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Risk spillover from crude oil prices to GCC stock market returns: New evidence during the COVID-19 outbreak

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ABSTRACT

In this study, we examine oil price extreme tail risk spillover to individual Gulf Cooperation Council (GCC) stock markets and quantify this spillover’s shift before and during the COVID-19 pandemic. A dynamic conditional correlation generalized autoregressive heteroscedastic (DCC-GARCH) model is employed to estimate three important measures of tail dependence risk: conditional value at risk (CoVaR), delta CoVaR (ΔCoVaR), and marginal expected shortfall (MES). Using daily data from January 2017 until May 2020, results point to significant systemic oil risk spillover in all GCC stock markets. In particular, the effect of oil price systemic risk on GCC stock market returns was significantly larger during COVID-19 than before the pandemic. Upon splitting COVID-19 into two phases based on severity, we identify Saudi Arabia as the only GCC market to have experienced significantly higher exposure to oil risk in Phase 1. Although all GCC stock markets received greater oil systemic risk spillover in Phase 2 of COVID-19, Saudi Arabia and the United Arab Emirates appeared more vulnerable to oil extreme risk than other countries. Our empirical findings reveal that investors should carefully consider the extreme oil risk effects on GCC stock markets when designing optimal portfolio strategies, minimizing portfolio risk, and adopting dynamic diversification process. Policymakers and regulators should also enact awareness, oversight, and action plans to minimize adverse oil risk effects.

1. Introduction

Crude oil is one of the most important commodities in nearly all world economies (Li & Wei, 2018). Gulf Cooperation Council (GCC) countries are classified as major oil suppliers for the global economy and possess roughly half of the world’s oil reserves (Mokni & Youssef, 2019). Therefore, oil prices have been proposed as a key global factor influencing GCC stock markets; the cash flow generated by oil greatly enhances business value, government budgets, and aggregate demand. Examining dynamic spillover between oil prices and these stock markets is thus crucial for portfolio diversification, risk management, and energy policymakers (Awartani & Maghyereh, 2013).

As oil-dependent economies, GCC countries have been exposed to a higher level of uncertainty during the last decade. The 2008–09 global financial crisis, the Arab Spring in 2011, the 2014–16 oil crisis, and other geopolitical risks that have arisen since 2015 are only a few examples. A large body of recent literature has shown that these events influence oil price volatility and impose additional risk

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1 Gulf Cooperation Council countries consist of Saudi Arabia, the United Arab Emirates, Kuwait, Qatar, Oman, and Bahrain.

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upon GCC stock markets (e.g., Awartani and Maghyereh, 2013; Mokni & Yousef, 2019; Alqahtani et al., 2019).

A novel coronavirus (COVID-19) was identified on December 31, 2019 in Wuhan, China and has since spread globally. The outbreak’s scale and trajectory led the World Health Organization to declare COVID-19 a global emergency on February 20, 2020 and to label it a pandemic nearly 2 weeks later, on March 11 (Ali et al., 2020). Apart from being a global public health concern, COVID-19 triggered a deep economic downturn worldwide; global gross domestic product growth is expected to decline by one-half a percentage point in 2020 (from 2.9% to 2.4%) (Gupta et al., 2020). The pandemic also evoked an unprecedented spike in uncertainty, lowered securities valuation, and brought the financial markets to their lowest levels since the 2008–09 global financial crisis (Salisu et al., 2020; Zhang et al., 2020). Additionally, COVID-19 has been responsible for the third major crash in oil prices over the last 13 years, following the global financial crisis and the oil price collapse in 2014–16 (Smear, 2020).

Two months after COVID-19 emerged in China, oil prices plummeted by 30%—the largest drop in oil prices since the Gulf War (Salisu et al., 2020). This collapse in oil prices refers mainly to the breakdown of negotiations between the Organization of Petroleum Exporting Countries (OPEC) and Russia regarding falling oil demand in early March 2020. In April 2020, OPEC and Russia reached a deal to cut oil production by approximately 9.7 million barrels a day in May and June. However, this deal may still be insufficient to meet the shortfall in oil demand (Arezki et al., 2020; Reuters, 2020). Declining oil prices have exacerbated the consequences of COVID-19 and brought severe negative shocks to GCC economies (World Bank Group, 2021): the region’s GDP is expected to contract by 4% in 2020. A sharp reduction in oil output, coupled with exceedingly low oil prices, has placed pressure on budget revenues and restricted governments’ ability to support activities and demand in key non-oil industries (Oxford Economics, 2020).

In addition to serving as a source of systemic risk (Sharif et al., 2020), the unique nature of the pandemic’s dual health and economic crises provides a unique research setting (Gupta et al., 2021) to examine the financial effects of COVID-19’s spread. Thus far, scholars have focused on the oil–stock nexus and substantiated risk spillover from global oil prices to worldwide stock markets. Such spillover tends to be more pronounced in the aftermath of economic, financial, and political crises (e.g., Bouri, 2015; Junttila et al., 2018; Liu et al., 2020; Sarwar et al., 2020; Balcilar et al., 2020). Whereas a small but growing body of work has considered the effects of the pandemic on financial markets, the impacts of COVID-19 on the dynamic association between oil prices and financial markets remain unclear (see Sakurai and Kurosaki, 2020; Salisu et al., 2020; Sharif et al., 2020; Wang et al., 2020).

Although recent studies have assessed extreme tail (systemic) risk spillover from oil prices to stock markets and explored the effects of different crises on this relationship (see Reboredo, 2015; Yu et al., 2018; Ji et al., 2020; Tiwari et al., 2020), researchers have paid little attention to the contribution of oil systemic risk to emerging markets under diverse market conditions and investment horizons (Li & Wei, 2018). So far, to the best of our knowledge, no such studies have considered the effect of the COVID-19 pandemic on co-movements between oil price systemic risk and GCC stock market returns. Thus, in this paper, we attempt to contribute to the literature by investigating oil price extreme tail risk spillover to GCC stock markets and quantifying this spillover’s shift before and during COVID-19.

Identifying how extreme oil risk spillover enhances the volatility of GCC stock markets is crucial for investors. In the case of oil and GCC stock markets’ structural dependence, investors must revise their investment strategies when oil prices move toward downside risk during COVID-19. Additionally, measuring extreme joint movements in GCC markets is essential to devising optimal portfolio strategies when investors have a utility function with minimized tail risk, in which case minimizing portfolio risk is critical. Importantly, in the wake of the COVID-19 pandemic, investors should consider the dynamic portfolio diversification process, where a potential jump in systemic risk is likely to change optimal portfolio weights (see Low et al., 2013; Reboredo, 2015).

In this study, Engle’s (2002) dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model is used to measure oil systemic risk spillover to GCC stock returns. Further, we measured downside risk spillover from crude oil prices to GCC stock markets before and after the COVID-19 period by applying two relatively new approaches: conditional value at risk (CoVaR) and delta CoVaR (ΔCoVaR). CoVaR, developed by Girardi and Ergün (2013) and Adrian and Brunnermeier (2016), can capture downside risk transmission by providing the VaR value for each GCC stock market conditional VaR of the oil market (see Li and Wei, 2018). ΔCoVaR measures the VaR for the stock market when the oil market experiences financial distress. For robustness and in line with Benoit et al. (2013), we took Acharya et al.’s (2012) concept of marginal expected shortfall (MES) as an alternative measure of systemic risk. MES assesses the short-run expected loss in daily GCC equity loss when the oil market truncates below a certain level to the unconditional oil market’s daily VaR (see Tiwari et al., 2020).

Our empirical analysis was conducted based on daily West Texas Intermediate (WTI) oil prices and GCC stock market indices (i.e., Saudi Arabia, the United Arab Emirates [UAE], Kuwait, Qatar, Oman, and Bahrain) covering the period from January 2017 to May 2020. We also considered this effect over two phases of COVID-19. Based on the three systemic risk measures (i.e., CoVaR, ΔCoVaR, and MES), throughout the study period, we found significant extreme tail risk spillover from oil prices to all GCC stock market returns. Further, GCC markets appeared to exhibit greater downside risk dependence with the oil market during COVID-19 than before the pandemic. Specifically, during Phase 1 of COVID-19, Saudi Arabia seemed to be the only significant oil systemic risk receiver given that it holds the largest stock market in the region and is the largest oil-exporting country in the world. In Phase 2, all GCC countries demonstrated a significant shift in systemic risk spillover effects from crude oil prices, with Saudi Arabia and the UAE receiving more extreme risk spillover than other countries.

The remainder of this paper is organized as follows. Section 2 presents a review of relevant literature. Section 3 describes our dataset, and our methodology is presented in Section 4. Section 5 reports and discusses the empirical results. Section 6 concludes the paper.
2. Review of relevant literature

The effects of oil prices on oil-exporting countries’ stock markets have been extensively investigated. Most studies have revealed that crude oil prices exert significant impacts and spillover on stock price returns (e.g., Mohammadi & Su, 2010; Filis et al., 2011; Guesmi, 2014; Boldanov et al., 2016; Yang et al., 2017; Khalfaoui et al., 2019; Mokni, 2020; Jiang & Yoon, 2020). Stock markets’ correlation with oil prices is well documented among GCC oil-dependent countries, with empirical studies showing dynamic return/volatility co-movements between oil and GCC stock markets (e.g., Arouri et al., 2011; Aloui et al., 2012; Aloui &d Hkiri, 2014; Jouini & Harrathi, 2014; Martin-Barragan et al., 2015; Maghyereh et al., 2017; Fenech & Vosgha, 2019; Alqahtani et al., 2019; Al-Yahyaeec et al., 2019; Mokni & Youssef, 2019).

Although a substantial volume of empirical literature has been devoted to investigating the oil–nexus for different equity markets around the world, systemic risk spillover from the crude oil market to the stock market has not been studied extensively; scholars only recently began to assess the nature of this spillover. Reboredo (2015) evaluated systemic risk and dependence between oil and renewable energy markets using CoVaR as a measure of systemic risk and uncovered significant time-varying average and symmetric tail dependence between oil returns and several global and sectoral renewable energy indices. Mensi et al. (2017) examined the dependence structure between crude oil prices and major regional developed stock markets (i.e., the S&P 500, Stoxx600, DJPI, and TSX indices). Using numerous measures of extreme risk (e.g., VaR, CoVaR, and ΔCoVaR), the authors found tail dependence between oil and all stock markets for the raw return series.

Li and Wei (2018) investigated the dependence structure between the crude oil market and China’s stock market over different investment horizons. Various measures of systemic risk indicated that, first, the recent financial crisis enhanced dependence between the crude oil market and China’s stock market. Second, the VaR of China’s stock market increased considerably around the financial crisis, but the average post-crisis VaR declined compared to the risk before the crisis. Third, risk spillover from crude oil prices to the Chinese stock market manifested in each sample period. Shahzad et al. (2018) assessed the dependence structure between oil systemic risk spillover and five Islamic stock markets (the Islamic Market World index; Islamic indices in the United States, United Kingdom, and Japan; and the Islamic Financials sector index). Results uncovered systemic risk spillover from oil to Islamic stock markets and vice versa, and such spillover significantly increased after the global financial crisis. In another study, Ji et al. (2018) identified significant risk spillover from energy to agriculture commodities using VaR and ΔCoVaR.

Yu et al. (2018) explored the contribution of crude oil risk to industry-level returns in the U.S. stock market using the ADCC-ΔCoVaR model. Their empirical results showed that oil contributed the greatest risk to the energy industry and the lowest risk to consumer staples. Moreover, the contribution of crude oil risk was frequently larger across these industries during the 2008 crisis. Tiwari et al. (2019) considered the dependence structure and systemic risk between oil prices and BRICS equity market indices using nonparametric conditional VaR causality (NCoVaR). Their NCoVaR analysis demonstrated a robust instantaneous dependence in both directions between almost all BRICS stock markets and the oil market.

Furthermore, Tiwari et al. (2020) investigated systemic risk and dependence between the oil and stock market indices of G7 economies using ΔCoVaR and MES to capture the risk spillover effects and provide evidence of systemic risk. Their findings indicated that oil price systemic risk contributed significantly more to G7 stock market returns during volatile times compared with stable times. Ji et al. (2020) evaluated risk spillover between BRICS stock returns and different types of oil shocks, combining the structural VaR model and time-varying copula-GARCH-based CoVaR approach. Findings showed that the shape of each country’s CoVaR differed depending on its unique market situation and domestic policies. Additionally, significant risk spillover was identified from oil-specific demand shock to stock returns in all BRICS countries.

Along a similar research line, Yang et al. (2021) considered risk spillover between China’s crude oil futures and international crude oil futures by constructing VaR connectedness networks. They discovered that the risk spillover between Chinese and international crude oil futures possessed clear time-varying characteristics and has risen sharply since the beginning of 2020, intensifying during the COVID-19 pandemic. Sun et al. (2020) employed a GARCH-Copula-CoVaR approach to address the debate over extreme risk spillover from the commodity market to the maritime market. Results provided new evidence of systemic risk transmission from the oil and ex-energy sectors to maritime markets. In addition, risk spillover in oil–freight index pairs varied after the global financial crisis compared with before. Meng et al. (2020) examined the impact of global crude oil price fluctuations on China’s commodity sectors. Using the time-varying copula-conditional value at risk (CoVaR) method, the authors found risk spillover effects from global crude oil price systemic risk on China’s commodity sectors. Uddin et al. (2020) assessed risk spillover under extreme market scenarios between the U.S. stock market and precious metals (i.e., gold, silver, and platinum) and oil using copula approach for tail dependence and CoVaR spillover measures. Results revealed that gold and oil co-moved symmetrically with the U.S. stock market under normal and extreme market scenarios.

Our study extends related literature given our aim to investigate oil systemic risk spillover effects and to examine the dependence
structure between oil and GCC stock markets during stable and uncertain periods. The consequences of the onset of the COVID-19 pandemic on risk spillover are also considered in this analysis. Moreover, we go beyond the common oil–stock nexus by investigating extreme risk spillover using three key measures of systemic risk: CoVaR, ΔCoVaR, and MES.

3. Data and descriptive analysis

In this study, our main concern is to examine the immediate (short) effect of COVID-19 outbreak and oil prices collapse on the dynamic systemic risk spillover from crude oil to GCC stock markets. Therefore, our selected COVID-19 outbreak period ranges from January 2, 2020 to May 28, 2020. Capturing data over this period thus facilitates a robust analysis into the reaction of stock markets as growth in the virus began, surged and peaked (O’Donnell et al. 2021). After this period, many governments around the world announced unprecedented economic rescue packages to mitigate the negative economic impact of COVID-19 on financial markets. Daily data were used to capture short-term dynamic risk spillover, which would otherwise appear weak on a longer time horizon (Kim et al., 2005). Daily-frequency data have been deemed more suitable when evaluating volatility spillover and have often been adopted in similar studies (Maghyereh et al., 2017; Yu et al., 2018; Salisu et al., 2020). For our purposes, oil (stock) returns are defined as the difference in the logarithms of two consecutive prices of a given price index as follows: \( r_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \times 100 \).

The study data covered the period of the COVID-19 pandemic, which began on December 31, 2019. This time frame enabled us to examine how systemic oil risk spillover has shifted as a result of this crisis. Following Sadorisky (2012) and Tsuji (2018), we used WTI crude oil futures prices, expressed in USD per barrel, as a benchmark of oil prices. WTI oil futures constitute the most widely traded oil contract, and corresponding prices typically serve as a reference for oil market and commodity portfolio management. Our sample included stock price indices for GCC member countries, namely Saudi Arabia, the UAE, Kuwait, Qatar, Oman, and Bahrain. All indices were collected from the Refinitiv Reuters database and expressed in USD.

Based on news reports from leading financial outlets (e.g., Wall Street Journal and Financial Times) and recent COVID-19 studies (e.g., Akhtaruzzaman et al., 2020; Salisu et al., 2020), the first case of COVID-19 was declared in China on December 31, 2019. The virus was considered an epidemic with normal levels of apparent risk until February 19, 2020. Similar to previous flu outbreaks, COVID-19 had a relatively small impact on global financial markets at the start of the pandemic, as people were not very concerned about the virus (Kinateder et al. 2021). The next day, COVID-19 was named a worldwide threat. Investors’ anxiety led to downward trends in oil prices and global financial market, which continue during the following three months.

During this uncertain period, the sudden drop in oil market prices is obvious, which caused by a combination of the substantial demand drop during the coronavirus outbreak and the tension in global oil market between Oil Petroleum Exporting Countries (OPEC) and Russia (Bandyopadhyay, 2021). With the intensified of the pandemic, a 30% sudden loss occurred in the oil prices, which is the highest fall after the Gulf War of 1991 (Chien et al., 2021; Prabheesh et al., 2020; Iqbal et al., 2020).

Besides, the impact on financial markets during the COVID-19 period was much faster and dramatic. Most global equity markets had experienced significant drops up to 60% (Seven & Yılmaz, 2021). There is a massive ruin of financial capital all through the stock markets (Baker et al., 2020). This happens mainly during February-May period of the year 2020, where the bulk of significant events have propagated the distress of volatile stock markets (Kinateder et al., 2021). Therefore, it has never been more important for investors to come up with how these extreme different events have affected the oil systemic risk spillover to stock markets.

Thus, to analyze differences in the effects of the COVID-19 pandemic on systemic risk spillover from crude oil prices to GCC stock markets, we split our sample into three sub-periods: Sub-period 1 (pre-COVID-19), covering January 2, 2017 to December 31, 2020; Sub-period 2 (COVID-19–Phase 1), covering January 2, 2020 to February 19, 2020; and Sub-period 3 (COVID-19–Phase 2), covering February 20, 2020 until May 28, 2020. Fig. 1 depicts historical price and return trends for WTI crude oil and GCC stock market indices. All return series remained fairly stable until the end of December 2019, after which they began to decline during Phase 1 of the pandemic and reached a trough during Phase 2. By this time, investors’ fears had intensified due to the virus’s worldwide spread and collapsing oil prices. Apart from deteriorating oil prices and stock returns, the pandemic spurred high market volatility as illustrated in the return graph.

Table 1 lists descriptive statistics for all GCC stock markets and the oil market for the full sample and for the periods before and after the onset of the COVID-19 pandemic (taking December 31, 2019 as the break point). Significant differences were apparent between the two sub-periods: during COVID-19, all returns were negative and lower than those before the pandemic, suggesting that all focal markets have been adversely affected by the outbreak. All market returns exhibited higher volatility episodes after the onset of COVID-19 as evidenced by increased standard deviations.

For the full and sub-sample periods, returns were negatively skewed in most cases, indicating that the series had longer left tails (extreme losses) than right tails (extreme gains). All kurtosis values exceeded 3, implying fat-tailed return distributions with higher peaks than corresponding normal distributions (Mensi et al., 2017). This departure from normality was substantiated by Jarque–Bera.

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2 For instance, Shaikh (2021) analyses the impact of COVID-19 pandemic on the energy markets; the selected COVID-19 outbreak ranges from December 29, 2019 to May 31, 2020. Salisu et al. (2020) examine oil-stock nexus during the COVID-19 pandemic. They select the post-COVID-19 period from March 11, 2020 to May 29, 2020. Mensi et al. (2021) explore spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. They select COVID-19 break period from January 2, 2020 to May 15, 2020. Kinateder et al. (2021) have chosen January 1, 2020 to May 19, 2020 for the COVID-19 period, which witness extreme events that lead to massive spikes in the Chicago Board Options Exchange’s (CBOE) Volatility Index (VIX). In other two studies, Pavlova and de Boyrie (2021) select the period of COVID-19 stock market crash from February 20 to May 29, 2020 and Pastor and Vorsatz (2020) choose February 20, to April 30, 2020 as the start and end of the COVID-19 stock market period.
test statistics, which were significant at the 1% level. Box-Pierce test statistics of $Q(20)$ and $Q^2(20)$ were also significant; that is, most return and squared rerun series demonstrated autocorrelation and heteroscedasticity. The augmented Dickey–Fuller test rejected the unit root null hypothesis, whereas the Kwiatkowski–Phillips–Schmidt–Shin test could not reject the stationarity null hypothesis at a 1% significance level. Finally, the unconditional correlation between oil returns and GCC stock market returns was positive across the entire sample period. Even so, correlation coefficients revealed that this dependence increased substantially during the COVID-19 crisis relative to the pre-COVID-19 sub-period.

4. Methodology

Our methodology follows a three-step approach. First, we estimated the VaR for the oil market index based on the univariate GARCH (1, 1) model. Second, we applied the bivariate AR (1)-DCC-GARCH (1, 1) model to estimate joint distributions of oil–stock market pairs. Third, building upon the DCC-GARCH model estimates, we calculated CoVaR and $\Delta$CoVaR for specific stock markets conditional on the VaR of the oil market (i.e., systemic risk exposure). This approach enabled our data to reflect the effects of severely distressing events such as COVID-19.

4.1. Step 1

In the first step, we estimated the unconditional VaR based on an estimation of the univariate GARCH (1, 1) model for the oil and stock markets. We assumed that each return series was expressed by the first order of an autoregressive AR (1) model as follows:

$$r_t = \mu_i + \delta_t r_{t-1} + \epsilon_{it},$$

$$\epsilon_{it} | \Omega_{t-1} \approx N(0, H_t)$$

where $r_t$ denotes the returns of the oil market or of a specific GCC stock market; $r_{t-1}$ is the autoregressive return, which accounts for potential serial correlation; $\mu_i$ is a constant; and $\delta_t$ is the parameter of autoregressive returns. $\epsilon_{it}$ is the error term conditional on past information $\Omega_{t-1}$ at time (t–1).
Table 1
Descriptive Statistics of the returns.

|                | WTI Oil | Saudi Arabia | UAE | Kuwait | Qatar | Oman | Bahrain |
|----------------|---------|--------------|-----|--------|-------|------|---------|
| **Full Period**|         |              |     |        |       |      |         |
| Mean           | -0.0526 | -0.0031      | -0.0472 | 0.0104 | -0.0040 | -0.0542 | 0.0051 |
| SD             | 3.6347  | 1.0673       | 1.2712 | 0.9010 | 1.0473  | 0.5202 | 0.5544  |
| Skewness       | -2.5184 | -1.2653      | -2.4484 | -3.6519 | -1.2459 | -1.6482 | -1.9734 |
| Kurtosis       | 43.6620 | 14.963       | 38.9070 | 38.6430 | 14.7200 | 17.9960 | 22.2340 |
| JB             | 71476** | 8520.8**     | 56896.0** | 57226.0** | 8246.8** | 12384.0 | 18868.0** |
| Q(20)          | 92.2295** | 53.2904**    | 72.8545** | 89.8432** | 36.8939** | 80.7114** | 119.1970 |
| Q(20)          | 361.2710** | 516.883**    | 607.1080** | 119.063** | 76.2550** | 83.7512** | 334.8322** |
| ADF            | -10.9017** | -11.0842**   | -11.0358** | -9.58621** | -11.2895 | -11.3453 | -8.9576** |
| KPSS           | 0.0983  | 0.1131       | 0.1360 | 0.0951 | 0.0926  | 0.232     | 0.2384  |
| Corr. Oil      | 0.2514  | 0.2304       | 0.2279 | 0.1826 | 0.1601  | 0.1899    | 0.1899  |
| **Pre-COVID-19 Period**|         |              |     |        |       |      |         |
| Mean           | 0.0164  | 0.0187       | -0.0192 | 0.0405 | 0.0010 | -0.0460 | 0.0356 |
| SD             | 1.8792  | 0.8365       | 0.7774 | 0.5746 | 0.9379 | 0.4271  | 0.4238 |
| Skewness       | -0.1590 | 0.1752       | -0.2921 | -0.4555 | -0.3926 | 0.0132  | 0.6357 |
| Kurtosis       | 8.4542  | 7.8118       | 6.2497 | 8.0412 | 12.0105 | 4.8895  | 7.3388 |
| JB             | 971.4** | 757.4**      | 354.8** | 854.0** | 2662.1** | 116.2** | 665.2** |
| Q(20)          | 32.9660** | 43.066**     | 49.981** | 52.2040** | 24.3100 | 64.1420** | 61.135** |
| Q(20)          | 31.7650** | 104.6100**   | 58.2860** | 135.0900** | 21.834 | 19.4740 | 51.4730** |
| ADF            | -29.9384** | -23.5648**   | -27.5441** | -22.7400** | -25.2269** | -21.7972** | -23.4958** |
| KPSS           | 0.0631  | 0.0439       | 0.0289 | 0.0963 | 0.1290 | 0.1192  | 0.1411 |
| Corr. Oil      | 0.0809  | 0.0429       | -0.0158 | 0.0811 | -0.0388 | 0.0121 |
| **During COVID-19 Period**|         |              |     |        |       |      |         |
| Mean           | -0.5618 | -0.1606      | -0.2538 | -0.2118 | -0.1074 | -0.1159 | -0.2194 |
| SD             | 9.2304  | 2.0990       | 3.0212 | 2.0871 | 1.6520 | 0.9639  | 1.0990 |
| Skewness       | -1.1371 | -1.3067      | -1.3198 | -2.1280 | -2.0342 | -2.0543 | -1.8930 |
| Kurtosis       | 9.1996  | 8.3442       | 10.6184 | 11.0259 | 14.5740 | 13.2376 | 10.9586 |
| JB             | 192.6** | 156.3**      | 287.1** | 364.5** | 364.7** | 537.5** | 338.6** |
| Q(20)          | 19.6370 | 23.1120      | 22.7400 | 26.7290 | 25.2750 | 22.0950 | 26.4590 |
| Q(20)          | 361.2710** | 516.883**    | 607.1080** | 119.063** | 76.2550** | 83.7512** | 334.8322** |
| ADF            | -10.7637** | -10.2023**   | 11.0002** | -8.6438** | -9.0613** | -0.74207** | -9.1311** |
| KPSS           | 0.2479  | 0.2056       | 0.1481 | 0.1831 | 0.1440 | 0.1757  | 0.1756 |
| Corr. Oil      | 0.3723  | 0.3018       | 0.3275 | 0.3119 | 0.3097 | 0.2992 |

Notes: The reported statistics are for daily returns of GCC stock markets indices and WTI crude oil prices for the period from January 2, 2017 to May 28, 2020. They are also calculated for the returns of two sub-periods referring to before and after the COVID-19 pandemic (taking December 31, 2019 as the break point). SD is the standard deviation. JB denotes the Jarque- Bera test for normality. Q(20) and Q(20) are Box-Pierce statistics for serial correlation in return and square returns up to 20 lags. ADF is the augmented Dicky-Fuller unit root test, while KPSS is the Kwiatkowski-Phillips-Schmidt-shin test for stationarity. **, * indicate statistical significance at 1% and 5% levels, respectively.

Each conditional variance \( h_t \) was next obtained from the univariate GARCH (1, 1) model:

\[
h_t = \omega_t + \alpha_{x,t-1} \epsilon_{x,t-1}^2 + \beta h_{x,t-1}
\]

where \( h_{x,t} \) is the conditional variance of each return series; \( \omega_t \) is a constant that measures unconditional volatility; \( \alpha_t \) captures the ARCH effect; and \( \beta \) captures the GARCH effect.

Given the return \( r_t \) of an individual market \( i \) at time \( t \) with a confidence level of \( q \), VaR is defined as the \( q \)th quantile of the return distribution (Ben Amor et al., 2019):

\[
P(r_t \leq \text{VaR}_q) = q
\]

Based on the parameter estimates of fitted GARCH (1, 1) models, we calculate VaR for oil (\( o \)) or GCC country (\( i \)) as follows:

\[
\text{VaR}_{q,i} = \Phi^{-1}(q) \sigma_{x,i}
\]

4.2. Step 2

We used the DCC specification of Tse and Tsui (2002) and Engle (2002) to obtain time-varying correlations. The conditional variance–covariance matrix, \( H_o \), can be written as follows:

\[
H_t = D_t^{-1/2} R_t D_t^{1/2}
\]

where \( D_t \) is the 2 x 2 diagonal matrix of the time-varying conditional standard deviation of residuals; and \( R_t \) is a matrix of time-varying conditional correlations, given by
\[ R_t = \begin{bmatrix} \text{diag}(Q_1)^{-1/2} \\ \text{diag}(Q_2)^{-1/2} \end{bmatrix} Q_t \begin{bmatrix} \text{diag}(Q_1)^{-1/2} \\ \text{diag}(Q_2)^{-1/2} \end{bmatrix} \]  

The positive definite matrix \( Q_t \) is denoted as

\[ Q_t = (1 - \theta_1 - \theta_2)Q + \theta_1(\nu_{t-1}^v + \nu_{t-1}^r) + \theta_2Q_{t-1} \]  

where \( Q' \) represents the 2 \( \times \) 2 unconditional covariance matrix of \( \nu_t \). The coefficients \( \theta_1 \) and \( \theta_2 \) are non-negative with a sum of less than unity. The dynamic correlation can be expressed as

\[ \rho_{12t} = \frac{q_{12t}}{\sqrt{q_{11t}q_{22t}}} \]  

In Eq. (8), \( \rho_{12t} \) and \( q_{12t} \) represent the time-varying conditional correlation and covariance, respectively, between each country’s oil returns and stock index returns. \( q_{11t} \) and \( q_{22t} \) denote the conditional variance of oil returns and stock index returns, respectively.

Following Alotaibi and Mishra (2017), Charles and Darné (2019), and Ahmed and Huo (2020), we estimated the DCC-GARCH model using the Broyden–Fletcher–Goldfarb–Shanno algorithm. The quasi-maximum likelihood estimator is generally consistent and asymptotically normal for GARCH models, as indicated by Bollerslev and Wooldridge (1992).

### 4.3. Step 3

In the third step, we determined CoVaR\(^{i,o} \) for the stock market \( i \), contingent on oil market \( o \) at time period \( t \), as the \( q^{th} \) quantile of the conditional distribution. This measure is defined as follows (Girardi and Ergün, 2013):

\[ P\left(r_{i}^t \leq \text{CoVaR}_{iq}^{i,o} / r_{o}^t \leq \text{VaR}_{o}^t \right) = q \]  

Based on Eq. (9), we calculated \( \Delta\text{CoVaR}\(^{i,o} \) “exposure” CoVaR, to evaluate the specific stock market’s \( i \) conditional \( \text{VaR}_{q}^i \) when specific oil prices moved from a normal state to a state of distress (i.e., a median state) (see Adrian & Brunnermeier, 2016):

\[ \Delta\text{CoVaR}_{iq}^{i,o} = \text{CoVaR}_{iq}^{i,o} - \text{CoVaR}_{iq}^{i,o} \]  

where \( b^o \) represents the oil’s benchmark (normal) state.

Following Girardi and Ergün (2013), under the assumption of a bivariate Gaussian distribution of different correlation values derived from the DCC-GARCH model, the stock market CoVaR\(^{i,o} \) has a closed form distribution defined by

\[ \text{CoVaR}_{iq}^{i,o} = \Phi^{-1}(q)\sigma_i \sqrt{1 - \rho_{12}^2} + \Phi^{-1}(q)\rho_{12}^2 \sigma_o \]  

where \( \rho_{12} \) is the conditional correlation between the oil and a specific market, \( \sigma_i \) is the market’s conditional standard deviation, and \( q \) is a confidence level equal to 5%.

To test the significance of risk spillover from crude oil to each GCC stock market, we compared the cumulative distribution for\( \text{CoVaR}_{iq}^{i,o} \) and \( \text{VaR}_{q}^i \) of the stock market using the Kolmogorov–Smirnov (K–S) bootstrapping approach proposed by Abadie (2002). Specifically, we formulated the following null and alternative hypotheses:

\[ H_0: \text{CoVaR}_{iq}^{i,o} = \text{VaR}_{q}^i \]
\[ H_1: \text{CoVaR}_{iq}^{i,o} < \text{VaR}_{q}^i \]

The K–S test can measure the difference between two cumulative quantile functions relying on the empirical distribution but without considering any underlying distribution function (Li & Wei, 2018).

The K–S test is defined as

\[ K_{nm} = \left( \frac{mn}{(m+n)^2} \right)^{1/2} \text{sub} | F_m(x) - G_n(x) | \]  

where \( F_m(x) \) and \( G_n(x) \) denote the cumulative conditional (CoVaR) and unconditional (VaR) quantile distribution functions for the GCC stock market, in that order; and \( m \) and \( n \) denote the size of the two samples.

Next, we examined whether systemic risk spillover following each phase of the COVID-19 pandemic was strong enough to drive significantly higher extreme loss risk from crude oil prices to each GCC stock market. We used the bootstrapping K–S approach to test the following hypothesis:

\[ H_0 = \frac{\text{Covar}_{iq}^{i,o}}{\text{VaR}_{q}^i} (\text{Pre}) = \frac{\text{Covar}_{iq}^{i,o}}{\text{VaR}_{q}^i} (\text{Phase} 1; \text{Phase} 2) \]
\[ H_1 = \frac{\text{Covar}_{iq}^{i,o}}{\text{VaR}_{q}^i} (\text{Pre}) < \frac{\text{Covar}_{iq}^{i,o}}{\text{VaR}_{q}^i} (\text{Phase} 1; \text{Phase} 2) \]
“Pre,” “Phase 1,” and “Phase 2” respectively denote January 2, 2017 to December 31, 2019; January 2, 2020 to February 19, 2020; and February 20, 2020 to May 28, 2020. Rejection of the null hypothesis implies that COVID-19–Phase 1 (COVID-19–Phase 2) oil systemic risk spillover magnitudes (in absolute values) are greater than in the pre-COVID-19 period for a given tail end (see Warshaw, 2019).

Furthermore, we calculated the market $\Delta \text{CoVaR}_i^{/o}$ to evaluate the contribution of crude oil marginal risk to a specific stock market’s unconditional risk. This measure can be calculated as the difference between the market’s CoVaR $i/o$ when oil prices are (or are not) in distress (see Ben Amor et al., 2019):

$$\Delta \text{CoVaR}_i^{/o} = \text{CoVaR}_i^{/o,\text{Pre}} - \text{CoVaR}_i^{/o,\text{Phase 2}}$$

(13)

Given that $\Phi^{-1}(50\%) = 0$, we can reduce $\Delta \text{CoVaR}_i^{/o}$ at each time point as

$$\Delta \text{CoVaR}_i^{/o} = \Phi^{-1}(q)i/o$$

(14)

The higher a stock market’s $\Delta \text{CoVaR}$ (in absolute value), the greater its exposure to crude oil extreme tail risk.

To test for the significance of the $\Delta \text{CoVaR}$s, we followed Bernal et al.’s (2014) and Drakos and Kouretas’ (2015) approach to rank GCC stock markets according to their exposure to oil systemic risk. Specifically, we used the bootstrapping K–S technique to test the null hypothesis that, during the overall sample period, the estimated $\Delta \text{CoVaR}$ was not statistically different from 0 against the alternative that it was statistically different from 0:

$$H_0 = \Delta \text{CoVaR}_i^{/o} = \text{CoVaR}_i^{/o,\text{Pre}} - \text{CoVaR}_i^{/o,\text{Phase 2}} = 0$$

$$H_1 = \Delta \text{CoVaR}_i^{/o} \neq 0$$

To examine the significant shift in marginal crude oil systemic risk spillover following each phase of the COVID-19 pandemic, we also used the bootstrapping K–S approach to test the following hypothesis:

$$H_0: \Delta \text{CoVaR}_i^{/o}(\text{Pre}) - \Delta \text{CoVaR}_j^{/o}(\text{Phase 1}; \text{Phase 2})$$

$$H_1: \Delta \text{CoVaR}_i^{/o}(\text{Pre}) < \Delta \text{CoVaR}_j^{/o}(\text{Phase 1}; \text{Phase 2})$$

Finally, we performed the dominance test to check whether a given stock market $i$ was indeed exposed to more marginal oil systemic risk than another stock market $j$. We again applied the bootstrapping K–S approach to test the following hypotheses (see Bernal et al., 2014):

$$H_0 = |\Delta \text{CoVaR}_i^{/o}| > |\Delta \text{CoVaR}_j^{/o}|$$

(15)

5. Empirical results

In this section, we provide our results based on the aforementioned three-step procedure to estimate CoVaR and $\Delta \text{CoVaR}$. Findings are presented during the full sample period, pre-COVID-19, and Phases 1 and 2 of COVID-19, respectively.

5.1. Results of steps 1 and 2: VaR and bivariate DCC-GARCH model estimation

We began our analysis by estimating the VaR for the oil and stock indexes. Bivariate AR (1)-DCC-GARCH (1,1) results for each GCC stock market during the full sample period are reported in Table 2. Short-term persistence in returns can be observed in all stock markets (except the UAE), as the estimated coefficient on the autoregressive term ($\rho$) is statistically significant at the 1% or 5% level. Additionally, in the conditional variance equation (Panel B), all estimated ARCH coefficients ($\alpha$) GARCH coefficients ($\beta$) are positive and significant, indicating a pronounced autocorrelation in the time-varying volatility; this finding is consistent with high volatility persistence (Batten et al. 2021). For the DCC results (Panel C), the estimate for the first DCC parameter ($\theta_1$) is positive and significant for all stock markets except Qatar and Bahrain. However, because the second DCC parameter ($\theta_2$) is highly significant for all stock markets, the conditional correlation can be considered time-varying. The sum of these estimated coefficients ($\theta_1 + \theta_2$) is less than unity for all cases, confirming highly persistent volatility in all sampled stock markets (see Kang & Yoon, 2019). Finally, diagnostic tests are presented in Panel D. Box-Pierce statistics of the 20th order show that the null hypothesis of no serial correlation in the standardized residuals and their squares cannot be rejected in nearly all univariate GARCH models. Furthermore, the Hosking (1980) and McLeod and Li (1983) test results generally convey no misspecification of the multivariate DCC-GARCH models.

5.2. Systemic risk spillover from WTI oil to GCC stock markets

Using parameter estimates of the bivariate DCC-GARCH model presented in Section 5.1, we computed downside CoVaR and $\Delta \text{CoVaR}$ values for GCC stock market returns at a 95% confidence level ($p = 0.05$) conditional on the VaR value for the WTI oil market.
### Table 2
DCC Results.

|                  | Saudi Arabia | UAE    | Kuwait | Qatar   | Oman    | Bahrain |
|------------------|--------------|--------|--------|---------|---------|---------|
| **Panel A: Mean Equation** |              |        |        |         |         |         |
| $\mu$            | 0.01396      | -0.0099| 0.0376 | 0.0164  | -0.0526**| 0.0224  |
|                  | (0.0328)     | (0.0278)| (0.0257)| (0.0340)| (0.0195)| (0.0172)|
| $\delta$         | 0.2275**     | -0.0008| 0.2485**| 0.0956* | 0.2758**| 0.1870**|
|                  | (0.0436)     | (0.0466)| (0.0591)| (0.0477)| (0.0385)| (0.0440)|
| **Panel A: Variance Equation** |              |        |        |         |         |         |
| $\omega$         | 0.0453*      | 0.0465**| 0.0286*| 0.0648* | 0.0216* | 0.0418**|
|                  | (0.0191)     | (0.0165)| (0.0134)| (0.0271)| (0.0103)| (0.0114)|
| $\alpha$         | 0.2044**     | 0.18104| 0.1823*| 0.1801* | 0.1398**| 0.1549**|
|                  | (0.0532)     | (0.0828)| (0.0807)| (0.0774)| (0.0530)| (0.0452)|
| $\beta$          | 0.7693**     | 0.8028**| 0.8021*| 0.7820* | 0.7736**| 0.6726**|
|                  | (0.0443)     | (0.0291)| (0.0244)| (0.0570)| (0.0751)| (0.0586)|
| **Panel A: DCC Equation** |              |        |        |         |         |         |
| $\rho_{io}$      | 0.1778**     | 0.1574 | 0.0213 | 0.1455**| 0.1234  | 0.0417  |
|                  | (0.0695)     | (0.1096)| (0.0828)| (0.547)| (0.1367)| (0.0540)|
| $\theta_1$       | 0.0253*      | 0.0361*| 0.0374*| 0.0080  | 0.0328* | 0.0422  |
|                  | (0.0104)     | (0.0189)| (0.0148)| (0.0138)| (0.0172)| (0.0260)|
| $\theta_2$       | 0.9460**     | 0.9127**| 0.9315**| 0.9327**| 0.9359**| 0.8108**|
|                  | (0.0252)     | (0.0337)| (0.0420)| (0.0505)| (0.0212)| (0.0813)|
| **Panel D: Diagnostic Tests** |              |        |        |         |         |         |
| LL               | -3074.6880   | -3171.061| -2849.590| -3153.411| -2505.224| -2521.812|
| BP Q(20)         | 13.4157      | 26.6140| 24.0418| 21.1536 [0.3881]| 18.7310 [0.5394]| 37.4279* [0.0103]|
|                  | [0.8588]     | [0.1465]| [0.2406]|        |        |        |
| BP Q$^2$(20)     | 11.4158      | 31.3920| 3.18225| 6.31865| 13.8021| 5.84343|
|                  | [0.9347]     | [0.0502]| [1.0000]| [0.9984]| [0.8404]| [0.9995]|
| Mc.-Li (20)      | 217.6070     | 84.8915| 93.8157| 84.3774| 82.0301| 102.958*|
|                  | [0.1740]     | [0.3049]| [0.1221]| [0.3187]| [0.3855]| [0.0364]|
| Hos (20)         | 218.0850     | 84.8539| 93.9991| 84.2531| 81.9725| 103.263*|
|                  | [0.1683]     | [0.3059]| [0.1204]| [0.3221]| [0.3872]| [0.0348]|

Notes: Panels A and B, and C show the estimated coefficients of the conditional mean, conditional variance and conditional correlation for all full-period from January 2, 2017 to May 28, 2020. $\rho_{io}$ is the expected value of the dynamic conditional correlations between stock market $i$ and oil market, while $\alpha$ and $\beta$ examine the influences of last period’s residuals and covariance on the current level of the covariance. The Panel D reports diagnostic test statistics for the univariate and multivariate standardized residuals for the DCC-GARCH(1,1) model. BP-Q (20) and BP$^2$-Q (20) stand for the Box–Pierce-Q statistics for standardized and standardized squared residuals, respectively, for up to 20 lags. Robust SE of the estimated coefficients are given in parenthesis and the p-values of the diagnostic tests are given in square brackets. Mc-L and Hos are McLeod and Li (1983) and Hosking (1980) tests for portmanteau autocorrelation statistics. The model is estimated by the quasi-maximum likelihood (QMLE) method which can be optimized by implementing BFGS algorithm. LL is the log-likelihood function value. ***, and * denote statistical significance at the 1% and 5% significance levels, respectively.

at a 95% confidence level ($\alpha = 0.05$). Then, we identified the extreme risk impact of oil price shock on stock returns (see Ji et al., 2020). Fig. 2 displays time-varying VaRs and CoVaRs for GCC stock returns conditional on the VaR of WTI oil price movements over the sample period. Based on this figure, across all markets, downside CoVaR values appear consistently smaller than their corresponding VaR values (i.e., CoVaR values are more negative than VaR values). We can thus infer that the extreme drop in oil prices led to spillover on the overall extreme losses for each GCC stock market’s returns. Moreover, the CoVaR of each GCC stock market remained relatively stable before and during the first phase of the COVID-19 period. However, after the second phase in late February 2020, the CoVaRs’ patterns declined drastically and exhibited severe fluctuations; as such, the GCC stock markets were exposed to a higher level of extreme risk at this time.

Table 3 presents CoVaR means and standard deviations for the six chosen GCC stock markets during the full study period. The mean of CoVaR is lower than the mean of VaR for all markets. This finding intuitively supports the inference based on Fig. 2 and is further confirmed by K–S bootstrap statistics under the null hypothesis that CoVaR, estimated during the full study period, is equal to its estimated counterpart VaR. Column 3 in Table 3 shows that the null hypothesis can be rejected at the 1% or 5% significance level, reflecting oil price systemic risk spillover to GCC markets during the sample period.

The results in Table 3 also reveal that oil risk exposure has differed among GCC stock markets: the UAE, Saudi Arabia, and Qatar were more vulnerable to oil price fluctuations than Kuwait, Oman, and Bahrain. One possible explanation for this trend is that the first three markets are larger than the other three. Additionally, Saudi Arabia and the UAE are main oil exporters in the GCC region, and their sensitivity to oil price shocks is relatively high.

To measure the marginal contribution of oil prices to the systemic risk of each GCC stock market, we computed $\Delta$CoVaR. Fig. 3 plots the $\Delta$CoVaR behavior of each market discussed in this paper over the entire study period. Consistent with CoVaR patterns, $\Delta$CoVaR showed similar fluctuations over time with stable movements up to the second phase of COVID-19. During this period, the evolution pattern of $\Delta$CoVaR dropped significantly compared with that before and during the first phase of the COVID-19 period, indicating an abrupt change in marginal systemic risk spillover from oil prices to GCC stock markets. This conclusion can be attributed to higher...
tensions and excessive volatility in these markets as a result of expectations about the oil market being plunged into distress. This finding is corroborated by summary statistics for the full sample period, displayed in Table 3. Referring to the means of $\Delta$CoVaRs, all values are negative, confirming overall adverse marginal risk spillover from oil prices to GCC stock markets. Moreover, the stock markets of the UAE, Saudi Arabia, and Qatar were continually more exposed to oil price distress than those of Kuwait, Oman, and Bahrain. Table 4 also lists K–S bootstrap statistics under the null hypothesis that the calculated CoVaR during the oil distress period is equal to that calculated for its normal state. For each GCC stock market, the null hypothesis can be rejected at the 1% or 5% significance level, suggesting that the contribution of oil price systemic risk to GCC stock markets tended to be higher when oil prices shifted toward a failure scenario during the whole sample period.

Fig. 2. Time series plots for VaR and CoVaR returns. Note: The figure depicts the time-series plots for value-at-risk (VaR) and conditional value-at-risk (CoVaR) for each country stock market returns. The sample period is January 2, 2017 to May 28, 2020. The figure shows a substantial shift in VaR and CoVaR during the second phase of COVID-19 outbreak. The VaR (CoVaR) is in the left (right) axis. Both of them are estimated using a 5% confidence level.

Table 3
Descriptive statistics and tests for downside value-at-risk (VaR), conditional value-at-risk (CoVaR) and delta value-at-risk ($\Delta$CoVaR) for GCC stock returns (Full period).

|        | VaR   | CoVaR  | $H_c$: CoVaR = VaR | $H_1$: CoVaR < VaR | $\Delta$CoVaR | $H_c$: $\Delta$CoVaR = 0 | $H_1$: $\Delta$CoVaR $\neq$ 0 |
|--------|-------|--------|-------------------|-------------------|---------------|----------------|-------------------|
| Saudi Arabia | −1.4684 | −1.6603 | 0.1385 | −0.2155 | 0.1352 |
|         | (0.9156) | (1.1564) | (0.0000) | (0.3156) | (0.0000) |
| UAE     | −1.7931 | −2.0121 | 0.1498 | −0.2433 | 0.1678 |
|         | (1.4157) | (1.7435) | (0.0000) | (0.4073) | (0.0000) |
| Kuwait  | −1.0454 | −1.0963 | 0.0595 | −0.0614 | 0.0586 |
|         | (0.8667) | (1.0499) | (0.0482) | (0.2592) | (0.0476) |
| Qatar   | −1.5541 | −1.7523 | 0.1971 | −0.2132 | 0.2095 |
|         | (0.6982) | (0.7969) | (0.0000) | (0.1116) | (0.0000) |
| Oman    | −0.84391 | −0.8813 | 0.06194 | −0.0430 | 0.0676 |
|         | (0.3997) | (0.4324) | (0.0332) | (0.1306) | (0.0174) |
| Bahrain | −0.64691 | −0.6743 | 0.1171 | −0.0297 | 0.12613 |
|         | (0.31180) | (0.3639) | (0.0000) | (0.0741) | (0.0000) |

Notes: Standard deviations for VaR and CoVaR and $\Delta$CoVaR are in parentheses. Bootstrapped p-values for the Kolmogorov-Smirnov (KS) statistics are in square brackets.

This finding is corroborated by summary statistics for the full sample period, displayed in Table 3. Referring to the means of $\Delta$CoVaRs, all values are negative, confirming overall adverse marginal risk spillover from oil prices to GCC stock markets. Moreover, the stock markets of the UAE, Saudi Arabia, and Qatar were continually more exposed to oil price distress than those of Kuwait, Oman, and Bahrain. Table 4 also lists K–S bootstrap statistics under the null hypothesis that the calculated CoVaR during the oil distress period is equal to that calculated for its normal state. For each GCC stock market, the null hypothesis can be rejected at the 1% or 5% significance level, suggesting that the contribution of oil price systemic risk to GCC stock markets tended to be higher when oil prices shifted toward a failure scenario during the whole sample period.
To obtain more precise impressions, we summarized the estimated CoVaR and ΔCoVaR and divided the full sample into three sub-periods: pre-CoVID-19 (January 5, 2017 to December 31, 2019); COVID-19–Phase 1 (January 2, 2020–February 19, 2020); and COVID-19–Phase 2 (February 20, 2020–May 28, 2020). The average and standard deviation values of CoVaR and ΔCoVaR during each sub-period are detailed in Table 4. Moreover, we calculated the K–S test (Table 5) to identify significant shifts in oil systemic risk spillover between the pre-COVID-19 period and the first and second phases of COVID-19, respectively.

Starting with the results of Phase 1, we found Saudi Arabia’s stock market to be the most vulnerable to negative oil extreme loss among selected GCC markets. The CoVaR and ΔCoVaR for this market show higher negative values compared with the pre-COVID-19 period. Additionally, corresponding K–S bootstrap statistics presented in Table 5 are the only two statistics that registered significant values among those for GCC stock markets.

Regarding the second phase of COVID-19, all GCC stock markets faced greater systemic risk from an extreme downward fluctuation in oil prices but at varying intensities. One possible reason for this discrepancy in oil systemic risk spillover may be due to the market

Fig. 3. Time series plots of ΔCoVaR. Note: The figure plots the daily ΔCoVaR, which measures the VaR for each country stock market when the oil market experiences financial distress. The sample period is January 2, 2017 to May 28, 2020. The figure shows a substantial shift in ΔCoVaR during the second phase of COVID-19 outbreak.

Table 4
Sub-periods summary statistics for downside value-at-risk (VaR), conditional value-at-risk (CoVaR) and delta value-at-risk (ΔCoVaR).

| Country     | Pre-CoVID-19 |   | COVID-19– Phase 1 |   | COVID-19– Phase 2 |   |
|-------------|--------------|---|------------------|---|------------------|---|
|             | VaR          | CoVaR | Δ CoVaR | VaR | CoVaR | Δ CoVaR | VaR  | CoVaR | Δ CoVaR |
| Saudi Arabia| −1.2970      | −1.4374 | −0.1551 | −1.4627 | −1.6484 | −0.2008 | −3.3798 | −4.1895 | −0.9071 |
|             | (0.4819)     | (0.5641) | (0.1533) | (0.3585) | (0.3845) | (0.0617) | (1.9984) | (2.5630) | (0.7030) |
| UAE         | −1.5009      | −1.6567 | −0.1709 | −1.5731 | −1.7195 | −0.1580 | −5.1667 | −6.1965 | −1.1090 |
|             | (0.3999)     | (0.4571) | (0.1356) | (0.2953) | (0.3224) | (0.1047) | (3.3518) | (4.2085) | (1.0519) |
| Kuwait      | −0.8673      | −0.8784 | −0.0160 | −1.1788 | −1.1027 | 0.0084  | −2.9565 | −3.5265 | −0.6136 |
|             | (0.3164)     | (0.3043) | (0.1097) | (0.5362) | (0.4150) | (0.1508) | (2.0594) | (2.5685) | (0.6204) |
| Qatar       | −1.4770      | −1.6633 | −0.2002 | −1.2788 | −1.4338 | −0.1660 | −2.5590 | −2.9351 | −0.3865 |
|             | (0.5122)     | (0.5818) | (0.0814) | (0.2103) | (0.2275) | (0.0277) | (1.4550) | (1.6641) | (0.2276) |
| Oman        | −0.7904      | −0.8101 | −0.0226 | −0.8500 | −0.8481 | 0.0004  | −1.4357 | −1.7051 | −0.2975 |
|             | (0.1780)     | (0.2000) | (0.0659) | (0.1630) | (0.1508) | (0.0486) | (0.8447) | (1.0972) | (0.3141) |
| Bahrain     | −0.5975      | −0.6180 | −0.0221 | −0.6370 | −0.6192 | 0.0170  | −1.2009 | −1.3417 | −0.1426 |
|             | (0.1395)     | (0.1442) | (0.0384) | (0.2456) | (0.2404) | (0.0256) | (0.8069) | (0.9768) | (0.1977) |

Note: Standard deviations for VaR and CoVaR and ΔCoVaR are in parentheses. Pre refers to January 2, 2017 to December 31, 2019, phase 1 refers to January 2, 2020 to February 19, 2020 and phase 2 refers to February 20, 2020 to May 28, 2020.
reflection of dual shocks of the oil demand crash: (1) global fear and uncertainty regarding the spread of COVID-19 and associated infections in the GCC region; and (2) the unexpected price war that erupted between the two leading oil producers (Russia and Saudi Arabia) (Stewart et al., 2020). For all markets, the CoVaR and ΔCoVaR have higher negative values compared to Phase 1 and pre-COVID-19. The affiliated K-S bootstrap statistics appear in Table 5 are significant at the 1% level. This result confirms that the extreme drop in oil prices during this phase of COVID-19 permeated GCC stock markets.

However, the stock markets in Saudi Arabia and the UAE recorded the largest decline in CoVaR and ΔCoVaR (see the last two columns in Table 4), indicating that these markets were less resistant to oil price shocks. This result is unsurprising as these countries represent the largest oil exporters and the greatest stock market capitalization in the GCC region. Therefore, these two markets would presumably be most susceptible to crude oil lower-tail events during the second phase of COVID-19. Conversely, oil price risk contributed less to systemic risk for the remaining GCC stock markets (i.e., Kuwait, Qatar, Oman, and Bahrain) as demonstrated by smaller negative CoVaR and ΔCoVaR values. Based on these results, investors and portfolio managers who invested in GCC stock markets during this period should hedge their portfolio positions against oil downside risk spillover by taking a short position in the oil market.

Finally, to obtain clear evidence on which GCC stock market was riskier (i.e., more exposed to oil systemic risk) than others during the second phase of COVID-19, we compared the ΔCoVaR for each market using the dominance test. Table 6 presents the results of K-S bootstrap statistics under the null hypothesis that ΔCoVaR for stock market \( i \) is less than (more negative than) ΔCoVaR stock market \( j \). Market \( i \) dominates market \( j \) if the K-S statistic is significant and K-SQ is close to zero (see Tiwari et al., 2020). The results in Table 6 showcase the UAE’s and Saudi Arabia’s dominance over Kuwait, Qatar, Oman, and Bahrain in receiving marginal systemic risk when oil prices become distressed. These results appear to substantiate our analysis of Tables 4 and 5.

5.3. Further systemic risk analysis: The MES measure

In this section, we estimate oil systemic risk contributions to GCC stock markets based on Acharya et al.’s (2012) MES measure and compare the findings with those obtained using the ΔCoVaR measure. We defined MES for each GCC stock market \( i \) as expected equity loss conditional on the oil market incurring a loss greater than its VaR(q) over a one-day period as follows (Tiwari et al., 2020):

\[
MES_i(r, q) = E(r_i | r_o \leq \text{VaR}(r_o, q))
\]

(16)

where a higher MES indicates that GCC stock market \( i \) is more vulnerable to extreme loss in the oil market.

The MES calculation under the AR-GARCH-DCC model can be stated as a function of tail expectations for the oil market index standardized return \( \varepsilon_{ot} \) and of tail expectations for the GCC market index \( i \) standardized idiosyncratic return \( \xi_{it} \) (see Abedifar et al., 2017; Gong et al., 2019):

\[
MES_i = \sigma_{oi} E_{-1} \left( \varepsilon_{ot} \varepsilon_{ow} < \frac{C}{\sigma_{ow}} \right) + \sigma_{ow} \sqrt{1 - \rho_{o}^{2}} + E_{-1} \left( \xi_{ow} \xi_{iw} < \frac{C}{\sigma_{ow}} \right)
\]

(17)

where \( \sigma_{oi} \) is the conditional standard deviation of the stock returns of country \( i \), \( \sigma_{ow} \) is the conditional standard deviation of the oil market

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Table 5
Shift in oil systemic risk spillover to GCC stock markets.

| Country        | CoVaR/VaR (pre) | ΔCoVaR | CoVaR/VaR (Phase 1) | ΔCoVaR | CoVaR/VaR (Phase 2) | ΔCoVaR |
|----------------|-----------------|--------|---------------------|--------|---------------------|--------|
| Saudi Arabia   | 0.3005 (0.0017) | 0.4134 (0.0000) | 0.3822 (0.0000) | 0.8311 (0.0000) |
| UAE            | 0.13943 (0.0000) | 0.1522 (0.0000) | 0.1588 (0.0000) | 0.7044 (0.0000) |
| Kuwait         | 0.1501 (0.0000) | 0.1618 (0.0000) | 0.2038 (0.0000) | 0.7498 (0.0000) |
| Qatar          | 0.0537 (0.0000) | 0.0484 (0.0000) | 0.0625 (0.0000) | 0.6225 (0.0000) |
| Oman           | 0.0805 (0.0000) | 0.0589 (0.0000) | 0.07826 (0.0000) | 0.6866 (0.0000) |
| Bahrain        | 0.0128 (0.0000) | 0.0154 (0.0000) | 0.09835 (0.0000) | 0.3822 (0.0000) |

Notes: The table presents the K-S test results of equalities of normalized CoVaR and ΔCoVaR for the pre-COVID-19 and each of COVID-19 phase 1 and COVID-19 phase 2 with bootstrapped p-values in parentheses.
index return, and $\rho_{it}$ is the time-varying correlation between stock and oil markets. $C$ is a threshold expression over a one-day period, equal to (VaR$_{ot}$ - $r_{ot}$). The tail conditional expectation $E_{t-1}(\varepsilon_{ot} < \frac{C}{\sigma_o})$ of standardized oil market residuals and the tail expectations $E_{t-1}(\xi_{it} < \frac{C}{\sigma})$ of standardized stock market residuals were obtained through nonparametric kernel estimation methods proposed by Scaillet (2004):

### Table 6
Dominance ΔCoVaR for COVID-19- Phase 2.

| Country    | Saudi Arabia | UAE         | Kuwait      | Qatar      | Oman      | Bahrain    |
|------------|--------------|-------------|-------------|------------|-----------|------------|
| Saudi Arabia | -            | 0.14493     | 0.4783      | 0.47726    | 0.6812    | 0.7826     |
|            | (0.2347)     | (0.0000)    | (0.0000)    | (0.0000)   | (0.0000)  | (0.0000)   |
| UAE        | 0.15942      | -           | 0.3768      | 0.4348     | 0.5797    | 0.6812     |
|            | (0.1731)     | (0.0000)    | (0.0000)    | (0.0000)   | (0.0000)  | (0.0000)   |
| Kuwait     | 0.0289       | 0.0000      | -           | 0.2753     | 0.2609    | 0.5652     |
|            | (0.9437)     | (1.0000)    | -           | (0.0053)   | (0.0091)  | (0.0000)   |
| Qatar      | 0.0000       | 0.0290      | 0.3478      | -          | 0.4638    | 0.6956     |
|            | (1.0000)     | (0.9437)    | (0.0002)    | -          | (0.0000)  | (0.0000)   |
| Oman       | 0.0000       | 0.0000      | 0.0000      | 0.0579     | -         | 0.4203     |
|            | (1.0000)     | (1.0000)    | (1.0000)    | (0.0053)   | -         | (0.0000)   |
| Bahrain    | 0.0000       | 0.0000      | 0.0000      | 0.0000     | 0.0000    | -          |
|            | (1.0000)     | (1.0000)    | (1.0000)    | (1.0000)   | (1.0000)  |             |

Note: p-values for the K-S statistics are in parentheses.

Running a significance test...

**Fig. 4.** MES for GCC countries. Note: The figure plots the daily marginal expected shortfall (MES) for each country stock market returns. MES assesses the short-run expected loss in daily equity loss when the oil market truncates below a certain level to the unconditional oil market’s daily VaR. The sample period is January 2, 2017 to May 28, 2020. The figure shows a substantial shift in MES during the second phase of COVID-19 outbreak.
where \( C \) equals \( \text{VaR}_{o/S}/\sigma_{o/S} \), \( h \) is an appropriately chosen bandwidth (usually \( 1.06 T^{-0.2} \)), \( K(x) \) is the Gaussian kernel function, and \( T \) is the number of observations.

Finally, assuming the standardized residuals are independent and identically distributed, the second part of the sum of Eq. (16) is equal to zero (see Meuleman & Vander Vennet, 2020).

Fig. 4 portrays the fluctuations in MES for GCC stock markets over the whole sample period from January 2017 to May 2020. The fluctuations remained relatively stable pre-COVID-19 and during Phase 1, implying that these markets were less exposed to lower-tail oil risk spillover. However, each market’s MES demonstrated a sharp downward trend starting from late February 2020 until the end of the sample period, highlighting the contribution of oil systemic risk during Phase 2. These results are in line with the \( \Delta\text{CoVaR} \) movements depicted in Fig. 3.

Table 4 summarizes results from applying the MES measure to the full sample period, pre-COVID-19, Phase 1, and Phase 2. Upon comparing the six GCC stock markets during the full sample period and pre-COVID-19, the stock markets in Saudi Arabia, the UAE, and Qatar seemed to suffer from the most oil systemic risk and accounted for most of it as well. However, during the first phase of COVID-19, only Saudi Arabia’s stock market was seriously hurt by the extreme decline in oil prices; its MES K-S bootstrap statistic is the only significant one among all GCC stock markets.

During the second phase of COVID-19, MES increased significantly (become more negative) for all GCC markets. All corresponding K-S bootstrap statistics appear in Table 4 are significant at the 1% level. Saudi Arabia and the UAE showed the highest average MES values, suggesting that after the pandemic spread worldwide, these two stock markets were more exposed to oil systemic risk than the remaining GCC markets. This result is supported by the dominance test results in Table 8 and confirms the \( \Delta\text{CoVaR} \) findings in Tables 4, 5, and 6.

Our results are in line with those obtained by the models that take interconnectedness by means of network models. This consistency suggests that during the turbulence periods, financial markets or sectors experienced higher inter-linkages, which increase the systemic risk and the probability of contagion.

For example, Billio et al. (2012) proposed several econometric measures of connectedness based on principal-components analysis and Granger-causality networks, and apply them to the monthly returns of hedge funds, banks, broker/dealers, and insurance companies from 1994 to 2008. They found that all four sectors became highly interrelated over the financial crisis periods, likely increasing the level of systemic risk in the finance and insurance industries through a complex and time-varying network of relationships. In other study, Ahelegbey et al. (2016) investigated empirically by means of Bayesian graphical vector autoregressive (BGVAR) model the linkages between financial and non-financial institutions. They ultimately assessed the interconnectedness of the return indexes of the 19 super-sectors of Euro Stoxx 600, sampled from January 2001 to August 2013. The authors observed stronger linkage between non-financial and financial super-sectors during the 2007–2009 financial crisis and the 2010–2013 European sovereign crisis. Abedifar et al. (2017) compared systemic resilience of three types of banks in six GCC member countries with Islamic, conventional, and mixed banks. Applying graphical network models to determine the most interconnected banking sector that can more easily spread a systemic shock to the whole system. Using a sample of observations on 79 publicly traded banks operating over the 2005–2014 period, they

| Table 7 |
| --- |
| Summary statistics for MES: Full and sub-study periods. |
| Full Period | Before | Phase 1 | K-S\(_{\text{ph1}}\) | Phase 2 | K-S\(_{\text{ph2}}\) |
| --- | --- | --- | --- | --- | --- |
| Saudi Arabia | –0.0115 | –0.0083 | –0.0105 | 0.4070 | –0.0597 | 0.8105 |
| (0.0162) | (0.0082) | (0.0028) | (0.0000) | (0.0400) | (0.0000) |
| UAE | –0.0114 | –0.0081 | –0.0074 | 0.1509 | –0.0781 | 0.7031 |
| (0.0192) | (0.0064) | (0.0049) | (0.1999) | (0.0551) | (0.0000) |
| Kuwait | –0.0035 | –0.0010 | 0.0006 | 0.1526 | –0.0551 | 0.7601 |
| (0.0142) | (0.0062) | (0.0086) | (0.1929) | (0.0310) | (0.0000) |
| Qatar | –0.0113 | –0.0107 | –0.0087 | 0.0535 | –0.0258 | 0.6199 |
| (0.0058) | (0.0042) | (0.0013) | (0.8169) | (0.0134) | (0.0000) |
| Oman | –0.0019 | –0.0010 | –0.0001 | 0.0551 | –0.0197 | 0.6943 |
| (0.0057) | (0.0030) | (0.0025) | (0.8071) | (0.0146) | (0.0000) |
| Bahrain | –0.0017 | –0.0014 | 0.0010 | 0.0140 | –0.0133 | 0.3778 |
| (0.0041) | (0.0024) | (0.0016) | (0.9861) | (0.0115) | (0.0000) |

Notes: The table reports average values for marginal expected shortfall (MES). K-S\(_{\text{ph1}}\) and K-S\(_{\text{ph2}}\) are the two-sample bootstrapped Kolmogorov-Smirnov (K-S) statistics for testing the null hypothesis of the equality of MES for pre-COVID-19 and each of COVID-19-Phase 1 and COVID-19-Phase 2, respectively. Standard deviations for MES are in parentheses. p-values for the K-S statistics are in square brackets.
found that mixed banks is the least resilient sector to a systemic event, it has the highest synchronicity with the market, and it is the most interconnected banking sector during crisis times.

Finally, it is important to address how big data and, specifically, tweet and Bloomberg data, could be useful in modelling the dynamic relationship between oil prices and stock markets. Cerchiello et al. (2017) indicated how to combine tweet based systemic risk networks with those obtained from financial market data. They argued that this approach is useful to estimate systemic risks and, therefore, to individuate the most vulnerable financial institutions. This is because it integrates two different, albeit complementary, sources of information: market prices and twitter textual data. Cerchiello and Nicola (2018) proposed an approach for assessing the spread of news contagious among countries along the considered time horizon. They focused on news taken from two public dataset: Reuters and Bloomberg. Using the Granger causality test to demonstrate a contagion/causation dynamic in the diffusion of the news, they found several significant causal relations. Fan et al. (2020) showed how to apply multi-source heterogeneous data effectively, especially text data, to the risk contagion of financial systems. The empirical Bayesian method is used to integrate the stock return correlation, sentiment correlation and marginal expected shortfall correlation based on the inverse Wishart distribution, which respectively reflects the risk changes of the financial system. The results revealed that network correlation is an important factor for financial risk contagion. Therefore, the authors suggested to start from multiple channels to monitor the correlation between financial institutions comprehensively.

6. Conclusions

The dependence structure between oil and GCC stock markets has long compelled researchers and policymakers to examine the effects of oil price shocks on stock returns, especially in the wake of economic, financial, and political crises during which oil price spillover effects are more pronounced. Recently, scholars have begun to evaluate systemic extreme tail risk dependence between oil prices and stock markets and to explore the effects of different crises on this relationship. However, studies have paid relatively little attention to the contribution of oil systemic risk to emerging markets under diverse market conditions and investment horizons (see Li and Wei, 2018). So far, to the best of our knowledge, no related research has focused on the impact of the unprecedented COVID-19 crisis on co-movement between oil price systemic risk and GCC stock market returns.

Therefore, this study investigated systemic risk spillover between the crude oil market and individual stock market returns for six GCC countries (Saudi Arabia, the UAE, Kuwait, Qatar, Oman, and Bahrain). It also quantified the evolution of such spillover before and during COVID-19. Based on daily data from January 2017 to December 2020, we adopted the bivariate DCC-GARCH model to calculate three important measures of extreme risk: CoVaR, ΔCoVaR, and MES. Throughout the study period, we found evidence of significant extreme tail spillover effects from the crude oil market to GCC stock markets. Notably, during the stress period (Phase 2 of the COVID-19 outbreak that commenced in February 2020), all GCC markets bore greater systemic risk from the crude oil market; however, Saudi Arabia and the UAE were exposed to greater oil risk than other markets. This result manifested because these two countries are closer to the oil market, in that they possess the largest stock market capitalization in the region and are ranked first and second among Gulf States in terms of oil exports.

These findings offer actionable guidance for investors and policymakers in the GCC region. All market participants should consider the importance of systemic risk spillover effects from the crude oil market to GCC stock markets. Ignoring this aspect of systemic risk may underestimate the appropriate level of contagion. For countries such as Saudi Arabia and the UAE, which are particularly sensitive to downside oil risk, investors should construct their portfolios more carefully. Additionally, measuring extreme joint movements of GCC markets is a key task for investors, such that minimizing portfolio risk is a critical issue in these markets. Furthermore, during COVID-19, investors should be aware of effective risk management and dynamic portfolio diversification strategies, where a potential jump in systemic risk can likely changes optimal portfolio weights (see Low et al., 2013; Reboredo, 2015). Finally, as argued by Salisu and Vo (2021), investors seeking to enhance their portfolio returns may need to assess the uncertainty associated with infectious diseases before making investment decisions.

As crude oil systemic risk and the GCC stock markets become more tightly linked, relevant regulators and policymakers should remain watchful. These stakeholders can also outline awareness, oversight, and action plans to minimize oil shock spillover effects to

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### Table 8

| Country        | Saudi Arabia | UAE | Kuwait | Qatar | Oman | Bahrain |
|----------------|--------------|-----|--------|-------|------|---------|
| Saudi Arabia   | –            | 0.2029 (0.0584) | 0.47826 (0.0000) | 0.5217 (0.0000) | 0.7391 (0.0000) | 0.7681 (0.0000) |
| UAE            | 0.1449 (0.2347) | –    | 0.3333 (0.0005) | 0.3476 (0.0002) | 0.6232 (0.0000) | 0.6522 (0.0000) |
| Kuwait         | 0.0725 (0.6961) | 0.0145 (0.9856) | –        | 0.3044 (0.0017) | 0.3478 (0.0002) | 0.5507 (0.0000) |
| Qatar          | 0.0000 (1.0000) | 0.0725 (0.6961) | 0.2899 (0.0030) | –    | 0.5362 (0.0000) | 0.6812 (0.0000) |
| Oman           | 0.0000 (1.0000) | 0.0000 (1.0000) | 0.0000 (1.0000) | 0.0435 (0.8777) | –    | 0.3913 (0.0000) |
| Bahrain        | 0.0000 (1.0000) | 0.0000 (1.0000) | 0.0000 (1.0000) | 0.0000 (1.0000) | 0.0145 (0.9856) | –    |

Note: p-values for the K-S statistics are in parentheses.
stock markets. In fact, dynamic policies are urgently needed to smooth oil systemic risk when it increases dramatically as well as to foster GCC financial markets’ resilience to distress, especially given the magnitude of the consequences of the COVID-19 pandemic.

Finally, while the main concern of this study is to examine the response of GCC stock markets to extreme oil price changes during the start, surge and peak stages of COVID-19, it is important to examine the nature of this response after our selected study period. The main reason is that after the early stage of COVID-19, many governments around the world, including GCC governments, announced economic rescue packages to mitigate the negative economic impact of COVID-19 pandemic on financial markets. Therefore, the GCC stock markets are expected to be less influenced by the oil systemic risk spillover. To validate this argument, we encourage future studies to extend our data set and assess the impact of GCC governments’ launched programs during the COVID-19 outbreak on the dynamic co-movements between crude oil prices and GCC stock markets.

CRediT authorship contribution statement

Bana Abuzayed: Conceptualization, Software, Formal analysis, Data curation, Visualization, Writing - original draft. Nedal Al-Fayoumi: Methodology, Software, Data curation, Writing - original draft, Writing - review & editing.

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