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The Role of Oil as a Determinant of Stock Market Interdependence: The Case of the USA and GCC

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Abstract

This paper focuses on oil as a key determinant in US-GCC stock market interdependence. The analysis uses monthly data over the period from January 2003 to December 2019. The interdependence between the US and GCC is established using the Asymmetric Dynamic Conditional Correlation model. We then investigate the impact of both oil and a range of macroeconomic variables on the nature of the correlation. Our results find that oil returns and volatility significantly explain changes in the US-GCC correlation. Echoing the recent financialization of oil, sub-sample analysis reveals the increasing importance of oil in determining interdependence. Further, the effect of oil displays asymmetric tail dependence with the correlation, where the oil impact is more pronounced in the upper tail of the correlation's conditional distribution. Both oil and financial shocks coincide with structural breaks in the correlation series. A series of robustness tests, including alternative correlation and oil measures continue to support the results.

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1. Introduction.

Over recent decades, both emerging and developed nations experience increasing globalisation and consequently higher levels of economic and financial integration (Beine et al., 2010). Increasing stock market integration occurs due to a rise in cross-border flows, lower financial barriers (Agénor, 2001) and technological advancements in trading (Issing, 2001). Empirical evidence shows that interdependence (correlations) among international stock markets is growing (e.g., Forbes and Rigobon, 2002; Kim et al. 2005; Longin and Solnik, 1995; Morana and Beltratti, 2008). This is detrimental to the benefits of international diversification and increases the transmission of shocks among financial markets (Karolyi and Stulz, 1996). Acknowledging the importance of disentangling the underlying causes of stock market interdependence, this study seeks to establish the role of oil as a key determinant of such interdependence. Studying stock market interdependence and establishing the factors that influence it, is crucial for both portfolio management and policy-makers.

The factors that affect stock return interdependence is an issue of ongoing research (e.g., Pretorius, 2002; Solnik et al., 1996; Longin and Solnik, 1995; Forbes and Chinn, 2004; Dumas et al., 2003; Wälti, 2011; King et al., 1994; Kiviaho et al., 2014). Generally, stocks are presumed to react to both macroeconomic fundamentals and financial variables. Further studies provide evidence that perceived market risk and uncertainty influence stock market co-movements (Connolly et al., 2007; Cai et al., 2009). Given the recent financialization of oil (Hamilton and Wu, 2012; Sadorsky, 2014; Silvennoinen and Thorp, 2013; Nadal et al., 2017), which means that oil has become an important asset class within investment portfolios, there is increasing potential for oil shocks to determine stock returns and stock market interdependence. Within this stream of research, a number of studies explore the influence of oil on stock markets (Sadorsky, 1999; Papapetrou, 2001; Park and Ratti, 2008; Le and Chang, 2015; Bjørnland, 2009; Basher et al. 2012; Kilian and Park, 2009; Jones and Kaul, 1996) and find that stock returns are significantly affected by oil market instabilities. Likewise, the literature stresses an asymmetric effect of oil on financial markets (Wang et al., 2013; Bjørnland, 2009). Park and Ratti (2008) document a positive relation between oil and stock returns in oil-exporting countries while the opposite is observed for oil-importing countries. While some studies focus on the co-movement of oil and stock returns (Filis et. al., 2011; Broadstock and Filis, 2014), others consider the oil price influence on the correlations of economic and financial variables (Nadal et al., 2017; Antonakakis et al., 2013). However, the role played by oil in stock market co-movements remains under-investigated.

To address this gap in the literature, we seek to establish the role of oil as a key factor that influences interdependence between the stock markets of major oil exporting nations and the US, as (historically) the world's largest oil importer and the largest global stock market. This paper contributes to the literature by combining different research perspectives: first, the interdependence among international stock markets; second, the analysis of the determinants of stock markets co-movements; third, the impact of oil on financial markets. We use a measure of interdependence in the US-GCC (Gulf Cooperation Council[1]) stock market pair, and assess the ability of oil, among other macroeconomic factors, to explain movements in the correlation. In examining this relation, we allow for time-variation in the nature of the explanatory factors and consider non-linear effects.

To generate the correlation series, we implement the Asymmetric Dynamic Conditional Correlation (ADCC) model of Cappiello et al. (2006). The time-varying correlation is an unobserved variable and thus we need to choose an estimation technique to proxy for it. We motivate the choice of the ADCC model because, first, the correlation dynamics are modelled jointly with the conditional variances and thus account for heteroscedasticity, which could bias correlation values (see, Forbes and Rigobon, 2002). Second, we allow for asymmetry in both

[1] The GCC bloc includes Saudi Arabia, the UAE, Bahrain, Qatar, Kuwait and Oman.

variances and correlations, which is widely observed in stock market series. Third, the DCC approach is known to be parsimonious and constitutes a direct technique to calculate correlations while avoiding the over-parameterisation problem that can afflict multivariate-GARCH models. Furthermore, Antonakakis et al. (2013) argue that this approach is superior to rolling correlations as it is not biased by the window length choice. To consider variation in stock market interdependencies, we utilise a Markov regime switching model to capture structural breaks in the correlations. Following Baur (2013), a quantile regression analysis is used to consider the impact of oil (and other factors) across different levels of the correlation.

In this paper, we seek to explain the correlation dynamics between the US S&P 500 and the MSCI GCC index. The latter is designed to capture the performance of the GCC stock markets. Kiviaho et al. (2014) state that the launch of frontier market mutual funds helps establish these markets as investment destinations. The six member states of the GCC jointly account for 40% and 23% of proven oil and gas reserves respectively (Sedik and Williams, 2011). The choice of the sampled countries is based on the view that the GCC nations are collectively the largest global exporters of oil. This distinctive nature may provide potential diversification opportunities, with Awartani and Maghyereh (2013) stating that the GCC correlation patterns with oil are expected to oppose those of oil importing nations, resulting in potential market segmentation and diversification opportunities. The US, thanks to the shale oil revolution, is becoming a conspicuous producer of oil, yet remains the second largest[2] importer, and by far the largest consumer of oil in the world. In addition to oil, we consider (and control for) the influence of other macroeconomic factors on the US-GCC correlation (e.g., a world stock portfolio, VIX, economic policy uncertainty and output).

In terms of the time-varying correlation, we observe a variable pattern, with notable upward movements in the US-GCC correlations especially during turbulent periods.

[2] http://www.worldstopexports.com/crude-oil-imports-by-country/.

Concerning the underlying causes of the interdependence process, we find that, first, oil returns and volatility, VIX and a world portfolio are the main drivers of US-GCC equity market interdependence. Second, our subsample analysis reveals that the impact of oil on the correlation is limited to the second sample period and thus is an increasing effect over time. Third, oil and financial shocks coincide with structural breaks in the US-GCC correlations. Fourth, oil returns and volatility display an asymmetric tail dependence with the US-GCC correlations where the oil impact prevails primarily in the upper tail of the correlation conditional distribution. We also consider the robustness of our results to alternative correlations and measures for oil. We believe that understanding the factors that impact the interdependence carries important information for investors and portfolio managers. Also, understanding what drives stock market interdependence will enable policy-makers to analyse the risks from stock market interdependencies on their domestic economy.

2. Literature Review.

The seminal work of Hamilton (1983) laid the foundation for a distinctive strand of research that examines the effect of oil on macroeconomic variables (see, Hamilton, 1996, 2003). As they reflect the state of the economy, the impact of oil on financial markets attracted a subsequent wave of research, including the early work of Jones and Kaul (1996) and Huang et al. (1996). Both papers provide conflicting results. Jones and Kaul (1996) report that oil price changes exert a negative impact on US stock returns, whereas Huang et al. (1996) do not support these findings, claiming that the effect of oil on stock markets is non-existent. Chen et al. (1986) use economic factors to explain the pricing of stocks. In accordance with Huang et al. (1996), Chen et al. (1986) state that returns generated by oil futures have no significant impact on stock market returns, and there is no benefit in considering the risk caused by oil price volatility on stock markets.

A further line of research examines the effect of oil price and volatility changes on stock returns in Vector Autoregressive (VAR) models, usually including additional macroeconomic control variables. For example, Sadorsky (1999) examining the US economy, includes industrial production, interest rates, the real oil price and real stock returns. Results show that positive volatility shocks explain a large proportion of the forecast error variance of stock returns compared to the negative ones. Both oil return and volatility shocks have significant effects on economic activity, while the opposite does not hold, which suggests the exogenous nature of the oil price.[3]

Lescaroux and Mignon (2008) investigate linkages between oil prices and macroeconomic and financial variables. Their results highlight the existence of a Granger causal link running from oil to stock returns in the short run. In the same vein, Park and Ratti (2008) examine the effect of oil on stocks in the US and the EU. Focusing on Asian markets, Le and Chang (2015) consider a VAR model including the oil price, interest rates and industrial production alongside stock returns. Using monthly data from Japan, Malaysia and Singapore from 1997 to 2013, they report, through sub-sample analysis, an increasing role for oil in influencing stock returns. In a more recent study, Diaz et al. (2016) examine the relation between oil returns volatility and stock returns in the G7 economies. Similar to Park and Ratti (2008), Diaz et al. (2016) report negative effects of oil volatility on stock returns. These negative effects are caused by oil volatility’s negative impact on economic activity.

Bjørnland (2009) and Jimenez-Rodriguez and Sanchez (2005) argue that higher oil prices represent an immediate transfer of wealth from oil importers to exporters. They maintain that if the governments of oil producing countries use the funds to purchase goods and services domestically, higher oil prices will increase the level of activity, including stock markets.

[3] Papapetrou (2001) and Bjørnland (2009) provide analyses of the links between oil proce shocks and local equity markets for Greece and Norway, respectively.

Hence, a positive association is anticipated between oil and stock returns for an oil-exporting country. Filis et al. (2011) include both oil importing and exporting countries in their analysis. Using monthly data from 1987 to 2009, an asymmetric correlation framework and following the oil price shock decomposition of Kilian (2009), the study provides evidence that the time-varying correlation of oil and stock returns does not differ between oil-importing and oil-exporting economies. Conversely, Mohanty et al. (2011) and Jouini (2013) document a positive link between oil and GCC markets. Furthermore, using monthly data, Jung and Park (2011) focus on Norway and Korea and document the heterogeneous response of stock market returns and volatility to different oil price shocks. In conformity with Park and Ratti (2008), Jung and Park (2011) explicitly attribute this to the fact that Norway is an oil exporter and Korea an oil-importer. Wang et al. (2013) maintain that the energy profile of the country (oil exporter/importer) influences the magnitude, duration and even direction of responses displayed by stock returns in reaction to oil price shocks.

Several studies consider the influence of oil on the correlation of economic and financial variables. For example, Nadal et al. (2017) examine the impact of oil price shocks on oil and stock return correlations. Antonakakis et al. (2013) establish oil price shocks as a factor to explain the change in correlations among US stock returns, policy uncertainty and VIX. Wang et al. (2013) consider the impact of oil price shocks on the degree of market dispersion as a measure of stock market interdependence. Kocaarslan et al. (2017) investigate the impact of oil, gold and currency volatility expectations on the US-BRIC stock market correlation.

Taking the above, three distinctive strands of literature emerge. First, the influence of oil return and volatility on stock returns. Second, the asymmetric effects of oil across oil importing/exporting economies. Third, the impact of oil price movements on the co-movement between financial and economic variables. These streams of research are combined here to establish oil as a key determinant of stocks market correlation. Many studies document heterogeneous reactions in stock returns to oil innovations (be they linear, Wang et al., 2013; or non-linear, Jiménez-Rodríguez, 2015) and explain these differences by the dependence versus the abundance of oil in the respective countries. Thus, we would expect that oil price increases will have a negative impact on the US-GCC correlation.[4]

3. Empirical Methodology.

Our main interest is in seeking to explain the correlation between US and GCC stock market returns. Thus, we use a set of explanatory variables in the following regression for the cross-market correlation:

$$\rho_{ij,t} = \alpha_0 + \Sigma_i \beta_i x_{i,t-1} + \varepsilon_t \tag{1}$$

Where $\rho_{ij,t}$ refers to the correlation between assets i and j at time period t, $x_{i,t-1}$ are the explanatory variables and ε_t is the random error term. In estimation of the above relation, there are several considerations, measuring the time-varying correlation between the two stock markets, the potential for breaks within the estimated relation and non-linear dynamics. We address each of these in the following sub-sections by discussing the dynamic correlation model, the Markov switching approach to allow for high and low correlation regimes and a quantile regression approach to capture differing behaviour across the range of correlations.

Asymmetric Dynamic Conditional Correlation Model (ADCC)

Our approach to estimating the correlation series is based on the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model pioneered by Engle (1982) and Bollerslev (1986). Correlations obtained using this methodology are preferred to traditional correlation coefficients as they account for heteroscedasticity. As noted by Forbes and Rigobon (2002),

[4] While oil production in the US has increased, the US is still the largest user of oil and the second largest importer. Thus, we expect oil price shocks to impact the US and GCC differently.

the presence of heteroscedasticity creates bias in correlations, notably, during high stress periods. This study uses the Dynamic Conditional Correlation (DCC)-GARCH class of model initially proposed by Engle (2002), which extends the constant conditional correlation model of Bollerslev (1990) by allowing for time-variation in conditional correlations. The ADCC-GARCH model of Cappiello et al. (2006) further extends the DCC-GARCH model by allowing for asymmetric movement in correlations in response to positive and negative news.

The DCC-GARCH model (Engle, 2002) for the time-varying correlation between market pair expresses the conditional covariance matrix as follows:

$$\Omega_t = D_t \Gamma_t D_t \tag{2}$$

Where D_t refers to the diagonal matrix of the conditional standard deviations and Γ_t is the matrix of conditional correlations. To estimate the model, individual GJR-GARCH(1,1) (Glosten et al., 1993) processes are estimated for each series. We implement the GJR-GARCH model as it allows for an asymmetric effect within the conditional variance as such:

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma \varepsilon_{t-i}^2 I_{t-i} + \beta h_{t-1}^2 \tag{3}$$

Where $I_t[\cdot]$ is an indicator function that takes the value of one when the lagged shock is negative ($\varepsilon_{t-1} < 0$) and zero for positive shocks. Here, asymmetry is captured by γ, with negative news having a greater impact on volatility when $\gamma > 0$, i.e., the effect of a negative shock on conditional variance is given by $(\alpha+\gamma)$ and positive shock by α. The standardised residuals (ξ_t) are then computed in the usual way:

$$\xi_t = D_t^{-1} \varepsilon_t. \tag{4}$$

With the correlations given by:

$$\Gamma = \frac{1}{T} \sum_{t=1}^{T} \xi_t \xi_t' \tag{5}$$

While imposing a constant correlation (Bollerslev, 1990) might be a useful simplifying assumption in certain circumstances, in the analysis here it is not relevant. Hence, we implement Engle's extension whereby the conditional correlation is allowed to exhibit time-variation in a manner similar to the GARCH(1,1) model. Specifically, conditional correlations fluctuate around their constant (unconditional) values as such:

$$Q_t = (1 - \alpha - \beta)\Gamma + \alpha \xi_{t-1}\xi_{t-1}^{'} + \beta Q_{t-1} \qquad (6)$$

where Q is the time-varying correlation matrix. The estimated correlations are standardised, $\rho_{ij,t} = \Gamma_{t,ij} = Q_{t,ij}/\sqrt{Q_{ii}}\sqrt{Q_{jj}}$, to ensure they lie between -1 and 1. This also ensures both a positive definite matrix as well as readily interpretable correlations.

Cappiello et al. (2006) introduce the ADCC model to allow for asymmetric effects in the correlation. Thus, equation (6) is extended as follows:

$$Q_{ij,t} = (1 - \alpha - \beta)\Gamma + \alpha(\xi_{i,t-1}\xi'_{j,t-1}) + \beta(Q_{ij,t-1}) + g(\varsigma_{t-1}\varsigma_{t-1}{}') \qquad (7)$$

Where $\varsigma_{it} = I[\bar{\xi}_{it} < 0] o \bar{\xi}_{it}$ the latter being the element by element Hadamard product of the residuals if shocks are negative, and $\bar{\varsigma}_t = 0$ otherwise. The term g thus captures asymmetric periods where both markets experience bad news (negative shocks). This study uses the diagonal version of the ADCC equation model, which is a special case of the Generalized ADCC (AG-DCC) model as the parameter matrices therein are replaced by scalars.[5]

Markov Switching Model

To consider break points in the data, we implement the Markov switching approach originally introduced by Hamilton (1989), which allows for switching in the regression intercept. The Markov switching model is given as follows:

$$\rho_{ij,t} = \mu_{st} + \Sigma_i \beta_i x_{i,t-1} + \sigma_{s,t} \varepsilon_t \qquad (8)$$

where, again, $\rho_{ij,t}$ is the correlation series, μ_{st} refers to the state dependent intercept and captures the average correlation in each regime (which can be referred to as high and low correlation periods), $x_{i,t}$ is the explanatory variables, σ_{st} is the regime-dependent volatility series and ε_t is

[5] The estimation of the parameters is carried out using quasi-maximum likelihood estimation (QMLE) that is robust to departures from normality of the series under regular conditions (see Bollerslev and Wooldridge, 1992).

the random error term, which is *iid* and normally distributed with a mean of zero and variance of one. The regime variable, s_t is assumed to follow a first-order Markov chain where the probability of being in one regime depends upon the previous state, with transition probabilities given by: $P_{(mn)} = P(s_t = m|s_{t-1} = n) = p_{mn}$. These probabilities can be collected in a transition matrix, which, allowing for two regimes, is given by:

$$\boldsymbol{P} = \begin{pmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{pmatrix} \tag{9}$$

where the *mn*-th element represents the probability of transitioning from regime *n* in period *t-1* to regime *m* in period *t*.

Quantile Regression

Quantile regression models the quantiles (partitions or sub-sets) of the dependent variable given the set of potential explanatory variables (Koenker and Bassett, 1978; Koenker and Hallock, 2001). The quantile regression therefore extends the linear model in equation (1) by allowing a different coefficient for each specified quantile:

$$\rho_{ij,t} = \alpha^{(q)} + \Sigma_i \beta_i^{(q)} x_{i,t-1} + \varepsilon_t \tag{10}$$

where $\alpha^{(q)}$ represents the constant term for each estimated quantile (q), $\beta^{(q)}$ is the slope coefficient that reveals the relation between the correlation and the explanatory variable at each quantile, and ε_t is the error term.

4. Data.

We collect monthly data from Thomson Reuters DataStream over the period from January 2003 to December 2019. The stock return data includes the US S&P 500 and the MSCI GCC index, used to construct the US-GCC correlation. The MSCI GCC Index captures large and mid-cap stocks across the six member states of the GCC (i.e., Saudi Arabia, Kuwait, the UAE, Bahrain, Oman and Qatar). The index includes 76 constituents, covering about 85% of the free float-adjusted market capitalisation in each country. To explain movement in the correlation series, we believe oil is a key determinant. Thus, we use the West Texas Intermediate (WTI) oil return and the square root of squared returns as a measure of volatility.[6] The use of WTI as a global measure of oil price movement is consistent with previous work (e.g., Diaz et al., 2016; Hamilton, 2009). Stock market indices are denominated in US$'s to reflect the perspective of a US investor.

As control variables, we consider the VIX, as a measure of market uncertainty (Connolly et al., 2005), the global economic policy uncertainty index (GEPU; Baker et al., 2016), the MSCI world index return and a measure of output.[7] The measure of output includes both industrial production growth and the Kilian (2009) index of economic activity. The choice of variables is motivated by previous work (e.g., Sadorsky, 1999; Kiviaho et al., 2014; Park and Ratti, 2008) and is designed to account for the economic and market environment. The necessity of controlling for common variables while studying stock return co-movements is stressed by Dickinson (2000), who argues that global stock markets are affected by a number of undiversified macroeconomic risks.

Table 1 reports the descriptive statistics for the differenced logarithms of the stock market and macroeconomic variables (the correlation series is differenced only). For each series, the mean values are close to zero and dwarfed by a larger standard deviation. There is evidence of skewness (of either sign) and excess kurtosis, with the Jarque-Bera test rejecting the null hypothesis of normality. A unit root test indicates that all series are stationary.

5. Empirical Results.

[6] The use of the squared return as a proxy of volatility is a common practice in academic literature (see Pagan and Schwert, 1990; West and Cho, 1995 and So, 2000). We take the square root to reduce the variance of this series and improve estimation accuracy.

[7] We also consider further macroeconomic variables, including inflation and interest rates, but the results are qualitatively similar to those reported below.

5.1. Correlation regression results

The correlation series from estimating the GJR-ADCC-GARCH model is presented in Figure 1 and indicates substantial time-variation in the correlation pattern, with significant increases and decreases in the correlation. The most notable spike coincides with the 2008 Subprime Crisis, which is consistent with the observation of increased correlations during turbulent time periods (Forbes and Rigobon, 2002; Solnik et al., 1996).

Table 2 presents the estimation results of equation (1), regressing the change in the correlation on oil returns, oil volatility, VIX, GEPU, a world stock portfolio and a measure of output (here, the growth rate of US industrial production). In this table, as noted above, oil return volatility is taken to be a proxy for the standard deviation through the square root of the squared oil return. Table 2 presents the results for the full sample, as well as a sample split intended to consider the post-financial crisis period as separate from the pre- and during crisis period. The full sample results show that an increase in oil returns leads to a statistically significant fall (with a coefficient value of -0.087) in the US-GCC correlation. This is consistent with our view that an oil price rise tends to favour the stock market returns in oil-exporting economies, while hurting the returns in an oil-importing market (Wang et al., 2013; Park and Ratti, 2008). The oil return volatility series exhibits a positive and significant affect (coefficient of 0.117). This indicates that higher volatility (risk) is associated with markets moving in the same direction and consistent with a contagion-type effect.

In addition to the oil related variables, the full sample results in Table 2 report that the VIX and the world portfolio exhibit statistically significant and negative effects on the stock return correlation. This suggests that both these variables have the same opposite impact on the US and GCC stock returns. These effects could be seen through a portfolio effect. The higher VIX suggests that US investors are less confident in US stocks and will consider hedging their US positions (through taking option positions). Part of this hedging action could also involve taking positions in overseas emerging and frontier markets, which exhibit different characteristics to US stocks. Likewise, a rise in world portfolio (which is dominated by US stocks), indicates greater confidence and investment in US stocks at the expense of alternative markets. Both effects drive US and GCC stock markets in different directions.

Considering the sub-sample analysis, in the first sub-sample (2003-2009), both VIX and the world portfolio retain their negative coefficient and statistical significance. However, the two oil related variables are not significant during this period, although they retain the same coefficient signs.[8] For the second sub-sample (2010-2019), again VIX and the world portfolio exhibit a negative and statistically significant relation, while both the oil variables are significant, negative for the oil return and positive for oil return volatility. Of interest, the magnitude of the coefficients increase for both these variables and most notably for the oil return (from -0.087 to -0.131). In this second sub-sample, the measure of output (US industrial production growth) exhibits a significant and negative effect on the correlation. This is consistent with the above portfolio argument, where a stronger US (global) economy would lead investors towards well-established stocks and away from those that might be perceived as more speculative.

In sum, the results reveal a key role for oil returns and volatility in the US-GCC correlation, but one that has changed over time.[9] In contrast, the effect of VIX and the world portfolio is broadly consistent over the sample. Notably, in line with the results of Le and Chang (2015), the sub-sample analysis demonstrates an increasing role for oil in explaining the variations of US-GCC interdependence. The increasing effect of oil on equity markets can be

[8] One might expect a relation between the correlation and oil during the financial crisis. An examination of the data, reveals that the US stock market fell from the end of 2007, with the recovery starting 2009:3. While the oil price fell from mid-2008, with the recovery also starting in 2009:3. This suggests that synchronicity between stock and oil markets began with the recovery rather than the crash phase following the financial crisis.

[9] We argue that although the US has increased oil production in the second sub-sample period, as it remains the world's biggest user of oil and the second largest importer, oil will impact its economy in a different manner to the GCC region that depends heavily on oil exports. Since, the financial crisis, oil and stocks exhibit greater synchronisation, leading to the significant impact on the correlation.

ascribed into two reasons. First, the aftermath of the financial crisis affects the dynamics of financial markets and their interaction with oil (Tsai, 2015). While oil and GCC stock markets are traditionally linked, the connection with the US stock market has increased as GCC markets become more liquid and integrated into global financial markets. For example, Arouri et al. (2011) note improving liquidity and access within GCC markets, while both Qatar and the UAE were classified as emerging, as opposed to frontier, markets in 2014 (with Saudi Arabia following in 2019) in recognition of their development. Second, oil and stock markets are increasingly linked due to the financialization of oil markets. This effect is the result of the increased participation and speculation of hedge funds and investors in the oil market (Hamilton and Wu, 2012; Sadorsky, 2014; Nadal et al., 2017; Maghyereh et al., 2016). Despite the fact that the introduction of WTI oil futures (traded at the New York mercantile exchange, NYMEX) dates back to 1983 (Huang et al, 1996), Figure 2 illustrates that the most notable increase in the volume of oil futures trading began around the time of the financial crisis but in a more pronounced manner after 2013.[10]

5.2 The role of oil and financial shocks

The existence of structural breaks is a common issue in macroeconomic series and they usually occur from exogenous shocks arising from economic or financial events. While Hamilton (1988) argues that abrupt government policy changes may induce such breaks, Hamilton (2005) states that breaks in financial series may correspond to financial crises. To account for these events, we utilise the Markov regime switching methodology. The Markov switching model of Hamilton (1989) involves multiple equations that describe the correlation's behaviour in different regimes. The switching mechanism between regimes is governed by a latent state

[10] Strictly speaking this is the volume of the New York Mercantile Exchange (NYMEX) WTI Crude Oil futures. The NYMEX became part of the CME Group in 2008.

variable that follows a first-order Markov chain. The usefulness of this methodology lies in its ability to capture breakpoints in time series without the need for predetermined dates. The Hamilton (1989) filter can also provide useful information about the nature of the correlations and the persistence of each state.

It is well established in the literature (see, for example, Solnik et al., 1996) that stock market co-movements increase during high-stress periods, thereby, an abrupt increase in correlation series may signal a turbulent period. We implement the Markov switching methodology to examine changes in the intercept of equation (8), which will define the average level of the correlation across two (high and low) regimes. While Hamilton (1989) states that the switching model could be used as an independent algorithm to define business cycles, the methodology here is used to verify the dates of shocks by relating the high regime to specific events. This is based on the above view that when large shocks in global factors occur, they affect financial markets simultaneously causing correlations to increase. Thus, correlations can be characterised by shifts between crisis and tranquil periods, where crisis dates and their duration are determined endogenously when a jump in correlations occur.

Figure 3 depicts the main outcome from the Markov-switching model. Figure 3 presents the smoothed probabilities together with the change in the correlation. We can observe that there are two regimes, one can be defined as a normal state and a second that can be defined as a high correlation change state. We do not report the full results for the sake of brevity, but the intercept, μ, in the low regime is -0.012 (t=6.33), while it is 0.155 (t=17.25) in the high regime. The expected duration in the low regime is eighteen months, while it is only one month in the high regime. The low regime is also stable, with a 95% probability of remaining in the same regime and a less than 10% chance of remaining in the same regime for the high regime. These results are consistent with the view that correlation dynamics can be characterised as exhibiting periods of relative stability punctuated by short-lived hikes.

In terms specific details, we observe that switches to the high correlation regime take place during April 2004, June 2006, several times over the financial crisis period between 2008 and 2010, June 2012, September 2015, February 2016, March 2018 and June 2019. These dates are linked to various economic and political events, including the geopolitical tensions in Iraq (2004) and the US Fed interest rate increase and GCC market bubble burst (2006). Further breaks reflect the financial crisis (2008-2010) and subsequent action by the Federal Reserve. Additional breaks include 'Black Monday' in August 2015,[11] oil price and stock market falls (2016), US-China trade disputes (2018) and US-EU currency tensions (2019). Overall, and in accordance with Hamilton (1988, 2005), both market turbulence and monetary policy actions precipitate breaks in the US-GCC co-movement pattern.

5.3 Oil influence during different levels of market interdependence

In this section we use the quantile regression approach to examine the conditioning behaviour of the oil return and volatility across different levels of stock market correlations. The quantile regression, developed by Koenker and Bassett (1978), estimates the effect of the explanatory variables on the conditional quantile of the dependant variable.

Figure 4 plots the quantile coefficient estimates for each variable across the different deciles together with the 95% confidence intervals.[12] This figure shows that the oil return and volatility have a stronger effect (either negatively or positively) at higher correlation values. For the oil return, the coefficient is marginally significant (or insignificant) for below median quantiles but becomes increasingly significant, and negative in value, above the median. For volatility, the coefficients around the median are borderline significant (at best) but become significant at the highest quantiles (there is also some indication that the lowest quantile is also

[11] Black Monday is the name given to the stock market crash that occurred on August 24, 2015. The incident was associated with concerns about the Chinese economy and uncertainty over the Yuan devaluation.
[12] Tabulated results are available upon request.

significant). The coefficient sign is positive throughout but becomes increasingly so at the highest quantiles (and, again, the first quantile). Elsewhere, the world portfolio and the VIX follow similar patterns, being positive below the median and increasingly negative above the median. Both the GEPU and industrial production growth variables are insignificant across the different quantiles.

The coefficient results represented in Figure 4 indicate a positive influence of both oil price declines and oil volatility increases on the US-GCC correlation. The dependence structure is asymmetric, where it exhibits upper tail dependence and (generally) lower tail independence. This can be rationalised by the importance of global factors during intense co-movement epochs (Solnik et al., 1996). A further reason for this behaviour is given by Longin and Solnik (1995), who argue that turbulent periods concur with high correlations. Within this scenario, an oil price fall means the absence of a safety cushion that may shield GCC markets from the ramifications of globally turbulent periods. This, in turn, could push GCC markets down and increasing the US-GCC correlation.

6. Robustness.

This section examines the robustness of our results from several different perspectives, including alternatives measures of the oil price, an alternative market (the EU) and an alternative asset (gold).[13]

6.1 Alternative oil price/volatility specifications

Our above results are based on using the square of oil returns as the measure of oil volatility, we then take the square root to improve estimation accuracy. Of course, there exists alternative

[13] We also consider an alternative proxy for output, namely the Kilian economic activity index, the results for which are reported in various tables.

approaches to obtain a volatility measure. As we are using a GARCH based correlation measure, one approach would be to use a GARCH model for the oil return. In the evolution of the GARCH literature, this has led to the development of realised volatility (Andersen and Bollerslev, 1998), which is obtained as the sum of squared higher frequency observations over the lower frequency period. Equally, within the empirical literature examining the link between oil and stock returns, non-linear specifications for oil price changes are suggested (see, for example, Jiménez-Rodríguez, 2015; Ciner, 2001).

GARCH/Realised Oil Return Volatility

The lower part of Table 2 presents the regression results of equation (1) where oil volatility is represented by the fitted values from a GARCH(1,1) model and by obtaining daily oil return observations, which are squared and summed over each month. These results show that oil returns and oil volatility maintain the same relation, negative for the former and positive for the latter, and are statistically significant, except for the GARCH obtained oil volatility. We believe, this is because the GARCH model produces a smoother fitted volatility series as opposed to more abrupt shifts obtained by the squared returns and realised volatility approaches. Nonetheless, the same pattern of behaviour is observed.

Net oil price increase

Proposed by Hamilton (1996), the Net Oil Price Increase (NOPI) is the first non-linear specification. NOPI compares the price of oil in each period with the maximum value observed during the preceding year.[14] If the value of the current price exceeds the previous twelve months maximum, the percentage change over the previous twelve months maximum is noted. However, if the price of oil is lower than that achieved at some point during the previous year,

[14] Hamilton (2003) expands the time horizon for the NOPI specification from one year to three years.

the series is defined to be zero. In short, NOPI is the difference between the current price and the maximum recorded price during the last twelve months if positive, and zero otherwise. Here, we follow Park and Ratti (2008) and calculate the preceding period over six months instead of one year.

The results of this analysis are presented at the top of Table 3, for both the full and sub-sample periods. The results here are consistent with those from Table 2. In the full sample and the second sub-sample, both NOPI and oil return volatility have a significant effect on the US-GCC correlation. The NOPI coefficient remains negative, while volatility still exhibits a positive impact. Although small in magnitude, the results show a strengthening of the relation from the first to the second sub-sample, as occurs with the oil return. Of the remaining variables, we see consistent results to those reported in Table 2, VIX and the world portfolio have a negative and significant effect for the full sample and across the two sub-samples. Of interest now, we see that economic activity (through the measure of Kilian, 2009) has a negative and significant effect in the first sub-sample.

Scaled oil price

The Scaled Oil Price (SOP) devised by Lee et al. (1995) is the second non-linear transformation we consider. The idea behind this specification is that the impact of oil price shocks depend on the stability of the oil price environment. A shock in a stable environment is likely to have a bigger impact on the economy than in a volatile environment. Jiménez-Rodríguez (2015) argues in favour of this specification in capturing non-linear oil effects. Empirically, Lee et al. (1995), using quarterly data, extract the standardised residual of an AR(4)-GARCH(1,1) process. Since data in this paper are sampled on a monthly basis, our calculations employ the standardised residuals of an AR(6)-GARCH (1,1) model.

The results in Table 3 show that the coefficient value of SOP is still negative but its level of statistical significance is lower than for NOPI (or the oil return). The coefficient is significant over the full sample but is only marginally (10%) significant in the second sub-sample. This contrasts with the conventional significance for both the oil return and the NOPI. The results show that oil volatility, VIX, the world portfolio and the Kilian economic activity measure exhibit the same sign and significance as for the NOPI and the oil return (except for the output measure) results.

Overall, both non-linear specifications reinforce the idea of the influence of the oil price over stock market co-movements. As with the oil return results, both NOPI and SOP demonstrate an increasing influencing on the US-GCC correlation and reflect a robust impact of oil on the US-GCC correlation.

6.2 Comparison with the EU

To examine the generality of the results for the US-GCC correlation results, we consider comparable analysis for the EU as one of the largest economic blocs and among the largest importers of oil. Unlike the US, EU oil production is limited to the North Sea, which is considerably lower than that of the US. To derive the EU-GCC correlations we obtain data for the MSCI EU index.

The results are presented in Table 4 and are equivalent to those in Tables 2 and 3 for the US correlation (we focus on the square root of the squared return for oil volatility). The results here are consistent with those reported for the US. The oil return and the non-linear transforms have a negative impact on the correlation, while the oil volatility series has a positive effect. As with the US, the significance of these results is found for both the full sample and the second sub-sample. Again, we see the strength of these coefficients increasing from the first to the second sub-samples. The VIX, world portfolio and Kilian economic activity (first sub-sample only) index also have a significant effect on the EU-GCC correlation.

The impact of oil on the correlation is larger for the EU. One reason for this is likely to be the advent of shale oil in the US that can lessen the impact of oil price shocks on the domestic market. Specifically, oil volatility will affect the GCC as it constitutes the main source of income and the EU, due the high level of imports. In contrast, the US has become more insulated from oil price volatility due to the rise of fracking and the shale oil industry.[15]

One argument could be advanced is that oil is proxying for an unknown variable that affects the correlations between all markets. Therefore, we also consider the impact of oil on the US-EU correlation (the EU imports less than 3% of its oil needs from the US). The results are reported in the top panel of Table 5. Here, we can see that neither the oil return nor oil volatility have a significant impact upon the US-EU correlation either over the full sample or in any sub-sample. Moreover, in addition to the lack of statistical significance, the nature of the coefficient signs is mixed. Indeed, across the full set of variables and sample periods there is limited evidence of statistical significance, with only the world portfolio exhibiting significance throughout. The VIX is significant in the first sub-sample, while economic activity has a significantly positive effect in the first sub-sample and a significantly negative effect in the second sub-sample.

A further consideration is that oil is proxying for an unknown variable that has an impact on the US and EU to GCC correlations but is not specific to oil. To this end, we replace the oil return and oil volatility with that of gold. Gold is argued to act as a safe haven asset in times of economic crises and thus, may be related to equity market correlations (Baur and Lucey, 2010). The second panel of Table 5 reports the results of equation (1) using the gold return and volatility. As can be observed, the gold related variables are statistically insignificant for each of the three correlations series over the full sample period. Again, the world portfolio,

[15] Average US oil production in 2003 was 5,649 thousand barrels per day, rising to 12,232 thousand barrels per day in 2019 (Source: US Energy Information Administration).

for all correlations, and the VIX, for the two GCC correlations, retain their significance.

6.3. Implied oil volatility

Sadorsky (1999) states that a positive change in oil volatility is an indicator of oil price uncertainty, arguing that oil volatility increases the option value linked with the waiting time to invest. Sadorsky (1999) further argues that the high uncertainty may overshadow the change in oil price. Therefore, we consider the oil VIX index as a measure of oil price uncertainty.

The Chicago Board Options Exchange (CBOE) introduced the oil implied volatility (Oil VIX) in 2007 as a forward-looking measure of oil volatility. Empirically, it is calculated from both call and put options, therefore reflecting market expectations of future volatility and tracks investor sentiment (Maghyereh et al., 2016). The introduction of the oil-VIX index dates back to 2007, thus, it is only employed over this period. The third panel of Table 5 demonstrate that the oil VIX has a positive and statistically significant effect on the US-GCC and EU-GCC correlations, but a positive and insignificant effect for the US-EU correlations.

6.4. Source of the Oil Shock

As a further exercise, we consider the source of the oil shock that impacts the correlation. Using a Structural Vector Autoregressive (VAR) model (which include the oil price, oil production and global economic activity), Kilian (2009) decomposes an oil price change into distinctive shocks for oil supply, which are attributable to shortfalls in oil production, oil demand, which are attributed to changes in aggregate demand that arise from the global economy, and precautionary demand, which are attributed to changes in demand for oil caused by expectations of future oil supply shortfalls.[16]

[16] See Kilian (2009) for full details of the methodology. In an alternative approach, Ready (2018) proposes a method to disentangle oil price shocks based on information on traded asset prices using return data on a global stock price index of oil producing firms. He identifies demand shocks as returns to an index of oil producing firms that are orthogonal to innovations in the VIX index and supply shocks as oil price changes that are orthogonal to

We use the decomposed oil shocks in equation (1), with the results reported in the final panel of Table 5. Again, we do this for the correlations between US-GCC, EU-GCC and US-EU. The results show a consistent pattern. First, as with the previous results, there is no relation between oil shocks and US-EU correlations. Second, the results for the US-GCC and EU-GCC correlations indicate that the driver for the effect of oil price changes on correlations arise from precautionary oil demand, with a negative relation as indicated above. This is consistent with Wang et al. (2013) and Jung and Park (2011), who argue in support of an asymmetric impact of precautionary oil demand shock on stocks among oil importers and exporters. This reflects the willingness of oil importers to pay a higher premium on oil prices to shield themselves from possible future shortfalls (Alquist and Kilian, 2010). This is consistent with our view that it is expectations of changes in future conditions that drive asset price movement.

7. Summary and Conclusions.

While Sadorsky (1999) establishes a link between stock and oil returns, the impact of oil on stocks is found to be heterogeneous and varies according to a country's dependence on oil (Bjørnland, 2009; Wang et al., 2013). In this study, we contribute to the literature by establishing whether oil is a key factor behind the co-movements of stocks among major oil importers and exporters and specifically, the US and the GCC. We include a range of global and domestic factors as controls in a monthly sample from January 2003 to December 2019.

In seeking to understand the drivers of stock market interdependence, our results show that the oil price change, oil volatility, oil precautionary demand shocks, a world portfolio and the VIX index are key explanatory variables for the US-GCC correlation. Sub-sample analysis reveals an increasing impact of oil on the US-GCC correlation over time. Further, the oil impact

demand shocks and to changes in the VIX.

is more pronounced in the upper tail of the correlation conditional distribution. Alternative specifications for the oil price such as NOPI and SOP confirm the significance of the oil price in explaining interdependence in the US-GCC pair. Furthermore, examining the EU-GCC correlation supports the role of the oil return and volatility in explaining its movement. Additional robustness tests show that oil does not affect the US-EU correlation or that gold (as an alternative asset) affects the stock market correlation.

The results suggest that oil plays a key role in the co-movement of international stock returns and that this is important for policy-makers and investors. Knowing how oil affects stock market movement will allow international investors to predict market movements and seek diversification opportunities. Policy-makers should also include oil when forming policies directed at financial stability as high interdependence is associated with financial spillovers (Karolyi and Stulz, 1996). This is particularly important as our results show that dependencies matter most when correlations are highest.

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TABLE 1 DESCRIPTIVE STATISTICS

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	DF-GLS test
Ch. Corr US-GCC	-0.001	0.046	2.730	14.267	0.00	-3.35
Ch. Corr EU-GCC	-0.001	0.060	2.202	10.980	0.00	-12.574
Ch. Corr US-EU	-0.001	0.021	-0.478	7.923	0.00	-6.842
Oil Return	0.003	0.088	-0.902	4.692	0.00	-5.166
Oil Volatility	0.066	0.057	1.704	7.058	0.00	-5.596
World Portfolio	0.006	0.037	-1.093	5.806	0.00	-2.249
Ch. VIX	-0.002	0.202	0.620	4.432	0.00	-17.692
VIX EU	-0.005	0.179	0.282	3.767	0.02	-13.410
Ch. GEPU	0.003	0.174	0.677	4.902	0.00	-14.632
Ch US IP	0.001	0.007	-2.073	13.100	0.00	-3.075
Ch EU IP	0.001	0.010	-0.681	5.031	0.00	-3.881
Kilian Index	0.017	0.594	0.774	11.289	0.00	-16.762

Notes. The notation is as follows: Ch. refers to the change in the series (differenced log, except for the correlation series, where the natural log is used in constructing the return series). The World Portfolio is the MSCI world index, the VIX and VIX EU is the Chicago Board Options Exchange volatility index and the European market equivalent, IP is Industrial Production Index (IP) and DF-GLS is the GLS detrended Dickey-Fuller unit root test.

TABLE 2 US-GCC CORRELATION ANALYSIS

Variables	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
Oil Return	-0.087 (-2.79)	-0.027 (-0.66)	-0.131 (-3.37)
Oil Volatility	0.117 (2.30)	0.115 (1.18)	0.138 (1.95)
VIX	-0.090 (-3.37)	-0.100 (-2.06)	-0.082 (-2.84)
GEPU	0.014 (0.93)	-0.010 (-0.50)	0.020 (0.87)
World	-0.557 (-2.75)	-0.684 (-2.11)	-0.469 (-2.30)
US IP	0.309 (0.50)	1.113 (1.43)	-1.392 (-2.60)
R-Sq	0.197	0.251	0.233
	Alternative Specifications		
	GARCH Volatility	Realised Volatility	Killian Output
Oil Return	-0.102 (-2.95)	-0.108 (-3.24)	-0.093 (-2.81)
Oil Volatility	0.029 (0.24)	0.026 (2.23)	0.132 (2.37)
VIX	-0.092 (-3.18)	-0.090 (-3.26)	-0.104 (-3.79)
GEPU	0.013 (0.91)	0.014 (1.04)	0.015 (0.95)
World	-0.577 (-2.72)	-0.565 (-2.61)	-0.589 (-3.07)
Econ Activity	0.134 (0.23)	0.082 (0.14)	-0.007 (-1.42)
R-Sq	0.179	0.198	0.228

Notes. Entries are the coefficients from equation (1) with Newey-West *t*-statistics in parenthesis. Concerning the fact that the correlation is a bound variable, between −1 and 1, applying the Fisher transformation of the correlation series does not affect the results.

TABLE 3. US-GCC CORRELATION ANALYSIS WITH ALTERNATIVE OIL PRICE SPECIFICATIONS

Variables	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
NOPI	-0.002 (-3.36)	-0.001 (-1.26)	-0.004 (-3.62)
Oil Volatility	0.180 (3.16)	0.111 (1.26)	0.253 (3.09)
VIX	-0.107 (-3.85)	-0.104 (-1.92)	-0.098 (-3.18)
GEPU	0.017 (1.08)	-0.009 (-0.56)	0.036 (1.46)
World	-0.640 (-3.31)	-0.651 (-2.21)	-0.487 (-2.05)
Kilian	-0.008 (-1.40)	-0.023 (-2.29)	-0.002 (-0.38)
R-Sq	0.223	0.298	0.223
	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
SOP	-0.009 (-2.33)	-0.003 (-0.99)	-0.011 (-1.65)
Oil Volatility	0.142 (2.63)	0.098 (1.07)	0.210 (2.80)
VIX	-0.106 (-3.84)	-0.102 (-1.89)	-0.101 (-3.05)
GEPU	0.017 (1.13)	-0.010 (-0.62)	0.038 (1.53)
World	-0.611 (-3.15)	-0.645 (-2.18)	-0.454 (-1.95)
Kilian	-0.007 (-1.38)	-0.021 (-2.20)	-0.002 (-0.44)
R-Sq	0.231	0.295	0.229

Notes. Entries are the coefficients from equation (1) with Newey-West *t*-statistics in parenthesis. Concerning the fact that the correlation is a bound variable, between −1 and 1, applying the Fisher transformation of the correlation series does not affect the results. The notation is as follows: NOPI is the Net Oil Price Increase, while SOP is the Scaled Oil Price.

TABLE 4. EU-GCC CORRELATIONS ANALYSIS

Variables	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
Oil Return	-0.114 (-2.42)	0.025 (0.39)	-0.202 (-3.46)
Oil Volatility	0.168 (2.04)	0.108 (0.91)	0.264 (3.02)
VIX	-0.079 (-2.65)	-0.063 (-1.02)	-0.069 (-1.82)
GEPU	0.006 (0.32)	-0.020 (-0.75)	0.020 (0.78)
World	-0.604 (-2.47)	-0.763 (-2.10)	-0.290 (-1.06)
Kilian	-0.004 (-0.75)	-0.016 (-2.61)	-0.002 (-0.38)
R-Sq	0.157	0.207	0.202
Alternative Oil Price - NOPI			
	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
NOPI	-0.003 (-2.67)	-0.001 (0.62)	-0.005 (-3.13)
Oil Volatility	0.226 (2.56)	0.104 (0.87)	0.374 (3.49)
VIX	-0.082 (2.80)	-0.062 (-1.02)	-0.071 (-1.95)
GEPU	0.009 (0.46)	-0.015 (-0.64)	0.028 (1.10)
World	-0.666 (-2.74)	-0.749 (-2.04)	-0.353 (-1.23)
Econ Activity	-0.004 (-0.81)	-0.015 (-3.26)	0.003 (0.06)
R-Sq	0.149	0.207	0.174
Alternative Oil Price - SOP			
	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
SOP	-0.010 (-2.08)	0.001 (0.15)	-0.017 (-2.10)
Oil Volatility	0.182 (2.14)	0.102 (0.81)	0.311 (3.31)
VIX	-0.081 (-2.75)	-0.063 (-1.05)	-0.075 (-1.95)
GEPU	0.009 (0.49)	-0.019 (-0.75)	0.029 (1.14)
World	-0.632 (-2.58)	-0.752 (-2.06)	-0.300 (-1.09)
Econ Activity	-0.003 (-0.59)	-0.015 (-2.89)	-0.001 (-0.11)
R-Sq	0.157	0.206	0.201

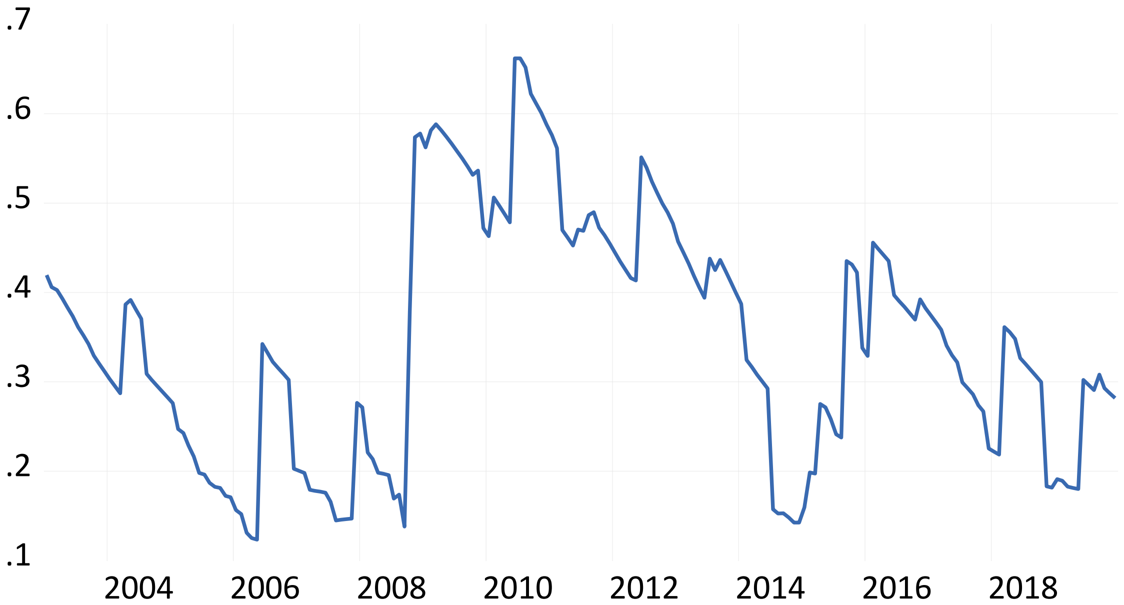
Notes. Entries are the coefficients from equation (1) with Newey-West *t*-statistics in parenthesis. Concerning the fact that the correlation is a bound variable, between −1 and 1, applying the Fisher transformation of the correlation series does not affect the results. The notation is as follows: NOPI is the Net Oil Price Increase, while SOP is the Scaled Oil Price.

TABLE 5. ROBUSTNESS

US-EU Correlations			
Variables	2003:1-2019:12	2003:1-2009:12	2010:1-2019:12
Oil Return	0.009 (0.52)	-0.006 (-0.43)	0.019 (0.68)
Oil Volatility	0.013 (0.62)	0.020 (1.09)	-0.005 (-0.12)
VIX	-0.014 (-1.42)	-0.021 (-2.11)	-0.019 (-1.38)
GEPU	0.011 (1.12)	0.011 (1.80)	0.010 (0.68)
World	-0.128 (-2.85)	-0.105 (-2.01)	-0.241 (-2.56)
US-IP	-0.134 (-0.49)	0.297 (2.04)	-1.224 (-2.27)
R-Sq	0.040	0.112	0.096
Correlations with Gold			
	US-GCC	EU-GCC	US-EU
Gold Return	-0.095 (-1.30)	-0.171 (-1.56)	0.025 (1.02)
Gold Volatility	-0.025 (-0.21)	-0.095 (-0.50)	-0.018 (-0.37)
VIX	-0.108 (-3.32)	-0.072 (-2.53)	-0.016 (-1.54)
GEPU	0.004 (0.21)	0.011 (0.38)	0.003 (0.38)
World	-0.719 (-2.96)	-0.726 (-3.13)	-0.137 (-2.78)
IP	-0.040 (-0.06)	-0.721 (-1.83)	-0.201 (-0.73)
R-Sq	0.185	0.135	0.055
Oil VIX			
	US-GCC	EU-GCC	US-EU
Oil VIX	0.085 (2.71)	0.112 (2.81)	0.019 (1.60)
VIX	-0.094 (-2.99)	-0.058 (-2.03)	-0.011 (-0.98)
GEPU	0.023 (1.12)	0.010 (0.40)	0.014 (0.98)
World	-0.578 (-2.30)	-0.521 (-1.89)	-0.114 (-2.45)
IP	-0.099 (-0.15)	-0.910 (-1.36)	-0.214 (-0.69)
R-Sq	0.235	0.195	0.059
Source of Oil Shocks			
	US-GCC	EU-GCC	US-EU
Oil Supply	-0.005 (-0.12)	-0.007 (-0.96)	-0.002 (-1.21)
Oil Demand	0.001 (0.06)	0.002 (0.25)	-0.003 (-0.12)
Oil Precaution	-0.015 (-3.89)	-0.015 (-2.82)	-0.001 (-0.30)
VIX	-0.114 (-4.08)	-0.090 (-3.07)	-0.019 (-1.96)
GEPU	0.020 (0.19)	0.014 (0.73)	0.012 (1.05)
World	-0.677 (-3.89)	-0.718 (-2.93)	-0.153 (-3.42)
IP	-0.005 (-0.79)	-0.001 (-0.07)	-0.002 (-0.43)
R-Sq	0.232	0.145	0.052

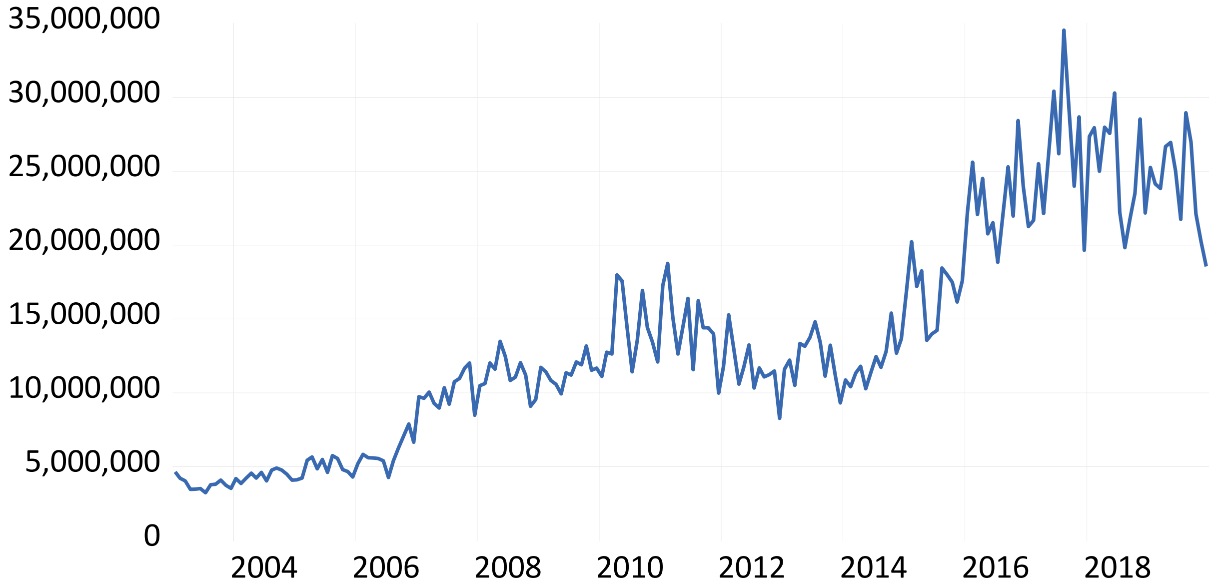
Notes. Entries are the coefficients from equation (1) with Newey-West *t*-statistics in parenthesis. Concerning the fact that the correlation is a bound variable, between −1 and 1, applying the Fisher transformation of the correlation series does not affect the results.

FIGURE 1 US-GCC CORRELATION FROM JANUARY 2003 TO DECEMBER 2019



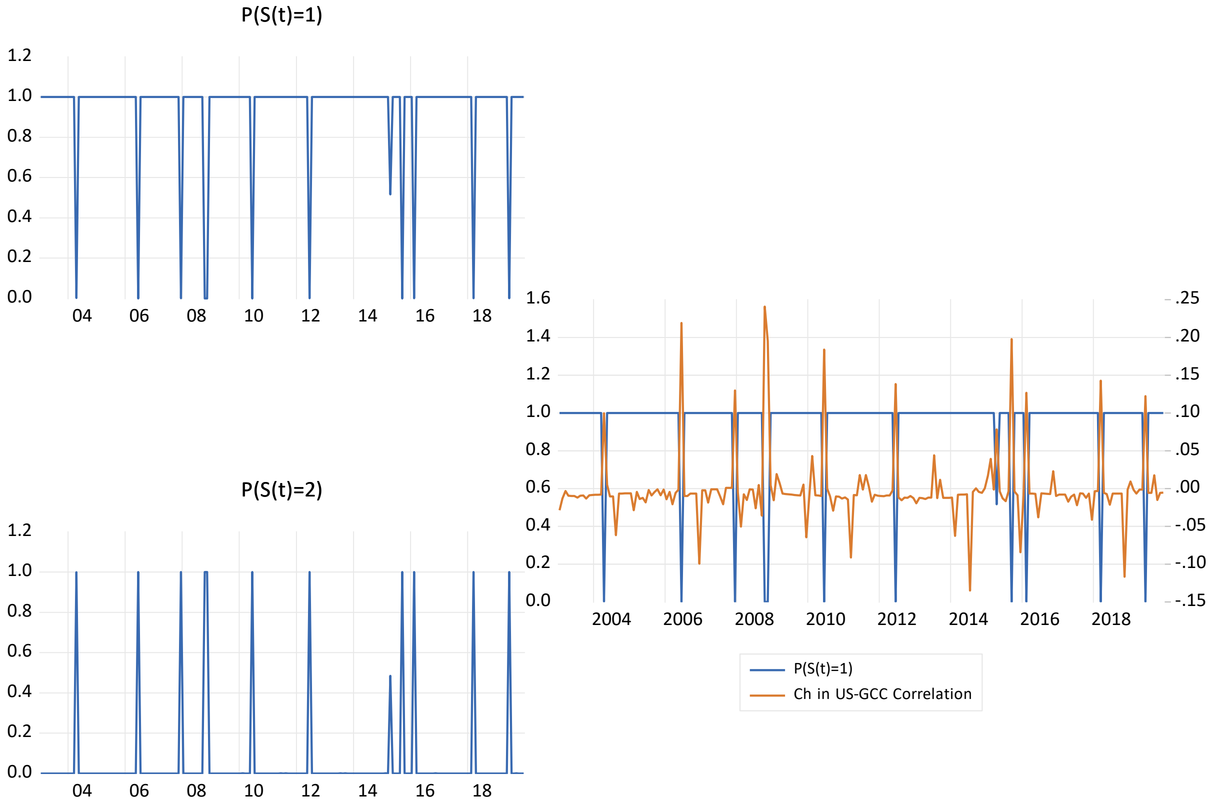
Note. The correlation series in the graph is obtained from a GJR-ADCC-GARCH model.

FIGURE 2 WTI CRUDE OIL FUTURES VOLUME



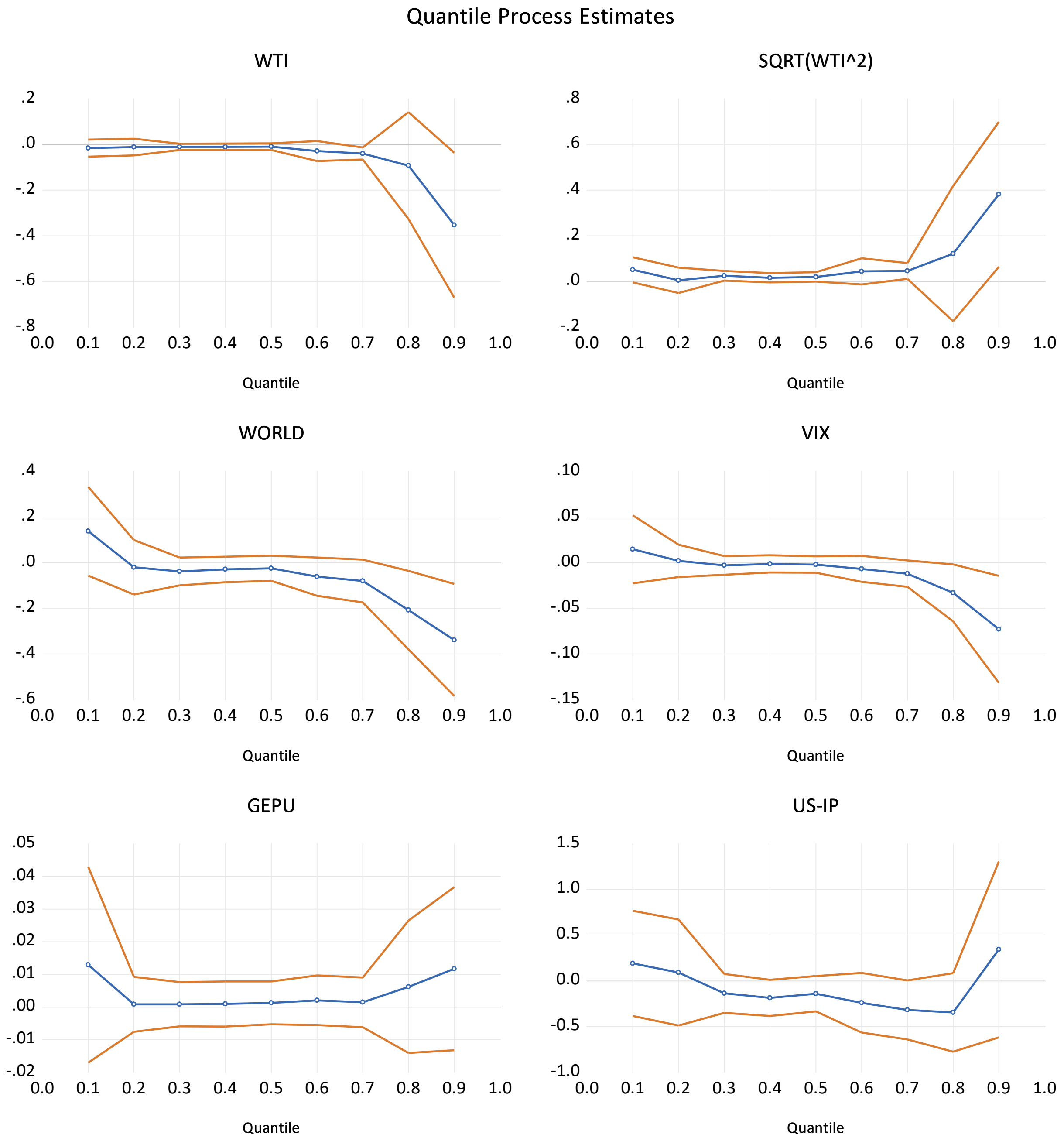
Source: Thomson Reuters DataStream.

FIGURE 3 US-GCC MARKOV-SWITCHING SMOOTH PROBABILITIES AND CHANGE IN CORRELATION



Notes. Based on the Kim (1994) filter, Figure 3 illustrates the smooth probabilities of each regime, this technique involves the estimation of probabilities using the entire sample. The high regime reflects jumps in correlation coefficients while the low regime corresponds with stable correlations.

FIGURE 4 US-GCC QUANTILE COEFFICIENTS



Notes. Quantile regression coefficients: vertical axes show coefficient estimates of variables over the correlation distribution; horizontal axes depict the quantiles of the dependent variable (US-GCC correlation); quantile regression error bars correspond to 95% confidence intervals. Concerning the fact that the correlation is a bound variable, between −1 and 1, applying the Fisher transformation of the correlation series does not affect the results.