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Contagion between Islamic and Conventional Banking: A GJR DCC-GARCH and VAR Analysis

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Abstract

This study aims testing the presence of contagion through Islamic and conventional banking systems during the subprime crisis. Specifically, we examine how far a shock striking conventional or Islamic banks is exported from one group to another or remain limited. Therefore, we adopt a GJR DCC-GARCH model to study the dynamic conditional correlation and the vector auto-regression VAR model in order to identify causality direction and the impact of a shock on the returns of each banking index. Hence, our results indicate that Islamic banks are not isolated from conventional banks while there is a contagion phenomenon between these two financial systems. Furthermore, we determined that during the crisis, Islamic banks could not absorb this effects and ensure stability because these banks were also affected by the crisis.

JEL Classification: G21, G32, G33

Keywords: Islamic finance, financial stability, volatility, GJR-DCC, VAR

1. Introduction

While Islamic banking system has improved throughout these years, the level of competition with conventional system has intensified too. Regarding the co-existence of Islamic and conventional banking and such differences in their foundations, the question of contagion risk between them in case of shocks become a major concern. The period of financial crises are a perfect experimental context to identify the relationship between these two industries in the event of financial distress. The series of crises faced by international financial institutions have raised several questions about the ability of each banking system (Islamic and conventional) to withstand financial and economic shocks. Most studies in the literature have compared Islamic to conventional banking separately and assume that there is no interaction between them. In this study, we try to fill in this gap by examining contagion risk between Islamic and conventional banks so as to see how far a shock that strikes conventional or Islamic banks is exported to the other system, or remain constrained.

Thereby, our paper is structured as follows. We first present a theoretical overview of banking contagion focusing on the different definitions proposed in the literature and the methods of its detection. Then, we present the methodology used to test the presence of this phenomenon on domestic and cross-country levels. Finally, we report the results.

2. Theoretical Context

In fact, the concept of contagion has been defined in several ways. According to Masson (1998), Kamisnsky and Reinhart (2000), contagion can be defined as the spread of financial market disturbances from one country to financial markets of other countries. This definition is used very frequently insofar as it takes into account shock transmission mechanisms. Other definitions have been proposed in the literature such as that of Pericoli and Sbracia (2001). For these authors, contagion is defined as a significant increase in co-movement of prices and quantities across markets following a crisis in a market or a group of markets. This definition places contagion as an excessive increase in co-movements against a certain standard. It is important to distinguish between normal co-movements due to simple excessive interdependences and co-movements due to financial turbulence. In the same way, Forbes and Rigon (2002) stated that contagion is explained by a change in transmission mechanisms during financial turbulence. Consequently, this change can be expressed as a significant increase in correlation across markets. Under this perspective, contagion is detected through investors' and speculators' behavior.

Indeed, financial crises are a relevant experiment to test the presence of financial or banking contagion. In late of 2007, the global economy experienced a severe financial crisis produced in the American real estate market and then spread to the rest of the world. This financial turbulence caused the failure and bankruptcy of several financial institutions in many countries. Therefore, there are two main channels contributed to the spread of this crisis. The first one is the direct exposure of financial institutions around the world to the mortgage market, through securitization transactions. The second one is the common shocks on asset markets, particularly real estate markets.

The presence of the interbank market was the source of banking contagion. The mission of an interbank market is to transfer liquidity between banks. Contagion risk is said to be triggered by liquidity shocks to the market, enabling the transmission of crises. According to Van and Weder (2001), in the presence of liquidity shocks or a financial crisis, investors rally to reconstruct their portfolios. Through share purchases and sales, they transfer risk from one institution to another or from one market to another. It is this kind of behavior that triggers contagion. According to Forbres and Rigobon (2001), this process causes an increase in correlation between financial assets. Worth noting is that this mechanism does not occur during financial stability but only during crisis periods. Nevertheless, Van Rijckeghen and Weder (2000) examined the notion of liquidity in the banking system. Indeed, banks react to a crisis in a country by a generalized reduction in credit granting depending on the borrowing countries. Therefore, investors will rebalance their portfolios, causing the spread of crises.

According to Hartmann et al (2004), bank contagion may be possible through two channels. The first leads to the bank's direct exposure to the interbank market. The second is information dissemination. In fact, banks resort to financial markets for liquidity if needed and for risk management too. Consequently, failure of a bank may have negative repercussions on the liquidity of other banks.

Banking contagion has been the subject of several studies. Furfine (2003) examined a database reflecting bilateral exposure to the US banking market and studied the impact of individual banking failures on other banks. This study proved that the concept of systemic risk exceeds that of interconnection of the interbank market. Upper and Worms (2004), who studied contagion in the German banking market, found that contagion risk in the interbank market mainly affects small German banks.

To study the vulnerability of the German banking system, Memmel and Stein (2008) examined data on bilateral exposure between all banks. They assumed that the interbank market itself is a contagion mechanism since contagion occurs when a bank fails. The results indicate that banking contagion depends in large part on the size of the failing bank and its interrelationships with other banks.

Moreover, among the factors behind banking contagion, the literature identifies information asymmetry. Information asymmetry is a very important factor in triggering contagion. During banking panics, depositors worry about their deposits, and they start to retain their deposits causing banking failures. Indeed, bankruptcy of a large number of banks suggests that dissemination of information to financial markets has deteriorated.

Finally, contagion may depend on the structure of interbank links. According to Allen and Gales (2000), the interbank market may take three structures. First is, the entire structures, in which banks are symmetrically related to any other bank. Second, the incomplete structure is where banks are related only to neighboring banks. Third, there is the incomplete and offline market structure. Several studies agree on the importance of the interbank market structure. Indeed, Elsinger and al (2002) used a model of complex networks for interbank market exposure and examined the consequences of macroeconomic shocks on the Austrian banking system. Interbank market structure and exposure size are important elements in determining contagion risk. Specifically, degree of completeness and heterogeneity of the interbank market are closely linked to contagion risk.

3. Method

To meet our research objectives, we use GJR-DCC model to identify the presence of contagion across these two banking industries on a domestic scale. We follow Forbes and Rigobon (2002) to identify contagion in that correlation which is a measure of contagion during a crisis. Indeed, an increase in correlation coefficient indicates contagion. These authors compared the intensity of financial links, before and after the crisis, between different markets. We do the same to examine co-movements between these two banking industries (Islamic and conventional) at the domestic level during the study period.

To identify contagion across the two banking systems during the crisis period, we introduce a return index for

Islamic and conventional banking industries for each country. This index represents the weighted average returns of banks according to their market capitalization to see the effect of bank size on the banking system.

Then we use the GJR-DCC model to examine dynamic conditional correlation between the return index of Islamic banks and that of conventional banks during the entire study period. We opted for the GJR-DCC model because the DCC-MGARCH model has been criticized for its symmetrical nature and its non-accountability of the asymmetric reaction of past shocks for current volatility. However, such researchs in the 1970s indicated that negative past returns increase volatility more strongly than past positive returns. Hence, reasons explaining this phenomenon come with a lot of controversy. According to Black (1976), decrease in the stock price of a leveraged firm worsens its solvency ratio. This increases intrinsic risk and therefore stock volatility. This is leverage theory.

To overcome this critical appraisal, we propose to use the GJR-GARCH model introduced by Glosten, Jagannathan and Runkle (1993). This is a nonlinear GARCH model to account for asymmetry in the conditional variance of a response to innovation. The principle of the GJR-GARCH model is the dynamics of conditional variance which admits a change regime and depends on the sign of past innovation. The difference between these two models lies in conditional variance. For the GJR-GARCH model, variance is written as:

$$\sigma_t^2 = \omega + \alpha_i \varepsilon_{t-i}^2 + \lambda \mathbb{I}_{[\varepsilon_{t-1<0}]} \varepsilon_{t-i}^2 + \beta_j \sigma_{t-j}^2 \tag{1}$$

Where $\mathbb{I}_{[\varepsilon_{t-1<0}]}$ denotes an indicator function such that $\mathbb{I}_{[\varepsilon_{t-1<0}]} = 1$ si $\varepsilon_{t-1}<0$, $\mathbb{I}_{[\varepsilon_{t-1<0}]} = 0$ otherwise. The parameter λ can model an asymmetric effect related to signs of past innovations ε_{t-1}. If $\lambda > 0$ (respectively if λ <0), a positive shock on past innovations at time t-1 is translated at time t by an increase (respectively decrease) in conditional variance, i.e. volatility of an r_t process. From the variance equation, we can directly distinguish coefficients specific to positive residuals $\alpha_{pos} = \alpha_1$ or to negative residuals $\alpha_{neg} = \alpha_1 + \lambda_1$.

The model can also be written as follows:

$$\sigma_t^2 = \omega + \alpha_{pos} \mathbb{I}_{[\varepsilon_{t-1>0}]} \varepsilon_{t-i}^2 + \alpha_{neg} \mathbb{I}_{[\varepsilon_{t-1<0}]} \varepsilon_{t-i}^2 + \beta_j \sigma_{t-j}^2 \tag{2}$$

In what follows, we try to apply analysis tools recently introduced in applied finance. These are the family of Dynamic Conditional Correlation models (DCC), which allow for the correlation matrix to be dynamic over time while retaining few parameters. GJR-DCC introduces equations describing the evolution of correlation coefficients between the banking index (Islamic or conventional) with that of the market index. Through this model, we can deduce dynamic conditional correlation between Islamic and conventional banking indices.

This model is proposed by Engle (2002) and Tse and Tsui (2002) and is written as follows:

$$\begin{cases} H_t = D_t R D_t \\ D_t = diag\,(\sqrt{h_{11t}}, \sqrt{h_{22t}}, \ldots, \sqrt{h_{NNt}}) \\ R_t = (diag Q_t)^{\frac{-1}{2}} Q_t (diag Q_t)^{\frac{-1}{2}} \end{cases} \tag{3}$$

Where

- $H_t = D_t R D_t$ represents the variance and covariance matrix of the two assets.
- D_t is a diagonal matrix of time-varying standard deviations collected from the estimated two univariate GJR -GARCH,
- The elements contained in D_t are generated by a GJR-GARCH (p, q), which also gives:

$$H_t = \begin{pmatrix} \sqrt{h_{it}} & 0 \\ 0_{P_i} & \sqrt{h_{0t}} \end{pmatrix} \begin{pmatrix} 1 & \rho_{i0,t} \\ \rho_{i0,t} & 1 \end{pmatrix} \begin{pmatrix} \sqrt{h_{it}} & 0 \\ 0 & \sqrt{h_{0t}} \end{pmatrix} \tag{4}$$

$$h_{it} = c_i + \sum_{p=1} (\alpha_{ip}\, \varepsilon^2{}_{it-p} + \lambda \mathbb{I}_{[\varepsilon_{t-1<0}]} \varepsilon_{t-i}^2) + \beta_j \sum_{q=1} \beta_{iq}\, h_{it-q} \quad ; \quad i = 1,2 \tag{5}$$

$R_t = [\rho_{ij,t}]$ represents the matrix of constant conditional correlation coefficients, $Q_t = [q_{ij,t}]$ is the covariance matrix of standardized residuals, of (N x N)dimension, symmetric and positive definite.

$$q_{ijt} = \bar{\rho}_{i,j} + \alpha\left(Z_{i,t-1} Z_{j,t-1} - \bar{\rho}_{i,j}\right) + \beta\left(q_{ijt-1} - \bar{\rho}_{i,j}\right) \tag{6}$$

$\bar{\rho}_{i,j}$ represents the unconditional correlations and $\rho_{ij,t} = \frac{q_{ijt}}{\sqrt{q_{iit}q_{jjt}}}$ represents dynamic conditional correlations.

In what follows, we use VAR developed by Christopher Sims, to examine dependence between the two banking industries in the different countries studied. (Cross-country contagion risk analysis)

The VAR (p) model is presented by:

$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \dots\dots\dots.\varphi_p X_{t-p} + \epsilon_t \tag{7}$$

Or equivalently:

$$\varphi\,(L)\,X_t = c + \epsilon_t \tag{8}$$

Where c, (n, 1) dimension, is a vector of constants, $\varphi\,(L) = \sum_{i=0}^{\infty} \varphi\, L^i$ or matrices φ_i, whatever i [0, p] of (n, n) dimension, fulfill $\varphi_0 = I_n$ and $\varphi_p \neq 0_n$. The vector (n, 1) of innovations ϵ_t is i.i.d.

In general, for x_{jt}, whatever j ϵ [1, n], we have:

$$\begin{aligned} x_{jt} &= c_1 + \varphi^1{}_{j1}\, x_{1\,t-1} + \varphi^1{}_{j2} x_{2\,t-1} + \dots + \varphi^1{}_{jj} x_{j\,t-1}. + \cdots. + \varphi^1{}_{jn}\, x_{n\,t-1} \\ &+ \varphi^2{}_{j1}\, x_{1\,t-2} + \varphi^2{}_{j2}\, x_{1\,t-2} + \dots + \varphi^2{}_{jj}\, x_{j\,t-2} + \cdots + \varphi^2{}_{jn}\, x_{n\,t-2} + \cdots \\ &+ \varphi^p{}_{j1}\, x_{1\,t-p} + \varphi^p{}_{j2}\, x_{2\,t-p} + \dots + \varphi^p{}_{jj}\, x_{j\,t-p} + \cdots + \varphi^p{}_{jn}\, x_{n\,t-p} \end{aligned} \tag{9}$$

This model captures interdependencies between multiple time series since the variables are treated symmetrically so that each series is explained by its own past values and the past values of the other variables. This allows us to examine the causal link between returns of Islamic banks and those of conventional banks and also to study the impulse response function to see whether the impact of a shock on the returns of conventional banks will instantly impact the returns of Islamic banks and vice versa.

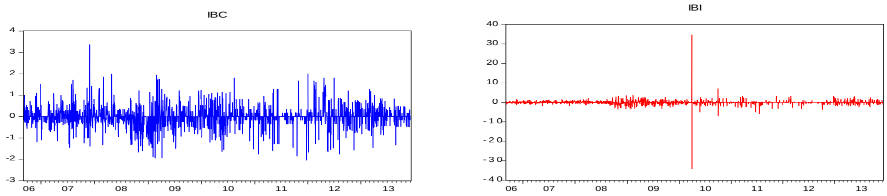
4. Data

Our sample consists of (51) listed banks in six Middle Eastern countries. These are Bahrain, Saudi Arabia, Kuwait, Qatar, Egypt and Turkey, with (12) Islamic banks and (39) conventional banks. The study period stretches from 04/09/2006 until 04/12/2013. We eliminate from the sample countries with no listed Islamic banks. Individual bank data are collected from the Datastream database.

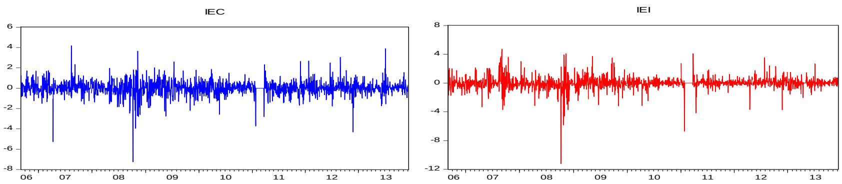
Table 1. Distribution of the sample according to type of bank

	Conventional banks	Islamic banks	Total
Bahrein	4	3	7
Saoudi-Arabia	6	2	8
Kuwait	4	3	7
Qatar	4	1	5
Egypt	8	1	9
Turkey	13	2	15
Total	39	12	51

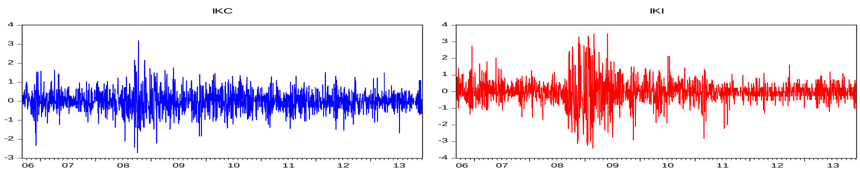
The figures below report the various indices' return series for conventional and Islamic banks. We notice that the two banking industries were affected by the subprime crisis, as there is a higher fluctuation of returns during the crisis period in each of the countries studied.



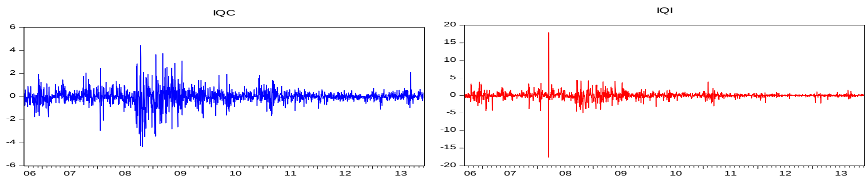
Bahrain banking index



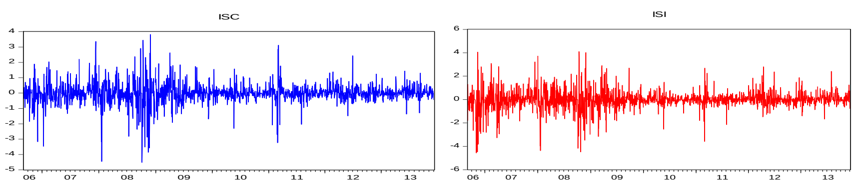
Egypt banking index



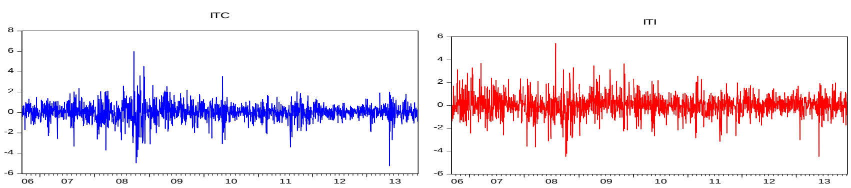
Kuwait banking index



Qatar banking index



Saoudi-Arabia banking index



Turkish banking index

Figure 1. Evolution of indices' returns for conventional and Islamic banks by country

* Blue represents returns of conventional banks, red represents returns of Islamic banks.

Table 2. Descriptive statistics of the indices returns for conventional banks by country

	Maximum	Minimum	Mean	Std. Dev.	Skewness	Kurtosis	JB	Q(12)	Q^2(12)	ARCH(12)
IBC	3,367677	-2,041751	-0,00603	0,49316	0,09825	6,91742	1178,861	15,415	107,70***	25,46864***
IEC	4,178965	-7,258714	-0,00107	0,72977	-0,85824	13,2023	8201,414	16,012*	29,677**	4,899138***
IKC	3,189077	-2,713107	-0,00319	0,54319	0,049886	5,13548	350,1929	12,212	357,33***	42,65021***
IQC	4,450436	-4,352939	0,00157	0,65674	-0,3246	12,0272	6276,482	24,089**	1491,2***	453,1254***
ISC	3,820643	-4,520034	-0,01384	0,65701	-0,50352	11,8641	6098,309	35,613***	_	_
ITC	5,987471	-5,243961	0,00862	0,83636	-0,34019	8,39039	2261,907	19,747**	521,39***	31,21118***

Table 3. Descriptive statistics of the indices returns for Islamic banks by country

	Maximum	Minimum	Mean	Std. Dev.	Skewness	Kurtosis	JB	Q(12)	Q^2(12)	ARCH(12)
IBI	34,69038	-34,11789	-0,03927	1,4185	0,346952	378,656	10813132	7,3338	248,52***	273,1774***
IEI	4,721702	-11,22019	-0,00031	0,88351	-1,35544	24,5155	36033,95	30,084**	141,97***	24,76301***
IKI	3,503147	-3,404023	0,00264	0,72666	-0,03081	7,47145	1532,318	24,24**	2519,2***	327,5458***
IQI	17,9431	-17,6031	-0,00502	1,0323	0,038313	100,623	730257,1	12,77	416,88***	415,3141***
ISI	4,107692	-4,573	-0,01057	0,78357	-0,34342	10,127	3928,245	12,232	416,88***	80,46517***
ITI	5,442047	-4,467844	0,01033	0,90719	-0,02498	5,93021	658,1014	8,1436	139,37***	46,65257***

According to Tables 1 and 2, return series are not normally distributed, hence the null hypothesis of normality is rejected because the probability of Jarque Bera test is less than 0.05. Skewness coefficients show that the marginal distributions are asymmetric; skewed to the right when values are positive and to the left when values are negative. We note first that kurtosis is very high, well above 3. Such a high kurtosis indicates that these banks have fat-tailed distributions. This phenomenon of excess kurtosis confirms the strong leptokurtic character of stock returns series. Similarly, the stationarity analysis shows that all return series are stationary. In addition, the heteroscedasticity test points to some ARCH effects, and that the null hypothesis of no autocorrelation is accepted because probability levels are greater than 5%, except for the Saudi Arabia conventional banking index.

5. Results

After estimating the univariate GJR-GARCH model for the Islamic and conventional banking indices in the presence of asymmetry effects, we found the parameters ($\lambda + \alpha$) and (α), which represent respectively the impact of the negative and positive shocks on variance. In other words, the more important they are, the more volatility increases after the shock. The results show that returns of Islamic banks are more volatile than those of conventional banks, whether the impact is positive or negative. Similarly, for the (β) coefficient, which represents return speed to minimum volatility, the results indicate that this coefficient is higher for conventional banks than for Islamic banks. Therefore, we can conclude that returns of conventional banks are less volatile than those of Islamic banks and conventional banks are more resistant to shocks than Islamic banks.

The results on dynamic conditional correlation between returns of Islamic and conventional banks using the GJR-DCC model present a positive correlation for the entire period of study for the different countries in our sample. Moreover, we also found that correlation between these two banking industries differs from one country to another with an unstable trend over time. This difference depends on co-movement between the two banking systems in each country. After a filtering test, we note that during the crisis correlation between returns of Islamic and conventional banks increased significantly in all studied countries, providing evidence of contagion between these two banking industries during the crisis period. However, after the crisis, correlation records a downward trend. We also found that the estimated parameters of the univariate GJR-GARCH models check the validity conditions of the model [$c>0$, $\alpha>0$, $\alpha+\lambda>0$, $\beta>0$ and theta (1) + theta (2) < 1]. Moreover, the parameters are statistically significant, suggesting that the adoption of a GJR-GARCH model is appropriate.

Table 4. Dynamic Conditional Correlation between Islamic and conventional banking indices GJR-DCC

	Conventional banking index				Islamic banking index				DCC	
	c	α1	λ1	β1	c	α2	λ2	β2	theta(1)	theta(2)
Bahrain	0.019970	0.089351	0.013236	0.823590	0.258388	0.139347	-0.223834	0.561004	0.015603	0.973191
	0.0147**	0.0009**	0.6764	0.0000***	0.2967	0.2174	0.0871**	0.1071	0.0306**	0.0000***
Egypte	0.054678	0.240538	0.058972	0.691672	0.120720	0.262256	0.033650	0.452981	0.041195	0.744948
	0.0000***	0.0000***	0.3298	0.0000***	0.0002***	0.0007***	0.8757	0.0000***	0.0490**	0.0000***
Kuwait	0.019330	0.102221	0.086698	0.800062	0.007970	0.119761	0.068046	0.839462	0.049154	0.924934
	0.0001***	0.0002**	0.0368	0.0000***	0.0004**	0.0000***	0.0412	0.0000***	0.0000***	0.0000***
Qatar	0.004640	0.137760	0.084659	0.841242	0.013842	0.386945	-0.001883	0.776538	0.058495	0.925867
	0.0009**	0.0000***	0.0226**	0.0000***	0.0021**	0.0002**	0.9804	0.0000***	0.0000***	0.0000***
Saoudia	0.012010	0.118885	0.167450	0.845823	0.014406	0.162157	0.194697	0.847104	0.030839	0.960195
	0.0015**	0.0005**	0.0050**	0.0000***	0.0086**	0.0033**	0.0203**	0.0000***	0.0005**	0.0000***
Turquie	0.024649	0.098307	0.082847	0.830225	0.145125	0.132260	0.135281	0.645653	0.041303	0.929718
	0.0001***	0.0000***	0.0083**	0.0000***	0.0000***	0.0002**	0.0126**	0.0000***	0.0001***	0.0000***

**Stability condition theta (1)+theta (2) < 1 is met*

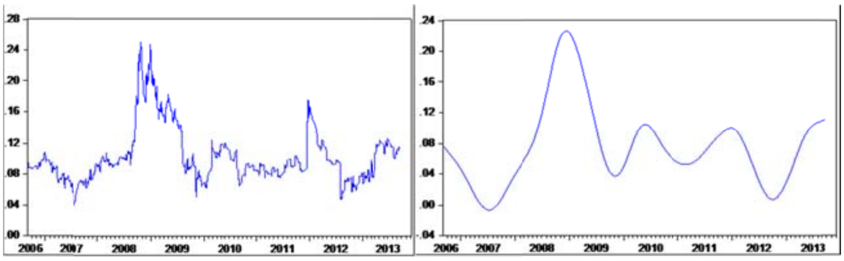


Figure 2. Dynamic conditional correlation between returns of Islamic and conventional banking indices of Bahrain

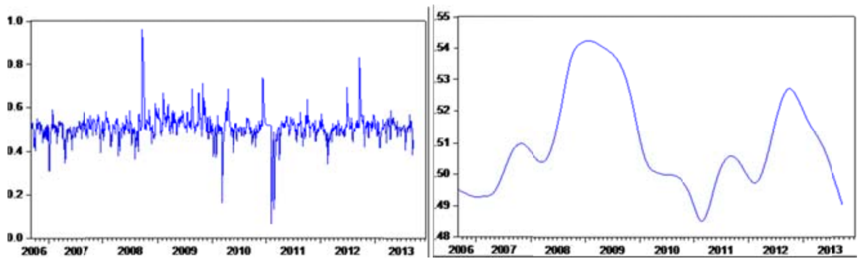


Figure 3. Dynamic conditional correlation between returns of Islamic and conventional banking indices of Egypt

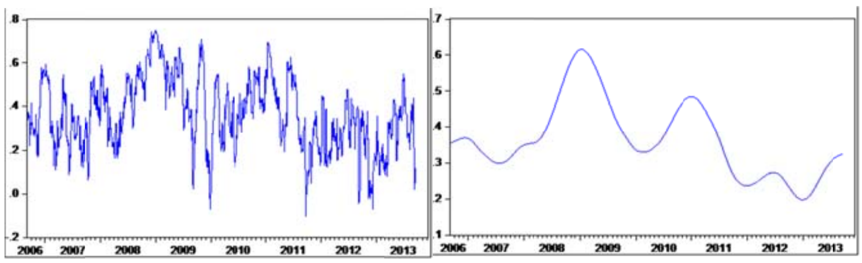


Figure 4. Dynamic conditional correlation between returns of Islamic and conventional banking indices of Kuwait

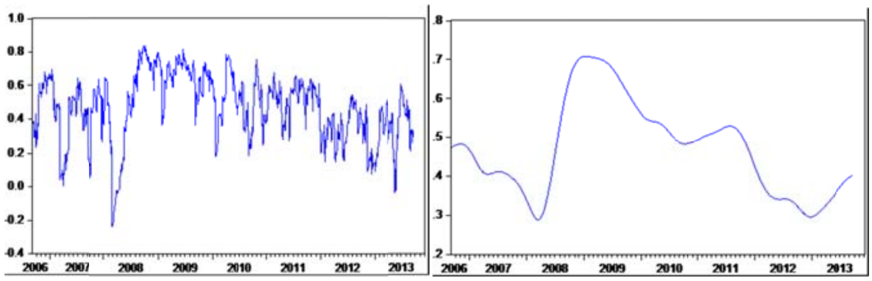


Figure 5. Dynamic conditional correlation between returns of Islamic and conventional banking indices of Qatar

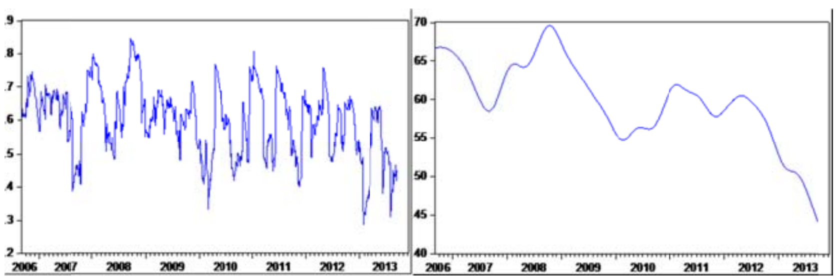


Figure 6. Dynamic conditional correlation between returns of Islamic and conventional banking indices of Saudi Arabia

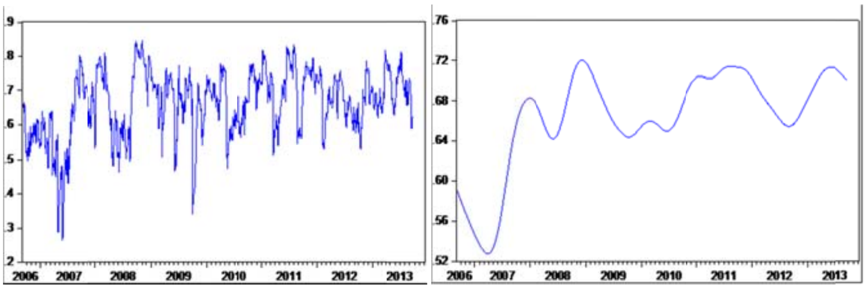


Figure 7. Dynamic conditional correlation between returns of Islamic and conventional banking indices of Turkey

We proceed then to examine cross-country contagion risk and assess the impact of the shock across these two banking industries as well as on the other banking industries of the countries studied. In order to confirm the relationship between Islamic banks and conventional banks across the different banking markets of the countries studied, we estimate a multi-step VAR model. First, it was deemed necessary to estimate our VAR and check for its stationarity. Next, we proceeded with causality tests and then with estimating impulse response functions.

Step 1: Estimation of VAR's stationarity

We should make sure that the two processes that are incorporated in our VAR model are stationary and we should decide on an optimal number of lag.

Table 5. Optimal number of lags

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-23070.04	NA	0.000145	25.21250	25.24863*	25.22582
1	-22653.03	828.0976	0.000107*	24.91429*	25.38396	25.08751*
2	-22515.95	270.4229	0.000108	24.92184	25.82506	25.25497
3	-22417.05	193.7995	0.000114	24.97111	26.30787	25.46413
4	-22295.93	235.7616	0.000116	24.99610	26.76640	25.64902
5	-22191.56	201.7734	0.000122	25.03939	27.24324	25.85222
6	-22082.31	209.7942	0.000126	25.07735	27.71473	26.05007
7	-21987.84	180.1773	0.000133	25.13144	28.20237	26.26407
8	-21872.73	218.0234*	0.000138	25.16300	28.66747	26.45552

* indicates lag order selected by the criterion

The unit root test shows that the series are stationary. We determined the order of the VAR model by minimizing the Akaike and Schwartz Information Criteria. As for daily data (only on the first working day of the week), we will estimate models up to an order of 1.

We retain a model with $p^* = 1$, which minimizes Akaike and Schwarz Information Criteria. We now proceed to estimating the VAR model.

Step 2: Estimation of the VAR model

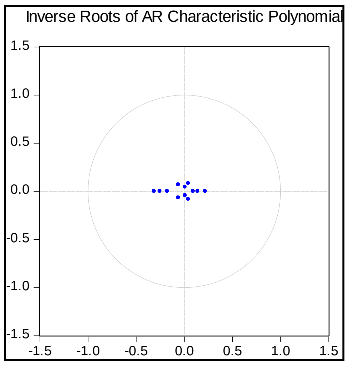
According to Table 5, we obtained an order 1 VAR. However, we notice that the coefficients associated with the lagged terms are significant at $\alpha = 5\%$, which may suggest a causal relationship between Islamic banks and conventional banks across the different studied countries.

Step 3: VAR stability

Now, we can check the stability of the VAR using the reverse roots associated with the AR of each variable. AR-associated reverse roots belong to the complex unit disc. VAR is therefore stationary. Similarly, we notice that all module roots are below 1, hence our VAR is stationary.

Table 6. Checking VAR's stability

Root	Modulus
-0.313453	0.313453
-0.251612	0.251612
0.219271	0.219271
-0.176720	0.176720
0.141236	0.141236
0.042660 - 0.082554i	0.092925
0.042660 + 0.082554i	0.092925
0.091907	0.091907
-0.060577 - 0.068210i	0.091226
-0.060577 + 0.068210i	0.091226
0.009856 - 0.043752i	0.044849
0.009856 + 0.043752i	0.044849



No root lies outside the unit circle.

VAR satisfies the stability condition

Step 4: Causality Analysis

The causality analysis will allow us to determine the statistically significant interaction of the variables in the model. This analysis is a necessary prerequisite to study the dynamics of the model. Causality tests, being bivariate, are two types that should be Granger tested. We therefore proceed to a Granger causality test using the previously-estimated VAR (1). Recall that Granger considers that a variable causes another if predictability of the former is improved when information on the latter is incorporated into the analysis. We obtained the following results.

Table 7. Causality Analysis (VAR Granger Causality)

rob	**IBC**	**IBI**	**IEC**	**IEI**	**IKC**	**IKI**	**IQC**	**IQI**	**ISC**	**ISI**	**ITC**	**ITI**
IBI	0.0526	0.5014	0.9017	0.5634	0.0523	0.9358	0.7820	0.6071	0.6948	0.1257	0.8446	0.4666
IEC	0.7002	0.8310	0.7705	0.8798	0.5603	0.7461	0.3243	0.3621	0.5743	0.1802	0.7074	0.9920
IEI	0.1225	0.7029	**0.0186**	0.1024	0.0736	0.0782	0.1898	0.5519	0.9997	0.5107	0.5083	0.0838
IKC	0.1409	0.9997	**0.0145**	**0.0252**	0.9984	0.7423	0.2561	0.2688	0.9238	0.5277	0.4538	0.9462
IKI	**0.0260**	**0.0000**	0.7443	0.3397	**0.0000**	**0.0001**	0.6539	0.8097	0.6557	0.4153	0.5901	0.1286
IQC	0.8335	0.1567	**0.0182**	0.1600	0.1103	0.0589	**0.0000**	**0.0002**	0.4619	0.5286	0.8267	0.4295
IQI	0.8510	0.2895	0.2349	0.8132	0.5620	0.0591	0.9038	**0.0000**	0.1208	0.6819	0.0992	0.5479
ISC	**0.0017**	0.4603	**0.0192**	**0.0027**	0.0635	0.0645	**0.0000**	**0.0382**	**0.0005**	**0.0226**	**0.0106**	**0.0094**
ISI	0.3038	0.3677	0.3289	0.5442	0.7397	0.2962	**0.0452**	**0.0013**	0.1892	**0.0238**	0.1370	0.3362
ITC	0.5569	0.9341	0.0670	0.1856	0.2885	**0.0084**	0.3802	0.3105	0.1359	0.9301	0.2919	0.5135
ITI	0.3931	0.2609	0.2974	0.1365	0.2869	0.0551	0.8717	0.9186	**0.0226**	**0.0319**	0.0937	0.4483
All	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0001**	**0.0030**	**0.0221**	0.0688

Hypothesis testing:

Y_{2t} does not cause Y_{1t}, if the following hypothesis is accepted H0 : $b_{11} = b_{12} = \ldots = b_{1P}$

Y_{1t} does not cause Y_{2t}, if the following hypothesis is accepted H0 : $a_{12} = a_{22} = \ldots = a_{2P}$

Decision rule at α = 5%:

If p > 5%, then H0 is accepted.

The Granger causality analysis of returns of conventional and Islamic banks operating in the different countries studied indicates that causality is bidirectional across the different banking markets, whether Islamic or conventional. Accordingly, the null hypothesis of no causality between Islamic banks and conventional banks is rejected and the opposite is true as well. Under GRANGER and with a threshold of 1 to 5% and during the studied period, reverse causality is statistically accepted. This allows us to conclude that Islamic banks are not isolated from conventional banks and there is contagion across these two industries since one depends on the other.

Table 8. Causality Analysis between returns of Islamic and conventional banking global indices (VAR Granger Causality)

Dependent variable: BC			
Excluded	Chi-sq	df	Prob.
BI	19.84821	4	0.0005
All	19.84821	4	0.0005
Dependent variable: BI			
Excluded	Chi-sq	df	Prob.
BC	70.77766	4	0.0000
All	70.77766	4	0.0000

In conclusion, we confirm the presence of a bilateral relationship between returns of Islamic and conventional banks. Determining causality direction allowed us to prove the existence of a contagion risk across the two banking systems. The presence of this phenomenon may be explained by the fact that Islamic banks are forced to adjust their profit rate based on the interest level applied by conventional banks to gain a competitive advantage. During a period of financial distress, such behavior can affect negatively Islamic banks. Furthermore, investors' behavior changes after a change in the dynamics volatility of Islamic and conventional banking index. These results are consistent with the results of Fakhfeh and Hchicha (2014). The authors found that the dynamics volatility of Islamic banks of the GCC countries is explained by contagion. This phenomenon is detected by increasing conditional correlation using a DCC MGARCH model.

Step 5: Impulse response functions

Following Granger causality tests, we highlighted two relationships. The first, return series of Islamic banks influence those of conventional banks. The second, return series of conventional banks influence those of Islamic banks. Hence, the fact of finding bidirectional Granger causality is very interesting in terms of banking risk analysis and forecasting. Bearing on the previous results, we are required to analyze shock effects on average returns of the two types of banking industry to see whether there is an effect between the two. The aim is to detect the magnitude of a shock in a banking system that strikes conventional or Islamic banks, its spread and its repercussions. We examined the shock effect over 10 periods.

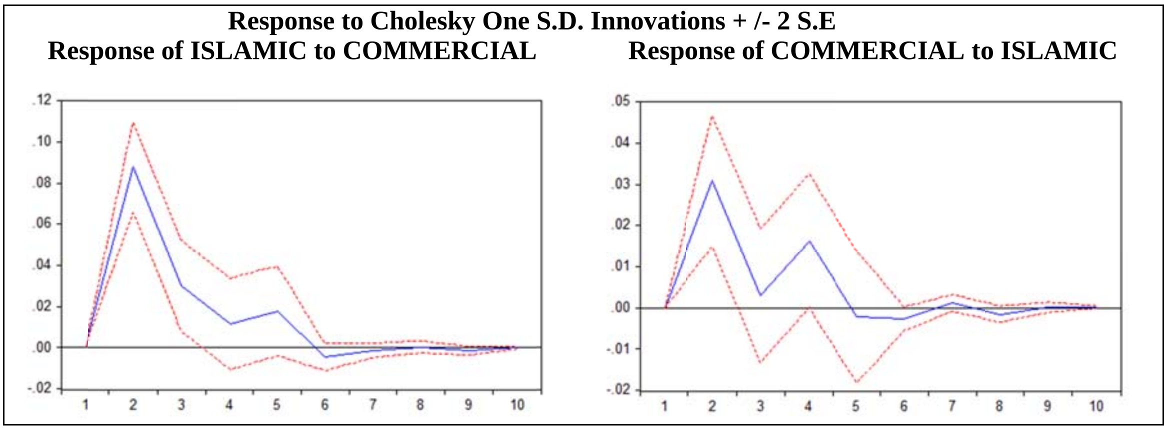


Figure 8. Impulse response functions: index returns for the entire sample

The chart below indicates that a shock in a conventional bank system causes significant repercussions, which result in increased volatility of returns. Returns of Islamic banks increased very significantly to disappear in the (6th) period. However, when Islamic banking is affected by a shock, we notice less important repercussions in terms of volatility of returns. The graph shows that the returns of conventional banks fluctuate less than those of Islamic banks. This trend vanishes after the (5th) period. We may conclude that during a shock, striking conventional or Islamic banks, its effect is not limited and spreads with different consequences on volatility. Returns of Islamic banks are more sensitive to shocks than those of conventional banks. These results are consistent with those reported using a univariate GJR-GARCH.

To better understand and deepen our knowledge of Islamic banking and its role in financial stability, systemic risk and contagion needs to be considered. In order to make Islamic banks systemically visible, their rapid increase in terms of size and interaction with conventional banks need to be examined. Similarly, the absence of Islamic hedging instruments may cause global instability that may have negative effects on the international banking system.

6. Conclusion

Regarding two types of banking industries which are Islamic and conventional banking, and with take into account different activities and different foundations, a special focus should be given to this field in order to analyze the effect of the two banking systems on financial stability and the relationship between them in case of distress. Thus, We obtained the following main results:

First, we estimated the univariate GJR-GARCH model on Islamic and conventional banking index in the presence of an asymmetry effect, we found that the returns of Islamic banks are more volatile than those of conventional banks, whether the shock is positive or negative. Similarly, for the (β) coefficient, which represents the return speed to minimum volatility, the results show that this coefficient is higher for conventional banks than for Islamic banks. Therefore, we may conclude that the returns of conventional banks are less volatile than those of Islamic banks and those conventional banks are more resilient to shocks than Islamic banks.

Second, we used the GJR-DCC model and the VAR model to examine contagion risk on a domestic and cross-country scale and analyze the effect of a shock to each banking system and its repercussions on the other in the different countries studied. The results pointed to the presence of contagion risk across both systems. We notice that during the crisis, correlation between the returns of Islamic banks and those of conventional banks increased significantly in all countries studied and providing evidence of contagion across these two banking systems during the crisis period. Similarly, the analyses cross-country contagion risk and the results of the VAR Granger causality test argue that there is a bilateral relationship between both systems in different banking markets.

In conclusion, during the crisis period, Islamic banking was not able to absorb its effects and ensure stability because it was also affected by the crisis.

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Appendix

Table 9. Estimation of Model VAR

	IBC	IBI	IEC	IEI	IKC	IKI	IQC	IQI	ISC	ISI	ITC	ITI
IBC(-1)	-0.010975	0.043650	-0.004257	0.024173	-0.050421	0.002772	-0.008456	0.024642	0.012269	-0.057457	-0.007882	0.031725
	(0.02359)	(0.06493)	(0.03445)	(0.04184)	(0.02598)	(0.03439)	(0.03056)	(0.04792)	(0.03127)	(0.03752)	(0.04022)	(0.04358)
	[-0.46522]	[0.67228]	[-0.12356]	[0.57774]	[-1.94076]	[0.08061]	[-0.27670]	[0.51420]	[0.39237]	[-1.53121]	[-0.19597]	[0.72802]
IBI(-1)	0.015910	-0.316266	-0.003497	0.002201	0.005265	-0.003874	-0.010482	-0.015196	0.006112	0.017500	-0.005254	-0.000151
	(0.00821)	(0.02259)	(0.01199)	(0.01456)	(0.00904)	(0.01196)	(0.01063)	(0.01668)	(0.01088)	(0.01306)	(0.01400)	(0.01516)
	[1.93827]	[-13.9985]	[-0.29172]	[0.15116]	[0.58242]	[-0.32380]	[-0.98573]	[-0.91130]	[0.56170]	[1.34025]	[-0.37542]	[-0.00998]
IEC(-1)	0.007166	-0.010930	0.069233	-0.053913	-0.036676	-0.047782	-0.031615	-0.022495	8.00E-06	0.019472	-0.020991	0.059443
	(0.01861)	(0.05123)	(0.02718)	(0.03301)	(0.02050)	(0.02713)	(0.02411)	(0.03781)	(0.02467)	(0.02961)	(0.03173)	(0.03438)
	[0.38502]	[-0.21337]	[2.54709]	[-1.63323]	[-1.78929]	[-1.76131]	[-1.31121]	[-0.59495]	[0.00032]	[0.65773]	[-0.66150]	[1.72898]
IEI(-1)	0.023351	-0.015873	0.051959	0.129744	-3.42E-05	-0.007248	0.022246	0.033971	-0.001916	-0.015189	0.019312	0.001885
	(0.01512)	(0.04162)	(0.02208)	(0.02682)	(0.01665)	(0.02204)	(0.01959)	(0.03072)	(0.02004)	(0.02405)	(0.02578)	(0.02793)
	[1.54427]	[-0.38140]	[2.35292]	[4.83781]	[-0.00205]	[-0.32886]	[1.13565]	[1.10593]	[-0.09562]	[-0.63150]	[0.74908]	[0.06750]
IKC(-1)	0.035729	2.66E-05	0.086646	0.096340	-0.091503	0.140413	-0.014096	0.011872	0.014343	0.031448	-0.022290	-0.068126
	(0.02427)	(0.06680)	(0.03544)	(0.04304)	(0.02673)	(0.03537)	(0.03144)	(0.04930)	(0.03217)	(0.03860)	(0.04138)	(0.04483)
	[1.47228]	[0.00040]	[2.44472]	[2.23824]	[-3.42361]	[3.96939]	[-0.44836]	[0.24080]	[0.44586]	[0.81467]	[-0.53872]	[-1.51969]
IKI(-1)	0.041182	0.212777	0.008812	-0.031329	0.082976	0.019216	0.108781	0.140225	-0.018041	-0.018544	0.006905	0.027002
	(0.01850)	(0.05092)	(0.02702)	(0.03281)	(0.02037)	(0.02697)	(0.02397)	(0.03758)	(0.02452)	(0.02943)	(0.03154)	(0.03417)
	[2.22606]	[4.17871]	[0.32614]	[-0.95478]	[4.07253]	[0.71260]	[4.53882]	[3.73113]	[-0.73569]	[-0.63016]	[0.21892]	[0.79012]
IQC(-1)	-0.004633	0.085931	-0.076039	-0.054937	0.038764	0.060698	-0.020500	0.200667	-0.045334	-0.014372	-0.061961	-0.024468
	(0.02204)	(0.06067)	(0.03219)	(0.03910)	(0.02428)	(0.03213)	(0.02856)	(0.04478)	(0.02922)	(0.03506)	(0.03758)	(0.04072)
	[-0.21016]	[1.41633]	[-2.36198]	[-1.40514]	[1.59673]	[1.88908]	[-0.71785]	[4.48112]	[-1.55152]	[-0.40989]	[-1.64860]	[-0.60089]
IQI(-1)	0.002535	0.039335	0.023407	-0.005655	-0.008615	0.037118	0.002113	-0.240945	0.062038	0.048944	0.058760	0.064727
	(0.01349)	(0.03713)	(0.01970)	(0.02393)	(0.01486)	(0.01967)	(0.01748)	(0.02741)	(0.01788)	(0.02146)	(0.02300)	(0.02492)
	[0.18791]	[1.05927]	[1.18794]	[-0.23631]	[-0.57981]	[1.88740]	[0.12087]	[-8.79100]	[3.46897]	[2.28058]	[2.55444]	[2.59712]
ISC(-1)	0.080901	0.052280	0.087974	0.136998	0.052579	0.069320	0.189401	0.108303	0.125225	0.092531	0.065230	0.045704
	(0.02573)	(0.07081)	(0.03757)	(0.04563)	(0.02833)	(0.03750)	(0.03333)	(0.05226)	(0.03410)	(0.04092)	(0.04386)	(0.04752)
	[3.14457]	[0.73831]	[2.34143]	[3.00233]	[1.85569]	[1.84850]	[5.68266]	[2.07222]	[3.67206]	[2.26108]	[1.48709]	[0.96169]
ISI(-1)	-0.022070	0.053204	0.030598	0.023086	-0.007853	0.032678	0.055682	0.140113	-0.037350	-0.009792	0.038563	-0.025901
	(0.02146)	(0.05907)	(0.03134)	(0.03806)	(0.02364)	(0.03128)	(0.02780)	(0.04360)	(0.02845)	(0.03414)	(0.03659)	(0.03964)
	[-1.02836]	[0.90071]	[0.97624]	[0.60650]	[-0.33224]	[1.04461]	[2.00273]	[3.21377]	[-1.31297]	[-0.28683]	[1.05391]	[-0.65335]
ITC(-1)	-0.011401	-0.004414	0.051921	0.045573	0.022688	0.074570	0.022066	0.039991	0.038367	0.002706	-0.008259	0.027185
	(0.01941)	(0.05342)	(0.02835)	(0.03442)	(0.02138)	(0.02829)	(0.02514)	(0.03943)	(0.02573)	(0.03087)	(0.03309)	(0.03585)
	[-0.58741]	[-0.08263]	[1.83169]	[1.32384]	[1.06138]	[2.63579]	[0.87759]	[1.01425]	[1.49128]	[0.08766]	[-0.24956]	[0.75824]
ITI(-1)	0.015004	0.054371	0.026740	0.046402	0.020608	-0.049130	-0.003675	0.003648	0.053094	0.059951	0.050208	0.049326
	(0.01757)	(0.04836)	(0.02566)	(0.03116)	(0.01935)	(0.02561)	(0.02276)	(0.03569)	(0.02329)	(0.02795)	(0.02996)	(0.03246)
	[0.85399]	[1.12432]	[1.04212]	[1.48903]	[1.06500]	[-1.91838]	[-0.16146]	[0.10221]	[2.27975]	[2.14511]	[1.67604]	[1.51981]
C	-0.004494	-0.051641	-0.000534	0.001123	-0.003670	0.004113	0.003980	-0.004641	-0.012406	-0.008285	0.009302	0.010445
	(0.01141)	(0.03141)	(0.01667)	(0.02024)	(0.01257)	(0.01663)	(0.01478)	(0.02318)	(0.01513)	(0.01815)	(0.01946)	(0.02108)
	[-0.39383]	[-1.64406]	[-0.03203]	[0.05548]	[-0.29202]	[0.24726]	[0.26921]	[-0.20017]	[-0.82014]	[-0.45639]	[0.47805]	[0.49545]
R-squared	0.024409	0.106460	0.048287	0.043411	0.024694	0.045336	0.076741	0.081179	0.034103	0.019439	0.013902	0.016230
Adj. R-squared	0.017995	0.100585	0.042029	0.037121	0.018281	0.039058	0.070670	0.075137	0.027752	0.012991	0.007418	0.009762