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Comparing regional and global spillovers to the GCC equity markets

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Abstract. *This paper explores the global and regional financial connectedness for equity markets in the Gulf Cooperation Council (GCC) countries. Our empirical research benefits from two econometric approaches; the Diebold and Yilmaz (2012) connectedness approach and the DCC-GARCH model. These are applied to an extensive dataset of relevant MSCI indexes that consist of daily frequency data. For empirical analysis, the MSCI country level indexes are used to construct regional indexes separately for each country within the selected region. Our results indicate that the GCC equity markets are more strongly integrated intra-regionally, when compared against their level of integration with global markets.*

Keywords: Regional equity markets; international finance; equity market spillovers; financial connectedness; globalization.

JEL Classification: C55, C58, F65, G01.

1. Introduction

With globalization, financial markets around the world have become increasingly interconnected. In this context, a given equity market may be vulnerable to spillovers not only from within its geographic region, but also from much farther yet developed equity markets. Several regional studies have been conducted across equity markets representing different geographical cluster of countries. These include studies conducted by Mohammadi and Tan (2015), Chow (2017) and Yoon et al (2019) for a sample of Asian countries and by Ogbuabor et al (2016) for Africa. These studies show that geographical clusters could have a lesser influence on intra-regional connectedness than we would expect; certain equity markets within a particular geographic cluster might exhibit greater levels of connectedness with major global equity markets outside the cluster in contrast to other markets within the regional cluster, as illustrated by Sehgal et al (2018) for South Asian economies. Contrarily, Beirne et al (2010) illustrated that whilst global markets significantly influence the Asian equity markets, regional markets are the most significant determinants of stock market behaviour for other regions, such as the Latin American and Middle Eastern clusters. Therefore, existing literature demonstrates that the contrast between global and regional spillovers for an equity market is likely to significantly vary across different geographic regions.

This study focuses particularly on the six Gulf Cooperation Council (GCC) countries; UAE, Saudi Arabia, Qatar, Kuwait, Oman, and Bahrain, and examines how their equity markets respond differently to global and regional shocks. By consistently applying the same methodologies individually for each of the GCC countries' equity indexes over the same time horizon, we could contrast how these countries react differently (or similarly) to shocks from global and regional markets. To achieve this, we construct separate regional indexes for each of the six GCC countries, each excluding the corresponding country's index (for unbiasedness). A Tri-variate DCC GARCH Model is constructed for each of the six countries, including their respective regional indexes and the MSCI World Index that represents global equity markets in developed economies. This provides us with the dynamic conditional correlations that reveal how the local equity markets are integrated with regional and global markets over time. In addition, we apply the generalized VAR framework with rolling window estimations of forecast error variance decompositions, as suggested by Diebold and Yilmaz (2012), to evaluate the dynamic connectedness of local equity markets with regional and global markets. This enables exploration of the directional flow of spillovers for each of the GCC countries by constructing the net pairwise spillover plots. Finally, we compare the results obtained from these two completely different methods for robustness of our conclusions.

This research contributes to the literature by expanding our knowledge on the equity markets' behavior of GCC countries; we learn more about the time varying flow of regional and global equity market spillovers to the GCC economies. Whilst shocks from the developed equity markets could have a detrimental effect on emerging equity markets, this effect may surpass their intra-regional connectedness. However, we have reasons to hypothesize that this may not be the case for the GCC; high levels of economic integration and trade within the region, cultural and geopolitical similarities, and the shared impact

following oil price fluctuations. This research also offers insight on whether smaller equity markets are more prone to shocks from within the region or from global markets. Despite market size differences amongst the cluster of countries, they also vary in the degree of trade openness. Therefore, this study helps identify whether countries with higher trade openness are more susceptible to shocks from global markets. The time varying analysis of these spillovers also helps us identify how equity markets react during crises events. Ultimately, this study has the potential to help develop better informed macro-prudential policies that mitigate the effects of a financial contagion.

2. Literature Review

Since the global financial crisis of 2007 – 2008, many researchers in the fields of economics and finance have studied factors that could predict future crisis events and estimate the directional flow of spillovers in case of a financial contagion. Minoiu et al (2015) found that examining the connectedness of financial markets could help predict financial crises events. They found that the financial connectedness of markets sharply increased during the period preceding a systemic crisis event. Their research indicated that the financial connectedness of equity markets could serve as an early warning sign. Diebold and Yilmaz (2015) explored the interconnectedness between different financial markets using the connectedness approach as an indicator of financial integration and risk. Highly integrated markets are at greater risk of being impacted from a financial contagion in comparison to the relatively isolated markets. Moreover, whilst cross-border financial connectedness could be seen as a byproduct of globalization, financial markets have also become increasingly vulnerable to spillovers from other markets, therefore being subject to greater financial risks. To examine the financial integration levels of equity markets, researchers have applied various econometric techniques, of which, the GARCH models, and the connectedness approach by Diebold and Yilmaz, are two of the most popular ones.

One of the most widely used methods to examine spillovers across the various financial markets has been introduced by Diebold and Yilmaz (2009, 2010, 2012, 2015) and it will be later discussed in our methodology. Diebold and Yilmaz (2009) examined the case for 19 global equity markets and analyzed the connectedness of their returns and volatilities. They used vector auto-regression (VAR) models to extract forecast errors that could be divided into two parts; Errors explainable by shocks to other data series, and errors due to un-explained idiosyncratic factors. Through this formulation, it is possible to determine what proportion of shocks to a particular data series could be explained due to spillovers from others. For instance, Diebold and Yilmaz (2009) found that the US equity market had a high level of connectedness with other markets and was a net contributor of return and volatility shocks to other countries. Meanwhile, Japan had a relatively lower level of connectedness and was a net recipient of volatility shocks from other economies.

The Diebold and Yilmaz approach has also been adopted by many researchers who have examined the macroeconomic and financial connectedness of the financial markets across different countries and regions. Various researchers have also studied clusters of representative countries to examine the regional connectedness of their equity markets.

These studies include Guimaraes-Filho and Hong (2016) for East Asia, Fowowe and Shuaibu (2016) for Africa, Mensi et al (2018) and Skrinjaric and Sego (2019) for Europe, Demirer et al (2019) for the United States, Belcaid and El Ghini (2019) for Morocco, Chow (2017), Hsu and Lee (2019) and Yoon et al (2019) for Asia, and Schmidbauer et al (2016) for Russia. Whilst these researchers have specifically studied the equity markets, many authors have also examined the interconnectedness between equity markets and crude oil (Schmidbauer and Roesch, 2013; Maghyereh et al, 2016; Husain et al, 2019; Awartani and Maghyereh, 2013; Yousuf and Zhai, 2022).

Several authors have examined the interconnectedness of equity markets and other financial markets, such as the foreign exchange markets and bonds markets across a sample of countries. These include Abbas et al (2019) for the G7 countries, Sobti (2018) for India, Chau and Deesomsak (2014), Uluceviz and Yilmaz (2018) for the United States, Uluceviz and Yilmaz (2020) for Switzerland, Magkonis and Tsopanakis (2019) for Europe, and Fernández-Rodríguez and Sosvilla-Rivero (2020) for a global sample of seven countries. Some of the other authors also used the methodology to examine other areas such as real estate (Antonakakis et al, 2018; Jiang and Aijo, 2018), and business cycles (Ahmad and Sehgal, 2018). Abbas et al (2019) examined the dynamic spillover effects occurring to stock market returns and volatilities from six macroeconomic factors; industrial protection, money supply, government bond rate, consumer price index, oil price and exchange rates. They conducted their empirical analysis individually for each of the G7 economies. Meanwhile, Yousuf (2024) examined the influence of news sentiments on the connectedness of GCC equity markets.

Current literature includes an important study on the GCC equity markets, conducted by Charfeddine and Al Refai (2019), who examined the connectedness between Qatar and the five other GCC countries between the years 2011 and 2018, in light of two specific crises events that happened during these times. The first of them referred to the unexpected large drop in oil prices during March 2014 and the second one referred to the June 2017 blockade on Qatar. Interestingly, during the first crisis in the time series, the total spillover connectedness within the region grew tremendously, whilst following the second crisis, it fell drastically. The authors examined the connectedness during three distinguished time periods: before the first crisis, between the first and second crisis, and after the second crisis. The level of connectedness between Qatar and other GCC countries did not change as much between the first two time periods as much as it did in comparison to the post second crisis event. One significant change following the first crisis was that the variance decomposition of Qatar stock returns showed an increase in directional connectedness from Dubai, from 6.7% to 16.5%. A major change after the blockade was that the directional connectedness from the GCC countries to Qatar significantly reduced, whilst remaining positive due to several reasons attributable to external sources, such as a common response to global oil price changes and the global investor sentiments about the overall geopolitical and economic risk within the region.

Another research on the GCC equity markets was conducted by Saadi-Sedik and Williams (2011) who apply GARCH models and find that the GCC equity markets are vulnerable to both intra-regional and extra-regional spillovers. They use the S&P 500 index as a proxy

for global spillovers, whilst other developed equity markets are excluded from the analysis. Their findings suggest that the inflow of shocks for the GCC markets peaked during the global financial crisis of 2007-2008. However, the time frame examined does not include major regional and global crises events that occurred over the past decade; the Arab Spring of early 2010s, the oil price crash of mid 2010s, the Qatar diplomatic crisis of 2017, and the global pandemic of 2020. This creates a gap in the literature that needs to explore the dynamic flow of connectedness and spillovers over the past decade. Furthermore, recent diversification strategies of GCC countries and an overall increase in the level of global financial integration may have caused significant changes to the connectedness dynamics and therefore, inferences from historic findings could be questionable. This provides us with an opportunity to explore the issues in further detail using a relatively recent, applying a combination of two different econometric methods.

In addition to Saadi-Sedik and Williams (2011), variations of the multivariate GARCH models have been popularly used by other researchers (Wang et al, 2005; Wang and Wang, 2010; Li and Giles, 2015). These models have become popular in modelling volatilities and forecasting due to their ease of application and the ability to control for serial autocorrelation of the variance term in an autoregressive moving average (ARMA) process. Furthermore, GARCH models have also been a preferred choice due to the variety of variations available such as the DCC-GARCH model that provides the dynamic conditional correlations, or the EGARCH model that captures asymmetric effects. The original GARCH model introduced by Bollerslev (1986), has been widely adapted due to its simplicity in application and the ability to control for heteroskedasticity. For these reasons, GARCH models have been widely adapted by researchers, especially for studies on stock market volatilities.

Bhar and Nikolova (2009) examined the dynamic correlation between return and volatility spillovers amongst BRIC countries using a bivariate EGARCH model. They found that amongst the BRIC countries, India had the strongest correlation with stock market volatilities, both within the cluster, and globally, followed by Brazil. China on the other hand exhibited the lowest level of integration and instead showed a negative correlation, suggesting that investors could consider this as an opportunity for diversification. EGARCH models are suitable towards computing volatility spillovers in stock markets, however further inferences regarding directional spillover effects and dynamic connectedness could be made based on the Diebold and Yilmaz approach. Similar diversification strategies have also been suggested by Mohammadi and Tan (2015) due to low correlation of equity market returns between the Chinese and US markets. Their conclusion was based on VAR models and three forms of GARCH models (BEKK, CCC and DCC). On the contrary, Hung (2019) used a Bi-variate BEKK-GARCH model and found strong unidirectional volatility spillovers from China to the Southeast Asian countries for their chosen time frame of study. A related study by Benlagha and El Omari (2021) conducted an analysis of five global stock markets using the DCC-GARCH approach. Their analysis also included two major commodities; oil and gold. Their results conformed to the intensification of spillovers during the recent crisis corresponding to the global pandemic, by intensification of the dynamic conditional correlations during the crisis event, compared to the pre-pandemic levels. They further used the connectedness

approach to conclude that the behaviour of both commodities differed from one another, such that oil was a net transmitter of shocks, whilst gold received shocks from the stock markets.

Researchers including Sehgal et al (2018) have utilized both, GARCH models and the Diebold and Yilmaz (2012) approach to examine the intra-regional connectedness of equity markets. They examine the time-varying connectedness amongst the equity markets of six South Asian countries; India, Pakistan, Bangladesh, Nepal, Sri Lanka, and Maldives. Unlike the results found for many other regions, the South Asian Association of Regional Cooperation (SAARC) member countries, exhibit a very low (near zero) level of financial integration. Sehgal et al (2018) have explained that the lack of intra-regional regional trade and investments amongst the SAARC countries could be a key explanatory factor for their results. Moreover, the author illustrates that the intra-regional connectedness amongst the equity markets of SAARC countries could also be significantly lower than the connectedness of SAARC countries with other Asian countries, such as member countries of the Association of Southeast Asian Nations (ASEAN). Both, GARCH models and the Diebold and Yilmaz approach, could be useful in providing a dynamic picture of the flow of spillovers. Assuming the connectedness is a dynamic concept that can rapidly change over time, we consider both these approaches suitable for our research. Yousuf and Zhai (2022) explored the global financial connectedness for GCC equity markets, utilizing both approaches. Doing so, they examined the connectedness of GCC equity markets with equity markets of the USA, Europe, and China, as well as crude oil. Extending their research, this paper includes separately constructed regional indexes for each of the six GCC countries to conduct a comparative study exploring global and intra-regional connectedness simultaneously.

The contrast between global and regional spillovers was also explored by Beirne et al (2010) who researched 41 emerging economies across four regions; Emerging Asia, Latin America, Emerging Europe, and MENA (Middle East & North Africa). They applied a trivariate GARCH model to examine the inflow of spillovers for each of the 41 emerging markets from the global equity market and from their respective regional equity market. They found mixed results for different countries, and in general, their results revealed that the Asian emerging markets were highly influenced by global spillovers, whilst the equity markets of Latin America and the Middle East, were relatively highly influenced by regional spillovers. Their sample included five countries from the Middle East; Egypt, Jordan, Kuwait, Lebanon and Saudi Arabia. Each of these countries, with the exception of Saudi Arabia, were significantly influenced by regional spillovers, whilst the Saudi equity market was influenced by global spillovers. Saudi Arabia being the largest equity market amongst the sample of Middle Eastern countries could be seen as an influential market causing intra-regional spillovers to other Middle Eastern equity markets, whilst itself being relatively highly influenced by the global equity market. Hence, smaller equity markets within the region may follow the key player resulting in directional spillovers from the Saudi equity market to other regional markets. A key emerging market within the region that was omitted in their study is of the UAE, which includes two major regional equity markets; the Dubai Financial Market (DFM) and the Abu Dhabi Securities Exchange (ADX).

Other studies that found evidence of spillovers from developed markets to emerging markets include Wang et al (2005) for equity markets of Pakistan, India and Sri Lanka, Hernandez et al (2020) for banks in South and North America, Li and Giles (2015) for China, India, Indonesia, Malaysia, Philippines and Thailand, and Yarovaya et al (2016) for a sample of 11 emerging markets across Asia, Europe, Africa and the Americas. For the banking sector, Hernandez et al (2020) examined the effect of spillovers from developed markets to emerging markets in the Americas and found that banks in developed markets had a strong influence on banks in emerging markets. Gębka and Serwa (2007) examined the intra-regional and inter-regional (global) connectedness for 12 emerging markets; four in Europe (Czech Republic, Hungary, Poland, Russia), four in Asia (Malaysia, South Korea, Taiwan, Thailand), and four in Latin America (Argentina, Brazil, Chile, Mexico). They found that whilst the correlation between equity markets of emerging economies can result from their common reaction to spillovers from the global capital markets, the spillovers from other regional markets can also be highly significant. They argue that equity markets sharing a common region are strategically interconnected due to similarities in their economic structures and policies. For these reasons, their results reveal that the intra-regional connectedness of equity markets could be significantly stronger than their inter-regional connectedness. Moreover, they extend their explanation to add that differences in trading hours due to having different time zones could be another significant factor contributing to higher intra-regional connectedness (and a relatively lower inter-regional connectedness). Overall, their results suggest that we could expect a higher level of intra-regional connectedness amongst the GCC equity markets, since the GCC countries not only operate under highly overlapping trading hours, but also have common economic structures and policies that distinguish the region from the rest of the world.

A related study for the GCC equity markets by Alotaibi and Mishra (2015) compared the impact of regional and global spillovers on the equity markets of five GCC countries; UAE, Qatar, Kuwait, Bahrain, and Oman. Their study utilizes the data for Saudi Arabia as a proxy for regional spillovers, since the Saudi equity market is considered as the largest equity market in the GCC, by market capitalization. Moreover, they consider the US equity markets as a proxy for global spillovers in their study. A major drawback in their study is the utilization of the Saudi equity market as a proxy for regional spillovers, omitting the study of global and regional spillovers for the Saudi equity market itself. This could be solved by introducing a separate GCC equity index for each of the GCC equity markets, by computing the market capitalization weighted average that excludes the equity market for which the index is being computed.

Our study on the global and regional spillovers is conducted using regional equity indexes established separately for each of the six GCC countries by computing the market capitalization weighted average for the other five markets. Moreover, we would utilize the MSCI World Index that covers a weighted average for the equity markets of 23 developed economies. Additionally, we apply both, the Diebold and Yilmaz (2012) approach, as well as the trivariate DCC-GARCH models to gather more robust and conclusive evidence on the impact of global and regional spillovers on the GCC equity markets. Our time varying analysis provides further insights on the dynamic flow of spillovers, illustrating how the inflow of regional and global spillovers to the GCC equity markets has evolved over time.

3. Data Collection and Description

Seven MSCI indexes are gathered for this study. Six of these are country-level indexes representing individual GCC member countries, and an additional index titled the MSCI World Index has been gathered as a representative of global equity markets (across 23 developed countries; excluding GCC countries). Our research utilizes these equity indexes for three reasons. First, the MSCI indexes would be gathered from a common source, computed using a standard approach, improving the comparability and reliability of our results. Second, the MSCI daily equity indexes were available for a longer timeframe, extending from 31st May 2005 until 31st December 2020. Third, the MSCI country-level index merges the equity indexes of DFM and ADX for the UAE, enabling a cross-country comparison.

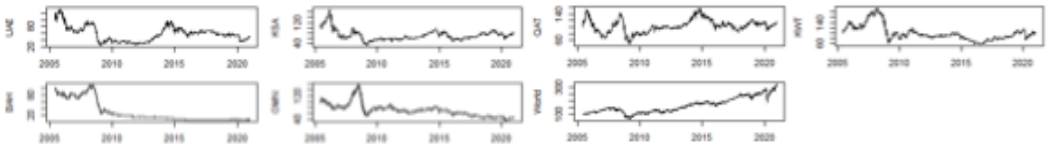
Our data covers stock market working days for a time frame extending over 15 years. This provides us with 4,069 observations (or 4,068 observations after taking the first difference). Hence, the daily-frequency data gathered provides sufficient observations to evaluate the time-varying effects of major global and regional events since mid-2000s. The MSCI equity indexes for each of the countries except for the UAE, represent their primary stock markets, whilst the UAE's index represents two stock markets: Dubai Financial Market (DFM) and the Abu Dhabi's Financial Market (ADX). Prior to further processing, data was indexed to set the base value of 100 on 31st May 2005, for each of the data series, by applying the equitation $\overline{X_t} = \left(\frac{X_t}{X_0}\right) \times 100$, where $\overline{X_t}$ represents the indexed value for a series X_t. These indexes are plotted in Figure 1.

The MSCI World Index represents 23 developed markets, distributed across three regions classified by MSCI; Americas, Europe & Middle East, and Pacific. The MSCI World Index disproportionately represents each country by considering the market size, hence representing approximately 85% of the free float-adjusted market capitalization for each country. Therefore, the largest share of the index is represented by the US equity markets at 65.53%, followed by Japan, United Kingdom, France, and Switzerland at 7.96%, 4.41%, 3.41%, and 3.23% shares respectively. Hence, whilst the MSCI World Index is a representative index for the developed equity markets globally, nearly 85% of the index is computed based on the equity markets of these five countries alone. The distribution of representative countries for the MSCI World Index, is drawn in Figure 2. It is helpful to note that the representative equity markets for the MSCI World Index are primarily located in countries that have very different trading hours compared to the GCC, since researchers have argued that the time zone differences may also impact the connectedness of global equity markets, causing markets to be better integrated intra-regionally (Gębka and Serwa, 2007; Lyocsa et al, 2019).

Next, we utilize the six MSCI country-level equity indexes to construct market capitalization weighted regional GCC indexes that are constructed separately, for each of the six GCC countries. This is to avoid an individual country's index being included within its regional index resulting in autocorrelation. Hence, we construct separate regional indexes for each country, excluding the country for which, the index is constructed. Whilst doing so, it is important to note that the GCC stock markets vary greatly by market

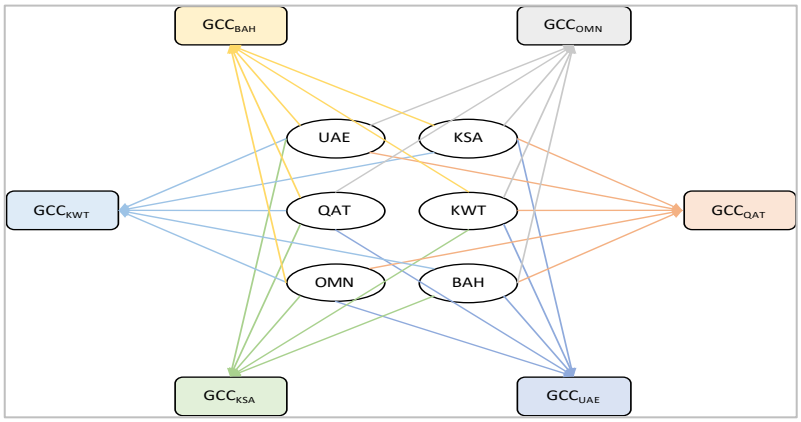
capitalization indicating significant differences in their market size. To account for these differences, regional indexes utilize weighted averages accounting for different market sizes. For example, the MSCI GCC Index is largely represented by the KSA's equity market due to its stock market being the largest regional market by market capitalization. Moreover, whilst the MSCI GCC Index exists, results from our connectedness study could be biased if this index were utilized due to autocorrelation. Hence, it is crucial to construct separate regional indexes in a manner outlined in Figure 2.

Figure 1. *MSCI Country Indexes for the GCC and the MSCI World Index.*



Note: These plots represent six country-level MSCI equity indexes, gathered for the six GCC countries, and the MSCI World Index, after indexing to set the base value of 100 for the first observation on 31st May 2005, for each series.

Figure 2. *Illustration of the GCC Regional Indexes for Each GCC Country*



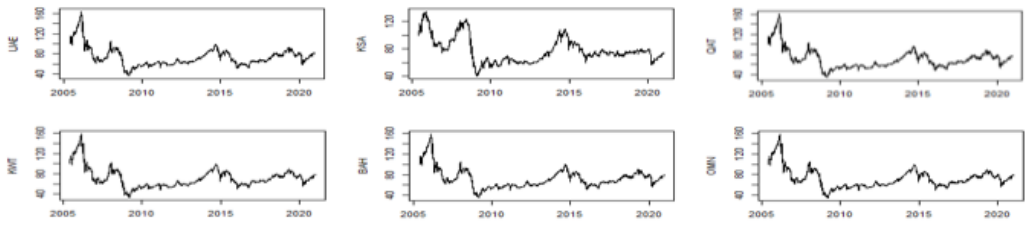
Note: This figure illustrates the use of five MSCI-country level indexes, in the construction of the GCC Regional Indexes for each of the six GCC countries. Hence, each regional index is constructed by taking the market capitalization weighted average for the other five GCC countries, to compute a regional index that excludes the country itself.

Our approach for the construction of regional indexes differs from other researchers such as Al Otaibi and Mishra (2015), who used the largest regional market as a proxy for the regional index, which in the case for the GCC is KSA. Such would prevent inclusion of the largest market, hence our approach effectively solves this issue. Therefore, to compute the regional index, we shall take the market capitalization weighted average of the "other five" countries for each of the six GCC countries. Weights would be attached based on market capitalization, to account for asymmetric market sizes within the region. Resultantly, we shall obtain six different regional indexes, for each country. The computation is based on the equation: $GCC\ Index_A = \sum_{i \neq A}^{6} \left(\frac{Market\ Cap_i}{(\sum_{i \neq A}^{6} Market\ Cap_i)} \times Country\ Index_i \right)$, where $GCC\ Index_A$ is the GCC Index

corresponding to country A. Once computed, the GCC regional indexes for each of the six countries, appear similar to each other, since each index includes a different set of five countries out of six, however, such an approach prevents us from the auto-correlation bias that would occur if the country being analyzed was also included in its regional index. The resultant indexes for each of the six GCC countries, are illustrated in Figure 3.

In order to extract the return on these indexes, we take the log deviation of each of the data series, to compute the daily rate of return for each of these indexes. This is done by simply computing $r_{it} = \ln(P_{it}) - \ln(P_{it-1})$, where P_{it} is the equity index for country or region i, at time t. The resultant daily equity return series for the MSCI country-level indexes are shown in Figure 4, alongside the resultant daily equity return series for the individual GCC equity indexes, as well as the MSCI World Index. Subsequently, the Dickey-Fuller Unit Root Test is applied on the return series, and stationarity is found, indicating that the return series are fit for time series analysis (Appendix A1). The descriptive statistics are provided in Table 1.

Figure 3. *GCC Indexes constructed for each individual GCC countries separately*



Note: The above plots represent GCC Indexes constructed separately for each country, using the market capitalization weighted average of the country-level equity indexes of all GCC countries, excluding the country for which the index is being generated (hence, representing all other regional equity markets, for each country).

Figure 4. *Log Deviations of Daily Country Level, Regional, and MSCI World Indexes*

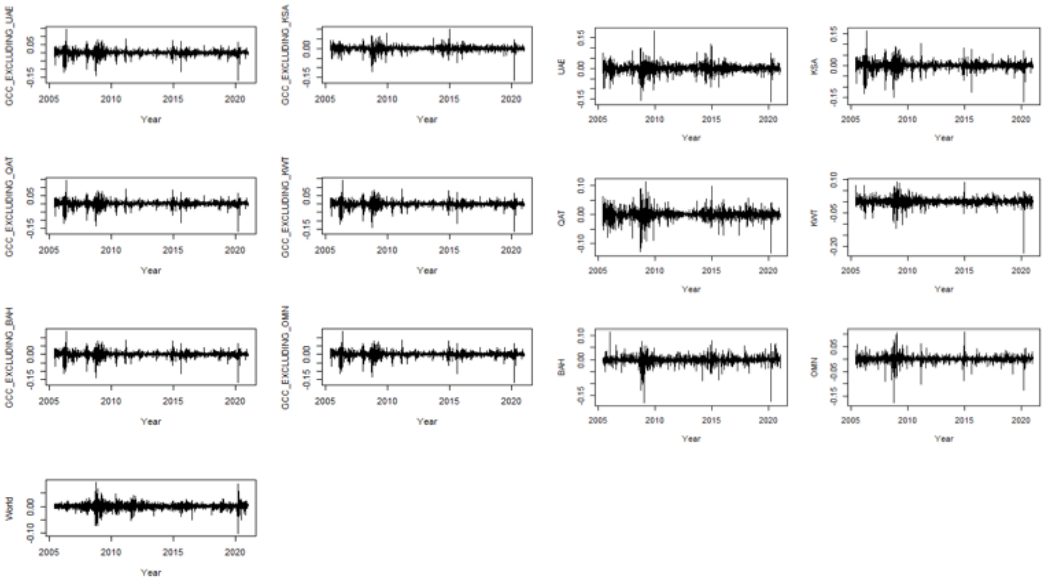


Table 1. *Descriptive Statistics for the GCC country-level and regional indexes, as well as the MSCI World Index.*

	MSCI KSA	MSCI UAE	MSCI QAT	MSCI KWT	MSCI BAH	MSCI OMN	
Mean	-0.0001	-0.0002	0.0000	0.0000	-0.0007	-0.0002	
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
Maximum	0.1623	0.1833	0.1127	0.0875	0.1150	0.1087	
Minimum	-0.1700	-0.1640	-0.1337	-0.2292	-0.1799	-0.1765	
Std. Dev.	0.0154	0.0168	0.0138	0.0130	0.0126	0.0114	
Skewness	-1.3961	-0.7324	-0.8609	-2.2499	-1.9637	-1.5842	
Kurtosis	20.5860	15.5296	14.9860	35.3967	31.0852	34.4132	
No. of Obs.	4,067	4,067	4,067	4,067	4,067	4,067	
	Regional Index KSA	**Regional Index UAE**	**Regional Index QAT**	**Regional Index KWT**	**Regional Index BAH**	**Regional Index OMN**	**MSCI WORLD**
Mean	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0003
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0007
Maximum	0.0999	0.1431	0.1433	0.1425	0.1368	0.1367	0.0910
Minimum	-0.1670	-0.1698	-0.1726	-0.1662	-0.1694	-0.1695	-0.1043
Std. Dev.	0.0114	0.0139	0.0140	0.0139	0.0135	0.0135	0.0106
Skewness	-1.8107	-1.6837	-1.6710	-1.6319	-1.7597	-1.7539	-0.7935
Kurtosis	25.5497	22.7738	22.4976	22.3104	23.3035	23.2423	13.4860
No. of Obs.	4,067	4,067	4,067	4,067	4,067	4,067	4,067

Note: The descriptive statistics are shown for each of the MSCI country-level indexes of each of the six GCC countries, as well as their market capitalization weighted regional equity indexes, and the MSCI World Index. The sample period ranges from 1st June 2005 until 31st December 2020.

4. Methodology

This research benefits from two different econometric methodologies that are applied to examine and compare the intra-regional and global spillovers for each of the six GCC countries. Each of these methods provide an opportunity to explore the intraregional connectedness of the regional equity markets and gain further insights. The first of these is proposed by Diebold and Yilmaz (2012), and the second is a Trivariate DCC-GARCH model proposed by Engle (2002). Both of these econometric methods allow us to explore the dynamic (time-varying) connectedness, whereby the tri-variate GARCH approach provides insights on the dynamic conditional correlations whilst the Diebold and Yilmaz (2012) approach provides further insights on the dynamic flow of spillovers as well as the net directional flow of these spillovers. These methods help us explore and compare between the magnitude of spillovers that the GCC equity markets receive from global markets versus other regional markets within the GCC. Both approaches are detailed in this section as follows.

5.1. The Diebold and Yilmaz (2012) Approach

Diebold and Yilmaz (2012) have used forecast error variance decompositions (FEVD) extracted from a Generalized Vector Autoregression (VAR) framework, introduced by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). We obtain these forecast errors from the VAR models, in order to segregate the time series shocks that are due to spillovers from other variables in the system of equations. This methodology is detailed as follows:

Consider a simple VAR Model, given in Matrix Form, where X_t is an (N x 1) vector of dependent variables. The lagged values of X_t are represented by vectors from X_{t-1} until X_{t-p}, ε_t is an (N x 1) vector of error terms, p is the chosen lag length and γ_t is the matrix of coefficients at every lag:

$$X_t = \gamma_1 X_{t-1} + \cdots + \gamma_p X_{t-p} + \varepsilon_t \tag{1}$$

In expanded matrix form, that would give:

$$\begin{bmatrix} X_{1t} \\ X_{2t} \\ \cdots \\ X_{Nt} \end{bmatrix} = \begin{bmatrix} \hat{\beta}_{1,1} & \cdots & \hat{\beta}_{1,N} \\ \cdots & \cdots & \cdots \\ \hat{\beta}_{N,1} & \cdots & \hat{\beta}_{N,N} \end{bmatrix}_1 \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \\ \cdots \\ X_{Nt-1} \end{bmatrix} + \cdots + \begin{bmatrix} \hat{\beta}_{1,1} & \cdots & \hat{\beta}_{1,N} \\ \cdots & \cdots & \cdots \\ \hat{\beta}_{N,1} & \cdots & \hat{\beta}_{N,N} \end{bmatrix}_p \begin{bmatrix} X_{1t-p} \\ X_{2t-p} \\ \cdots \\ X_{Nt-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \cdots \\ \varepsilon_{Nt} \end{bmatrix} \tag{2}$$

Next, consider a moving average representation for X_t that can be explained by observed values of the error terms:

$$X_t = \sum_{i}^{\infty} A_i \, \varepsilon_{t-i} \, ; \; i > 0 \tag{3}$$

The distribution of coefficient matrix A_i follows the recursion, such that $A_i = \gamma_1 A_{i-1} + \gamma_2 A_{i-2} + \cdots + \gamma_p A_{i-p}$. The moving averages component in the Generalized VAR framework, provides the coefficient matrices that can be used to extract forecast error variance decompositions, which are fundamental for the purpose of this study. An advantage of using the Generalized VAR framework to extract forecast error variance decompositions is that this framework is independent to the ordering of variables, unlike the previously applied Cholesky factorization (Diebold and Yilmaz, 2009). Finally, to compute the forecast variance decompositions, the forecast error variance $\varphi_{i,j}$ is estimated by choosing a specific forecast horizon H, whereby i represents the shock recipient and j represents the transmitter of shocks:

$$\varphi_{i,j}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h e_j)^2}{\sum_{h=0}^{H-1} (e_i' \, A_h \sum A_h' \, e_i)} \tag{4}$$

In the above equation, σ_{ii} is the standard deviation of the error term for the i^{th} equation, e_i is a binary selection operator, which takes the value of 1 for the i^{th} element, or 0 otherwise. Furthermore, the summation takes the aggregate of different layers of the coefficient matrix A_h based on the selected forecast horizon. This is the variance matrix for the error term, that was initially computed as a part of the Generalized VAR framework. Therefore, the numerator is a representative of the total squared forecast errors occurring from j to i for a selected forecast horizon. These are scaled by the standard deviation and the denominator, which represents the total squared forecast errors occurring to i. However, based on the construct of $\varphi_{i,j}$, the row sums are not normalized yet. Hence, an extra step is taken to normalize each of the row sums to be equal to 1, so the values for $\varphi_{i,j}$ can make further interpretative sense, as a percentage figure.

$$a\tilde{\varphi}_{i,j} = \frac{\varphi_{i,j}}{\sum_{j=1}^{N} \varphi_{i,j}} \tag{5}$$

These forecast error variance shares can explain the extent to which, the errors occurring to a particular variable are caused by spillovers received from other variables in the system of equations. For all possible combinations of i and j, it is possible to construct an $N \times N$ table, which is referred to, as the connectedness table. The non-diagonal elements of this table represent directional spillovers from j to i, whilst each of the diagonal elements represent shocks to an individual series, which are not explainable by spillovers from others, but are instead, a result of various idiosyncratic factors. Hence, for a study involving five time series variables, the $N \times N$ matrix would appear as follows:

$$\begin{bmatrix} \tilde{\varphi}_{1,1} & \cdots & \tilde{\varphi}_{1,5} \\ \vdots & \ddots & \vdots \\ \tilde{\varphi}_{5,1} & \cdots & \tilde{\varphi}_{5,5} \end{bmatrix} \tag{6}$$

Whereby the non-diagonal row and column sums provide the net spillovers from and to other variables, respectively. For further clarification, these terms are explained as follows:

$$Total\ spillovers\ from\ others\ for\ i^{th} variable = \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\varphi}_{i,j} \tag{7}$$

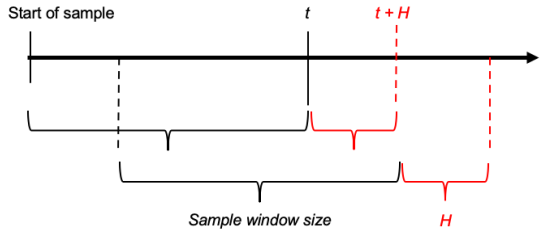
$$Total\ spillovers\ to\ others\ for\ j^{th} variable = \sum_{\substack{i=1 \\ i \neq j}}^{N} \tilde{\varphi}_{i,j} \tag{8}$$

These values can be multiplied by a hundred, for ease of interpretation in percentages. The net spillovers for a particular variable is the difference between the above two, which denotes whether a particular financial market is a net recipient or a net transmitter of shocks. Furthermore, the total spillovers index can be computed by taking the summation of all non-diagonal elements of the connectedness matrix and dividing it by the summation of all elements of the matrix including the diagonals. By the construct of $\tilde{\varphi}_{i,j}$, as each row sums up to 1, all elements of the matrix sum up to N. Therefore, the total spillovers index is denoted as follows:

$$S = \frac{\sum_{i,j=1}^{N} (\tilde{\varphi}_{i,j})}{N} \times 100 \tag{9}$$

The total spillover index is a dynamic concept that is expected to vary over time and be affected due to major global and regional events. Therefore, the spillover index could be estimated repeatedly for rolling samples of a specific sample window length to examine the dynamic connectedness over an extended time frame. These sample windows can also be seen as a number of overlapping subsets of the overall time series data with equal number of observations. The rolling window method can be illustrated in Figure 5.

Figure 5. An illustration of rolling sample analysis



Note: This figure illustrates the rolling window approach for the estimation of forecast-error variance decompositions using rolling sub-samples of length labeled "sample window size", which used to forecast a time horizon "H", whilst the next sub-sample is selected for the same length, after every time interval equal to "H".

The rolling sample method uses a specific sample window size, which in the above diagram could be denoted from the interval between the start of the sample until time " t ". This fixed interval is re-estimated with lags of " H ", which is the forecast horizon. For instance, data for an interval at time " t " is used to forecast for the following " H " number of stock market days. This is called an *H-step* ahead forecast, and is repeatedly estimated for equal sample window lengths, which are chosen at a specified lag " H ".

5.2. The DCC-GARCH Approach

The dynamic conditional correlation (DCC) GARCH models were introduced by Engle (2002), and have since, been widely adopted by researchers as a tool to measure time varying conditional correlations amongst stock market indexes. The DCC-GARCH model is a one of the many multivariate GARCH models, which are specified as follows:

$$r_t = \mu_t + \alpha_t \tag{10}$$

$$\alpha_t = {H_t}^{1/2} + \varepsilon_t \tag{11}$$

Where r_t is the vector of returns of N financial indexes at time t, μ_t is an $N \times 1$ vector of the expected value of the conditional r_t, whilst α_t is an $N \times 1$ vector of mean corrected return for r_t at time t; such that the expected value of α_t is zero and its conditional variance is defined by the $N \times N$ matrix H_t. Note that ${H_t}^{1/2}$ can be obtained by a Cholesky factorization of H_t. Lastly, ε_t is an $N \times 1$ vector of independent and identically distributed errors.

There are various classes of multivariate GARCH models that differ in their specification of the conditional covariance matrix H_t. For our research, we will apply the DCC-GARCH model due its ability to model time varying conditional correlations, which would allow us to explore the dynamic flow of volatility spillovers. It is helpful to note that DCC-GARCH is an extension of the Constant Conditional Correlation (CCC) GARCH model, which specifies H_t as follows:

$$H_t = D_t R D_t \tag{12}$$

Whereby, D_t is the conditional standard deviation, represented by the diagonal elements of H_t, such that $D_t = diag(h_{1t}^{\frac{1}{2}}, h_{2t}^{\frac{1}{2}}, \dots, h_{Nt}^{\frac{1}{2}})$, whilst $R = [\rho_{ij}]$ is the positive definite constant correlation matrix with diagonal elements equating to 1, such that $\rho_{ij} = 1$ for every $i = j$. This ensures that H_t is always a positive definite matrix and its off-diagonal elements are given as:

$$[H_t]_{ij} = h_{it}^{\frac{1}{2}} \times h_{jt}^{\frac{1}{2}} \times \rho_{ij}; i \neq j \tag{13}$$

Although the CCC-GARCH model is easier and relatively straight-forward to compute, due to its correlation matrix R, being constant, it can be restrictive for the same reason. Therefore, the DCC-GARCH model allows for a time varying correlation matrix R_t, whereby R_t must be positive definite for t, for H_t to also be positive definite throughout the entire time series. Hence, the DCC-GARCH model is specified as follows:

$$H_t = D_t R_t D_t \tag{14}$$

Where R_t represents the conditional correlations matrix of standardized disturbances ϵ_t in α_t, such that $\epsilon_t = {D_t}^{-1}\alpha_t$ which has a normal distribution of $N(0, R_t)$. Therefore, R_t is a symmetric matrix, that also assumes the value of 1, for its diagonal elements:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \cdots & \rho_{1N,t} \\ \rho_{12,t} & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \rho_{N-1,N,t} \\ \rho_{1N,t} & \cdots & \cdots & \rho_{N-1,N,t} & 1 \end{bmatrix} \tag{15}$$

Next, in order to ensure that R_t is a positive definite matrix that captures dynamic conditional correlations, R_t is defined by the DCC-GARCH model as a function of Q_t, which is the conditional covariance matrix of the standardized disturbances ϵ_t. Note that the conditional covariance matrix given below as Q_t, is time varying whilst the unconditional covariance matrix of ϵ_t given below as $\bar{Q}$, is constant over time.

$$R_t = diag\left({q_{11t}}^{1/2} \dots {q_{NNt}}^{1/2}\right) * Q_t * diag\left({q_{11t}}^{1/2} \dots {q_{NNt}}^{1/2}\right) \tag{16}$$

$$Q_t = (1 - a - b)\bar{Q} + a(\epsilon_{t-1} * {\epsilon^T}_{t-1}) + bQ_{t-1} \tag{17}$$

$$\bar{Q} = COV(\epsilon_t * {\epsilon^T}_t) = E(\epsilon_t * {\epsilon^T}_t) = \frac{\sum_{t=1}^{T}(\epsilon_t * {\epsilon^T}_t)}{T} \tag{18}$$

Note that introducing the diagonal matrix $diag\left({q_{11t}}^{1/2} \dots {q_{NNt}}^{1/2}\right)$ in R_t, provides a scaling effect that ensures that every element of R_t is either less than, or equal to 1. Furthermore, the scalar parameters a and b must be non-negative, whilst their sum must be less than 1, for the model to be stable. If a and b are both equal to zero, then by construction, we have $Q_t = \bar{Q}$, in which case, the CCC-GARCH model would be sufficient to estimate the correlation matrix H_t.

Whist the DCC-GARCH model is well suited for modeling volatilities, a detailed account of dynamic return connectedness can be provided using the Diebold and Yilmaz (2012) approach. Using both approaches would allow us to examine the average connectedness between equity indexes over the time frame of our study, and the time varying flow of return spillovers across these indexes.

5. Empirical Findings and Discussion

Our research findings presented in this section contribute to the wider literature on financial connectedness, and in particular, extend the works of two prior studies that compared the global and regional spillovers for the GCC. Saadi-Sedik and Williams (2011) compared the global and regional spillovers for the GCC applying GARCH models on a dataset that extends until the end of 2000s, hence excluding major crises events that occurred over the past decade, such as the Arab Spring of early 2010s, the oil price crash of mid 2010s and the COVID-19 outbreak. Our study uses a larger and comparatively recent dataset, applying multiple methodologies. Meanwhile, Alotaibi and Mishra, (2015) utilized the largest regional equity market of Saudi Arabia as the proxy to examine regional spillovers, hence omitting the analysis of global and regional spillovers for the Saudi equity market itself. Our study includes each market through constructing a separate regional index for each country, including Saudi Arabia. Lastly, both studies assume the US equity markets as a sole representative of the global equity market, ignoring any spillovers that may arise from other global markets. Our study uses a rather more inclusive index; the MSCI World Index as a proxy for global spillovers. Using two distinct econometric approaches, we conduct the analysis separately for each of the 6 GCC countries. Results and corresponding discussion for each approach are presented independently in this section.

5.1. Results from the Diebold and Yilmaz (2012) Approach

In this analysis of global and regional spillovers for the GCC equity markets, we conduct the dynamic connectedness study, separately for each of the six GCC countries. The resultant connectedness tables are illustrated as Appendix A2, and the inflow of intra-regional and extra-regional spillovers, along with the net connected (computed as the difference between the outflow and inflow of spillovers), are summarized in Table 2.

Table 2. *Regional and Extra-regional Inflow of Spillovers and Connectedness*

	Inflow of regional spillovers	Net regional connectedness	Inflow of extra-regional spillovers	Net extra-regional connectedness
UAE	16.79	-0.09	7.61	-3.50
Saudi Arabia	17.81	-0.22	4.71	-0.84
Qatar	13.39	-0.54	7.07	-4.94
Kuwait	10.07	-0.50	2.28	0.83
Bahrain	6.33	-0.72	2.11	-0.11
Oman	11.45	-0.36	5.11	-3.40

Notes: The above table indicates the inflows and net inflows of spillovers from regional markets and global or extra-regional markets for each of the GCC's country-level indexes. The results represent a static overview of the connectedness for the 2005 – 2020 time period. Values for the construction of the above table are drawn from the individual connectedness tables for each country, constructed based on the Diebold and Yilmaz (2012) approach.

For each of the GCC countries, the inflow of regional spillovers are greater than the inflow of spillovers from equity markets in developed economies. This compliments our findings from the tri-variate GARCH models presented in the previous section. Moreover, the net regional connectedness for each of the countries is computed by deducting the outflow of spillovers from the inflow of spillovers. Each of the GCC countries are net recipients of spillovers, however the net regional connectedness is at low levels overall, suggesting that whilst these countries are recipients of shocks from within the region, they are also transmitters of shocks to other countries within the region. The lowest of these net regional connectedness figures corresponds to that of the UAE, at -0.09%. Being significantly close to zero, we could infer that whilst nearly 16.79 percent of shocks to the UAE could be explained by shocks occurring to other GCC countries, 16.70 percent of shocks occurring to other GCC countries can also be explained by shocks occurring to the UAE's equity markets, hence nullifying the net effect. On the other hand, the net inflow of spillovers from global markets is significantly higher, perhaps due to the absence of strong reciprocities of spillovers transmitted from the GCC to the rest of the world. For instance, whilst the UAE may transmit minor spillovers to other countries, the inflow of spillovers are 3.50 percent higher than the outflow of spillovers.

Overall, the UAE, Saudi Arabia and Qatar are the largest recipients of shocks from global markets, although the magnitude of these spillovers are smaller, compared to inflow of shocks from within the region, or also compared to other studies on other emerging markets that apply a similar methodology. Moreover, the UAE equity markets are the largest recipient of spillovers from the global markets as 7.61% of the forecast error variances for the UAE could be explained by fluctuations in the global markets. These findings complement the claims of Wang and Wang (2010), who support the argument that equity markets in countries with higher trade openness are relatively highly integrated with global markets. Following the UAE, the equity market of Qatar was the second highest recipient of spillovers from global markets, with 7.07% of the forecast error variances for Qatar, being explained by fluctuations in the global markets. It is insightful to note that the exact same ranking is also observed for the proportion of expats residing in the GCC, with the UAE taking the first place at 89%, followed by Qatar at 86% (Shayah and Sun, 2019).

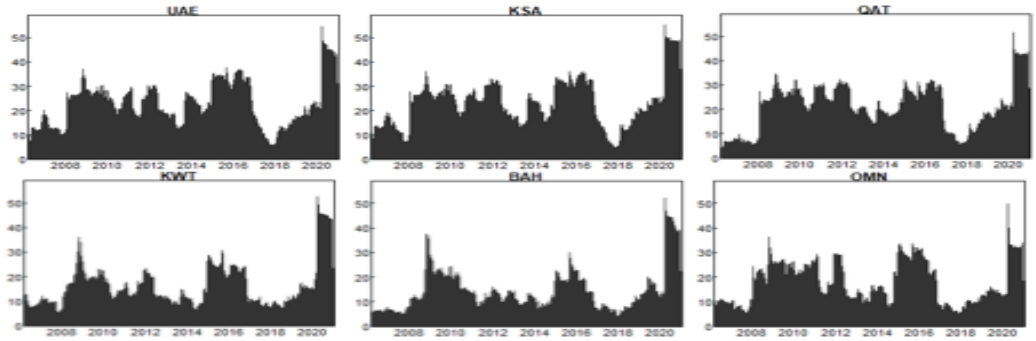
Interestingly, Bahrain received the least amount of spillovers from global markets at 2.11 percent, whilst it is also the largest net recipient of intra-regional shocks. Insightfully, it tells us a story. Since Bahrain is the smallest country within the region that forms an economic bloc, most of its trade occurs with Saudi Arabia; the largest country within the region and the only country it is geographically connected to, via land through a bridge. Much of the trade that occurs with global markets, also usually occurs via re-exports through other regional markets, especially Dammam, Saudi Arabia, and Dubai, United Arab Emirates. Hence, another hypothetical explanatory reason behind the low inflow of extra-regional spillovers to Bahrain, could be that these global spillovers may indirectly flow into Bahrain, getting accounted for, as regional spillovers. In either case, it makes intuitive sense that Bahrain may have higher net intra-regional spillovers and low extra-regional spillovers, compared to other GCC countries.

So far, we have evaluated the average connectedness throughout the entire time frame of our study. However, the connectedness levels can change over time. Hence, we also

examine the time varying connectedness using the rolling sample window approach, as elaborated in our methodology. The total dynamic connectedness plots (Figure 6), provide insights on the total level of connectedness across the three variables (domestic, regional and global indexes) for each of the six individual analyses. These plots reveal how the level of financial integration has varied over time. These can be interpreted as the proportion of forecast errors of the equity market returns that can be explained due to shocks occurring to other variables within the analysis. Subsequently, we can examine the specific net pairwise connectedness for the individual equity markets with the regional and global equity markets.

There are three major peaks across each of the total connectedness indexes for the six GCC countries, each representing one a global events; the global financial crisis of 2007-2008, the oil price crash of mid-2010s, and the global pandemic of 2020. These results complement the findings of other researchers including Diebold and Yilmaz (2015), who claimed that the connectedness of financial markets generally intensifies during crises events. Each connectedness index has peaked during the recent global pandemic, far beyond the previous crisis events, except for Oman. Ignoring a very slight peak of a few days, the impact of the global pandemic for Oman, is at levels comparable to the previous crises events. In addition to its low exposure to foreign markets compared to some of the other countries within the region, Oman also has a significantly low population density. Various studies have already shown a statistically significant and inverse correlation between population densities and the spread of COVID-19 (Kadi and Khelfaoui, 2020; Coşkun et al, 2020; Bray et al, 2020). This indicates more space and less crowdedness, which may have given Oman a comparative advantage in its fight against the virus. Unlike other crises events, the Qatar diplomatic crisis event showed a significantly noticeable decline in connected levels across all countries except for Kuwait and Oman. Although Kuwait and Oman also saw a decline in connectedness during this period, the magnitude of this decline was relatively lower. Intuitively, this would be expected since Kuwait and Oman were the only two GCC countries that did not participate in the blockade.

Figure 6. *Total Connectedness Plots*



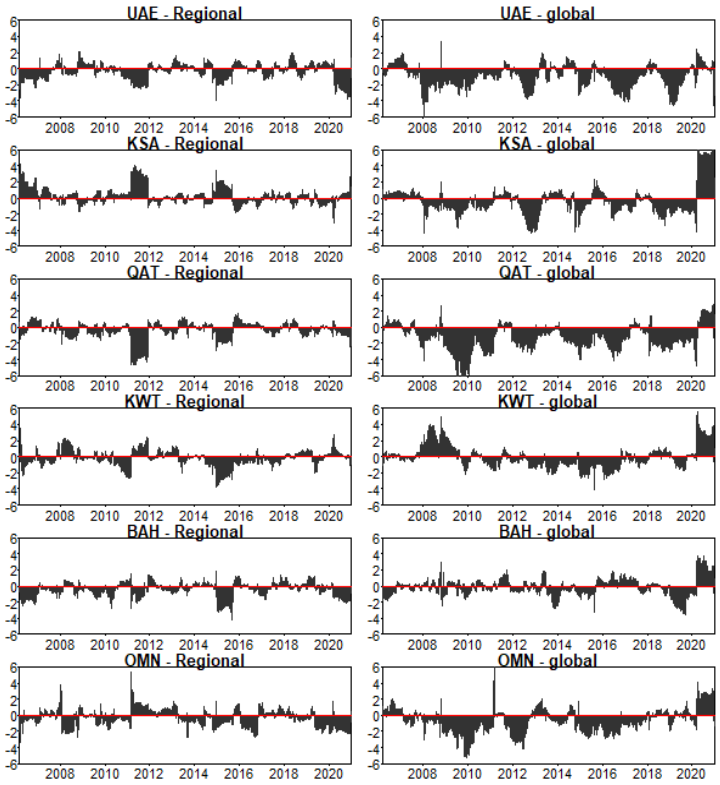
Note: The total connectedness plots represent the total dynamic connectedness for each GCC equity index, with their corresponding regional index and the MSCI World Index. The values could be interpreted as the total dynamic spillovers index, based on the Diebold and Yilmaz (2012) approach.

Overall, Saudi Arabia and the UAE exhibited the highest level of connectedness over the time frame, with an average total connectedness index of 18.99 percent and 18.28 percent,

respectively. On the other hand, Bahrain exhibited the lowest level of connectedness across all GCC countries, averaging at 9.21 percent, followed by Kuwait and Oman at 12.00 percent and 13.39 percent, respectively. In the study by Beirne et al (2010) that examined the inflow of global and regional spillovers for emerging markets including two countries from the GCC; Saudi Arabia and Kuwait, Saudi Arabia was the only one of the five Middle Eastern countries in the sample that received significant spillovers from global markets whilst the remaining Middle Eastern countries in their sample were more significantly influenced by regional spillovers. Whilst the UAE was not included in their study, it could also be expected for the UAE to top the chart for the total connectedness as Wang and Wang (2010) have argued that the higher connectedness could be associated with a greater degree of market openness, which is the highest for the UAE, amongst the GCC countries.

Whilst these total connectedness plots tell us about the general connectedness levels, without the global or regional distinction, we could obtain further insights from the net dynamic connectedness plots that our following discussion would be based on. The plots drawn in Figure 7, illustrate the time varying flow of net directional spillovers for between each country and the GCC regional index, as well as between each country and the MSCI World Index.

Figure 7. *Net Pairwise Connectedness Plots*



Note: The above plots represent the net dynamic pairwise connectedness for each GCC equity index, with their corresponding regional index (plots on the left) and the MSCI World Index (plots on the right). The amounts are computed based on the Diebold and Yilmaz (2012) approach, and could be interpreted in percentage terms. Values above zero, represent net transmission of shocks, and vice versa.

The net spillovers between most GCC countries and their respective regional indexes, represented by the plots on the left-hand side of Figure 7, appear to be closer to zero, compared to the net spillover plots for global markets on the right-hand side. This is even though the total inflow of spillovers from within the region, are higher, as shown from the connectedness tables. Perhaps, this could be explained by the bidirectional nature of spillovers within the region, in contrast to the predominantly unidirectional flow of spillovers from the global markets. During the aftermath of the global financial crisis of 2007-2008 and the Arab spring of early 2010s, Saudi Arabian equity markets take the role of net transmitter of spillovers, whilst the UAE and Qatar predominantly become the net recipients of shocks. The UAE and Qatar are both international markets that have significantly high proportions of foreign residents and foreign investment, not only compared to the rest of the GCC, but also in comparison with the rest of the world. Therefore, it makes intuitive sense that during times of political instability within the region, equity markets of these two countries may become more susceptible to spillovers from other markets. Furthermore, it also appears to be the case for the global inflow of spillovers that Qatar is the largest proportional net recipient of spillovers from global markets, followed by the UAE.

The net inflow of spillovers from global markets to the UAE, Qatar and Oman, were most prominent during the aftermath of the global financial crisis of 2007-2008, followed by the Arab spring of early 2010s and the oil price crash of mid-2010s. However, towards the end of the net global spillover plots for most of the GCC countries, there was an unexpected hike where the GCC appears to be a net transmitter of shocks to global markets, which is highly unlikely due to the relative market sizes. An alternative explanation for these hikes could be a common factor that raised the connectedness overall, which in this case was the COVID-19 outbreak. Since the COVID-19 outbreak had affected the Middle East earlier than the United States, the GCC equity markets could have captured this effect in the net-pairwise spillover plots. Here, it is helpful to note that the US Equity markets constitute of a significantly large proportion; 66.45% of the MSCI World Index and its COVID-19 infection rates for the year 2020, only peaked by mid-December, whilst the 2020 infection rates for Saudi Arabia, the largest GCC country by population, peaked 6 months earlier during mid-June. Therefore, the chronological order of the COVID-19 contagion across countries could explain the net-pairwise spillover plots for the year 2020.

5.2. Results from the Trivariate DCC-GARCH Models

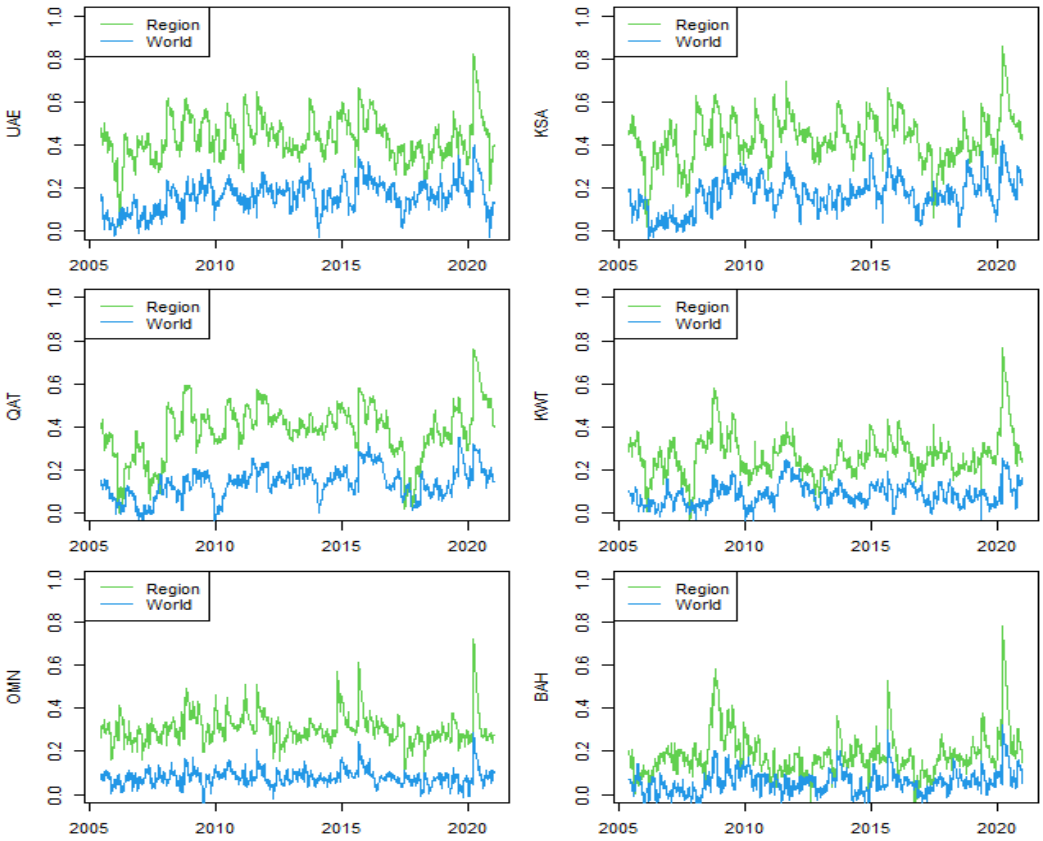
In the previous section, we explored the flow of spillovers for the GCC countries using the Diebold and Yilmaz (2012) approach. In this section, we can examine if our results from applying the tri-variate DCC-GARCH Models complement these findings. Each tri-variate DCC-GARCH analysis illustrates the regional and global intertemporal flow of dynamic conditional correlations, as demonstrated in Figure 10.

Several inferences could be made based on our outcomes of the tri-variate DCC GARCH models, presented in Figure 10. A general observation is that each country exhibits significantly higher intra-regional spillovers in contrast to spillovers from the global equity markets. This could potentially be due to the salient features of the GCC region, that not only functions as an economic bloc, but also shares common cultures, policy implications and geopolitical features. Furthermore, the GCC countries react differently to oil price

shocks, compared to most developed markets that use oil as inputs. Therefore, whilst it is expected that the countries within the GCC might be highly integrated within the region, the connectedness levels of these equity markets with the MSCI World Index may not be as high as the intra-regional connectedness.

Another observation made from our results is that the dynamic conditional correlations intensify during crises events. This compliments prior research by Yousuf and Zhai (2022), suggesting that regional equity markets become increasingly connectedness during times of uncertainty as they lack a strong sense of direction and look towards one another more so, than they otherwise would. This was most obvious for the global pandemic of 2020, the oil price crash of mid-2010s and the global financial crisis of 2007-2008. However, the global financial crisis of 2007-2008 did not have a prominent impact on the dynamic conditional correlations of Oman, possibly due to its relatively lower level of exposure to the equity markets in developed economies that represent the MSCI World Index.

Figure 10. *Dynamic Conditional Correlations with Regional and Global Markets*



Note: The above time-series plots illustrate the dynamic conditional correlations based on the multi-variate DCC-GARCH models, computed for each individual GCC country. The regional time-series (in green), represents the dynamic conditional correlations for the given country's equity market with the equity markets of other GCC countries, whilst the "world" time-series (in blue), represents the dynamic conditional correlations for the given country, with the MSCI World Index.

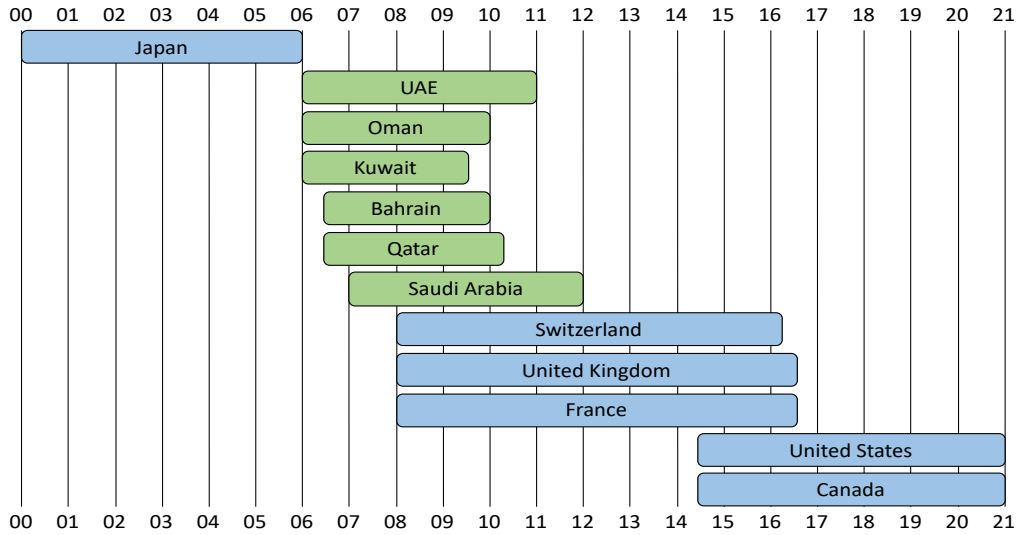
Impact of the COVID-19 outbreak had the highest effect on connectedness of GCC countries as the dynamic conditional correlations peaked for both global and regional equity markets. However, this impact was much stronger for the intra-regional spillovers as the dynamic conditional correlations reached an all-time high at values near 80% for all countries. On the other hand, the Qatar diplomatic crisis of 2017 had an inverse impact on the financial connectedness levels of GCC countries, especially for Qatar itself. This was the first time in a decade for Qatar that their dynamic spillovers from within the region plummeted to values near zero and dropped below the amount of dynamic spillovers from equity markets of developed economies from outside the region.

Interestingly, the two smallest equity markets within the region; Bahrain and Oman, exhibit the lowest levels of integration with the rest of the world. This contradicts the assumptions made by Wang and Wang (2010) that the high connectedness effect of emerging markets with the developed markets could be due to their small relative size. Our results show that in general, the GCC countries have stronger dynamic conditional correlations within the region, than external to the region. These overall results complement the findings of Saadi-Sedik and Williams (2011), and Alotaibi and Mishra (2015), who have found that the GCC equity markets are influenced by both regional and global spillovers. More specifically, our results support the claims of Beirne et al (2010) and Alotaibi and Mishra (2015), where they have argued that the inflow of spillovers from within the region, may be stronger than the inflow of spillovers from global markets external to the GCC. Additionally, our results also reveal that whilst the dynamic conditional correlations do not exhibit any strong patterns of growth for spillovers within the region, integration with global markets external to the region have trended upwards for the UAE, Saudi Arabia, and Qatar. Nonetheless, the spillovers from within the region remain high and above the spillovers from the MSCI World Index.

Our results complement the findings of Gębka and Serwa (2007) and Lyocsa et al (2019), who also argue that the intra-regional spillovers could be significantly stronger, whilst explaining that the time zone differences could account for the higher intra-regional connectedness amongst equity markets within the same region. Gębka and Serwa (2007) examined the case for equity markets across 12 emerging economies and claimed that whilst the equity markets of emerging economies can be correlated due to their common reaction to the developed equity markets, they are also likely to be strongly intra-regional connected due to common trading hours, in addition to having similar economic conditions and policies. To compare the trading hours of the GCC countries with the global markets, we first extract the trading hours of equity markets for each of the six countries and for the top six constituent countries that represent the MSCI World Index. Next, we convert each of their working hours into Greenwich Mean Time (GMT) for ease of comparison, as shown in Figure 10. Reviewing the trading hours on a common plot shows the discrepancies as pointed out by Gębka and Serwa (2007) for other emerging markets. The GCC countries not only share common economic structures and policies, but also operate during largely overlapping trading hours, as opposed to the markets represented by the MSCI World Index. Hence, our findings complement the claims of Gębka and Serwa (2007) and Lyocsa et al (2019), who argue that equity markets with largely overlapping

trading hours are also likely to be significantly interconnectedness, since the spillovers are expected to be higher for markets that operate during common trading hours.

Figure 10. *GCC Trading Hours versus the top six constituents of the MSCI World Index*



Note: All times are represented in GMT; the GCC countries are represented in green, whilst the top six constituents of the MSCI World Index are represented in blue; the trading hours for each country, are gathered from https://www.tradinghours.com/markets.

6. Conclusion

We have explored the interconnectedness for each of the GCC countries, against their respective GCC regional indexes and the MSCI World Index. Doing so, we implement tri-variate DCC-GARCH models and the Diebold and Yilmaz (2012) approach, both of which, are two of the most popular methods adapted by researchers to conduct similar studies. Our results from both methods, reveal that the GCC equity markets to varying degrees, are affected by shocks from both regional and global markets. Furthermore, the amount of spillovers from regional markets are higher than the extra-regional spillovers, perhaps due to the distinguishing features of the GCC countries that they share. Therefore, the GCC markets continue to provide diversification opportunities to international investors and portfolio managers. However, exploring individual countries and sectors within the GCC would be essential, since despite common trends, there are several idiosyncrasies that also prevail. For instance, whilst the equity markets of Bahrain have the lowest extra-regional inflow of spillovers compared to the other GCC countries, Bahrain is also the highest net recipient of regional shocks. Meanwhile, the UAE and Qatar are the two largest net recipients of shocks from the global markets, which makes intuitive sense, due to their exposure to foreign markets and high international trade openness levels.

As countries became more and more isolated due to the recent outbreak of the COVID-19, their financial markets have become more connected than they have ever been in over a

decade. Both stock market returns and volatilities of the GCC countries closely follow each other during crises events more than they would otherwise normally do so. Our results complement Charfeddine and Al Refai (2019) and Yousuf and Zhai (2022) regarding the intensification of spillovers during significant global and regional events, including the inverse effect of the Qatar Diplomatic crisis. Interestingly, all countries except for Oman, show that the impact of the recent global pandemic was significantly higher than any of the previous crisis events over the entire time frame of our study. As for Oman, low population densities and low exposure to global markets compared to most of the other GCC countries, could've have acted as a semi-shield against a larger contagion. Overall, the total connectedness index has exhibited an upward trend over the past few years. With the continuously increasing levels of financial integration, entirely avoiding a contagion corresponding to a financial crisis may no longer be an option. Nonetheless, examining the directional flow of spillovers will help foresee the transmission of spillovers if an exogenous shock occurs to a specific equity market or region.

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Appendixes

A1. Unit Root Testing.

	t-Stat values for variables used in the daily dataset			
	Observations = 4,066	**Observations = 4,065**	**Observations = 4,066**	**Observations = 4,065**
	no constant, no lag	**no constant, with lag**	**with constant, no lag**	**with constant, with lag**
UAE	-59.031	-41.039	-59.03	-41.04
KSA	-62.072	-43.325	-62.066	-43.321
QAT	-60.434	-42.343	-60.427	-42.338
KWT	-61.704	-42.995	-61.697	-42.989
BAH	-61.662	-42.953	-61.832	-43.127
OMN	-58.485	-41.226	-58.492	-41.234
GCC_EXCL_UAE	-61.588	-42.825	-61.581	-42.821
GCC_EXCL_KSA	-58.991	-39.885	-58.986	-39.883
GCC_EXCL_QAT	-61.526	-42.822	-61.52	-42.818
GCC_EXCL_KWT	-61.184	-42.536	-61.178	-42.533
GCC_EXCL_BAH	-61.163	-42.465	-61.156	-42.461
GCC_EXCL_OMN	-61.181	-42.482	-61.175	-42.479
WORLD	-60.178	-43.421	-60.212	-43.459
	Critical Values for Dickey-Fuller t-Dist			
	1%	5%	10%	
No constant	-2.58	-1.95	-1.62	
With constant	-3.43	-2.86	-2.57	

A2. Tables for Global and Intra-regional Connectedness.

The following results illustrate six connectedness tables representing the global and intra-regional connectedness for the six MSCI country-level indexes of the GCC countries.

		UAE	GCC	WORLD	FROM OTHERS
UAE	UAE	75.59	16.79	7.61	24.41
	GCC	16.7	77.98	5.32	22.02
	WORLD	4.11	4.31	91.58	8.42
	TO OTHERS	20.82	21.10	12.93	TCI
	NET DIRECTIONAL	-3.59	-0.92	4.51	18.28
KSA	KSA	77.48	17.81	4.71	22.52
	GCC	17.59	73.86	8.55	26.14
	WORLD	3.87	4.44	91.69	8.31
	TO OTHERS	21.46	22.25	13.26	TCI
	NET DIRECTIONAL	-1.06	-3.89	4.95	18.99
QAT	QAT	79.54	13.39	7.07	20.46
	GCC	12.85	81.30	5.85	18.70
	WORLD	2.13	4.59	93.28	6.72
	TO OTHERS	14.98	17.99	12.92	TCI
	NET DIRECTIONAL	-5.48	-0.72	6.2	15.30
KWT	KWT	87.65	10.07	2.28	12.35
	GCC	9.57	83.95	6.48	16.05
	WORLD	3.11	4.48	92.41	7.59
	TO OTHERS	12.68	14.55	8.76	TCI
	NET DIRECTIONAL	0.34	-1.51	1.17	12.00
OMN	OMN	83.44	11.45	5.11	16.56
	GCC	11.09	82.66	6.24	17.34
	WORLD	1.71	4.55	93.74	6.26
	TO OTHERS	12.80	16.00	11.36	TCI
	NET DIRECTIONAL	-3.76	-1.34	5.10	13.39
BAH	BAH	91.56	6.33	2.11	8.44
	GCC	5.61	87.53	6.86	12.47
	WORLD	2.00	4.72	93.28	6.72
	TO OTHERS	7.61	11.05	8.96	TCI
	NET DIRECTIONAL	-0.83	-1.41	2.25	9.21