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Abstract

This paper examines financial spillovers between the four largest equity markets, by market capitalization, in the GCC region using a VAR-GARCH (1,1) framework that sheds light on interdependence as well as contagion following the 2014 oil crisis. The UAE being a federation including two stock exchanges (Abu Dhabi and Dubai), it is possible to test whether being part of a federal union matters more than market size in terms of financial integration. Our results suggest that the latter is more important, since we find no evidence of linkages between the Abu Dhabi and Dubai markets. By contrast, there are significant spillover effects, both in the mean and in the volatility, from the larger markets of Saudi Arabia and Qatar to the two smaller ones of the UAE, which confirms that market capitalization is a more important determinant of financial integration than belonging to a federal union. Further, contagion appears to have occurred, i.e. spillovers from the larger markets have become stronger as a result of the 2014 oil crisis. Finally, there is also evidence of spillovers from the smaller to the larger markets.

Keywords: Stock Markets, GCC, Volatility transmission.

JEL Classification: C32, F36, G15.

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1 Introduction

In recent decades the October 1987 stock market crash in the US, the 1992 European Exchange Rate mechanism (ERM) crisis, the 1997 East Asia crisis and the 2008 global financial crisis have generated renewed interest among academics, policy makers and practitioners in understanding the transmission of shocks across financial markets, both developed and emerging. Following the seminal paper by King and Wadhwani (1990), one strand of the literature has used conditional correlation analysis to test for shifts in the linkages between financial markets during crisis periods; those are defined as contagion, whilst the term interdependence is normally used to refer to linkages that do not change over time. However, the validity of such tests is affected by key features of the data generating process such as heteroscedasticity and endogeneity, and also by the existence of common factors (King et al., 1994; Forbes and Rigobon, 2002; Corsetti et al., 2005; Caporale et al., 2005). Dungey et al. (2002, 2003) adopted a different approach and estimated dynamic latent factor models to test for contagion in bond and stock markets during crisis episodes. Bekaert et al. (2005) used an alternative factor model that allows for time-varying integration with global markets, and identified contagion as "excess correlation", that is, cross-country correlations between the model residuals during crisis periods.

Several episodes of turbulence in developed financial markets in the first decade of this century are the motivation for recent studies analysing spillover effects from those markets to the emerging ones; in particular, Beirne et al. (2013) test for changes in the transmission mechanism (contagion) during turbulent periods in mature markets, and provide evidence of shifts in the volatility spillovers from mature to emerging markets at such times; further, they find that the conditional variance increases in most emerging markets during these episodes, but there is only limited evidence of shifts in the conditional correlations between mature and emerging markets.

This paper focuses on the linkages between the four largest stock markets in the Gulf Cooperation Council (GCC) region, namely Abu Dhabi, Dubai, Saudi Arabia and Qatar. Specifically, it estimates a VAR-GARCH (1,1) model allowing for spillovers in both the first and the second moments (i.e. mean and variance) at the daily frequency. The adopted framework is suitable to test for both interdependence (the existence of spillover effects) and contagion (shifts in the corresponding parameters as a result of a crisis, in this case the 2014 oil crisis) between all four stock markets. Unlike the present one, most previous studies had only considered unidirectional spillovers from the larger (Saudi Arabia) to the smaller stock markets in the region (Suliman, 2011), overlooking the possibility of spillovers in the opposite direction. Two notable exceptions are Khalifa et al. (2011) and Al-Maadid et al. (2018). The former, using a Multi-Chain Markov Switching (MCMS) model, examine volatility transmission between six GCC stock markets and three global markets (S&P 500 index, Oil-WTI prices and MSCI- world); the latter investigate the effects of the recent political tension in the Arabian peninsula on the linkages between the stock markets of the leading GCC countries.

It is noteworthy that Dubai and Abu Dhabi are both part of the United Arab Emirates (UAE). This is therefore a rather unique case of a country, namely the UAE, including more than one stock exchange, the only well-known precedent being that of the regional US exchanges in the 1960s. Given the limited size of the UEA, the existence of more than a single stock exchange is likely to affect the liquidity and trading volumes of those markets; the presence of separate regulatory authorities (the Securities and Commodities Authority for Abu Dhabi and the Financial Services Authority for Dubai) is another important factor to take into account. The two markets have in fact pursued different strategies, with Abu Dhabi focusing on internal growth and Dubai aiming to mirror developments in the main international financial markets. The possibly negative consequences of market fragmentation in the UAE and the potentially beneficial network effects of consolidation have been recently debated. Differences in their governance and business models, as well as the possibility of hierarchies resulting from consolidation, are the main arguments that have been used against a merger (for further details, see Paltrinieri, 2015).

The current set-up offers an interesting opportunity to test whether the "large country effect" or being part of a federal state is a more important factor for financial integration, in this case whether or not the linkages between the stock markets of Abu Dhabi and Dubai, that belong to the same country, are stronger than those with the largest markets in the region, namely Qatar, and Saudi Arabia ; our modelling approach is particularly suitable for addressing such issues.

The layout of the paper is as follows. Section 2 outlines the econometric modelling approach. Section 3 describes the data and presents the empirical findings. Section 4 summarises the main findings and offers some concluding remarks.

2 The model

We represent the first and second moments of the GCC stock market returns using a VAR-GARCH(1,1) process. In its most general specification the model takes the following form:

$$\mathbf{x}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{x}_{t-1} + (Control_{t-1}) + \mathbf{u}_t \tag{1}$$

where $\mathbf{x}_t = (SaudiArabia_t, Dubai_t, Qatar_t, Abu - Dhabi_t)$ and $\mathbf{x}_{t-1}$ is the corresponding vector of lagged variables. The residual vector $\mathbf{u}_t = (u_{1,t}, u_{2,t}, u_{3,t}, u_{4,t})$ is four-variate and normally distributed $\mathbf{u}_t \mid I_{t-1} \sim (\mathbf{0}, H_t)$, its conditional variance covariance matrix being given by:

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} & h_{13t} & h_{14t} \\ h_{21t} & h_{22t} & h_{23t} & h_{24t} \\ h_{31t} & h_{32t} & h_{33t} & h_{34t} \\ h_{41t} & h_{42t} & h_{43t} & h_{44t} \end{bmatrix} \tag{2}$$

The parameter vector of the mean return equation (1) includes the constant $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)$, and the autoregressive term, $\boldsymbol{\beta} = (\beta_{11}, \beta_{12}, \beta_{13}, \beta_{14} \mid \beta_{21}, \beta_{22}, \beta_{23}, \beta_{24} \mid \beta_{31}, \beta_{32}, \beta_{33}, \beta_{34} \mid \beta_{41}, \beta_{42}, \beta_{43}, \beta_{44})$, which measures the cross country linkages between stock market returns. Furthermore, we control for global market and oil shocks using the VIX (as a proxy for global uncertainty) and the change in crude oil prices respectively. The parameter matrices for the variance Equation (2) are C (which is restricted to be upper triangular), and A and G. Therefore, the second moment takes the following form[1]:

[1] The parameters (a_{21}) and (a_{31}) in Equation (3) measure the volatility spillovers running from Saudi Arabia to Dubai and Qatar respectively. The possible effect of the downturn trend in oil prices on those linkages is

$$H_t = C'C + A' \begin{bmatrix} u_{1,t-1}^2 & u_{2,t-1}u_{1,t-1} & u_{3,t-1}u_{1,t-1} & u_{4,t-1}u_{1,t-1} \\ u_{1,t-1}u_{2,t-1} & u_{2,t-1}^2 & u_{3,t-1}u_{2,t-1} & u_{4,t-1}u_{2,t-1} \\ u_{1,t-1}u_{3,t-1} & u_{2,t-1}u_{3,t-1} & u_{3,t-1}^2 & u_{4,t-1}u_{3,t-1} \\ u_{1,t-1}u_{4,t-1} & u_{2,t-1}u_{4,t-1} & u_{3,t-1}u_{4,t-1} & u_{4,t-1}^2 \end{bmatrix} A + G'H_{t-1}G \quad (3)$$

where

$$A = \begin{bmatrix} a_{11} & a_{12}+a_{12}^* & a_{13}+a_{13}^* & a_{14}+a_{14}^* \\ a_{21}+a_{21}^* & a_{22} & a_{23}+a_{23}^* & a_{24}+a_{24}^* \\ a_{31}+a_{31}^* & a_{32}+a_{32}^* & a_{33} & a_{34}+a_{34}^* \\ a_{41}+a_{41}^* & a_{42}+a_{42}^* & a_{43}+a_{43}^* & a_{44} \end{bmatrix};$$

$$G = \begin{bmatrix} g_{11} & g_{12}+g_{12}^* & g_{13}+g_{13}^* & g_{14}+g_{14}^* \\ g_{21}+g_{21}^* & g_{22} & g_{23}+g_{23}^* & g_{24}+g_{24}^* \\ g_{31}+g_{31}^* & g_{32}+g_{32}^* & g_{33} & g_{34}+g_{34}^* \\ g_{41}+g_{41}^* & g_{42}+g_{42}^* & g_{43}+g_{43}^* & g_{44} \end{bmatrix}$$

Equation (3) models the dynamic process of H_t as a linear function of its own past values H_{t-1} and the past values of the squared innovations $\left(u_{1,t-1}^2, u_{2,t-1}^2, u_{3,t-1}^2, u_{4,t-1}^2\right)$. The parameters of (3) are given by C, which is restricted to be upper triangular, and the two matrices A and G. The BEKK representation guarantees by construction that the covariance matrix in the system is positive definite. In order to account for the possible effects of the recent oil price downturn, we also include a dummy variable (denoted by *) with a switch on 14 November 2014 (which is the day prices started to fall dramatically). Given a sample of T observations, a vector of unknown parameters θ and a 4×1 vector of variables $\mathbf{x}_t$, the conditional density function for model (1) is:

$$f(\mathbf{x}_t | I_{t-1}; \theta) = (2\pi)^{-1} |H_t|^{-1/2} \exp\left(-\frac{\mathbf{u}_t'\left(H_t^{-1}\right)\mathbf{u}_t}{2}\right) \quad (4)$$

The log-likelihood function is:

$$L = \sum_{t=1}^{T} \log f(\mathbf{x}_t | I_{t-1}; \theta) \quad (5)$$

where θ is the vector of unknown parameters. The standard errors are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals.

3 Empirical Analysis

We use daily data (from Bloomberg) on the stock market indexes for the largest GCC markets (by market capitalization) namely Abu Dhabi, Dubai, Qatar and Saudi Arabia; the sample period goes from 01/9/2010 to 30/4/2017, for a total of 1640 observations; daily returns are

captured by $(a_{21} + a_{21}^*)$ and $(a_{31} + a_{31}^*)$.

defined as the logarithmic differences of the four stock market indices which are shown in Figure 1.

In order to test the adequacy of the estimated models, Ljung - Box portmanteau tests were performed on the standardized and squared standardized residuals. Overall, the results indicate that the VAR-GARCH(1,1) specification is data congruent and captures satisfactorily the persistence of stock returns and of their volatility. The estimated parameters of the VAR-GARCH(1,1) model with the associated robust p-values and likelihood function values are presented in Table 1. We select the optimal lag length of the mean equation using the Schwarz information criterion. The estimated mean of daily returns is positive for all four stock markets, the highest mean return being 0.103 in the case of Dubai.

The results suggest that there are significant dynamic linkages in both the first and the second moments. In particular, we find positive and significant (bi-directional) mean spillovers at the standard 5% significance level in most cases, Abu Dhabi being the only market that does not affect the others. The largest spillovers appear to run from the Saudi to the Dubai market ($\beta_{21} = 0.157$) and from the Qatari to the Dubai one ($\beta_{23} = 0.105$) . The VIX index, which controls for global financial uncertainty, does not affect the four indices, whilst the change in crude oil prices has a significant impact, especially in the cases of Qatar and Dubai, with the spillovers becoming stronger after the beginning of the oil crisis in November 2014.

Please Insert Table1 and Figure1 about here

Causality linkages[2] in the conditional variance vary in magnitude across countries (note that the signs on cross-market volatilities cannot be determined). Specifically, it appears that there are volatility spillovers from the Qatar and Saudi Arabia stock markets to the Dubai and Abu Dhabi ones, whilst there is no evidence of such spillovers in the opposite direction. Furthermore, there is evidence that the 2014 oil crisis affected the causality-in-variance dynamics. In particular, during the crisis volatility in Abu Dhabi was affected significantly by that in Saudi Arabia ($a^*_{41} = -0.392$) , Dubai ($a^*_{42} = 0.427$) and Qatar ($a^*_{43} = -0.256$); the strongest post-2014 volatility effects are found to be running from the Saudi to the Dubai market ($a^*_{21} = 0.517$).

4 Conclusions

This paper has examined financial spillovers between the four largest equity markets, by market capitalization, in the GCC region using a VAR-GARCH (1,1) framework that sheds light on interdependence as well as contagion following the 2014 oil crisis. The GCC countries are a particularly interesting case because one of them, namely the UAE, is a federation including two stock exchanges (Abu Dhabi and Dubai); therefore it is possible to test whether being part of a federal union matters more than market size in terms of financial integration.

Our results suggest that the latter is more important , since we find no evidence of linkages between the Abu Dhabi and Dubai markets, even though both of them have only UAE companies listed. By contrast, there are significant spillover effects, both in the mean

[2]Please note that the term causality refers to Granger causality and therefore a structural interpretation is not appropriate.

and the volatility, from the larger markets of Saudi Arabia and Qatar to the two smaller ones in the UAE, which confirms that market capitalization is a more important determinant of financial integration than belonging to a federal union. Further, contagion appears to have occurred, i.e. spillovers from the larger markets have become stronger as a result of the 2014 oil crisis. Finally, there is also evidence of spillovers from the smaller to the larger markets, which indicates that other economic factors and financial market characteristics also affect the financial transmission mechanisms; future work will investigate more thoroughly such issues.

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TABLE 1: Estimated VAR-GARCH(1,1) model

Saudi Arabia		Dubai		Qatar		Abu-Dhabi	
Conditional Mean Equation							
α_1	0.061 (0.002)	α_2	0.103 (0.000)	α_3	0.069 (0.006)	α_4	0.062 (0.000)
β_{11}	0.216 (0.000)	β_{22}	0.084 (0.005)	β_{33}	0.124 (0.000)	β_{44}	-0.002 (0.942)
β_{12}	0.049 (0.033)	β_{21}	0.157 (0.000)	β_{31}	0.027 (0.044)	β_{41}	0.088 (0.000)
β_{13}	0.085 (0.000)	β_{23}	0.105 (0.031)	β_{32}	0.088 (0.000)	β_{42}	0.017 (0.125)
β_{14}	-0.027 (0.451)	β_{24}	-0.009 (0.874)	β_{34}	-0.031 (0.381)	β_{43}	0.061 (0.015)
VIX	-0.009 (0.637)	VIX	0.015 (0.563)	VIX	0.025 (0.271)	VIX	-0.007 (0.609)
Oil	0.057 (0.000)	Oil	0.231 (0.000)	Oil	0.288 (0.000)	Oil	0.063 (0.000)
Oil^*	0.088 (0.000)	Oil^*	0.216 (0.000)	Oil^*	0.295 (0.000)	Oil^*	0.075 (0.000)
Conditional Variance Equation							
c_{11}	-0.001 (0.000)	c_{22}	-0.364 (0.000)	c_{33}	0.008 (0.000)	c_{44}	0.401 (0.000)
g_{11}	-0.662 (0.000)	g_{22}	0.801 (0.000)	g_{33}	-0.811 (0.000)	g_{44}	0.776 (0.000)
g_{12}	0.149 (0.317)	g_{21}	0.218 (0.032)	g_{31}	-0.666 (0.000)	g_{41}	-0.514 (0.000)
g^*_{12}	0.496 (0.008)	g^*_{21}	0.215 (0.089)	g^*_{31}	0.193 (0.155)	g^*_{41}	0.239 (0.304)
g_{13}	0.447 (0.000)	g_{23}	-0.163 (0.121)	g_{32}	-0.476 (0.205)	g_{42}	0.276 (0.122)
g^*_{13}	-0.348 (0.000)	g^*_{23}	-0.229 (0.119)	g^*_{32}	0.072 (0.853)	g^*_{42}	-0.657 (0.000)
g_{14}	0.046 (0.428)	g_{24}	0.162 (0.000)	g_{34}	-0.206 (0.169)	g_{43}	0.404 (0.001)
g^*_{14}	0.225 (0.012)	g^*_{24}	0.053 (0.145)	g^*_{34}	0.187 (0.368)	g^*_{43}	0.227 (0.261)
a_{11}	0.311 (0.000)	a_{22}	0.217 (0.001)	a_{33}	-0.173 (0.013)	a_{44}	0.397 (0.001)
a_{12}	0.165 (0.009)	a_{21}	-0.002 (0.933)	a_{31}	0.171 (0.011)	a_{41}	-0.015 (0.757)
a^*_{12}	-0.370 (0.001)	a^*_{21}	0.517 (0.001)	a^*_{31}	0.187 (0.339)	a^*_{41}	-0.392 (0.041)
a_{13}	0.087 (0.013)	a_{23}	-0.033 (0.392)	a_{32}	0.197 (0.011)	a_{42}	0.051 (0.589)
a^*_{13}	-0.207 (0.001)	a^*_{23}	0.121 (0.193)	a^*_{32}	-0.066 (0.755)	a^*_{42}	0.427 (0.025)
a_{14}	0.144 (0.008)	a_{24}	0.063 (0.037)	a_{34}	0.257 (0.000)	a_{43}	0.034 (0.561)
a^*_{14}	-0.189 (0.123)	a^*_{24}	-0.111 (0.241)	a^*_{34}	0.211 (0.153)	a^*_{43}	-0.256 (0.026)
Lik.	-5436.91						
LB	8.73		5.14		7.01		9.19
LB^2	9.44		6.99		8.93		7.44

Note: P-values, reported in round brackets, are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals. LB and LB^2 are the Ljung-Box test (1978) of significance of autocorrelations of ten lags in the standardized and standardized squared residuals respectively. The parameters β_{12}, β_{13} and β_{14} measure the Granger causality effect of Dubai, Qatar and Abu Dhabi stock markets on Saudi Arabia; whereas a_{21}, a_{31} and a_{41} measure the causality in variance effect. The covariance stationarity condition is satisfied by all the estimated models, all the eigenvalues of $A \otimes A + G \otimes G$ being less than one in modulus.

Figure 1: Stock Market Returns