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Recent trends in economic research

Predictability of GCC stock returns: The role of geopolitical risk and crude oil returns

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ABSTRACT

Stock return predictability has always been one of the central themes of finance literature, given its crucial implications for investment decisions, risk management, and financial and monetary policymaking. This paper evaluates the in-sample and out-of-sample stock return predictive power of the global and Saudi geopolitical risk indices and crude oil returns in the context of six Gulf Cooperation Council (GCC) countries. Monthly data from February 2007 to December 2019 and the feasible generalized least square (FGLS) estimator for predictive modelling by Westerlund and Narayan (2012, 2015) are used. Global and Saudi GPR indices show weak evidence of in-sample predictability of excess stock returns. However, the out-of-sample forecasts show that only the global geopolitical risk index provides superior prediction in the context of Kuwaiti and Omani stock markets, compared to the historical average benchmark model. Crude oil prices are shown to be a better predictor in most cases, in both in-sample and out-of-sample forecast models. The results imply that crude oil returns can be used for active prediction of GCC stock market returns, once econometric issues are accounted for. The findings remain mostly unaffected when excess risk adjusted returns are used.

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1. Introduction

Stock price or stock return forecasting has always been a central theme of the finance literature, given its crucial implications for investment decisions, risk management, and financial and monetary policymaking (Apergis et al., 2018). The central questions of the literature on stock return prediction are, firstly, whether stock returns are predictable. If the answer to this question is “yes”, then another question follows immediately, “how?” There is a vast amount of past evidence that attempts to answer at least one of these questions. Regarding whether stock returns are predictable, a number of empirical studies yield positive results for the out-of-sample predictability of stock returns (see, inter alia, Campbell and Thompson, 2008; Gupta and Modise, 2013; Narayan and Gupta, 2015; Phan et al., 2018; Tissaoui and Azibi, 2019). On the other hand, several other studies argue that in-sample evidence tends to be supportive of predictability while out-of-sample evidence tests tend to reject the hypothesis of significant prediction (Inoue and Kilian, 2005; Rapach and Wohar, 2006; Welch and Goyal, 2008; Apergis et al., 2018). Regarding the question of how, scholars employ numerous variables as potential predictors of future stock returns. The types of predictors commonly adopted in predictive modelling include financial variables and ratios (see, among others Cakici et al., 2013; Campbell and Shiller, 1988; Fama and French,
feasible generalized least squares (FGLS) model. On this note, the academic literature offers various explanations for the conduct both in-sample and out-of-sample predictability analysis using the Westerlund and Narayan (2012, 2015) comparative analysis between the predictive power of geopolitical risk indices and that of crude oil prices. Thirdly, nonparametric models. However, our paper differs in three aspects. Firstly, it focuses on the predictability of GCC stock indices, our paper is closest to Charfeddine and Al Refai (2019) who apply connectedness measures among the GCC region, which includes some of the nations that have been particularly exposed to geopolitical tension (e.g., Arab uprisings, wars). In turbulent regions such as the GCC, political instability, security concerns, and military tensions are quite common. For example, cities in Saudi Arabia have come under missile and drone attacks from Yemeni rebels several times since the onset of the Saudi Arabian-led intervention in Yemen in 2015. Stocks in the GCC region are issued by corporations that are particularly exposed to geopolitical tensions, which makes geopolitical risk a systematic risk element that can shape economic fundamentals in GCC stock markets. For example, on June 5, 2017, a diplomatic rift between Qatar and its Gulf neighbours (Saudi Arabia, UAE, and Bahrain) led the Qatari stock market index to plunge more than 7% on a single day. At the same time, stock indices in GCC countries are highly sensitive to crude oil prices (Arouri and Rault, 2012; Alqahtani et al., 2019). In fact, the GCC region encompasses leading oil-producers and oil-exporters and the largest concentration of crude oil producing and exporting countries as well as reserves of around 497 billion barrels of crude oil, which represents almost 34% of the world’s estimated proven crude reserves. Furthermore, crude oil prices and geopolitical risk are correlated (Kollia et al., 2013; Cunado et al., 2019).

Given the above discussion, we contribute to the literature on stock return predictability for emerging markets by examining GCC stock markets. Specifically, we examine the predictive power of geopolitical risk for GCC stock indices and compare it to that of crude oil returns. This is important as it allows us to determine whether geopolitical risk index or crude oil returns perform better in predicting GCC stock returns, an unexplored research subject.

Our analysis is related to a strand of literature that examines the economic linkages between stock markets and geopolitical risk, which mostly concentrates on large developed economies and large emerging economies (Antonakakis et al., 2017; Balcilar et al., 2018; Bouras et al., 2018; Clance et al., 2018; Bouri et al., 2019). In the understudied context of GCC stock indices, our paper is closest to Charfeddine and Al Refai (2019) who apply connectedness measures among the stock returns of GCC countries and examine how the blockade on Qatar shaped the system of connectedness, and Mnasri and Nechi (2016) who take an event study approach and examine the effect of terrorist attacks on the stock market volatility of several emerging markets, including GCC markets. However, both Mnasri and Nechi (2016) and Charfeddine and Al Refai (2019) ignore stock return predictability and overlook the predictive ability of geopolitical risk comparative to crude oil for GCC stock returns. In terms of stock return predictability based on geopolitical risk, our paper is related to that of Apergis et al. (2018) who consider 23 global defence companies. Apergis et al. (2018) use both a Granger causality test and a nonparametric approach, and show that the geopolitical risk index exerts only mild predictive power over stock returns as shown by the Granger causality test, and find no evidence of stock return predictability from the nonparametric models. However, our paper differs in three aspects. Firstly, it focuses on the predictability of GCC stock market returns based on the Saudi Arabia geopolitical risk index and a global geopolitical risk index. Secondly, it includes a comparative analysis between the predictive power of geopolitical risk indices and that of crude oil prices. Thirdly, it conducts both in-sample and out-of-sample predictability analysis using the Westerlund and Narayan (2012, 2015) feasible generalized least square (FGLS) model. On this note, the academic literature offers various explanations for the

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1 Other studies (e.g., Tissoussi and Azibi, 2019) consider Saudi stock return-volatility predictabilities but their focus is on the role of stock volatility risk.

2 A related strand of literature considers the effect of the Israeli–Hezbollah War (Bouri, 2014) and the Arab uprisings (Bouri et al., 2016).

3 https://www.bbc.com/news/world-middle-east-48608213

4 https://www.reuters.com/article/markets-qatar/update-1-qatar-stock-market-tumbles-on-diplomatic-rift-with-saudi-gcc-states-idUSL8N1J20SW

5 https://www.kapsarc.org/research/publications/crude-oil-reserves-metrics-of-gcc-members/
common disagreement between in-sample tests and out-of-sample forecasts. Stambaugh (1999), Lanne (2002), Lewellen (2004), and Westerlund and Narayan (2012, 2015) believe that the insignificant out-of-sample evidence and generally mixed findings in the literature are mainly due to the data attributes of financial variables. For example, the majority of financial and economic variables tend to be persistent in that past innovations of the variable itself are correlated with the current value of the variable (Lanne, 2002). One possible way to tackle the issue of data attributes is to employ a proper estimator for the predictive regression model (Westerlund and Narayan, 2012).

The current paper has several novelties. Firstly, it is the first of its kind to examine the ability of two geopolitical risk indices, the global geopolitical risk index and the Saudi geopolitical risk index, to predict the stock returns of GCC countries that represent a significant part of the emerging economies which remain largely understudied in the stock-geopolitical risk nexus. The main motivation for using two geopolitical risk indices is to examine whether the GCC stock markets are more responsive to international-induced risk or regional-induced risk. Our empirical findings provide valuable insight for stock market participants in the GCC markets by showing whether current levels of geopolitical risk, and either global or Saudi geopolitical risk, can improve predictions of future stock returns in the Gulf region. Secondly, this paper comparatively examines the stock return predictive power of geopolitical risk versus crude oil price, which is important for investment decisions, asset pricing, and policymaking. The motivation for considering crude oil prices as a stock price predictor in GCC stock markets is that the economies and the stock markets of oil rich GCC countries are shaped by the level of oil prices, suggesting the ability of crude oil prices to predict GCC stock returns. Thirdly, this paper uses the newly developed Westerlund and Narayan (2012, 2015) FGLS estimator to construct a predictive regression. The FGLS estimator is robust to the presence of an endogenous and persistent predictor, as well as conditional heteroscedasticity. The FGLS estimator is expected to overcome the common econometric challenges faced when a least squares class of estimator is used. Furthermore, this paper performs out-of-sample forecasts across various forecast horizons, which effectively rules out the possibility of data mining. Fourthly, it confirms the robustness of the main findings by re-estimating the models based on excess returns adjusted for market risk factors and macroeconomic factors.

The remainder of this paper is structured as follows. Section 2 describes the dataset and the stock return predictive models. Section 3 reports and discusses the in-sample and out-of-sample forecast results. Finally, Section 4 concludes.

2. Data and methodology

2.1. The data

This study employs monthly data spanning February 2007 to December 2019, amounting to 155 observations. It uses three sets of data, stock indices, geopolitical risk indices, and crude oil prices. The first set consists of monthly excess stock index returns of six GCC countries, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE. The monthly stock index excess return is computed as the difference between the nominal (raw) stock index return and the risk-free rate (i.e., three-month rate in each GCC country) (see, among others, Narayan and Bannigidadmath, 2015). The second dataset consists of two geopolitical risk indices, the global GPR and Saudi GPR indices. The global GPR index measures geopolitical tensions that have potential worldwide impact. The Saudi GPR index is a country-specific GRP index that measures regional geopolitical tensions originating from Saudi Arabia. Both GPR indices are used in their natural log-transformations. The GPR is a newly developed indicator for measuring the cross-border geopolitical tension of a given region or country. According to its constructors, Caldara et al. (2018), the levels and changes of the GPR index result from an automated text search based on the electronic headlines and contents of 11 national (US) and international newspapers. Specifically, the GPR index counts the number of news articles that contain words related to geopolitical tensions and computes the share of these articles against the total number of articles per month. An increase in the GPR index indicates a higher frequency of related words appearing in the news, thereby implying rising geopolitical risk in the region of interest. All GPR indices have a base period of 2000 to 2009, in which the indices are averaged to 100. The GPR and country specific GPR indices are currently hosted and published by Boston College. The use of a GPR index in measuring geopolitical risk is seen in, inter alia, Antonakakis et al. (2017), Apergis et al. (2018), Bouras et al. (2018), and Bouri et al. (2019). For crude oil prices, we use Brent oil spot prices. Accordingly, crude oil returns are computed based on the first log-difference of crude oil spot prices. All data are extracted from the DataStream database, except the GPR indices which are taken from Caldara et al. (2018).

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6 As of August 2018, five of the six GCC countries have only one national stock exchange, the exception being UAE with three stock exchanges, the Abu Dhabi Securities Exchange (ADX), the Dubai Financial Market (DFM), and the NASDAQ Dubai. The ADX is selected of the three exchanges to represent the equity market in UAE since the NASDAQ Dubai is more international-oriented and the Abu Dhabi General Index is statistically indifferent compared to DFM General Index.

7 The stock market return of each GCC country is measured by the first log-difference of the stock market index.

8 The newspapers are The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post.
2.2. The predictive model: Westerlund–Narayan FGLS estimator

To evaluate the predictive power of geopolitical risk for GCC stock returns, a simple predictive regression for \( t \) period is constructed as follows:

\[
\text{RET}_{t+h} = \alpha + \beta X_t + \epsilon_{t+h}
\]

(1)

where \( \text{RET} \) represents the excess stock returns of GCC markets, \( X \) is either the global GPR index, the Saudi GPR index, or crude oil returns, \( \alpha \) is the intercept term, and \( \epsilon_t \) is the forecast error at \( h \) lead periods. The in-sample stock return predictive power of the GPR (crude oil returns) can be tested using a simple \( t \)-test with the null hypothesis of \( \beta = 0 \), in which rejection of the null hypothesis indicates that GPR (crude oil returns) carries a significant in-sample stock return predictive power in the context of GCC countries.

Since the predictive model (1) involves financial data (RET) and a macroeconomic indicator (GPR or crude oil returns), using the ordinary least square (OLS) method to estimate the parameters in (1) is likely to suffer from the presence of a persistent predictor, endogeneity, and heteroscedasticity (Westerlund and Narayan, 2012, 2015). Consequently, the OLS estimates are biased and inefficient. To resolve the issues of endogeneity and a persistent predictor, Stambaugh (1999) developed the bias-adjusted least square (ALS) estimator for predictive regression using financial data, which was later extended by Lewellen (2004). The algebraic representation of the ALS model is:

\[
\text{RET}_{t+h} = \alpha + \beta X_t + \gamma (\Delta X_{t+h}) + v_{t+h}
\]

(2)

where \( \Delta \) is the difference operator. Since Eq. (2) captures both persistency and endogeneity of the predictor in the predictive model, it is robust to the presence of persistency and endogeneity issues (Lewellen, 2004; Westerlund and Narayan, 2012).

Finally, while the ALS estimator adopted in Eq. (2) is free from the problems of persistency and endogeneity, it may still suffer from ARCH effects as the estimator ignores the possible presence of heteroscedasticity. Therefore, Westerlund and Narayan (2012) propose weighting the ALS estimators by \( 1/\sigma^2 \), which is obtained by estimating the error variance as in Eq. (3) by appropriate ARCH modelling (Westerlund and Narayan, 2012; Phan et al., 2015, 2019). Subsequently, Eq. (2) is modified to:

\[
\text{RET}^*_{t+h} = a^* + \beta^* X_t + \gamma^* (\Delta X_{t+h}) + v_{t+h}^*
\]

(3)

where \( \text{RET}^*_{t+h} = \text{RET}_{t+h}/\sigma^2 \), \( a^* = a/\sigma^2 \), \( \beta^* = \beta/\sigma^2 \), \( \gamma^* = \gamma/\sigma^2 \), and \( v_{t+h}^* = v_{t+h}/\sigma^2 \). The feasible generalized least square (FGLS) estimators \( a^* \), \( \beta^* \) and \( \gamma^* \) are therefore robust to the presence of persistency, endogeneity, and heteroscedasticity in the model.  

2.3. Evaluation of in-sample and out-of-sample performance

As mentioned, the literature on stock return predictions lacks consensus about the evidence from in-sample and out-of-sample tests. The question of whether the in-sample or out-of-sample approach is superior is beyond the scope of this study. Still, this study takes both in-sample and out-of-sample approaches to forecasting GCC stock returns and hence the findings contribute to that debate. Specifically, this study uses half the sample, February 2007 to June 2013, to generate the forecast (Narayan et al., 2014) and applies three measures for the out-of-sample forecasting evaluation, the relative Theil U, the out-of-sample \( R \)-squared (OOSR\(^2\)) statistic of Campbell and Thompson (2008), and the MSE-adjusted statistic of Clark and West (2007).

3. Results and discussion

3.1. In-sample analysis

This section provides the estimated predictive regression models for all GCC countries, using the OLS, ALS, and FGLS estimators. The results are summarized in Tables 1–3. In each of the three tables, Panels A, B, and C report the estimated coefficients of the first predictor (global GPR), second predictor (Saudi GPR), and third predictor (crude oil returns), respectively. In each panel, we present the results of the serial correlation LM test and ARCH test for each model up to 12 lags to indicate whether the applied model is free from serial correlation and heteroscedasticity.

Table 1 presents the results obtained from OLS regressions, which clearly reveals that the three predictive models suffer from the presence of the ARCH effect. This is evident based on the high ARCH-LM statistics, resulting in the rejection of the null hypothesis of no ARCH effect at conventional levels, except for the model for Saudi Arabia. Additionally, most models exhibit autocorrelation at the conventional levels of significance. According to classical regression theory, the presence of heteroscedasticity and autocorrelation negates the efficiency of OLS estimates. Therefore, the loss of efficiency may

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9 Notably, in all the predictive models that we apply in this study, our dependent variable is the excess returns computed using the 3-month rates.
Table 1
Estimated predictive regression using OLS estimator.

| Predictand: Excess returns |
|-----------------------------|
| **Panel A: Global GPR**     |
| GPR_{t-1}                  | 0.0044 | −0.0012 | −0.0189** | −0.0224 | −0.0097** | −0.0086 |
| Constant                   | −0.0302 | −0.0041 | −0.0744*** | 0.1003  | 0.0336   | 0.0336  |
| R²                         | 0.0039 | 0.0001  | 0.0264    | 0.0235  | 0.0642   | 0.0053  |
| LM(12)                     | 28.8948*** | 16.4243 | 33.5875*** | 13.4688 | 13.0259  | 11.7814 |
| ARCH(12)                   | 42.0289*** | 23.6497** | 33.1210*** | 46.6195*** | 13.4680 | 30.2038*** |
| **Panel B: Saudi GPR**     |
| GPR_{t-1}                  | 0.0258*** | 0.0335 | 0.0362**  | 0.0003  | 0.0344   | 0.0459*** |
| Constant                   | −0.1292*** | −0.1645** | −0.1780** | −0.0264 | −0.1667  | −0.2167*** |
| R²                         | 0.0444 | 0.0225  | 0.0326    | 0.0100  | 0.0179   | 0.0512   |
| LM(12)                     | 24.7732*** | 16.8039 | 32.6512*** | 14.8519 | 12.6936  | 14.2659  |
| ARCH(12)                   | 35.3860*** | 22.9740** | 27.3457*** | 42.0206*** | 14.3403 | 22.3197*** |
| **Panel C: Crude oil returns** |
| Oil returns_{t-1}          | 0.0512 | 0.1395*** | 0.1679*** | 0.1367** | 0.1372** | 0.0849   |
| Constant                   | −0.0102*** | −0.0100** | −0.0199** | −0.0004 | −0.0082  | −0.0050  |
| R²                         | 0.0234 | 0.0523  | 0.0936    | 0.0394  | 0.0382   | 0.0234   |
| LM(12)                     | 26.9188*** | 14.0311 | 27.3457*** | 12.3000 | 10.8379  | 11.2023  |
| ARCH(12)                   | 39.2860*** | 22.9740** | 27.3457*** | 42.0206*** | 14.3403 | 22.3197*** |

Notes: $R^2$ = R-squared; LM(12) denotes Breusch–Godfrey serial correlation LM test up to 12 lags; ARCH(12) denotes the heteroscedasticity ARCH test up to 12 lags; *, **, *** denote statistical significance at 5% and 1%, respectively.

Table 2
Estimated predictive regression using ALS estimator.

| Predictand: Excess returns |
|-----------------------------|
| **Panel A: Global GPR**     |
| GPR_{t-1}                  | 0.0053 | −0.0008 | −0.0211** | −0.0237 | −0.0068 | −0.0095 |
| ∆GPR                       | 0.0036 | 0.0017 | −0.0069  | 0.1060  | 0.0225  | 0.0379  |
| Constant                   | −0.0340 | −0.0059 | 0.0844    | 0.0024  | 0.0072  | 0.0068  |
| R²                         | 0.0050 | 0.0001  | 0.0292    | 0.0241  | 0.0072  | 0.0068  |
| LM(12)                     | 28.7480*** | 16.4845 | 33.6326*** | 13.3946 | 13.3438 | 11.7427 |
| ARCH(12)                   | 41.6741*** | 22.6671** | 21.2502*** | 40.9210*** | 17.2379 | 19.2839 |
| **Panel B: Saudi GPR**     |
| GPR_{t-1}                  | 0.0197 | 0.0179 | 0.0292    | 0.0077  | 0.0220  | 0.0291** |
| ∆GPR                       | −0.0159 | −0.0406 | −0.0182  | −0.0452  | −0.0060 | −0.0176  |
| Constant                   | −0.1011** | −0.0927 | −0.1457  | −0.0361  | −0.1560 | −0.1855** |
| R²                         | 0.5518 | 0.0436  | 0.0378    | 0.0304  | 0.0182  | 0.0561  |
| LM(12)                     | 25.1807** | 16.9422 | 31.8427*** | 15.0311 | 12.7101 | 14.3402 |
| ARCH(12)                   | 39.4475*** | 24.9597** | 30.9384*** | 47.2892*** | 13.9131 | 22.2768** |
| **Panel C: Crude oil returns** |
| Oil returns_{t-1}          | 0.1048*** | 0.2563** | 0.3266*** | 0.3581*** | 0.3280*** | 0.2742*** |
| ∆Oil returns               | 0.0657** | 0.1435*** | 0.1951*** | 0.2722*** | 0.2345*** | 0.2327*** |
| Constant                   | −0.1036** | −0.0101** | −0.0111** | −0.0008  | −0.0085 | −0.0052  |
| R²                         | 0.0609 | 0.1058  | 0.2161    | 0.1907  | 0.1463  | 0.1940  |
| LM(12)                     | 31.9147*** | 13.8214 | 25.2375** | 17.3516 | 7.7390  | 12.5477 |
| ARCH(12)                   | 11.7369 | 16.9208 | 7.0437    | 36.7042*** | 23.3851** | 12.1245 |

Notes: See notes to Table 1.

explain why the coefficients on the three predictors appear to be statistically insignificant in all OLS models. Therefore, the OLS results are expectedly suboptimal, mainly due to the presence of the persistent predictor, autocorrelation, and conditional heteroscedasticity.

Table 2 shows the estimated predictive regression using the ALS estimator by Lewellen (2004). There are some improvements observed in terms of the significance of the three predictors’ coefficients compared to the OLS estimates, in particular in the models involving crude oil returns as a predictor. This may be due to the capacity of the ALS estimator to capture the endogeneity and persistency of the predictor. Still, there is not much sign of improvement in terms of the diagnostic checks, in which most predictive models have the same issues as the OLS models. The presence of serial
correlation and heteroscedasticity in the ALS models are unexpected yet reasonable, as the design of the bias-adjusted least squares estimator is intended only for capturing the persistency and endogeneity of the predictor. The model estimated using the ALS approach is far from forecasting-fitted, as the presence of the ARCH effect and the autocorrelation are not accounted for.

Table 3 reports the estimated predictive regression using the FGLS estimator by Westerlund and Narayan (2012, 2015). One can observe significant improvement in terms of the results of the two diagnostic checks, autocorrelation and heteroscedasticity. This result is not surprising given that the FGLS estimator is expected to be both unbiased and efficient (Westerlund and Narayan, 2012). Panel A shows that the results using the Global GPR as a predictor are quite comparable to those previously reported in Tables 1 and 2. Panel A shows that most of the coefficients for the global GPR are statistically insignificant, except for Omani and Saudi stock returns, which are weakly significant at the 5% level. Panel B indicates that the Saudi GPR shows economic significance on the stock returns of Saudi markets at the 1% significance level. Furthermore, Panel C shows that crude oil returns possess a strong power in predicting stock returns in most GCC countries. In fact, crude oil returns have significant in-sample prediction power in five stock return models, those of Kuwait, Oman, Qatar, Saudi Arabia, and UAE. Overall, our in-sample estimation results indicate that crude oil returns possess a strong predictive power in forecasting GCC stock markets excess returns. According to the adjusted $R^2$ reported, and except for Bahrain, the forecasting power of crude oil returns is stronger than either of the two GPR indices. This supportive evidence from in-sample tests is consistent with numerous earlier studies (see, among others Campbell and Shiller, 1988; Chiang and Hughes, 2017; Narayan et al., 2014; Phan et al., 2015).

### 3.2. Out-of-sample forecasting

Having analysed the in-sample performance of the predictive models, this section assesses the out-of-sample predictability of each model. As evident from the earlier section, the OLS and ALS estimators are not well suited for prediction analysis, therefore the out-of-sample tests only consider the FGLS models. We assess the out-of-sample forecasting by comparing the forecasting accuracy of two models, the competition (unrestricted) model and the benchmark (restricted) model (Narayan et al., 2014; Phan et al., 2019). Using 50% of the sample as an in-sample period (February 2007 to June 2013), we produce forecasts of excess returns for the rest of the sample (June 2013, December 2019). We employ three measures for the out-of-sample forecasting evaluation, the relative Theil U, the out-of-sample $R^2$ statistic of Campbell and Thompson (2008), and the forecasting mean squared error (MSE)-adjusted statistic of Clark and West (2007). The relative Theil U statistic is the ratio of the Theil U from the unrestricted model (also called the competition model) to the restricted, i.e. constant return, model (also called the benchmark model). When the relative Theil U is less than one, it implies that forecasts based on the unrestricted model outperform the forecasts based on the restricted model (Narayan et al., 2014). $OOSR^2$ is used to compare the accuracy of the forecasting MSE from the unrestricted and restricted models. Specifically, $OOSR^2$ represents the percentage reduction of the mean squared predictive error (MSPE) of the unrestricted model to the MSPE of the restricted model. A positive $OOSR^2$ value indicates that the forecasting of
the unrestricted model is more accurate than that of the restricted model (Phan et al., 2018). The MSE-adjusted statistic of Clark and West (2007) is used to test the null hypothesis \( OOSR^2 < 0 \), against the alternative hypothesis \( OOSR^2 > 0 \). *, **, and *** imply rejection of the null hypothesis at the 10%, 5%, and 1% levels of significance, respectively.

Table 4 summarizes the three out-of-sample forecasting evaluation measures, relative Theil U, out-of-sample R-squared (\( OOSR^2 \)) statistic, and MSE-adjusted statistic. Firstly, the relative Theil U results indicate that the forecasts from the unrestricted model are better than those obtained from the restricted model in at least two cases for each predictor (Kuwait and Oman for Global GPR; Bahrain, Oman, and UAE for Saudi GPR; and Kuwait, Oman, and Saudi Arabia for crude oil returns). Secondly, the \( OOSR^2 \) results show that the unrestricted model outperforms the restricted model in one case (Bahrain) for the Global GPR, in three cases (Bahrain, Kuwait, and Qatar) for the Saudi GPR, and in three cases (Kuwait, Qatar, and Saudi Arabia) for crude oil returns. Thirdly, the null hypothesis \( OOSR^2 < 0 \) is rejected in at least three cases for Global GPR and crude oil returns. The most appropriate forecasting model uses crude oil returns, since the null is rejected for all six indices, followed by Global GPR, for which the null is rejected for three of the six indices. Therefore, crude oil returns provide solid evidence of out-of-sample predictability, since the null is rejected in all cases. Conversely, there is no acceptable out-of-sample forecasting model for the Saudi GPR. Overall, the MSE-adjusted statistic of Clark and West (2007) provides the greatest evidence in favour of the unrestricted model. Furthermore, most of the out-of-sample forecasting evaluation measures indicate the superiority of the prediction model involving crude oil returns.

### 3.3 Sensitivity analysis

In this section, we conduct two sensitivity exercises. In the first, given that the choice of out-of-sample forecasting period is arbitrary, we assess the out-of-sample forecasting evaluation using a different length of training set. Specifically, we use 60% of the sample as an in-sample period (February 2007 to October 2014). The results from the out-of-sample forecasting evaluation of the FGLS estimator are reported in Table 5. They show that the forecasts from the unrestricted model are better than those obtained from the restricted model in two cases for each predictor, mainly in Panels B and C, which is comparable to the results reported in Table 4.12

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11 Notably, a positive \( OOSR^2 \) implies that a forecasting model using the predictor to forecast excess returns outperforms the constant returns model.

12 We assess the robustness of the out-of-sample forecasting evaluation using 40% of the sample period as an in-sample period (February 2007 to April 2012). Unreported results indicate somewhat similar results to those reported in Table 5.
|                  | Relative Theil U | OOSR² | MSE-adjusted, p-value |
|------------------|------------------|-------|-----------------------|
| **Panel A: Global GPR** |                  |       |                       |
| Bahrain          | 1.0537           | 0.0160| 0.4180                |
| Kuwait           | 1.0835           | −0.0645| 0.0000                |
| Oman             | 1.0384           | −0.2512| 0.0000                |
| Qatar            | 1.8656           | −0.0396| 0.7109                |
| Saudi            | 1.0537           | −0.2082| 0.0000                |
| UAE              | 1.1572           | −0.1632| 0.3200                |
| **Panel B: Saudi GPR** |                  |       |                       |
| Bahrain          | **0.9728**       | **0.1020**| 0.4091                |
| Kuwait           | 1.0845           | −0.0119| 0.7781                |
| Oman             | 1.0143           | −0.1632| 0.8109                |
| Qatar            | 1.3598           | **0.0486**| 0.3579                |
| Saudi            | 1.0628           | −0.2805| 0.2271                |
| UAE              | **0.9471**       | −0.0217| 0.3702                |
| **Panel C: Crude oil returns** |                  |       |                       |
| Bahrain          | 1.6913           | −0.2656| 0.0000                |
| Kuwait           | 1.0835           | −0.0307| 0.0000                |
| Oman             | **0.8313**       | −0.1963| 0.0000                |
| Qatar            | 1.5883           | **0.0682**| 0.0000                |
| Saudi            | **0.8646**       | **0.1763**| 0.0000                |
| UAE              | 1.1109           | −0.2324| 0.0000                |

Notes: See notes to Table 4.

In the second exercise, we assess the sensitivity of our predictability results to the use of excess risk adjusted returns that account for risk free rates, market risk factors and macroeconomic factors. Following the existing literature, we compute excess risk adjusted returns using risk free rates, world stock returns, global economic policy uncertainty (GEPu), and the Chicago Board Options Exchange (CBOE) VIX. The results reported in Table 6 show strong predictive content of crude oil returns for GCC stock market returns, which is comparable to the results reported in Table 3. In fact, these in-sample estimation results, including the adjusted R²-s, indicate that the forecasting power of crude oil returns is stronger than either of the two GPR indices.

We also evaluate the out-of-sample forecasting of the excess risk adjusted returns using the relative Theil U, out-of-sample R-squared (OOSR²) statistic, and MSE-adjusted statistic. The results in Table 7 show a more prominently significant out-of-sample predictive power from crude oil returns to most GCC stock returns than from the GPR indices.

4. Conclusion

This paper evaluates the in-sample and out-of-sample performance of two GPR indices (global GPR and Saudi GPR) and crude oil returns in predicting GCC stock returns using various estimators, specifically the ordinary least squares (OLS) estimator, the bias-adjusted least squares (ALS) estimator (Stambaugh, 1999; Lewellen, 2004), and the feasible generalized least squares (FGLS) estimator (Westerlund and Narayan, 2012). The in-sample and out-of-sample tests under various forecasting windows reveal some important findings. Firstly, the reported predictive models with OLS estimates and ALS estimates fail to address various econometric issues and are therefore unfit for GCC stock return forecasting. Likewise, the in-sample results show that the FGLS estimator outperforms both OLS and ALS estimators in terms of econometric performance across all GCC stock returns. Moreover, the FGLS models show that global geopolitical risk has significant in-sample stock return predictive power in the markets of Oman and Saudi Arabia, whereas the Saudi global geopolitical risk possesses significant in-sample stock return predictive power in the Saudi stock market only. However, these results do not hold when risk adjusted returns are used. Crude oil returns show significant predictive power for all GCC stock returns, except those of Bahrain, and the results hold when risk adjusted returns are used. Secondly, while the in-sample tests provide positive outcomes for the predictive power of the GPR indices and crude oil returns with the use of the FGLS estimator, the out-of-sample forecasts provide mixed findings. For example, there is no acceptable out-of-sample forecasting model for the Saudi GPR, whereas some significant evidence is shown for the global GPR. Importantly, we note the superiority of the out-of-sample prediction model involving crude oil returns.

It is recommended that crude oil returns be considered for active prediction of GCC stock market returns, once econometric issues are accounted for. The predictability of crude oil returns is especially effective in the Kuwaiti, Omani, Qatari, Saudi, and UAE stock markets. Likewise, investment banks and forecasters could consider incorporating crude oil returns into their predictive models to improve the accuracy of their forecasts.
returns along with traditional predictors in their forecasts of GCC stock market returns. The empirical results shed light on the methodological issues of related studies. Using various estimators reveals that the choice of estimator matters for stock return prediction. Thus, researchers and practitioners should properly consider the characteristics of their predictors prior to making any stock return forecasts.

Given that stock markets have been strongly affected by the COVID-19 outbreak, predictability might be disturbed by this unprecedented risk. This is based on the rationale that predictability is time-varying and can be altered by the presence of structural breaks, such as those due to the COVID-19 outbreak. Accordingly, as part of the agenda for future research, two research possibilities emerge. Firstly, the issue of time-varying predictability as documented by Devpura et al. (2018), and secondly, the structural break predictability indicated by Devpura et al. (2019).

Table 6
Estimated predictive regression using FGLS estimator — Excess risk adjusted returns.

| Predictand: Excess risk adjusted returns | Bahrain | Kuwait | Oman | Qatar | Saudi | UAE |
|------------------------------------------|---------|--------|------|-------|-------|-----|
| **Panel A: Global GPR**                  |         |        |      |       |       |     |
| GPR\(_{t-1}\)                             | 0.0000  | 0.0014 | −0.0010 | 0.0010 | 0.0004 | −0.0022 |
| ∆GPR                                     | 0.0005 | 0.0132 | −0.0034 | −0.0014 | 0.0184 | −0.0072 |
| Constant                                 | −14.9469 | −7.8538 | −2.7286 | −1.3583 | −2.5930 | 2.6054 |
| R\(^2\)                                  | 0.0001 | 0.0140 | 0.0054 | 0.0012 | 0.0131 | 0.0033 |
| LM(12)                                    | 29.0792*** | 5.2605 | 22.3556** | 14.9563 | 9.8805 | 8.6760 |
| ARCH(12)                                  | 16.4129 | 7.6738 | 13.4329 | 20.0344 | 9.2072 | 11.7613 |
| **Panel B: Saudi GPR**                    |         |        |      |       |       |     |
| GPR\(_{t-1}\)                             | 0.0008 | 0.0017 | −0.0004 | 0.0024 | 0.0029 | 0.0047 |
| ∆GPR                                     | −0.0245** | −0.0335** | −0.0045 | −0.0324 | 0.0001 | −0.0339 |
| Constant                                 | −20.1230 | −9.0622** | −6.8388 | −3.6990 | −6.9358 | −12.6240 |
| R\(^2\)                                  | 0.0381 | 0.0511 | 0.0010 | 0.0249 | 0.0092 | 0.0293 |
| LM(12)                                    | 31.9603*** | 8.7802 | 15.4662 | 14.0226 | 9.7708 | 11.4725 |
| ARCH(12)                                  | 20.4120 | 8.6511 | 9.7874 | 24.5540** | 9.8516 | 11.7980 |
| **Panel C: Crude oil returns**            |         |        |      |       |       |     |
| Oil returns\(_{t-1}\)                     | 0.0982*** | 0.1439*** | 0.2865*** | 0.3401*** | 0.1285*** | 0.2230*** |
| ∆Oil returns                             | 0.0492 | 0.1011*** | 0.1864*** | 0.2925*** | 0.2373*** | 0.2209*** |
| Constant                                 | −14.8263*** | −4.0159** | −5.7071*** | 0.4579 | −2.0112 | −1.3594 |
| R\(^2\)                                  | 0.0556 | 0.0519 | 0.1729 | 0.2415 | 0.3998 | 0.1667 |
| LM(12)                                    | 34.7377*** | 12.0495 | 15.2094 | 14.2737 | 4.8804 | 10.4148 |
| ARCH(12)                                  | 20.5497 | 11.3984 | 8.2668 | 19.1581 | 15.2357 | 11.3638 |

Notes: See notes to Table 1.

Table 7
Out-of-sample forecasting evaluation of the FGLS estimator — Excess risk adjusted returns (50% in-sample period).

| Relative Theil U | OOSR\(^2\) | MSE-adjusted, p-value |
|------------------|------------|-----------------------|
| **Panel A: Global GPR** |           |                       |
| Bahrain          | 0.9872 | −0.0543 | 0.0000 |
| Kuwait           | 0.9670 | 0.0142 | 0.0000 |
| Oman             | 0.9809 | −0.5334 | 0.0000 |
| Qatar            | 1.2398 | −0.0430 | 0.0000 |
| Saudi            | 1.0028 | −0.0639 | 0.0000 |
| UAE              | 1.2940 | −0.2853 | 0.0000 |
| **Panel B: Saudi GPR** |           |                       |
| Bahrain          | 0.9024 | 0.0470 | 0.0000 |
| Kuwait           | 1.3125 | −0.2981 | 0.0000 |
| Oman             | 1.0455 | −0.2687 | 0.0000 |
| Qatar            | 0.9697 | 0.0145 | 0.0000 |
| Saudi            | 1.0884 | −0.0483 | 0.0000 |
| UAE              | 0.9108 | −0.1065 | 0.0000 |
| **Panel C: Crude oil returns** |           |                       |
| Bahrain          | 1.0291 | 0.1228 | 0.0000 |
| Kuwait           | 1.1088 | 0.0282 | 0.0000 |
| Oman             | 0.8744 | −0.0102 | 0.0000 |
| Qatar            | 4.0954 | −0.0752 | 0.0000 |
| Saudi            | 0.8559 | 0.1624 | 0.0000 |
| UAE              | 1.0282 | −0.1623 | 0.0000 |

Note: See notes to Table 4.
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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