.203 [0.069]**	
	ETA		-0.122 [0.063]'	-0.224 [0.049]***
Asset Quality	(A) LLRI			
	LLRG		0.08 [0.023]***	0.079 [0.022]***
Management Quality	(M) L.TA		0.137 [0.02]***	0.096 [0.022]***
Earnings Adequacy	(E) NIM		0.206 [0.041]***	0.23 [0.041]***
	ROAA		0.131 [0.028]***	0.127 [0.029]***
Liquidity Adequacy	(L) NLTA			
	LATDB			
Intercept (IBs)		-0.072 [0.015]***	-0.755 [0.164]***	-0.656 [0.177]***

CB-Sub, that represent a higher level of Islamic finance activities, increased it. Finally, the movement from CB-Sub to IB, which are the fully fledged Islamic banking business models, lowers again the coefficient. In a previous study performed on the European banks, the same non-linear relationship was observed as a result of the diversification effect on banks idiosyncratic risks (Baele et al., 2007).

Model 2 results reveal that both Capital adequacy proxies, TR1 and ETA, have a negative effect on excess market returns, but such an effect is significant only for TR1.

We believe that the lack of significance of ETA is due to the differences in the two main business models, as the Islamic activities are equity based, while conventional ones are debt based: thus, in terms of ETA, they together mask each other's effect. The negative coefficient sign of TR1 reflects that the more

capitalized banks are expected to have lower excess returns and, thus, lower
710 risk.

In terms of Asset quality, we observe that only LLRG has a positive significant effect on the level of banks excess return, which reflects that the market participants positively appreciate a higher percentage of reserves coverage.

With regards to Management quality, as gauged by L.TA, it is positively
715 highly significant in determining the excess returns. This also implies that large size banks are expected to have higher excess returns and thus higher risk. Indeed it was found that the size of a bank is one of the main factors that determine if contagion occurs (Krause and Giansante, 2012 and Chira et al., 2013).

720 In relation to Earnings adequacy, represented by NIM and ROAA, both of them are found to have a positive significant effect on excess stock market returns.

Referring to Liquidity adequacy, the model does not return any significant ratio. This may be again due to the aggregation of different bank types.

725 In Model 3 we regress both bank type and financial indicators from CAMELS. The results of this model are consistent with those in model 2, with minor changes in the magnitude of the coefficients, except for the omission of TR1 and the almost double increase in ETA, with the same negative effect.

Model 3 allows us to make comparisons between our differential stability
730 results and the available literature.

For instance, the literature referred to IBs as better capitalized than CBs, implying a lower level of risk and better stability (Abedifar et al., 2013; Beck et al., 2013; Bourkhis and Nabi, 2013; Olson and Zoubi, 2008). This is confirmed by our results. In terms of asset quality, the LLRG ratio was found to be lower
735 for IBs (Khediri et al., 2015 and Abedifar et al., 2013); indeed, our results show that the excess returns of IBs are lower.

Furthermore, NIM does not capture the total profitability of the bank compared to ROAA, and knowing that the Islamic banking business model is interest-free in its transactions, we expect that NIM will have a lower effect on IBs. In

740 fact, NIM refers to non-interest activities, in particular it represents the operating profit margin between IBs loans and payments that they provide to profit loss sharing accounts. In this respect, Abedifar et al. (2013) pointed out that IBs have an implicit interest rate that is less affected by domestic rate fluctuations in comparison with conventional banks.

745 ROAA represents the overall average profitability, and it was found that IBs are in general more profitable than CBs in this respect (Abedifar et al., 2013; Beck et al., 2013; Bourkhis and Nabi, 2013; Hasan and Dridi, 2011; Khediri et al., 2015; Olson and Zoubi, 2008); our results confirm these findings.

Model 4 includes regressing excess returns on bank type, balance sheet indicators and the interaction between them, to test for additional significant differences in the excess returns that are not explained by bank type or CAMELS indicators separately. The results of the model are described in Table 4, where we report only significant effects.

Table 4 about here

755 The results of Model 4 do not directly include the IBs dummy but they include its effect in both the intercept and in the CAMELS coefficients that do not have interaction terms.

In terms of bank type effects, comparing them to the results of model 3 in Table 2, the pure business models of CBs and IBs keep their signs, yet with a larger magnitude, CB-Win maintains the same sign, but becomes non significant, and, finally, CB-Sub changes its sign, from positive to negative. These changes are due to the inclusion of interaction terms that absorb part of the return variability, previously unexplained. In fact the R^2 of model 4 is three times higher than that of Model 3.

765 The non-linear effect in the level of diversification of Islamic banking activities that we previously found remains, indicating that after a certain threshold there will be an inversion in the effect of diversification. This change in the threshold level may stem not only from the interaction effects but also from the presence of weak and strong economies, with weak economies depending more on CBs and stronger ones depending more on IB, as we have noticed in the

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Table 4: Linear regression results of Model 4

		Dependent variable: Sensitivity (S): Quarterly Excess Stock Market Return				
		Independent Variables:				
Bank Type Dummy	dummy CB				2.621	
					[0.585]***	
			dummy CB-Win			0.668
						[0.687]
	dummy CB-Sub			-4.271		
					[0.925]***	
Independent Variables		CAMEL	CB * CAMEL	CB-Win * CAMEL	CB-Sub * CAMEL	
Capital Adequacy	(C)	TR1	-0.446		0.649	0.561
			[0.1]***		[0.185]***	[0.261]*
		ETA	-0.031	-0.372	-0.341	0.89
			[0.082]	[0.139]**	[0.17]*	[0.277]**
Asset Quality	(A)	LLRI				
		LLRG		0.08	0.079	
				[0.023]***	[0.022]***	
Management Quality	(M)	L.TA	0.121	-0.259	-0.136	0.211
			[0.027]***	[0.062]***	[0.061]*	[0.107]*
Earnings Adequacy	(E)	NIM	0.247	-0.298	-0.179	-0.281
			[0.042]***	[0.056]***	[0.101].	[0.107]**
		ROAA	0.312	0.327	0.16	0.742
			[0.054]***	[0.096]***	[0.065]*	[0.096]***
Liquidity Adequacy	(L)	NLTA	-0.071	0.393	0.388	0.509
			[0.048]	[0.17]*	[0.172]*	[0.213]*
		LATDB	-0.243	-0.372	0.367	1.019
			[0.088]**	[0.139]**	[0.14]**	[0.161]***
Intercept (IBs)						-1.356
						[0.414]**

previous subsections.

We now consider the changes in the CAMELS variables coefficients. In terms of Capital adequacy, TR1 and ETA both have a negative overall effect on excess returns as in models 2 and 3. Looking at the interaction terms for CBs we have a further negative significance effect for ETA; it corresponds to saying that a one unit increase in the CBs ETA will be penalized by an additional 37 basis points penalization with respect to Islamic banks, indicating their higher risk profile. CB-Wins have a similar penalisation, yet counterbalanced by a positively significant TR1, which means that CB-Wins positively benefit from the diversification into Islamic banking activities that lower their leverage risk. As we move further into CB-Sub, we find that both TR1 and ETA become positive, which indicates that the market positively rewards CB-Sub for a higher

capitalization and leverage. In summary, the market favors the diversification of a conventional banking system into Islamic banking activities, although up to a certain threshold, since a non-linear relation between Islamic banking activities and excess stock market returns holds, as previously pointed out.

Concerning Asset quality, not only LLRG (as in Table 3) but also LLRI have a positive and significant effect on excess returns variation. Looking at the interaction terms, we find evidence of a further negative effect for all non IB types. In detail, CBs have a negative coefficient for both LLRI and LLRG, reflecting that they are negatively penalized by the market for their higher level of coverage and higher credit risk. As for CB-Win, only LLRI is negatively significant. The same relation holds in CB-Sub interaction but at a moderate lower level than it is for CB-Win, which is consistent with the Islamic subsidiaries business model characteristics.

In terms of Management quality, we obtain the same positive effect of L.TA on excess return as in Table 3. Looking at the interaction terms, CBs and to a lesser extent CB-Win, add an incremental negative effect. This means that larger CBs (as well as CB-Win, to some extent) assume more risks than larger IBs, and this lowers their market valuation. This result is not consistent with the "too big to fail" notion but it is so with the findings of Shajari and Mohebikhah (2012). For CB-Wins, the coefficient has the same negative effect, but with a lower value. This can be explained by the lower risk level assumed by a bank as it introduces Islamic services. Instead, the CB-subs incremental coefficient of L.TA is positive, and this confirms the non linear relation between Islamic banking activities and excess market returns.

Referring to Earnings adequacy, both NIM and ROAA have a significantly positive effect, as in Table 3. Looking at the interaction terms, in relation to IBs, we find that even though Islamic financing activities are not interest bearing in comparison to conventional ones, their products are assessed by the market from an interest bearing perspective as a proxy for their profit loss sharing principle, and reflecting that NIM for IBs is a representative measure of the IBs profit operating margin. Indeed the interaction coefficients show that the

NIM effect is more positive for Islamic banks, whereas ROAA is more positive
815 for other bank types. This outcome reflects the fact that the market negatively
prices the increase in interest-income sources for the hybrids between Islamic
and conventional banks, while it favors their increase in ROAA.

In regards to Liquidity adequacy and differently from what occurred in Ta-
ble 3, significant effects appear. At a general level, both NLTA and LATDB
820 have a negative significant effect on excess returns, with the latter having the
stronger magnitude. These effects are corrected by the positive coefficients of
all interaction terms, excluding that for LATDB for CBs. The NLTA effect on
excess return corresponds to illiquidity of long term assets in IBs (Ainley, 2000),
however; the LATDB negative effect does not match our expectations as IBs
825 were found to retain a higher cash percentage of deposits but a lower percent-
age to assets in comparison with CBs (Olson and Zoubi, 2008). However, other
studies found that IBs are more liquid than CBs (Khediri et al., 2015).

6. Conclusions

The main aim of this paper was to investigate whether and how Islamic
830 financial services support financial stability, based on how they affect systematic
and idiosyncratic risk correlations.

To achieve this aim we have proposed a novel financial network model, based
on graphical Gaussian models, that decomposes banks returns in country mean
returns plus bank specific excess returns, with the additional introduction of a
835 bank type covariate, that explains both, and of CAMELS based balance sheet
indicators that explain bank excess returns in terms of a regression model.

The application of our models show that the higher the diversifications of
Islamic finance activities, the higher the stability of the banking system. The
results also indicate that, as the CB-Sub group is more stable than CBs but less
840 stable than CB-Win and IBs, there is an optimal level of diversification beyond
which either the system converts to IBs, or find and set the optimal level of
operations within the subsidiaries so as not to exceed it.

Both the systematic and the idiosyncratic analysis are favorable in terms of supporting the ability of the Islamic banking model to enhance the financial and economic stability. This finding confirms what available in the Islamic research literature on banking stability.

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