Dependence patterns across Gulf Arab stock markets: a copula approach

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Dependence Patterns across Gulf Arab Stock Markets: A Copula Approach

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Abstract

Underpinned by rising hydrocarbon revenues, the stock markets of the six GCC (Gulf Cooperation Council) countries have demonstrated significant integration over the past decade. This paper studies the dependence patterns of the bivariate distribution of returns across seven GCC stock markets over the period 2004-2013 using copula models. The results of the marginal models indicate strong volatility persistence in all the seven equity markets. The results from the copula models indicate that the conditional dependence across all 21 pairs of equity markets' returns is not strictly symmetric in that the lower tail dependence is significantly greater that the upper tail dependence. The stock markets of Abu Dhabi and Dubai appear as the primary source of asymmetric dependence across the different equity market pairs.

Keywords: Copula, tail dependence, GCC stock markets.

JEL Classifications: G15

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1. Introduction

Underpinned by soaring hydrocarbon export revenues, the six Gulf Cooperation Council (GCC) countries[4] have experienced a rapid transformation of their economies since the start of this millennium. In a span of one decade (2001–2010), the combined real GDP of the GCC countries rose from a little over $500 billion to nearly $900 billion, making it the fastest growing region in the world. The GCC financial sector also expanded in tandem with a buoyant economy. For example, over the same period the market capitalization of listed companies in the GCC region increased from over $100 billion to over $700 billion (in nominal terms). In addition—thanks to persistently rising oil prices during much of the last decade—the GCC countries now manage some of the largest sovereign wealth funds in the world.

As the GCC economies are predominantly hydrocarbon based and hence are not well diversified, the financial sector plays a key role in the economic activity in the non-hydrocarbon sector. Together with the real estate sector, the financial sector offers the opportunity to retails investors in GCC countries to make use of their savings into investable assets such as equities. But, as investment in the real estate sector is generally more lumpier than other economic sectors, in the context of the GCC region, the financial sector provides the primary medium to channel surplus funds into short- and medium-term investments. Rapid increase in per capita income, lack of availability of investment opportunities in fixed income securities (barring bank deposits), and the lifting of the barriers of cross-border investment among the GCC-based investors (but not necessarily for foreign investors) have made the national stock markets as the most attractive area of business of financial assets (both trading and investment) within GCC's non-hydrocarbon economy.

Although information on the extent of the volume of capital flows within the GCC financial market is limited, the intra-regional demand for GCC securities by

[4] The six countries of the GCC are Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE).

Bahrain and Kuwait (the only countries for which data is published by the CPIS[5]) shows an increasing trend. For example, between 2001 and 2010, the share of GCC equities in Bahrain's total portfolio investment rose from 10% to 21%, while for Kuwait the share rose from 26% to 48%.[6] The relatively high share of investment coming from other GCC countries in Kuwait is consistent with the phenomenon of portfolio "GCC bias" documented by Balli et al. (2009). Increased financial and economic integration as well as the changes in the geo-political and geo-economic environments in the aftermath of the 9/11 attacks are the likely reasons for the higher intra-regional private capital flows among the GCC countries.

Given the paramount importance of the stock markets in the GCC region, this paper aims to investigate the dependence patterns of equity returns among the seven stock markets of the GCC countries. There are at least three reasons why this subject deserves a closer study. First, from investors' perspective understating the nature of dependence is critical in building a diversified portfolio. If, say, stock markets of Bahrain and Saudi Arabia closely follow each other, there will be little or no risk-reducing opportunities for portfolio diversification. Second, from an academic point of view, this paper uses a new approach to analyze a widely discussed subject in the related literature: the *degree* and the *structure* of financial market integration among the GCC countries. Hence, our analysis complements existing studies while providing new insight on the co-movements of equity returns in the GCC stock markets. Third, from policymakers' perspective, the knowledge of the nature of equity market dependence can serve as the basis for designing a more healthier financial system.

Concretely, we apply the copula models to analyze the tail dependence structure across 21 pairs of equity returns comprising seven GCC stock markets over the period 2004–2013. Accounting for tail dependence is critical as the effects of extreme events such as market crashes or financial crises on returns are usually observed in the tails of the distribution of equity returns, which standard measures of dependence such as

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[5] Coordinated Portfolio Investment Survey (CPIS) published by the International Monetary Fund.
[6] See Nechi (2010) for a discussion on the extent of the volume of trade and financial flows among GCC countries.

linear correlation coefficients are not able to locate. For example, it has been widely observed that market crashes often occur in different countries at about the same time period despite the correlation among those markets is fairly low (Sun et al., 2009). The recent global financial crisis has vividly demonstrated this phenomenon – see McKinsey Global Institute (2009) for an illustration. By connecting the marginal distributions of asset returns to restore joint distributions, copula functions not only measure the degree of dependence but also discover the structure of dependence (Hu, 2006). Figuring out what is correlated with what is informative but not decisive, and a portfolio based on mere correlations is inevitably fragile. That is why the structure of dependence provides more insight about the extent of diversification benefit than pairs of assets/markets chosen using correlation coefficients.

A number of studies apply the copula method to investigate dependence patterns across financial markets, but primarily using data from advanced countries. Longin and Solnik (2001), Ang and Chen (2002), Hu (2006) and Hong et al. (2007) find asymmetrical tail dependence implying that the markets are more likely to crash together than to boom together, or vice versa. Jondeau et al. (2007), Chollete et al. (2009) and Giacomini et al. (2009) document more extreme dependence in downturns/crashes. Recently, Yang and Hamori (2013) uncover left tail dependence between developed and emerging stock markets, but comparably higher correlations in the post-2007 financial crisis period due to the contagion effect. Outside the equity markets, Patton (2006) finds that the mark-dollar and yen-dollar exchange rates are more correlated when they are depreciating against the dollar than when they are appreciating. Whereas Ning (2010) finds symmetric upper and lower dependence between equity and foreign exchange markets. Further discussion on the co-movements between markets, particularly the GCC financial markets, is provided in Section 2.

However, to date, there has been no study analyzing the co-movements among GCC stock markets using copula methods. This paper attempts to fill the gap by using copula approach to investigate the dependence structure of GCC stock markets. Using AR(k)-t-GARCH(p,q) framework to model the marginal distribution of returns for each

GCC equity index, we specify the joint copula models for the 21 pairs of daily log-returns comprising seven equity markets in Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, Abu Dhabi and Dubai, over the 2004–2013 period.

The rest of the paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 discusses the econometric methodologies employed throughout the paper. Section 4 presents data and some preliminary findings. Section 5 presents the main findings of the analysis. Section 6 concludes the paper.

2. A brief literature review on GCC financial market integration

This section reviews selected published studies on the extent of market integration or return comovements between GCC equity markets. As our primary focus is to gain an understanding of the degree and structure of dependence among the GCC equity markets, we have refrained from reviewing contributions that examine whether GCC equity markets are efficient, the sensitivity of equity prices to oil prices, and the spillover of shocks from world markets into GCC markets, among others topic of investigations. Most existing studies use cointegration or vector autoregression (VAR) techniques to examine market integration, while few studies rely on regime switching models to assess the changing nature of market integration.

Based on weekly returns from pre-2000 period, a time when most GCC equity markets were in the early stages of development, Assaf (2003) found substantial evidence of interdependence and feedback effects among GCC stock markets. Further evidence based on VAR and Granger causality tests shows that the Bahraini market plays a dominant role in influencing the GCC markets, and none of the markets are completely efficient in processing regional news into an investment plan.[7] The influence of Bahrain has diminished gradually as other regional markets begun to position

[7] A decade ago, Bahrain was a more developed financial market both in terms of size and diversity compared to her regional peers. For example, in 2000, 41 companies were listed in the Bahraini equity market, a figure that was reached in Qatar in 2012. Moreover, Bahrain hosted nearly 200 financial institutions (including 18 fully Islamic banks) and more than 100 insurance companies. See Assaf (2003) for further details.

themselves. Alkulaib et al. (2009) found that the UAE stock market leads all the markets in the GCC and MENA region, which is a consequence of UAE's series of bold moves in promoting itself as the biggest financial hub in the Middle East. Alkulaib et al. also find that compared to the MENA region, the GCC markets are financially more integrated. Similarly, Simpson (2008) found that the UAE market has the strongest influence over equity prices in Saudi Arabia, perhaps reflecting the strength of latter's investment in the former.

In related work, Al-Deehani and Moosa (2006) interpret the strong volatility spillover from Kuwait to Bahrain and Saudi Arabia as an indication of increased market integration between stock markets of these countries. Al-Khazali et al. (2006) find the existence of a common stochastic trend that links together the equity markets of Bahrain, Kuwait, Oman and Saudi Arabia. Their finding of a long-run equilibrium relation implies little or no diversification benefits over the long horizon, although short-term gains remain a possibility. Bley and Chen (2006) find that despite return heterogeneity, GCC markets display increasing integration over the 2000–2004 period. Arouri and Nguyen (2010) observe significant but small comovements of returns between GCC equity markets, suggesting some room for diversification benefits. On the basis of a quick disappearance of arbitrage opportunity in the GCC, Espinoza et al. (2011) concluded that GCC equity markets are more integrated than many emerging economies' stock markets.

The focus on the diversification benefits of market integration between GCC markets has been the central theme of the empirical literature. Applying the autoregressive distributed lag approach to cointegration, Marashdeh and Shrestha (2010) find that GCC stock markets are not fully integrated and hence offer arbitrage opportunities between some markets in the region. The empirical evidence in Ravichandran and Maloain (2010) reveal that the short- and long-run relationships among GCC markets strengthen (both regional and globally) after a crisis than before it. Demirer (2013) uses two measures of diversification (i.e., correlation index and return dispersion) and finds a strong link between market volatility and the cross-sectional distribution of returns in most GCC markets, implying limited opportunity for portfolio diversification benefit using domestic stocks only. Balli et al. (2013) show that portfolios diversified across GCC-wide sectors perform better than portfolios diversified across GCC national equity markets. In particular, portfolios diversified with a mix of GCC-wide sector and national equities produce higher returns than portfolios made up of pure GCC national equity indices or GCC-wide sector indices.

Employing a three-state Markov-switching model, Balcilar et al. (2013a) showed that, whereas developed markets transit from low to high to crash; in the GCC markets crash regime is the intermediate regime between the low and high volatility regimes, implying that GCC markets can potentially crash without any prior signaling. Their results suggest no effective portfolio diversification during periods of market stress, although increased multi-market volatility opens up profitable investment opportunities through options contracts.

Though distinguished, existing literature did not address the issue of dependence patterns between GCC equity markets, which is the main focus of the present analysis. However, recently Naifar and Al Dohaiman (2013) studied the dependence patterns between oil price changes and macroeconomic variables (stock market return, short-term interest rate and inflation rate) in the GCC using three Archimedean copulas (Gumbel, Clayton, and Frank). Their results indicate that the dependence patterns between these series vary both across countries and across time (i.e., before and after the recent global financial crisis). Boubaker and Sghaier (2013) use similar copula functions to model the dependence patterns between daily oil price changes and stock market returns in six GCC countries. They find that oil price changes and stock returns exhibit left tail dependence in all countries except Oman, where the relationship provides right tail dependence. They also find that the tail dependence coefficients are high in financial stress period than normal period implying the presence of contagion effect.

In this paper, we take a more definitive approach by investigating the *bilateral* dependence patterns for all 21 pairs of equity markets in the GCC using copula functions. We consider three types of dependence structure: (i) the *Gaussian copula* allows for equal degrees of positive and negative dependence but does not allow for tail dependence, (ii) the *Student t*-copula allows for symmetric tail dependence and (iii) the *symmetrized Joe-Clayton* (SJC) copula allows for asymmetric dependence in the tails. As discussed above, the copula approach presents several advantages in analyzing financial markets comovements and provides a crucial perspective on the ability to deal with risk in intra-regional cross-market portfolio diversification. To our knowledge, no academic work uses copula to model the comovement at the bilateral stock market returns of GCC countries.

3. Methodology

The most basic way to capture dependence among two random variables (X and Y) is by the Pearson's linear coefficient or the non-parametric measures of Kendall's tau and Spearman's rho statistics. However, these standard measures do not provide any information about the dependence structure (i.e., tail dependence) between the variables. Given that financial time series generally exhibit fat-tails behavior, we need to use a proper method that is capable of identifying not just the linear association between variables, but also the tail dependence of the bivariate return distribution between two securities. In this regard, the copula (or "link" in Latin) is a more informative measure of dependence. The main idea of a copula function, which is due to Sklar (1959),[8] is that "any n-dimensional joint distribution function may be decomposed into its n marginal distributions, and a *copula*, which completely describes the dependence between the n variables" (Patton, 2006, p. 528). Hence, by exploiting the Sklar's theorem, one can study the dependence structure by first specifying models for the marginal distributions of a multivariate distribution of interest (here stock returns), and then specifying a copula (Patton, 2006). Succinctly put, "copulas are functions that

[8] The original article was written in French by Sklar in 1959, and an English version was published in 1973 by Sklar (cf. Sklar, 1973). This information is originally cited in Trivedi and Zimmer (2005).

connect multivariate distributions to their one-dimensional margins" (Trivedi and Zimmer, 2005, p. 3).

The rest of the section presents an overview of the various copula models used to investigate the dependence patterns among 21 pairs of stock returns representing seven stock markets/indices from the GCC region. We first discuss the marginal models for each stock index/market, followed by an overview of the joint copula. The use of notation is kept to a minimum as excellent discussion of copulas can be found, among others, in Trivedi and Zimmer (2005). The discussion presented below has been benefitted from Ning (2010).

3.1 Marginal (GARCH) models

Prior studies have documented that daily asset returns exhibit some common characteristics such as fat-tails, long memory, and conditional heteroscedasticity. Thus, we consider the autoregressive (AR) and the generalized autoregressive conditional heteroscedasticity (GARCH) model with the student *t* distribution as our marginal model to capture all the characteristics for each stock index return. The AR(*k*)-*t*-GARCH(*p*,*q*) model has found to provide a reasonable fit in capturing most common stylized facts of asset returns (Bollerslev, 1987). The specification of the AR(*k*)-*t*-GARCH(*p*,*q*) model is given as follows:

$$R_{i,t} = \mu_i + \sum_{i=1}^{k} \delta_{i,k}\, r_{i,t-k} + \varepsilon_{i,t} \qquad (1)$$

$$\sigma_{i,t}^2 = \omega_i + \sum_{i=1}^{p} \alpha_{i,p}\, \varepsilon_{i,t-p}^2 + \sum_{i=1}^{q} \beta_{i,q}\, \sigma_{i,t-p}^2 \qquad (2)$$

$$\sqrt{\frac{DF}{\sigma_{i,t}^2 \times (DF-2)}} \times \varepsilon_{i,t} \sim iid\, t_{DF}$$

where $r_{i,t}$ is the returns for the *i*th asset at time *t*; $\varepsilon_{i,t}$ denote real-valued discrete-time stochastic process for the *i*th asset at time *t*; $\sigma_{i,t}^2$ denote the variance of $\varepsilon_{i,t}$; and DF is the degree of freedom for the *t* distribution. The subscripts *k*, *p*, and *q* represent the order of the autoregressive terms, ARCH terms, and GARCH terms, respectively.

3.2 Copulas

The idea of a copula is to separate a joint distribution function F_{XY} into a segment that describes the dependence between X and Y, and into segments that only describe the marginal behavior. Denote F_X and F_Y the margins, then according to Sklar's theorem there exists a copula C such that for all $x, y \in [-\propto, \propto]$:

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)) \quad (3)$$

If F_X and F_Y are continuous then C is unique, otherwise C is uniquely defined on Range F_X × Range F_Y. Conversely, if C is a copula and F_X and F_Y are univariate cumulative distribution functions (CDF), respectively, then F_{XY} defined in equation (3) is a joint distribution function with margins F_X and F_Y.

One of the important properties of a copula is the tail dependence which measures the probability that both variables are in their lower and upper joint tails. Intuitively, upper (lower) tail dependence refers to the relative amount of mass in the upper (lower) quantile of the distribution. In addition, the tail dependence between X and Y is invariant under strictly increasing transformation of X and Y. Following prior studies, we define the left (lower) and right (upper) tail dependence coefficients as:

$$\lambda_L = \lim_{u\to 0} P\{F_Y(y) \le u | F_X(x) \le u\} = \lim_{u\to 0} \frac{C(u,u)}{u} \quad (4)$$

$$\lambda_U = \lim_{u\to 1} P\{F_Y(y) \ge u | F_X(x) \ge u\} = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u} \quad (5)$$

where λ_L and $\lambda_U \in [0,1]$. If λ_L or λ_U are positive, X and Y tend to be left (lower) or right (upper) tail dependent.

To capture different patterns of tail dependence, we use three joint copula models that have been studies in the literature: the Gaussian, Student t, and the symmetrized Joe-Clayton (SJC) copulas. Let u and v be the cumulative density functions of the standardized residuals from the marginal models and $0 \le u,\ v \le 1$, and ρ denotes the linear correlation coefficient. Then the Gaussian copula is given by:

$$C(u, v; \rho) = S_\rho(S^{-1}(u), S^{-1}(v);\ \rho) \quad (6)$$

where S_ρ is the bivariate normal distribution function with the correlation coefficient ρ and S^{-1} is the inverse function of the univariate normal distribution. In general, Gaussian copula has zero tail dependence.

Furthermore, if we use υ to measure degree of freedom for the Student t distribution, which captures the strength of symmetric extreme dependence, then the t-copula exhibits the following form:

$$C_{\upsilon,\rho}(u,v) = t_{\upsilon,\rho}\left(t_{\upsilon}^{-1}(u), t_{\upsilon}^{-1}(v)\right) \quad (7)$$

where $t_{\upsilon,\rho}$ is the bivariate student t distribution with degree of freedom υ and the correlation coefficient ρ. t^{-1} is the inverse function of the univeriate Student t distribution. In general, Student's t-copula has symmetric tail dependence. Hereafter, we use τ to denote symmetric tail dependence of Student's t-copula.

To better capture and understand both lower and upper tail dependence, we also use the SJC copula, which is a modified Joe-Clayton copula of Joe (1997). Let the Joe-Clayton copula be:

$$C_{JC}(u,v|\lambda_L,\lambda_U) = 1 - \left\{1 - \left[(1-(1-u)^h)^{-\delta} + (1-(1-v)^h)^{-\delta} - 1\right]^{-\frac{1}{\delta}}\right\}^{\frac{1}{h}},$$

$$where\ \ h = \frac{1}{\log_2(2-\lambda_U)}, \lambda_U \in (0,1), and\ \delta = \frac{1}{\log_2(\lambda_L)}, \lambda_L \in (0,1).$$

Then SJC copula is defined as

$$C_{SJC}(u,v|\lambda_L,\lambda_U) = 0.5\left(C_{JC}(u,v|\lambda_L,\lambda_U) + C_{JC}(1-u,1-v|\lambda_L,\lambda_U) + u + v - 1\right) \quad (8)$$

where $\lambda_L$and λ_U refer to lower and upper tail dependence, respectively.

3.3 Goodness-of-fit tests

Prior studies (e.g., Patton, 2006; Ning, 2010) document that the validated and corrected specifications of the marginal models are essential to the joint copula models. To ensure the goodness-of-fit of the marginal distribution of each index return, we use the Breusch-Godfrey Lagrange Multipier (BGLM) and Kolmogorov-Simirnov (KS) tests to examine serial correlation of each CDF of the standardized residuals from the margin and to test whether the marginal CDF of each index return is uniform(0,1), respectively. We also employ Akaile information criterion (AIC) and Bayesian information criterion (BIC) to evaluate the performance of copula models.

4. Data and preliminaries

Our data set includes daily closing prices of seven stock markets in the GCC region. These include Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, Abu Dhabi and Dubai. Both Abu Dhabi and Dubai exchanges are located in the United Arab Emirates. The data span from 1st January 2004 to 31st December 2013, providing 10 years of historical equity prices. Except for Kuwait, all prices were obtained from Bloomberg, while the Kuwaiti data were taken from the website of Kuwait Stock Exchange.[9] The data represent only trading days, all official holidays have been eliminated from the data. Additional adjustments have been made to reflect the changes of the start of two-day weekend from Thursday-Friday to a Friday-Saturday weekend in 2013 in Oman and Saudi Arabia.

While the daily raw data is used for country-specific descriptive statistics as reported in Tables 1 and 2, for the main empirical analysis we use a slightly truncated version of the original data. This is because of the differences in trading days and weekends in some markets, which if not corrected, will deliver inaccurate statistical inference. To overcome this pitfall, we use daily trading days that are common across the seven Gulf markets. In any given week, except on public holidays, all seven markets are open from Sunday to Wednesday. We, therefore, consider these four common days a week as the basis for our multivariate analyses. This issue is particularly important for estimating the pairwise copula models, which require that the sample observations of pair *i* and *j* must be of same length and represent the same time observations. While the potential loss of observations due to this adjustment is not trivial (about 400–450, or15% of the total sample), the resulting gain in statistical accuracy is expected to overcompensate this loss. Recently Balcilar et al. (2013b) utilized three trading days a

[9] Concretely, the country or market indices considered in this study are the Bahrain All Share Index, Kuwait All Share Index, MSM 30 Index for Oman, QE 20 Index for Qatar, Tadawul All Share Index for Saudi Arabia, ADX General Index for Abu Dhabi and the DFM General Index for Dubai. These are the indices most widely used in the literature.

week (Monday to Wednesday) to account for the different trading days and weekends in the GCC region.

Table 1 presents selected summary statistics of daily returns for all seven equity markets. Except for Bahrain, the daily returns are positive in the remaining six markets, with Dubai exhibiting the highest daily return followed by Qatar, Oman and Abu Dhabi. The daily standard deviation of returns seems to follow the standard risk-return trade-off; that is, higher levels of risk are associated with higher potential returns (e.g., Dubai, Qatar), and lower levels of risk are associated with lower potential returns (e.g., Bahrain, Kuwait). In general, a standard deviation value of 1 implies that a one percent increase (in daily return) is within one standard deviation. The third row in Table 1 presents the Sharpe ratio, which looks at the relationship between an asset's return and its variability. The higher the ratio, the more reward there is for a given amount of risk. The results show that the MSM 30 index of Oman provided the best risk-adjusted return over the sample period, followed by market indices of Abu Dhabi, Dubai and Qatar. The worst performing market was Bahrain, where a negative value of Sharpe ratio indicates a bear market.

Besides volatility (i.e., standard deviation), from a financial perspective, skewness and kurtosis are considered important measures of risk. A generally accepted conclusion is that investors dislike highly negative skewness and high kurtosis of their investment portfolios (Kim and White 2004). The estimated sample coefficients of skewness and kurtosis display the presence of negative skewness and excess kurtosis. To determine the statistical significance of these distributional metrics, we apply the unconditional skewness and kurtosis tests statistics of Bai and Ng (2005), which are robust to dependent and non-Gaussian data.[10] The p-values for skewness indicate that we cannot reject the null hypothesis of symmetry for all seven markets at the 5% level. On the contrary, the use of standard asymptotic test—which assumes that data are iid and normally distributed—strongly rejects the null hypothesis of symmetry in all cases.

[10] A test for conditional skewness and kurtosis can be obtained by applying the Bai and Ng (2005) test to the standardised residuals, such as those from the GARCH model.

Thus, the use of Bai and Ng (2005) allows us to reach an important conclusion that there is no clear evidence of unconditional asymmetry in the returns of GCC financial markets. The finding of unconditional symmetry in return has strong implication for risk management as well as capital asset price model (CAPM) for emerging countries that incorporate skewness and kurtosis (Hwang and Satchell 1999). Whereas, the results of the sample kurtosis coefficients indicate the presence of fat-tailed behavior, as the null hypothesis of the test (i.e., kurtosis = 3) is strongly rejected at the 5% level. The incidence of fat-tail in financial time series has led Bollerslev (1987) to suggest the use of *t*-distribution in GARCH-class models to match the excess sample kurtosis, as discussed further below. The significantly positive first-order autocorrelation coefficients imply that the daily returns exhibit some memory, such that the efficient market or random walk hypothesis does not hold strictly. Finally, the Bai and Ng (2005) test for normality—which extends the standard Jarque-Bera test to weakly dependent data—strongly rejects the null hypothesis of normality in the return distribution.

It is also instructive to look at the yearly returns, to facilitate comparisons with other investment opportunities. Table 2 displays the yearly returns—computed as the sum of 240 to 250 daily log returns—across the seven stock markets. Over the sample period, GCC countries' stock markets have experienced two substantial crushes: in 2006 and in 2008. The 2006 crush was associated with a speculative bubble that had built up in the first half of 2000s—thanks to rising oil prices—before bursting in 2006. As can be seen from Table 2, the stock market of Saudi Arabia took the hardest hit posting a nearly –75% return in 2006. The other hardest-hit markets were Dubai, Abu Dhabi and Qatar whose returns fell by 57%, 55% and 44%, respectively. In fact, this stunning decline in Gulf equity markets has led to the popularity of Islamic finance among retail investors in the region. On the contrary, the stock markets of Bahrain and Oman posted positive returns, perhaps a reflection of the lower share of oil to output in these economies, compared with the remaining four oil-rich economies. However, in the 2008 global financial crisis, all seven markets were severely affected, albeit at varying magnitude. The financial market of Dubai was the hardest hit, which was the result of the bursting of Dubai's real estate bubble and the post-Lehman shut-down of international capital mobility that also had ramifications for other financial markets in the region.[11] Whereas, the losses of returns in 2011 were the results of the combined effect of the Arab Spring revolt, sovereign debt distresses in Europe (GCC's major financial partner) and negative market sentiment (KAMCO 2012). Over the entire sample, the Dubai market leads the region posting the highest average yearly returns, followed by Qatar, Oman and Abu Dhabi. To view it another way, the average equity premium – the extra return generated by stocks over the risk-free asset – of Dubai's Financial Market Index was well above its regional counterparts; while, Bahrain remains the worst market performer in the region. However, Dubai's top performance was the result of a spectacular rally in 2013—thanks to its booming real estate sector—during which its index gained over 100%. To a great extent, a similar rally in stock prices was also observed in Abu Dhabi during 2013. Therefore, if we adjust for the unusual rally in equity prices in 2013, Qatar and Oman stand out as the stable and high performing destinations for investors.

Table 3 presents the correlation coefficients of daily returns. For the reasons explained above, these coefficients are obtained using the four trading days a week (Sunday to Wednesday) returns. The results show that returns are positively and statistically significantly correlated across the seven markets. The average correlation coefficient is 0.29 according to the Pearson's measure, which is well above that the correlation coefficient of 0.12 obtained by Bley and Chen (2006) for the six GCC markets over the period 2000–2004. However, Bley and Chen (2006) used weekly returns, while our correlation coefficients are based on daily data. If we use weekly returns over the sample period 2004–2013, the average of correlation coefficients increases to 0.40. This provides an indication that the extent of stock market integration in the GCC region has increased over the past decade. As a final remark, the higher correlation coefficients of Pearson, compared with Spearman and Kendall measures, possibly suggest the

[11] See Khamis and Senhadji et al. (2010) for an assessment of the impact of the global financial crisis on the GCC countries.

presence of outlying observations in the tails of return distribution, as is evident from the high kurtosis reported in Table 1.

5. Main empirical results

This section is divided into three parts. The first part presents the results of the marginal models (i.e., the country-specific GARCH models). The second part discusses a contingency table using the empirical copula table of Knight et al. (2005) to evaluate the performance of an estimate of dependence, while the third part presents the results of the dependence patterns based on the joint coupla models.

5.1 Marginal models

We first estimate the marginal models: the AR(k)-$t-$GARCH(p,q) type models for each asset return series. The autoregressive parameter k is set to a maximum of 10, and the insignificant (with significant level of 5%) autoregressive terms are deleted. We experimented on GARCH terms up to p = 2 and q = 2, and select the specification that provides the best possible representation of the GARCH parameters (i.e., statistical significance, lower information criteria) for each country. The use of t-distribution allows to capture any fat-tails present in the return data.

Table 4 presents the results of the marginal models. Several remarks are in order. First, except for Saudi Arabia, a GARCH(1,2) model is selected for each of the remaining six markets; while a GARCH(2,1) model is chosen for Saudi Arabia. For the GARCH(1,2) model, Nelson and Cao (1992) show that the following inequality restrictions must be satisfied to ensure that the estimated GARCH model is not misspecified. The conditions for GARCH(1,2) model include: (i) $\omega \geq 0$, (ii) $\alpha_1 \geq 0$, (iii) $0 \leq \beta_1$, (iv) $\beta_1 + \beta_2 < 1$, and (v) $\beta_1^2 + 4\beta_2 \geq 0$. Similarly, for the GARCH(2,1) model the conditions are: (i) $\omega \geq 0$, (ii) $\alpha_1 \geq 0$, (iii) $0 \leq \beta_1 < 1$, and (iv) $\beta_1\alpha_1 + \alpha_2 \geq 0$. These constraints are less stringent than those proposed by Bollerslev (1986). As can be seen, the estimated GARCH coefficients satisfy the inequality constraints, indicating that the GARCH models are not misspecified. Second, for some returns there is evidence of a long memory with higher order autoregressive terms being statistically significant. Third, the results indicate strong volatility persistence in all the seven markets. Similar estimates of high volatility persistence for the GCC markets were also obtained by Abdmoulah (2010) and Awartani and Maghyeren (2013). Furthermore, empirical results in Rao (2008), Hammoudeh et al. (2009) and Balli et al. (2013) show that the volatility dynamics in GCC markets are better explained by their past (own) volatilities rather than regional or global shocks, which possibly explain the incidence of high volatility persistence in the GCC markets.

Table 5 reports the goodness-of-fit test results of our marginal distribution models. For BGLM serial correlation tests, we estimate the first four moments of u, that is, $(u - \bar{u})^k$ for $k = 1, 2, 3, 4$ on its 30 lags of each four moments respectively, where u is defined as the probability integral transforms of the standardized residuals from the marginal models. The p-values are all above 5% except the second moment of the probability transforms of Kuwait and Abu Dhabi index margins. These results suggest that there is no serial correlation in the probability transform of each marginal distribution of seven index returns. The p-values from KS tests are all above 80%, providing a strong evidence that the probability integral transforms of each marginal distribution of seven index returns are uniform (0,1). Overall, the goodness-of-fit tests suggest that the marginal models are correctly specified and thus are valid to be employed in the joint copula models.

5.2 Contingency table of tail dependence

The conventional dependence measures such as correlation coefficients presented in Table 3 are useful in knowing the linear association between two series, but these measures are not adequate in knowing the general and/or asymmetric modes of dependence between the variables of interest. To get a feel of the dependence structure among the seven GCC stock markets, we apply the empirical copula table of Knight et al. (2005) and used in Ning (2010). The procedure is essentially estimating the joint frequency distribution of two random variables, and is done in the following ways. First we rank the pair of return series in ascending order and then we divide each series evenly into 7 bins. The choice of 7 bins is purely ad hoc, as it can be any other number. Bin 1 includes the observations with the lowest return values and Bin 7 contains observations with the highest return values. Viewed this way, we would be able find out whether lower returns in one stock market are associated with lower returns in another stock market. Next, we count the numbers of observations that are in cell (i, j), i.e., the frequency of each pair in the 7×7 matrix. The information on the dependence structure from the frequency table can be extracted as follows: if the two series are perfectly positively correlated, we would expect that most observations lie on the diagonal; if the series are independent, then we would expect that the numbers in each cell are about the same. In particular, if the series are perfectly negatively correlated, most observations should lie on the diagonal connecting the upper-right corner and the lower-left corner; If there is positive lower tail dependence between the two series, we would expect that more observations lie in cell (1,1). If positive upper tail dependence exists, we would expect large number in cell (7, 7).

Table 6 presents the contingency tables for all the 21 pairs. Consider, for example, cell (1,1) of the Bahrain–Kuwait pair. Cell (1,1,) has a joint frequency of 81, which means that out of 2012 observations, there are 81 occurrences when both returns lie in their respective lowest 14th percentiles (1/7 quantile). This number is the largest among all cells in the Bahrain-Kuwait pair, indicating the evidence of lower tail dependence. Take another example, the lower-right corner (cell (7,7)) in the Abu Dhabi–Dubai pair, which shows 138 occurrences out of 2012 observations when both Abu Dhabi and Dubai returns lie in their higher 14th percentiles. In fact, the results from the 21 market pairs show that the highest and the second highest number of occurrences are located in the (1,1) and (7,7) cells, respectively. This suggests that there is evidence of both “lower tail” and “upper tail” dependence among the returns of the GCC stock market. [12] Moreover, this tail dependence is slightly tilted towards lower tail

[12] The absence of upper tail dependence between Bahrain-Qatar and Bahrain-Saudi Arabia is also consistence with the weak correlation estimates evident in Table 3.

dependence, since the number of occurrences in cell (1,1) are always higher than that of cell (7,7). Intuitively, this implies that the GCC stock markets react more coordinately to a negative exogenous shock than to a positive exogenous shock. This result complements the finding of Balcilar et al. (2013a) who linked a crash in these markets to a chain automobile accident. This (conditional) asymmetry in the data becomes more prominent through the tail dependence functions of the copula, as discussed below.

5.3 Copula tail dependence

Table 7 presents estimated coefficients for the Gaussian copula, Student *t*-copula and the symmetrized Joe-Clayton copula for 21 combination of pairs comprising returns of seven GCC stock indices. For all pairs, the dependence parameters (the correlation coefficient, ρ, in both Gaussian and *t*-copulas), the degree of freedom (DoF) ϑ in the *t*-copula, and the upper (λ_U) and lower (λ_L) tail dependence parameters in the SJC copulas are positive and strongly significant. The parameter τ captures the tail dependence of *t*-copulas.[13] For instance, the correlation coefficient estimates from the Gaussian copulas range from 0.0290 to 0.5729, while those from the Student's *t*-copula model range from 0.0201 to 0.5714. These estimated parameters are very close to the linear correlation coefficients from the data as shown in Table 3. The DoFs ϑ in the *t*-copula ranged between 3 and 11, indicating strong co-movements and tail dependence in each pair. It also suggests that Gaussian copula which does not allow for tail dependence, is not sufficient in modeling the dependence of the stock indices pairs.

The estimated tail dependence coefficients indicate that, for 20 out of 21 pairs, the extent of λ_L is always higher than that of λ_U, implying that there is substantially higher dependence in the lower tail of the distribution (negative extremes) than in the higher tail (positive extremes). According to Longin and Solnik (2001), when the correlation on the left tail is much more than the correlation on the right tail, a bear market state, rather than volatility, is the driving force increasing dependence across international

[13] Student's *t* copula has symmetric tail dependence whereas Gaussian copula has zero tail dependence.

equity markets. Our findings corroborate their proposition. Moreover, this observation suggests that the dependence structure is not symmetric since symmetry implies that the difference $\lambda_L - \lambda_U$ should be zero.

The results also indicate that the Abu Dhabi–Dubai pair has the highest lower and upper tail dependence, which is to be expected since both markets are located in the same country (i.e., the UAE) so that the dynamics of response to a shock is faster in these markets than their regional counterparts.[14] In fact, the two stock exchanges in the UAE is a possible cause of asymmetric dependence among the equity markets in the GCC region. Letting $Asymmetry = \lambda_L - \lambda_U > 0$ to denote an indicator of conditional asymmetry, eight of the top ten pairs[15] with $Asymmetry > .10$ are paired with either Duabi or Abu Dhabi equity markets.[16] While the presence of asymmetric dependence may point to gains that are economically significant, it should not be overlooked that such dependence mainly concerns downside risk co-movement in the lower tail of distribution. Put differently, given the evidence that equity returns in the GCC tend to move downward in a declining market more than they move upward in a rising market implies that investors "require a higher premium for holding assets that covary strongly with the market when the market declines" (Ang et al., p. 1191, 2006). A common explanation for this asymmetry is that investors are more sensitive to bad news than good news in other markets (Hu, 2006). Furthermore, investors' exposure to news media may play an important role in informing investors about foreign markets (Shiller, 2001).

Among the parameters of the upper tail dependence, the pairs consisting of Abu Dhabi–Dubai, Qatar–Abu Dhabi, Kuwait–Abu Dhabi, Qatar–Dubai, and Oman–Qatar

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[14] Maghyereh and Awartani (2012) find that returns and volatilities of the Dubai Financial Market (DFM) have predictive effects on the future dynamics of the Abu Dhabi Stock Exchange (ADSE), and not the other way around. A likely explanation for this result is that the DFM market is more liquid than the ADSE. Moreover, the DFM has more relaxed trading rules than the ADSE (Maghyereh and Awartani, 2012).

[15] These top ten pairs exhibiting highest asymmetric tail dependence include, in descending order, Abu Dhabi–Dubai, Qatar–Dubai, Oman–Dubai, Kuwait–Dubai, Bahrain–Oman, Qatar–Abu Dhabi, Bahrain–Dubai, Oman–Abu Dhabi, Bahrain–Kuwait, and Bahrain–Abu Dhabi.

[16] This confirms the findings of Alkulaib et al. (2009), who find that the UAE's stock market leads all the markets in the GCC region.

exhibit the highest right tail correlations, suggesting that these markets rise together during a boom period. Whereas, the equity markets of Bahrain and Saudi Arabia do not commove with other regional markets during period of rising returns. In the case of Saudi Arabia, who's market is more segmented and closed, Balcilar et al. (2013a) observe that the proportion of market returns corresponding to the 'crash' regime is highly volatile and persistent than its regional peers. To put his into perspective, the average duration of the crash regime is 27.67 days in Saudi Arabia, compared to a mere 1.29 days in Abu Dhabi. Whereas, the lowest average daily returns documented in Bahrain over the sample period possibly explains the weak upper tail dependence among all the pairs vis-à-vis Bahrain.

While capturing asymmetric tail dependence is tempting from the perspective of international portfolio diversification, then extent of asymmetry observed in the data may not necessarily be statistically significant. Indeed, a comparison of the relative performance of the copula models using information criteria and the log likelihoods suggests that the Student *t*-copula consistently performs better than the Gaussian and the symmetrized Joe-Clayton copulas. To better understand symmetric tail dependence, we further employ a likelihood ratio test to formally examine whether each pair of stock exchanges in the GCC markets exhibits a symmetric tail dependence. Table 8 shows the test results with the null hypothesis: $\lambda_L = \lambda_U$. All p-values are larger than 0.01, suggesting that we can't reject the null of symmetric tail dependence at the 1% significant level. This evidence further supports the Student *t*-copula. According to these results, the dependence pattern of nearly all pairs of equity returns display symmetric tail dependence suggesting that the GCC stock markets crash and boom together.

6. Conclusions

In this paper, we investigated the degree of dependence of the bivariate distribution of equity returns in six GCC countries using copula methods over the period 2004–2013. More specifically, we consider three types of dependence structure:

(i) the Gaussian copula allows for equal degrees of positive and negative dependence but does not allow for tail dependence, (ii) the Student *t*-copula allows for symmetric tail dependence and (iii) the symmetrized Joe-Clayton (SJC) copula allows for asymmetric dependence in the tails. Our main finding is that the conditional dependence across all 21 pairs of equity markets returns is not strictly symmetric in that the lower tail dependence is significantly greater that the upper tail dependence. This implies that a bear market state, rather than volatility, is the driving force increasing dependence across the GCC equity markets. Moreover, the stock markets of Abu Dhabi and Dubai appear as the primary source of asymmetric dependence across the different equity market pairs. The results of the marginal models indicate strong volatility persistence in all the seven markets. For investors seeking to diversify their portfolio into GCC financial markets should bear in mind that ignoring the joint downside risk of these markets would amplify errors in evaluating the risk of the underlying portfolios.

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Table 1. Summary statistics of market returns

	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai
Mean returns (%)	-0.002	0.018	0.037	0.038	0.026	0.036	0.049
Std. Dev.	0.625	0.804	1.113	1.510	1.718	1.282	1.838
Sharpe ratio $\times$ 100	-0.320	2.238	3.324	2.516	1.513	2.808	2.665
Skewness	-0.406	-0.538	-0.817	-0.352	-1.077	-0.104	-0.103
BN p-values	(0.924)	(0.999)	(0.946)	(0.911)	(0.999)	(0.629)	(0.687)
AS p-values	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.035)	(0.042)
Kurtosis	9.256	6.964	19.331	9.637	11.409	11.739	8.231
BN p-values	(0.000)	(0.000)	(0.002)	(0.008)	(0.000)	(0.000)	(0.002)
AS p-values	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1) coefficient	0.135***	0.253***	0.225***	0.231***	0.073***	0.199***	0.037*
BN Normality test	15.137***	30.111***	7.586***	13.281***	24.506***	22.369***	15.527***
Observations	2427	2452	2422	2504	2491	2479	2478

NOTE: Sharpe ratio is a risk-adjusted measure of return. A higher Sharpe ratio indicates a higher investment return per unit of risk. Skewness and kurtosis are the sample coefficients for the observed series. BN and AS give the p-values for the unconditional skewness and kurtosis tests of Bai and Ng (2005) and the standard asymptotic tests, respectively. BN normality test refers to the test statistics of Bai and Ng (2005). *** and * indicate statistical significance at the 1% and 10% levels, respectively.

Table 2. Annual returns across the GCC stock markets (percent)

Year	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai	US 10-year Treasury Bond
2004	28.274	29.002	21.331	49.794	60.585	55.840	92.234	4.27
2005	21.351	57.978	36.773	53.189	72.020	51.294	106.328	4.29
2006	0.987	-12.826	13.533	-43.798	-74.510	-54.586	-56.799	4.80
2007	21.710	22.113	48.169	29.499	33.034	42.647	36.272	4.63
2008	-42.347	-47.854	-55.022	-33.022	-83.217	-64.423	-128.792	3.66
2009	-21.281	-10.522	20.047	1.055	24.261	13.798	9.734	3.26
2010	-1.798	-0.713	5.886	22.115	7.836	-0.869	-10.087	3.22
2011	-22.499	-17.923	-17.066	1.115	-3.114	-12.417	-18.629	2.78
2012	-7.071	2.044	1.147	-4.903	5.804	9.089	18.137	1.80
2013	15.868	24.074	17.091	21.651	22.714	48.905	73.087	2.34
Long-run Avg. Returns (2004–2013)	**-0.681**	**4.537**	**9.189**	**9.670**	**6.541**	**8.928**	**12.149**	**3.505**
Equity Premium	**-4.186**	**1.032**	**5.684**	**6.165**	**3.036**	**5.423**	**8.644**	

SOURCE: Bloomberg, Federal Reserve Bank of St. Louis, Authors' calculations.
NOTE: The yearly returns are computed as the sum of daily returns, which include about 245 trading days in a given year. The equity premium for each market is obtained by subtracting the long-run average of the US 10-year bond yields (i.e., 3.505%) from the respective long-run average of equity returns.

Table 3. Correlation coefficients of market returns

Variables	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi
A: Pearson correlation						
Kuwait	0.213***					
Oman	0.263***	0.183***				
Qatar	0.212***	0.213***	0.428***			
Saudi Arabia	0.121***	0.087***	0.268***	0.310***		
Abu Dhabi	0.211***	0.174***	0.362***	0.393***	0.355***	
Dubai	0.221***	0.152***	0.373***	0.377***	0.372***	0.671***
B: Kendall's tau						
Kuwait	0.121***					
Oman	0.109***	0.086***				
Qatar	0.076***	0.082***	0.180***			
Saudi Arabia	0.037**	0.041***	0.114***	0.150***		
Abu Dhabi	0.091***	0.062***	0.213***	0.237***	0.158***	
Dubai	0.092***	0.071***	0.192***	0.215***	0.189***	0.420***
C. Spearman's rho						
Kuwait	0.178***					
Oman	0.160***	0.126***				
Qatar	0.113***	0.118***	0.259***			
Saudi Arabia	0.055**	0.060***	0.164***	0.213***		
Abu Dhabi	0.134***	0.092***	0.305***	0.335***	0.227***	
Dubai	0.136***	0.104***	0.278***	0.305***	0.272***	0.574***

NOTE: Total observations equal 2012 cover the period 2004–2013. Pearson correlation is used for normally distributed data, while Kendall and Spearman correlations are suggested for non-normal data. *** and ** indicate statistical significance at the 1% and 5% level, respectively.

Table 4. Marginal models

Parameters	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai
				A. Mean equation			
μ	-0.003	0.055***	0.042***	0.043**	0.121***	0.024	0.045
AR(1)		0.156***	0.205***	0.151***	0.084***	0.157***	
AR(2)		0.057**					0.054**
AR(3)							
AR(4)		0.048**				0.040**	0.058***
AR(5)		0.053***					
AR(6)	0.052***						
AR(7)							
AR(8)	0.047***	0.073***		0.049**	0.045**		0.052***
AR(9)							
AR(10)							
				B. Variance equation			
ω	0.028***	0.037***	0.035***	0.022***	0.042***	0.063***	0.129***
α_1	0.177***	0.247***	0.266***	0.247***	0.158***	0.304***	0.176***
α_2					0.035		
β_1	0.343*	0.393**	0.413**	0.506**	0.837***	0.528**	0.590**
β_2	0.494***	0.332**	0.350**	0.300		0.242	0.237

NOTE: Total observations equal 2002. The coefficients μ and ω are the intercept of mean and variance equations, respectively. The parameters α_i and β_i refer to the ARCH and GARCH effects, respectively. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

[a] Presents *p*-values at 10 lags.

Table 5. Goodness of fit tests

Parameters	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	Abu Dhabi	Dubai
BGLM[b] first moment	0.804	0.074	0.463	0.080	0.263	0.105	0.873
BGLM second moment	0.234	0.265	0.180	0.139	0.725	0.606	0.479
BGLM third moment	0.900	0.011**	0.490	0.058	0.222	0.011**	0.234
BGLM fourth moment	0.144	0.359	0.106	0.206	0.677	0.537	0.504
KS test[c]	0.861	0.999	0.962	0.999	0.999	0.999	0.999

[a] Presents *p*-values at 30 lags.
[b] Breusch-Godfrey serial correlation LM test.
[c] Kolmogorov-Simirnov tests.

Table 6. Joint frequency table

Bahrain–Kuwait

81	44	40	29	29	29	36
55	47	40	43	42	31	29
33	38	44	50	48	46	29
32	41	42	48	50	40	34
30	39	59	46	29	38	47
24	42	37	31	44	57	52
33	36	26	40	46	46	**60**

Bahrain–Oman

84	36	40	38	22	34	34
43	45	47	29	42	45	36
45	40	37	43	61	31	31
27	44	51	62	45	27	31
29	45	38	39	44	51	42
35	46	42	38	38	46	42
25	31	33	38	36	53	**71**

Bahrain–Qatar

76	34	34	35	27	36	46
47	46	42	43	37	39	33
34	34	44	39	**62**	44	31
42	44	39	44	45	41	32
35	44	38	49	45	43	34
27	46	46	39	35	44	50
27	39	45	38	37	40	61

Bahrain–Saudi Arabia

77	34	33	28	32	37	47
42	38	35	35	48	45	44
38	38	49	47	46	36	34
34	45	44	47	46	36	35
31	44	**52**	45	36	44	36
34	44	39	39	48	43	40
32	44	39	43	32	46	51

Bahrain–Abu Dhabi

83	38	34	35	26	29	43
44	47	46	41	34	43	32
40	31	55	41	44	39	38
19	55	39	46	51	46	31
30	44	47	42	47	41	37
40	42	35	39	43	47	41
32	30	32	43	43	42	**65**

Bahrain–Dubai

78	40	30	38	36	28	38
46	42	44	34	42	39	40
44	42	41	40	50	37	34
24	43	57	47	46	47	23
34	35	50	47	31	54	37
30	48	38	42	40	41	48
32	37	28	39	43	41	**67**

Kuwait–Oman

73	38	30	34	35	31	47
37	56	47	47	33	40	27
38	50	43	44	40	43	30
36	42	50	42	50	30	37
29	37	40	42	47	52	41
35	37	43	46	46	41	39
40	27	35	32	37	50	**66**

Kuwait–Qatar

87	37	25	27	32	39	41
42	39	53	31	41	40	41
32	45	47	57	37	42	28
27	46	43	46	48	45	32
28	44	55	45	48	46	22
32	42	37	39	45	45	47
40	34	28	42	37	30	**76**

Kuwait–Saudi Arabia

69	37	20	34	30	38	60
43	50	39	35	41	41	38
30	40	60	39	48	44	27
32	45	49	43	49	36	33
33	43	50	57	41	37	27
41	43	45	40	40	43	35
40	29	28	36	39	48	**67**

Kuwait–Abu Dhabi

78	32	33	28	28	44	45
39	49	39	40	43	45	32
40	45	41	49	51	36	26
28	38	55	44	50	38	34
27	46	38	50	49	41	37
33	42	40	47	37	44	44
43	35	42	29	30	39	**69**

Kuwait–Dubai

73	50	32	27	30	32	44
39	46	42	45	38	39	38
35	41	42	53	43	45	29
33	37	49	49	48	43	28
31	42	35	40	54	46	40
30	35	53	41	44	38	46
47	36	35	32	31	44	**62**

Oman–Qatar

109	38	33	24	31	27	26
38	51	53	43	38	28	36
31	49	56	44	40	40	28
26	49	42	49	54	44	23
27	42	44	49	38	46	42
26	36	36	51	44	49	45
31	22	24	27	43	53	**87**

Table 6. Joint frequency table (continued)

Oman–Saudi Arabia

87	38	24	30	29	31	49
47	58	39	36	46	32	29
28	50	60	43	40	33	34
29	38	51	50	54	37	28
33	35	39	58	47	44	32
28	35	47	32	42	60	43
36	33	31	35	30	50	**72**

Oman–Abu Dhabi

109	46	39	30	23	20	21
48	56	48	47	36	28	24
32	46	54	39	50	38	29
21	52	35	48	54	47	30
20	29	57	47	50	41	44
26	32	37	45	46	55	46
32	26	18	31	29	58	**93**

Oman–Dubai

106	50	30	28	24	27	23
45	49	43	44	46	37	23
42	43	53	49	40	27	34
25	39	47	54	49	38	35
23	30	54	45	49	50	37
23	43	35	41	43	51	51
24	33	26	26	37	57	**84**

Qatar–Saudi Arabia

104	40	24	26	24	25	45
36	54	43	43	32	43	36
27	57	63	48	39	35	19
37	40	52	28	56	40	34
26	31	50	60	44	52	25
29	38	36	52	47	40	45
29	27	23	27	46	52	**83**

Qatar–Abu Dhabi

124	45	34	25	21	13	26
46	66	43	33	37	35	27
27	49	44	65	55	28	20
20	34	51	49	56	52	25
20	36	48	53	48	53	30
25	34	39	36	38	59	56
26	23	29	26	33	47	**103**

Qatar–Dubai

123	43	27	16	22	30	27
55	66	29	37	42	31	27
25	53	58	52	44	31	25
21	29	57	48	52	45	35
21	40	45	53	47	46	36
23	30	41	49	47	48	49
20	26	31	32	34	56	**88**

Saudi Arabia–Abu Dhabi

100	50	33	30	24	22	29
36	55	55	36	47	34	24
30	44	49	51	49	40	28
19	29	46	52	56	47	35
29	35	44	43	47	48	42
36	43	36	48	35	44	45
38	31	25	27	30	52	**84**

Saudi Arabia–Dubai

103	44	32	34	26	28	21
50	52	50	32	45	35	23
27	51	51	57	41	41	23
27	29	42	53	46	51	36
24	43	49	42	42	47	41
28	34	41	42	56	37	49
29	34	23	27	32	48	**94**

Abu Dhabi–Dubai

168	48	27	12	14	9	10
53	85	51	36	31	20	11
23	48	75	51	39	36	16
14	35	52	69	56	38	23
8	37	37	65	55	57	29
9	24	30	38	55	71	60
13	10	16	16	38	56	**138**

NOTE: Total observations are 2012. Cell (i,j) is the joint frequency of returns of two markets ranked in ascending order and is divided evenly into seven bins. See the text for further details.

Table 7: Estimation of the joint copula parameters and tail dependence

Parameters	Gaussian copula	*t*-copula	Symmetric Joe Clayton Copula	Gaussian copula	*t*-copula	Symmetric Joe Clayton Copula	Gaussian copula	*t*-copula	Symmetric Joe Clayton Copula
	Bahrain – Kuwait			Bahrain – Oman			Bahrain – Qatar		
ρ	0.195	0.190		0.165	0.143		0.139	0.117	
	(0.0004)	(0.0005)		(0.0004)	(0.0005)		(0.0004)	(0.0005)	
υ		11.249			5.804			7.174	
		(0.0736)			(0.0200)			(0.030)	
λ_U			0.008			0.000			0.011
			(0.0003)			(0.0001)			(0.0003)
λ_L			0.111			0.120			0.056
			(0.0005)			(0.0006)			(0.0005)
τ		0.013			0.059			0.034	
AIC	-88.431	-101.938	**-110.667**	-63.086	**-112.009**	-110.280	-44.630	**-76.407**	-72.972
BIC	-88.429	-101.932	**-110.662**	-63.083	**-112.004**	-110.275	-44.628	**-76.402**	-72.967
LL	-44.216	-50.969	**-55.334**	-31.543	**-56.005**	-55.141	-22.315	**-38.204**	-36.487
	Bahrain – Saudi			Bahrain – ADX			Bahrain – Dubai		
ρ	0.029	0.020		0.1369	0.109		0.154	0.131	
	(0.0004)	(0.0005)		(0.0004)	(0.0005)		(0.0004)	(0.0005)	
υ		7.613			5.664			6.796	
		(0.032)			(0.019)			(0.027)	
λ_U			0.0000			0.0000			0.0000
			(0 + 0.0000i)			(0 + 0.0000i)			(0 + 0.0000i)
λ_L			0.006			0.101			0.116
			(0.0002)			(0.0004)			(0.0004)
τ		0.019			0.055			0.040	
AIC	-1.914	**-34.233**	-10.975	-42.934	**-92.587**	-84.081	-54.807	-90.430	**-100.661**

BIC	-1.911	**-34.228**	-10.970	-42.932	**-92.582**	-84.076	-54.805	-90.425	**-100.656**
LL	-0.957	**-17.117**	-5.488	-21.467	**-46.294**	-42.041	-27.404	-45.216	**-50.331**
	Kuwait – Oman			Kuwait – Qatar			Kuwait – Saudi		
ρ	0.144	0.138		0.160	0.157		0.115	0.106	
	(0.0004)	(0.0005)		(0.0004)	(0.0005)		(0.0004)	(0.0005)	
υ		5.585			4.462			4.895	
		(0.018)			(0.012)			(0.014)	
λ_U			0.008			0.025			0.003
			(0.0003)			(0.0004)			(0.0002)
λ_L			0.073			0.080			0.050
			(0.0005)			(0.0005)			(0.0005)
τ		0.063			0.097			0.072	
AIC	-47.943	**-101.134**	-77.940	-59.360	**-133.139**	-93.624	-30.470	**-95.281**	-55.901
BIC	-47.940	**-101.129**	-77.935	-59.357	**-133.134**	-93.619	-30.468	**-95.276**	-55.895
LL	-23.972	**-50.567**	-38.971	-29.680	**-66.570**	-46.813	-15.235	**-47.641**	-27.951
	Kuwait – ADX			Kuwait – Dubai			Oman – Qatar		
ρ	0.167	0.164		0.187	0.188		0.257	0.214	
	(0.0004)	(0.0005)		(0.0004)	(0.0005)		(0.0004)	(0.0005)	
υ		4.196			5.216			3.291	
		(0.010)			(0.0163)			(0.0070)	
λ_U			0.011			0.007			0.076
			(0.0003)			(0.0003)			(0.0005)
λ_L			0.110			0.133			0.176
			(0.0006)			(0.0006)			(0.0005)
τ		0.109			0.083			0.166	
AIC	-64.811	**-154.854**	-106.541	-81.642	**-142.565**	-125.781	-155.755	**-284.998**	-245.945
BIC	-64.808	**-154.849**	-106.536	-81.640	**-142.560**	-125.776	-155.752	**-284.993**	-245.940
LL	-32.406	**-77.428**	-53.271	-40.821	**-71.283**	-62.891	-77.878	**-142.500**	-122.973
	Oman – Saudi			Oman – ADX			Oman – Dubai		
ρ	0.114	0.101		0.227	0.208		0.235	0.202	

	(0.0004)	(0.0005)		(0.0004)	(0.0005)		(0.0004)	(0.0005)	
υ		4.157			3.756			4.156	
		(0.0105)			(0.0089)			(0.011)	
λ_U			0.001			0.048			0.030
			(0.0001)			(0.0005)			(0.0004)
λ_L			0.069			0.154			0.174
			(0.0005)			(0.0005)			(0.0005)
τ		0.093			0.140			0.121	
AIC	-29.825	**-126.137**	-66.569	-120.345	**-227.458**	-187.171	-129.500	**-213.388**	-203.422
BIC	-29.822	**-126.132**	-66.564	-120.342	**-227.453**	-187.166	-129.497	**-213.383**	-203.417
LL	-14.912	**-63.069**	-33.285	-60.172	**-113.730**	-93.586	-64.750	**-106.695**	-101.712
	Qatar – Saudi			Qatar – ADX			Qatar – Dubai		
ρ	0.127	0.120		0.339	0.347		0.315	0.315	
	(0.0004)	(0.0005)		(0.0004)	(0.0004)		(0.0004)	(0.0005)	
υ		4.058			3.469			3.322	
		(0.0099)			(0.0076)			(0.007)	
λ_U			0.001			0.131			0.095
			(0.0001)			(0.0006)			(0.0006)
λ_L			0.083			0.248			0.243
			(0.0006)			(0.0005)			(0.0005)
τ		0.102			0.207			0.202	
AIC	-37.186	**-136.440**	-75.282	-277.155	**-415.211**	-360.867	-238.694	**-382.373**	-329.223
BIC	-37.183	**-136.435**	-75.277	-277.153	**-415.206**	-360.862	-238.692	**-382.368**	-329.218
LL	-18.593	**-68.221**	-37.641	-138.578	**-207.606**	-180.434	-119.347	**-191.187**	-164.612
	Saudi – ADX			Saudi – Dubai			ADX – Dubai		
ρ	0.147	0.130		0.190	0.177		0.572	0.571	
	(0.0004)	(0.0005)		(0.0004)	(0.0005)		(0.0002)	(0.0003)	
υ		3.743			5.214			2.935	
		(0.0087)			(0.0163)			(0.0062)	
λ_U			0.024			0.026			0.317

			(0.0004)			(0.0004)			(0.0006)
λ_L			0.076			0.108			0.489
			(0.0005)			(0.0005)			(0.0003)
τ		0.117			0.080			0.400	
AIC	-49.978	**-160.995**	-97.549	-83.843	**-144.867**	-125.772	-903.278	**-1096.100**	-1078.900
BIC	-49.955	**-160.990**	-97.544	-83.840	**-144.862**	-125.767	-903.275	**-1096.100**	-1078.900
LL	-24.978	**-80.498**	-48.775	-41.922	**-72.434**	-62.887	-451.638	**-548.000**	-539.500

NOTE: This table presents the copula estimates by using Gaussian copula, *t*-copula, and SJC copula, respectively. ρ denotes the linear correlation coefficient estimates of the Gaussian copula and t-copula parameters. υ represents the degree of freedom estimate in the *t*-copula parameter. τ estimates the symmetric tail dependence of *t*-copula. λ_U and λ_L measure the upper and lower tail dependence of SJC copula. Standard errors of copula estimation are reported in parentheses.

Table 8: Likelihood ratio test: Symmetric tail dependence

Stock Market Pairs	p-values
Bahrain–Kuwait	0.651
Bahrain–Oman	0.724
Bahrain–Qatar	0.813
Bahrain–Saudi Arabia	0.780
Bahrain–Abu Dhabi	0.658
Bahrain–Dubai	0.688
Kuwait–Oman	0.703
Kuwait–Qatar	0.887
Kuwait–Saudi Arabia	0.805
Kuwait–Abu Dhabi	0.770
Kuwait–Dubai	0.703
Oman–Qatar	0.764
Oman–Saudi Arabia	0.729
Oman–Abu Dhabi	0.687
Oman–Dubai	0.635
Qatar–Saudi Arabia	0.688
Qatar–Abu Dhabi	0.661
Qatar–Dubai	0.623
Saudi Arabia–Abu Dhabi	0.742
Saudi Arabia–Dubai	0.721
Abu Dhabi–Dubai	0.597

NOTE: This table reports the likelihood ratio tests for whether tail dependence of each pair of the returns in the GCC stock markets is symmetric. The p-values which are larger than 0.01 indicate the acceptance of the null hypothesis of symmetric tail dependence.