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# Improving the Forecast Accuracy of Oil-Exchange Rate Nexus in GCC Countries

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## Abstract

This paper renders new evidence on the predictability of GCC dollar exchange rates using crude oil prices relying on the approach of Westerlund [1] [2] that accounts for salient features of the predictor. The results show the presence of significant in-sample predictability of exchange rates using crude oil prices (Brent and WTI prices) across the GCC countries. The results of forecast evaluation based on the root mean square error (RMSE), Campbell-Thompson (C-T) statistic and Diebold-Mariano (D-M) statistic are rather mixed. The superior forecast performance of the oil-based exchange rate model is highly sensitive to the choice of benchmark time-series models. We, however, conclude the overwhelming forecast performance of time-series models (namely, AR, ARMA, and ARFIMA) over our oil-based exchange rate model in predicting exchange rates across the GCC region.

## Keywords

Oil Price, Exchange Rate, Forecast Evaluation, GCC Countries

## 1. Introduction

Many economies, developing and developed, depend on oil for a variety of needs especially in the production of many goods and services [3]. To further stress the importance of oil, fluctuations in oil prices have been linked to many economic challenges such as economic recessions, trade deficits, high inflation, low values for stocks and bonds and high uncertainty for investment [4] [5] [6]. In this light, a number of studies have highlighted how changes in oil price influence these macroeconomic variables [3]. Generally, empirical evidences that establish the relationship between oil price and exchange rate are less substantial and as well mixed. From the scanty literature, a shred of evidence suggests that movements in oil prices determine the value of a currency [3] [7]-[15]. Given the

shred of evidence explaining the dynamics of oil price-exchange rate relationship, we explore this nexus for the GCC countries. There is a dearth of studies in this regard on the predictability of exchange rate with oil price for oil-exporting countries in general and the GCC in particular despite their high dependence on crude oil. This serves as a motivation for the present study.

Thus, the present study contributes to the literature in the following ways. First, it evaluates both the in-sample and out-of-sample forecast performance of oil-based exchange rate model relative to time series models. Second, it accounts for some important features of oil price which may have implications on its forecast performance. Consequently, the approach of Westerlund [1] [2], which accommodates salient features such as endogeneity, persistence and conditional heteroscedasticity in the predictors of a series, is employed. The choice of GCC countries in this study is deliberate. Unlike other oil-exporting nations, these countries share similar characteristics given the increasing economic integration among them (an instance is the adoption of pegged exchange rates against the US dollars).

Following this section, the rest of the paper is structured as follows. The next section provides a brief review of the literature followed by Section 3, which presents the predictive model for estimation and the underlying forecasting procedures. Section 4 contains preliminary analyses of data features. Section 5 discusses the results while Section 6 concludes the paper.

## 2. Literature Review

The literature has widely taken care of the relationship between exchange rate and oil prices. It must be re-stated from the beginning of this review that most studies are impact analysis focus; very few consider exchange rate forecast through oil price, most especially in the GCC countries. The study of the relationship received much more attention for the United States dollar and currencies of industrial and developed economies, along with OPEC and other oil exporting countries. On the results discovered; the bulk of the studies attesting to the relationship between oil prices and exchange rates argue that movements in oil prices determine the value of a currency. For example, while studying real oil prices in the post Bretton Woods era and their relationship with 16 OECD countries' real exchange rates, Chaudhuri [7] among others found that, in 13 of the 16 economies studied, co-integration is discovered between the two series and oil price volatility cause movements in real exchange rate. In support of this discovery, Nikbakht [13] conducted panel analysis of 7 OPEC countries employing monthly data spanning the years 2000 to 2007. The research applies co-integration analysis also and discovered evidences that real oil prices drives fluctuations in the real exchange rates, confirming a long run link between the two for pooled series. VARs and ECMs have been adopted in the long run impacts study; many other approaches were also adopted such as that found in [7]. According to Amin [14], in the G7 countries, most results point out that oil

prices have significant predictive power on real exchange rates along with evidence of a long run link between the two variables employing different oil price measures. In addition, considering periods of structural breaks and noticeable turn arounds, Turhan *et al.* [15] confirm that the relationship between oil prices and nominal exchange rates assumes more significant pose after the financial crises of 2008 for some selected emerging countries.

The mixed nature of the various results discovered is no more news, it is important to point out from here that while some impact analyses find positive relationship, some are negative. A group claims that a rise in oil prices leads to the appreciation of the currency under study. For instance, Amano and Norden [16] study Germany, Japan and the United States and confirm the major findings of Chaudhuri [7] and Nikbakht [13]. It is also contended that in the long run a rise in the price of oil will result in the real appreciation of the US dollar against the currencies of 15 other industrial countries post the Bretton Woods era. In agreement to this, the economies of the United States, Eurozone, OPEC and China are analysed byBénassy-Quéré, *et al.* [17]. Based on their analysis, in the long run, a 10 percent rise in the price of oil spurs about 4.3 percent appreciation of the US dollar, with a sluggish return of the US dollar exchange rate to its long run equilibrium value. For the GCC however, Alotaibi [18] concludes that positive oil price shocks dominate currency movements continuously in all GCC countries except in UAE and Qatar, where demand shocks are more persistent. Coudert, *et al.* [10] also corroborated by deducing that an increase in oil prices promotes real appreciation of the oil exporter's exchange currency in the long run and that to a large extent, pegged currencies maintain the behavior of their anchors. Likewise, using four-variable structural VAR models, Korhonen, *et al.* [11] argue that a positive oil shock would cause currency appreciation against the USD.

For the other side of coin however, another group of researchers claims that a rise in oil prices would actually worsen the value of a currency leading to its depreciation against other currencies. For instance, as claimed by Akram [8] increasing oil prices, in a negative non-linear way, affect nominal exchange rates in the short run only, and claims that the strength of this effect depends on the level and trend of oil prices. Akram [8] finds the link to be insignificant in the long run. Comparatively, Trygubenko [9] employs a number of empirical models and concludes that rising oil prices significantly depreciate the USD in the short run. Like Akram [8] however, he finds no relation between the two variables in the long run. Concurring to this, Al-Mulali, *et al.* [19] emphasized a long run relationship between the UAE dirham's real exchange rate and oil prices but while recognizing the impact of positive oil price shocks on domestic prices, the authors conclude that a 1 percent increase in oil prices causes 0.16 percent depreciation in the real value of the dirham.

A major gap in the literature relates to the fact that virtually all the known studies involve impact (in-sample) analyses while the issue of predictability between oil price and exchange rate has received very little attention. This is the

gap the study intends to fill.

## 3. Methodology and Data

### 3.1. Estimation Approach

We begin our methodology by specifying a bivariate single predictive model where crude oil price is hypothesized as a predictor of exchange rate:

$$s_t = \alpha + \lambda p_{t-1} + \varepsilon_t \tag{1}$$

where $s_t$ is the log of dollar exchange rate for each of the six GCC countries' currencies involving Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirate; and $p_t$ is the log of crude oil prices where Brent price and WTI price are used separately in the estimation process. Thus, we have two predictive models for each of the oil price series across the six GCC countries considered (details about the data utilized are provided in the section that follows). The $\varepsilon_t$ is zero mean idiosyncratic error term on exchange rate and the coefficient $\lambda$ measures the relative impact of crude oil prices on exchange rate and the underlying null hypothesis of no predictability is that $\lambda = 0$.

In order to resolve any probable endogeneity bias resulting from the correlation between $p_t$ and $\varepsilon_t$ as well as any potential persistence effect, we follow the approach of Lewellen [20] and Westerlund [1] [2]. This bias is not unexpected since a single predictor (oil price) is accounted for in the predictive model for exchange rate as in Equation (1) whereas in reality there are several predictors that influence the latter which are not captured in the analyses. Excluding these variables will bias the regression estimates [20]. In addition, oil price is recently found to be endogenous as it responds to the interplay between supply shock (due to global oil supply) and demand shock (due to the real level of economic activity) [21] and therefore correcting for this inherent endogeneity becomes important in the estimation process. In fact, Lewellen [20] finds that ignoring such bias has implications on the forecast results. The underlying predictive model that accounts for these effects can be specified as:

$$s_t = \alpha + \lambda_{adj} p_{t-1} + \gamma \left( p_t - \rho_0 p_{t-1} \right) + \eta_t \tag{2}$$

where the parameter $\lambda_{adj} = \lambda - \gamma \left( \rho - \rho_0 \right)$ is the bias adjusted OLS estimator of Lewellen [20] which corrects for any persistence effect in the predictive model. The additional term $\gamma \left( p_t - \rho_0 p_{t-1} \right)$ corrects for any endogeneity bias resulting from the correlation between $p_t$ and $\eta_t$. Accounting for endogeneity bias here is important since there could be several determinants of stock prices which are suppressed in Equation (1). Such omissions could introduce endogeneity bias resulting from probable correlations between $p_t$ and $\eta_t$. To resolve the conditional heteroscedasticity effect, we estimate the predictive model using the ML-ARCH (Maximum Likelihood-Autoregressive Conditional Heteroscedasticity) estimator.

In addition, three forecast measures are used to evaluate the in-sample and out-of-sample forecasts: the root mean square error (also called the mean square

error), the (C-T hereafter) test [22] and the test (D-M hereafter) [23]. The C-T test statistic is computed as $1 - \left( \widehat{MSE}_1 / \widehat{MSE}_0 \right)$, where $\widehat{MSE}_0$ and $\widehat{MSE}_1$ are the mean square error (*MSE*) obtained from the restricted and the unrestricted models, respectively. In the present case, our oil-based exchange rate model in Equation (1) stands as the unrestricted model, whereas time-series models including AR(1), ARMA (1, 1) and ARFIMA (1, d, 1), where "d" is the order of integration which is neither zero nor unity. A positive value of the statistic implies that our oil-based exchange rate model is preferred to the time-series models in predicting exchange rates; otherwise, it does not. By implication, a positive C-T statistic obtains from the fact that RMSE associated with our predictive model is less than that associated with the time-series models; but the reverse is the case for a negative C-T statistic. The D-M test is also used as a complementary test and it tests whether the difference between the forecast errors of two competing predictive models is statistically significant (or different from zero). While the D-M test is not suitable for small samples (which is not a concern given the large samples used for analyses), the test is however valid when the forecast errors are found to be non-Gaussian, nonzero mean, serially correlated, and contemporaneously correlated. A negative value and statistical significance of the D-M statistic at the conventional levels of 1%, 5% and 10% imply that our oil-based exchange rate model significantly outperforms the time-series models; otherwise, it does not.

## 3.2. Data Description and Source

We focus attention on the foreign exchange markets of the six GCC countries, namely, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirate so as to examine the sensitivity of the US dollar exchange rates in each country to changes in crude oil prices. We collect daily data on the two variables of interest, namely, the US dollar exchange rate of the six GCC countries' currencies and crude oil prices, comprising Brent price and West Texas Intermediate (WTI) price from various sources and over different time periods for most of the countries. All the data used for analyses were sourced from the Bloomberg terminal and the scope ranges from the period of 8th January, 1999 to 15th September, 2017. This applies to the US dollar exchange rates of the GCC countries except Kuwait's whose exchange rate data ranged from 8th January, 1999 to 1st September, 2017. Thus, the analyses are conducted based on the available data for the individual countries.

## 4. Preliminary Analysis

### 4.1. Descriptive Statistics

Table 1 presents the summary of descriptive statistics so as to observe the statistical features of dollar exchange rates and crude oil prices (Brent and WTI prices) for the GCC countries over their respective full sample periods. Both exchange rates and crude prices are in their natural log forms. We observe that

**Table 1.** Descriptive statistics.

| Variable | Mean | Std. | Skw. | Kurt. | J-B stat | Autocorrelation | | | Heteroscedasticity | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | $k = 30$ | $k = 60$ | $k = 90$ | $k = 30$ | $k = 60$ | $k = 90$ |
| $p_t^{br}$ | 3.974 | 0.587 | −0.353 | 2.19 | 46.9*** | 118.25*** | 154.44*** | 179.03*** | 1.381* | 1.352** | 1.791*** |
| $p_t^{wti}$ | 3.96 | 0.533 | −0.377 | 2.234 | 46.98*** | 127.49*** | 157.15*** | 185.98*** | 1.591** | 1.194 | 1.332** |
| | | | | | $s_t$ | | | | | | |
| Bahrain | 1.301 | 0.011 | -31.19 | 973.9 | 38,492,311*** | 0.0003 | 0.0019 | 0.0074 | 1.521** | 1.114 | 0.881 |
| Kuwait | −1.231 | 0.039 | −0.447 | 2.348 | 49.631 | 243.49*** | 297.44*** | 343.6*** | 12.952*** | 6.914*** | 4.591*** |
| Oman | −0.955 | 0.011 | −31.159 | 972.6 | 38,387,969*** | 0.0045 | 0.0117 | 0.0228 | 2.532*** | 1.694*** | 1.347** |
| Qatar | 1.292 | 0.01 | −30.006 | 927.1 | 34,870,761*** | 34.97 | 34.978 | 34.991 | 171,976.9*** | 81,595.8*** | 51,426.9*** |
| Saudi Arabia | 1.321 | 0.011 | −31.087 | 969.6 | 38,151,058*** | 0.0016 | 0.007 | 0.0247 | 0.266 | 0.248 | 0.375 |
| United Arab Emirate | 1.301 | 0.011 | −31.191 | 973.9 | 38,492,811*** | 0.0003 | 0.0026 | 0.0074 | 1.521** | 1.114 | 0.881 |

**Note**: $p_t^{br}$, $p_t^{wti}$, and $s_t$ are respectively, the natural logs of Brent price, WTI price, and exchange rate. Std is standard deviation, Skw is skewness, Kurt is Kurtosis, and J-B stands for Jarque-Bera. For autocorrelation and heteroscedasticity tests, the reported values are the Ljung-Box test Q-statistics for the former and the ARCH-LM test F-statistics in the case of the latter. We consider three different lag lengths ($k$) of 30, 60, and 90 for robustness. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM test is that there is no conditional heteroscedasticity. ***, ** and * imply the rejection of the null hypothesis in both cases at 1%, 5% and 10% levels of significance, respectively.

both Brent and WTI prices have approximately equal mean values. Also, dollar exchange rate has the same average values in the cases of Bahrain and the United Arab Emirate, with Saudi Arabia having the highest average dollar exchange rate and Oman having the lowest average dollar exchange rate in the group. In terms of standard deviation, Brent price is more volatile than the WTI price. Similarly, among the GCC countries, dollar exchange rate in Kuwait is the most volatile while that in Qatar is the least volatile, with other dollar exchange rates remaining equally volatile.

We also take account of other statistical features including skweness, kurtosis and Jarque-Bera statistic. In terms of skewness, we observe that the both the crude oil prices (Brent and WTI prices) and the dollar exchange rates across the six GCC countries are negatively skewed In terms of kurtosis, crude oil prices and Kuwaiti dollar exchange rate are largely platykurtic (for kurtosis values being less than 3.0), while the remaining five dollar exchange rates are generally leptokurtic (for kurtosis values being greater than 3.0). In addition, Jarque-Bera statistics indicate that both the crude oil prices and all the dollar exchange rates except the Kuwait's do not follow normal distribution.

## 4.2. Autocorrelation and Heteroscedasticity Test Results

Here, we conduct autocorrelation and heteroscedasticity tests using Ljung-Box test Q-statistics and Autoregressive conditional heteroscedasticity lagrangian multiplier (ARCH-LM) test F-statistics, respectively (see Table 1) over the full

sample period. We consider three different lag lengths (k) of 30, 60, and 90 for robustness. With respect to the predictors (crude oil prices), our results show the presence of significant serial dependence and conditional heterosedasticity at both lower and higher orders. Results are however mixed in the case of dollar exchange rates across the GCC countries. The dollar exchange rates in the GCC countries except the Kuwait'sdo not suffer from serial correlation at both lower and higher orders. Generally, GCC dollar exchange rates, except Saudi Arabia's, exhibit conditional heteroscedasticity at both lower and higher orders mostly in some quarters.

### 4.3. The Persistence and Endogeneity Test Results

To further strengthen the choice of estimator, we test for persistence and endogeneity in the predictors, which comprise crude oil prices (Brent and WTI prices) in this case (see Table 2) over the full sample period. The persistence test has the null hypothesis of no persistence effect in the predictors. The coefficient of the AR(1) process was estimated for each predictor using OLS estimator and the results were found to be close or equal to one which is often the features of series with higher order of integration, thus, suggesting that the predictors (crude oil prices) contain persistent effects. We, however, observe that our predictors are

Table 2. Persistence and endogeneity test results for predictors.

| | Persistence | | Endogeneity | |
|---|---|---|---|---|
| | $p_t^{br}$ | $p_t^{wti}$ | $p_t^{br}$ | $p_t^{wti}$ |
| | | $s_t$ | | |
| Bahrain | 0.994*** | 0.994*** | −0.008 | −0.007 |
| Kuwait | 0.994*** | 0.994*** | 0.053*** | 0.059*** |
| Oman | 0.994*** | 0.994*** | −0.008 | −0.006 |
| Qatar | 0.994*** | 0.994*** | −0.008 | −0.007 |
| Saudi Arabia | 0.994*** | 0.994*** | −0.009 | −0.008 |
| United Arab Emirate | 0.994*** | 0.994*** | −0.008 | −0.007 |

Note: This table reports the endogeneity and persistence test results. Starting with the former, the test follows a three-step procedure: First, we run the following predictive regression model: $s_t = \alpha + \beta x_{t-1} + \varepsilon_{s,t}$ where $s_t$ represents exchange rate and $x_{t-1}$ is the predictor variable (which are crude oil prices, in this case). In the second step, we follow [1] [2] and model the predictor variable as follows: $x_t = \mu(1-\rho) + \rho x_{t-1} + \varepsilon_{s,t}$ and in the final step, the relationship between the error terms is captured using the following regression: $\varepsilon_{s,t} = \lambda \varepsilon_{x,t-1} + \eta_t$. If the coefficient $\lambda$ is statistically different from zero at any of the conventional chosen levels of significance such as ***, ** and * for 1%, 5% and 10%, respectively; then, the predictor variable is endogenous. For the latter however, the persistence test is conducted by regressing a first order autoregressive process for the predictor, for example: $z_t = \omega + \rho z_{t-1} + \vartheta_t$ using OLS estimator. The first order autocorrelation coefficient ($\rho$) captures the persistence effect and is reported for each of the predictors. The null is that there is presence of persistence effect if $\rho$ is statistically significant and the closer the value to one the higher the degree of persistence.

largely exogenous across the GCC countries, with Kuwait being an exception.

## 5. Discussion of Results

In line with [8] [12] [24] [25], we explore in-sample predictability of the theoretical model, which in this case is the oil-based exchange rate model. The in-sample forecast is conducted using 75% of the full sample. The out-of-sample forecast, on the other hand, is based on three forecast horizons, namely, 30, 60, and 90 days. First, we seek to validate the opposing findings of [24] [25] in determining the direction of predictability between commodity prices (in which crude oil price is a part) and dollar exchange rates. Also, in order to evaluate the forecast performance of our predictive model (that is, oil-based exchange rate model) against time-series models (AR, ARMA, and ARFIMA), we employ the root mean square error (RMSE), Campbell-Thompson (C-T) statistic, and Diebold-Mariano statistic. By implication, a positive C-T stat coupled with a negative D-M stat implies that the preferred model is our predictive model, and hence it is said to significantly outperform time-series models in predicting exchange rates. However, a negative C-T stat coupled with a positive D-M stat is an indication that time-series models significantly outperforms our predictive model in predicting exchange rates; hence, they constitute the preferred model. Similarly, we seek to investigate whether in-sample predictability and forecast evaluation tests are responsive to choice of oil price series (Brent and WTI prices) across the entire GCC countries. Predictability graphs are presented for both the oil-based exchange rate model (using Brent price) and the time-series models for the GCC countries. Also, the predictability graphs of the oil-based exchange rate model (using WTI price) for the GCC countries are presented in the Appendix.

### 5.1. In-Sample Predictability Results: Do Oil Prices Matter in Exchange Rate Behaviour?

The predictability power of a potential economic predictor hinges on the statistical significance of the first-order autoregressive coefficient in the theoretical (predictive) model at the conventional levels of significance, namely, 1%, 5%, and 10%. It can be observed that irrespective of measures of oil price series (Brent and WTI prices), the null hypothesis of no predictability is rejected at 1% level of significance (see Table 3). We, therefore, conclude that crude oil prices play a significant role in predicting the behaviour of dollar exchange rates across the entire GCC countries. Our result affirms the previous findings of [12][1] and [25]. We also establish a negative linkage between crude oil prices (Brent and WTI) and dollar exchange rates across the entire GCC region. This supports the findings of [11], [12], and [15] that higher oil price leads to appreciation of the net oil-exporting currencies against the US dollar.

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[1]Lizardo, *et al.* [12] conclude that oil prices do have a role in the information set when modeling the US dollar movements.

**Table 3.** In-sample predictability of exchange rates using oil prices (Brent and WTI prices).

| | $s_t$ | |
| --- | --- | --- |
| | $p_t^{br}$ | $p_t^{wti}$ |
| Bahrain | −0.0000114*** (0.000000112) | −0.0000129*** (0.000000112) |
| Kuwait | −0.049*** (0.0003) | −0.054*** (0.0004) |
| Oman | −0.0000264*** (0.000000401) | −0.0000896*** (0.0000000337) |
| Qatar | 0.994*** (0.002) | 0.994*** (0.002) |
| Saudi Arabia | −0.0000319*** (0.000000232) | −0.0000478*** (0.000000265) |
| United Arab Emirate | −0.0000123*** (0.000000111) | −0.0000153*** (0.000000113) |

**Note**: The in-sample predictability in a bivariate model case is obtained by estimating the equation $s_t = \mu + \delta z_{t-1} + \eta \left( z_t - \rho z_{t-1} \right) + \varepsilon_t$ where $\delta$ denotes the coefficient on the predictor $z$, which in this case stands for crude oil prices. We employ both Brent and WTI prices as proxies for crude oil prices. ***implies the rejection of the null hypothesis of no predictability at 1% level of significance. The values in parentheses are the standard errors associated with the first-order autoregressive coefficients in our predictive model. Here, we consider 75% of the full sample data.

## 5.2. Forecast Evaluation: Can Oil-Based Exchange Rate Model Beat Time Series Models?

We further compare the in-sample and out-of-sample forecast performance of our oil-based exchange rate model with three time-series models including AR, ARMA, and ARFIMA using the RMSE, the C-T and the D-M statistics (see Tables 4-9). Our results are however mixed. For Kuwait and Saudi Arabia, we find that our oil-based predictive exchange rate model significantly outperforms the time series models both in-sample and out-of-sample, irrespective of the choice of oil price series and the choice of benchmark time-series models[2]. This conclusion is reached on the basis of positive C-T statistics (see Table 6 and Table 7), negative and significant D-M statistics (see Table 8 and Table 9), with the RMSE associated with our predictive model being smaller than that of the time-series models (compare Table 4 and Table 5).

We however establish an opposing conclusion of the superior forecast performance of the time-series models (AR, ARMA and ARFIMA) over our predictive exchange rate model in the cases of Bahrain, Qatar, and the United Arab Emirate both in-sample and out-of-sample, irrespective of the choice of oil price series, and the choice of benchmark time-series models. This conclusion is reached on the basis of negative C-T statistics (see Table 6 and Table 7), positive and significant D-M statistics (see Table 8 and Table 9), with the RMSE associated with our predictive model being greater than that of the time-series models (compare Table 4 and Table 5). In addition, our results show that Oman's dollar exchange rate behaviour is highly sensitive to the choice of benchmark time-series models: while AR and ARMA models predict the dollar exchange rate better than our predictive model, the reverse is the case for the ARFIMA model using both in-sample and out-of-sample periods.

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[2]This result parallels the findings of [8].

Table 4. In-sample and Out-of-sample forecast evaluation of Oil-based exchange rate Models (RMSE).

| | $s_t$ | | | | | |
| --- | --- | --- | --- | --- | --- | --- |
| | $p_t^{br}$ | | | $p_t^{wti}$ | | |
| | In-sample | Out-of-sample | | In-sample | Out-of-sample | |
| | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ |
| Bahrain | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| Kuwait | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.018 |
| Oman | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| Qatar | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| Saudi Arabia | 0.0006 | 0.0006 | 0.0005 | 0.0006 | 0.0006 | 0.0005 |
| United Arab Emirate | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |

Note: Capturing 75% of the full sample, we evaluate the in-sample and out-of-sample forecast performance (using 30 and 60 days as the forecast horizons) of our predictive model, which in this case is the oil-based exchange rate model (using Brent and WTI prices) with the aid of root mean square error (RMSE). The smaller the root mean square error (RMSE), the greater the predictive power of a model and vice versa.

Table 5. In-sample and Out-of-sample forecast evaluation of Time-series Models (RMSE).

| | AR* | | | ARMA** | | | ARFIMA*** | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | In-sample | Out-of-sample | | In-sample | Out-of-sample | | In-sample | Out-of-sample | |
| | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ |
| Bahrain | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| Kuwait | 0.039 | 0.039 | 0.039 | 0.036 | 0.036 | 0.036 | 0.040 | 0.039 | 0.039 |
| Oman | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| Qatar | 0.0003 | 0.0002 | 0.0002 | 0.0003 | 0.0002 | 0.0002 | 0.0003 | 0.0002 | 0.0002 |
| Saudi Arabia | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| United Arab Emirate | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |

Note: *AR stands for autoregressive process/model; **ARMA for autoregressive moving average, and process/model, and ***ARFIMA for fractionally integrated autoregressive moving average process/model. Capturing 75% of the full sample, we evaluate the predictive power of the ARFIMA model both for the in-sample data and out-of-sample data cutting across the forecast horizons of 30 and 60 days using the root mean square error (RMSE). The smaller the root mean square error (RMSE), the greater the predictive power of a model and vice versa.

On the whole, we conclude the overwhelming predictive power of time-series models over our oil-based exchange rate model across the GCC region. That time-series models (AR, ARMA, and ARFIMA), in the majority of cases, predict exchange rates better than our oil-based exchange rate model can do is reflected in the predictability graphs associated with both models (Compare Figure 1 and Figure 2, and refer to the Appendix for the predictability graphs using WTI price). This result could be informed by the fixed exchange rate regime practiced

**Table 6.** In-sample and out-of-sample forecast evaluation of Oil-based exchange rate model (OEM) and Time-series Models using C-T test. (Brent price case)

| | OEM versus AR | | | OEM versus ARMA | | | OEM versus ARFIMA | | |
|---|---|---|---|---|---|---|---|---|---|
| | In-sample | Out-of-sample | | In-sample | Out-of-sample | | In-sample | Out-of-sample | |
| | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ |
| Bahrain | −0.029 | −0.029 | −0.028 | −0.029 | −0.029 | −0.028 | −0.028 | −0.028 | −0.027 |
| Kuwait | 0.508 | 0.513 | 0.519 | 0.468 | 0.472 | 0.478 | 0.519 | 0.520 | 0.523 |
| Oman | −0.009 | −0.009 | −0.008 | −0.009 | −0.009 | −0.008 | 0.028 | 0.027 | 0.023 |
| Qatar | −0.094 | −0.084 | −0.067 | −0.094 | −0.085 | −0.068 | −0.090 | −0.083 | −0.069 |
| Saudi Arabia | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.004 | 0.003 | 0.003 |
| United Arab Emirate | −0.028 | −0.027 | −0.026 | −0.030 | −0.029 | −0.028 | −0.028 | −0.027 | −0.026 |

**Note**: The Campbell-Thompson (C-T) test statistics as used here compares the unrestricted model, which in this case is the oil-based exchange rate model (using Brent price) with the time-series models (AR, ARMA, and ARFIMA), which constitute the class of restricted models. Positive C-T stat implies that the oil-based exchange rate model (using Brent price) is preferred to AR, MA, ARMA, and ARFIMA models in predicting exchange rates using the in-sample data covering 75% of the full sample and the out-of-sample forecast horizons of 30 and 60 days. On the other hand, negative C-T stat implies that AR, MA, ARMA, and ARFIMA models are preferred to the oil-based exchange rate model (using Brent price) in predicting exchange rates using the in-sample data covering 75% of the full sample the out-of-sample forecast horizons of 30 and 60 days.

**Table 7.** In-sample and out-of-sample forecast evaluation of Oil-based exchange rate model (OEM) and Time-series Models using C-T test (WTI price case).

| | OEM versus AR | | | OEM versus ARMA | | | OEM versus ARFIMA | | |
|---|---|---|---|---|---|---|---|---|---|
| | In-sample | Out-of-sample | | In-sample | Out-of-sample | | In-sample | Out-of-sample | |
| | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ |
| Bahrain | −0.027 | −0.026 | −0.025 | −0.027 | −0.027 | −0.026 | −0.026 | −0.026 | −0.024 |
| Kuwait | 0.519 | 0.524 | 0.529 | 0.479 | 0.483 | 0.489 | 0.529 | 0.531 | 0.533 |
| Oman | 0.011 | 0.011 | 0.011 | −0.007 | −0.008 | −0.006 | 0.029 | 0.028 | 0.024 |
| Qatar | −0.109 | −0.099 | −0.082 | −0.109 | −0.099 | −0.082 | −0.106 | −0.098 | −0.084 |
| Saudi Arabia | 0.005 | 0.004 | 0.004 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |
| United Arab Emirate | −0.024 | −0.024 | −0.023 | −0.028 | −0.028 | −0.026 | −0.025 | −0.025 | −0.023 |

**Note**: The Campbell-Thompson (C-T) test statistics as used here compares the unrestricted model, which in this case is the oil-based exchange rate model (using WTI price) with the time-series models (AR, ARMA, and ARFIMA), which constitute the class of restricted models. Positive C-T stat implies that the oil-based exchange rate model (using WTI price) is preferred to AR, ARMA, and ARFIMA models in predicting exchange rates using the in-sample data covering 75% of the full sample and the out-of-sample forecast horizons of 30 and 60 days. On the other hand, negative C-T stat implies that AR, ARMA, and ARFIMA models are preferred to the oil-based exchange rate model (using WTI price) in predicting exchange rates using the in-sample data covering 75% of the full sample the out-of-sample forecast horizons of 30 and 60 days.
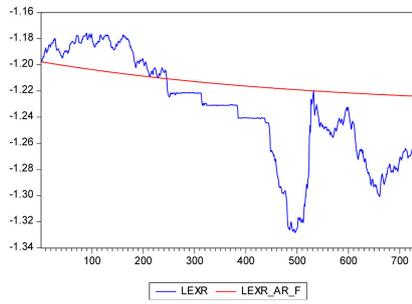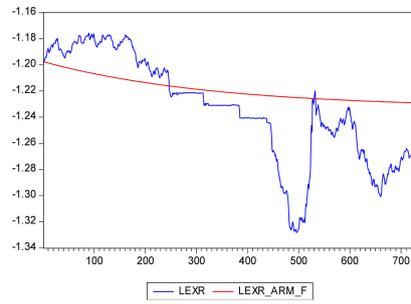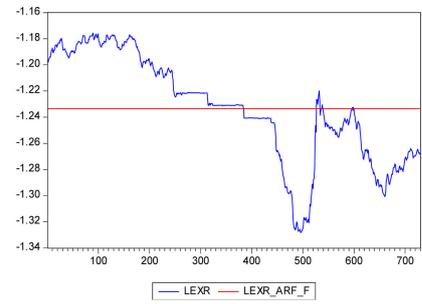
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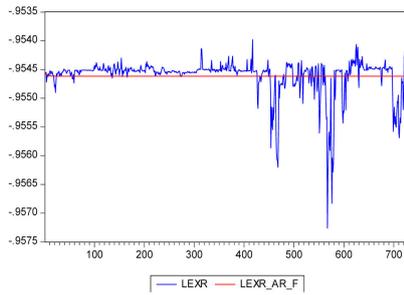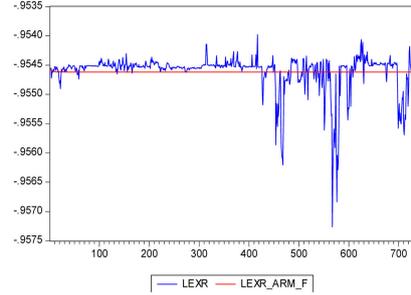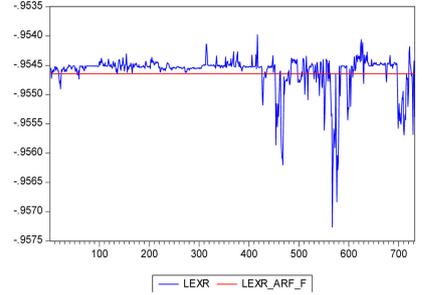
(d)                                    (e)                                    (f)
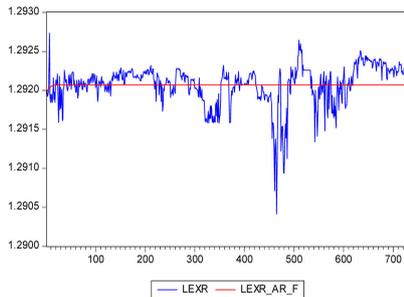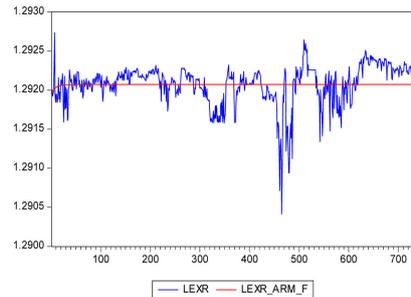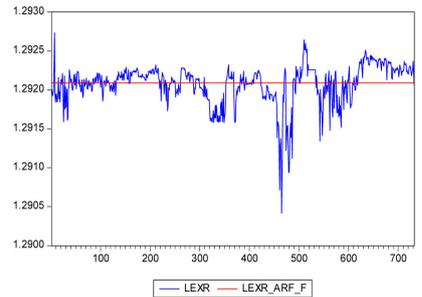
(g)                                    (h)                                    (i)
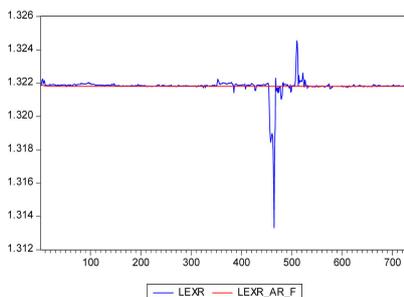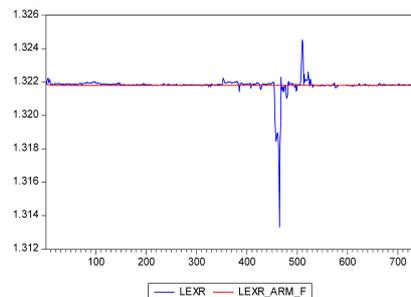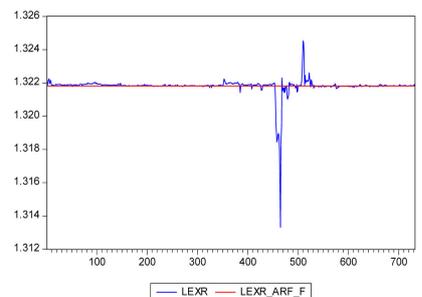
(j)                                    (k)                                    (l)
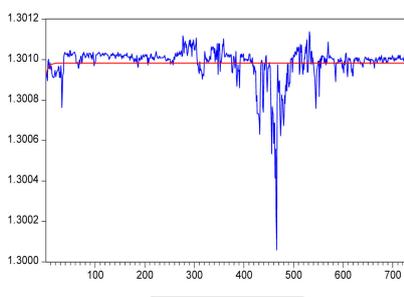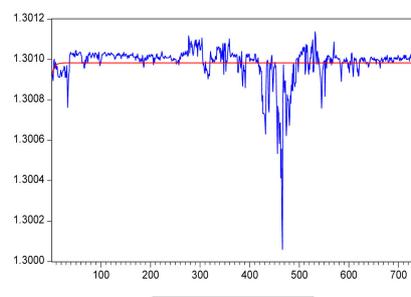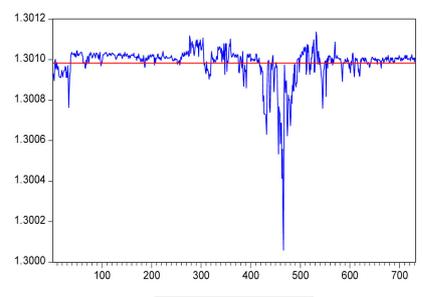
(m)                                    (n)                                    (o)
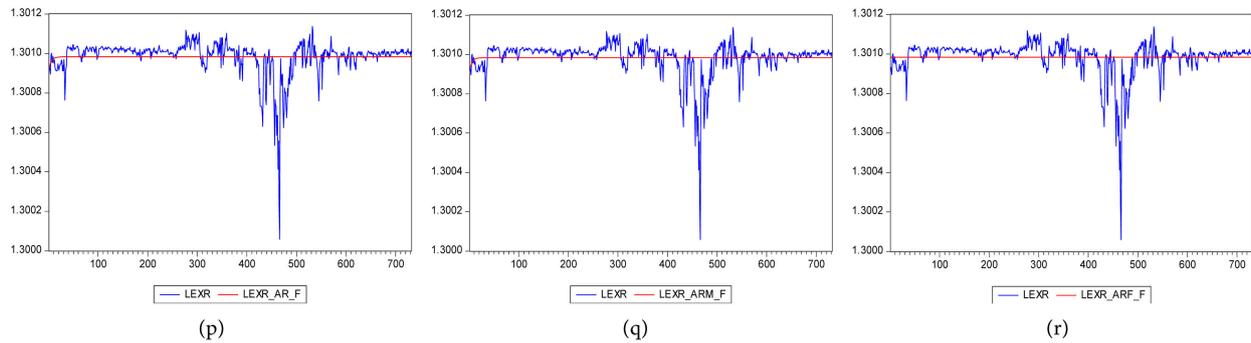
**Figure 1.** Predictability graphs for Time-series models. (a) AR_ Kuwait; (b) ARMA_ Kuwait; (c) ARFIMA_Kuwait; (d) AR_Oman; (e) ARMA_Oman; (f) ARFIMA_Oman; (g) AR_ Qatar; (h) RMA_Qatar; (i) ARFIMA_Qatar; (j) AR_ Saudi Arabia; (k) ARMA_ Saudi Arabia; (l) ARFIMA_ Saudi Arabia; (m) AR_ UAE; (n) ARMA_ UAE; (o) ARFIMA_ UAE; (p) AR_ Bahrain; (q) ARMA_ Bahrain; (r) ARFIMA_ Bahrain.

**Table 8.** In-sample and out-of-sample forecast evaluation of Oil-based exchange rate model (OEM) and Time-series Models using D-M test (Brent price case).

| | OEM versus AR | | | OEM versus ARMA | | | OEM versus ARFIMA | | |
|---|---|---|---|---|---|---|---|---|---|
| | In-sample | Out-of-sample | | In-sample | Out-of-sample | | In-sample | Out-of-sample | |
| | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ |
| Bahrain | 3.224*** | 3.179*** | 3.053*** | 3.240*** | 3.199*** | 3.072*** | 3.146*** | 3.105*** | 2.977*** |
| Kuwait | −15.956*** | −16.548*** | −17.257*** | −15.280*** | −15.773*** | −16.397*** | −24.269*** | −24.549*** | −25.044*** |
| Oman | 1.494 | 1.540 | 1.309 | 1.541 | 1.589 | 1.356 | −6.433*** | −6.023*** | −5.053*** |
| Qatar | 4.821*** | 4.365*** | 3.532*** | 4.831*** | 4.374*** | 3.541*** | 5.423*** | 5.012*** | 4.209*** |
| Saudi Arabia | −10.329*** | −10.146*** | −9.890*** | −10.985*** | −10.824*** | −10.599*** | −6.152*** | −6.031*** | −5.856 |
| United Arab Emirate | 3.121*** | 3.074*** | 2.948*** | 3.252*** | 3.215*** | 3.087*** | 3.129*** | 3.085*** | 2.957*** |

**Note:** The Diebold-Mariano (D-M) test statistic as used here compares the forecast errors of the unrestricted model, which in this case is the oil-based exchange rate model (using Brent price) and the restricted model comprising the time-series models (AR, ARMA, and ARFIMA). The negative and statistical significance at 1% (***), 5% (**) and 10% (*) implies that the oil-based exchange rate model (using Brent price) significantly outperforms the AR, ARMA, and ARFIMA models using in-sample data covering 75% of the full sample and out-of-sample forecast horizons of 30 and 60 days. However, the positive and statistical significance at 1% (***), 5% (**) and 10% (*) implies that the AR, ARMA, and ARFIMA models significantly outperform the oil-based exchange rate model (using Brent price) using in-sample data covering 75% of the full sample and out-of-sample forecast horizons of 30 and 60 days.

**Table 9.** In-sample and out-of-sample forecast evaluation of Oil-based exchange rate model (OEM) and Time-series Models using D-M test (WTI price case).

| | OEM versus AR | | | OEM versus ARMA | | | OEM versus ARFIMA | | |
|---|---|---|---|---|---|---|---|---|---|
| | In-sample | Out-of-sample | | In-sample | Out-of-sample | | In-sample | Out-of-sample | |
| | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ | | $h = 30$ | $h = 60$ |
| Bahrain | 3.081*** | 3.032*** | 2.903*** | 3.118*** | 3.070*** | 2.941*** | 3.022*** | 2.974*** | 2.843*** |
| Kuwait | −15.418*** | −15.988*** | −16.653*** | −14.673*** | −15.145*** | −15.721*** | −23.245*** | −23.526*** | −23.975*** |
| Oman | −4.539*** | −4.515*** | −4.320*** | 1.251 | 1.307 | 1.076 | −6.424*** | −6.033*** | −5.108*** |
| Qatar | 5.352*** | 4.902*** | 4.104*** | 5.359*** | 4.909*** | 4.112*** | 6.006*** | 5.598*** | 4.834*** |
| Saudi Arabia | −6.917*** | −6.798*** | −6.637*** | −11.411*** | −11.299*** | −11.158*** | −6.573*** | −6.481*** | −6.351*** |
| United Arab Emirate | 2.888*** | 2.835*** | 2.707*** | 3.146*** | 3.100*** | 2.971*** | 2.981*** | 2.932*** | 2.802*** |

**Note:** The Diebold-Mariano (D-M) test statistic as used here compares the forecast errors of the unrestricted model, which in this case is the oil-based exchange rate model (using WTI price) and the restricted model comprising the time-series models (AR, ARMA, and ARFIMA). The negative and statistical significance at 1% (***), 5% (**) and 10% (*) implies that the oil-based exchange rate model (using WTI price) significantly outperforms the AR, ARMA, and ARFIMA models using in-sample data covering 75% of the full sample and out-of-sample forecast horizons of 30 and 60 days. However, the positive and statistical significance at 1% (***), 5% (**) and 10% (*) implies that the AR, ARMA, and ARFIMA models significantly outperform the oil-based exchange rate model (using WTI price) using in-sample data covering 75% of the full sample and out-of-sample forecast horizons of 30 and 60 days.
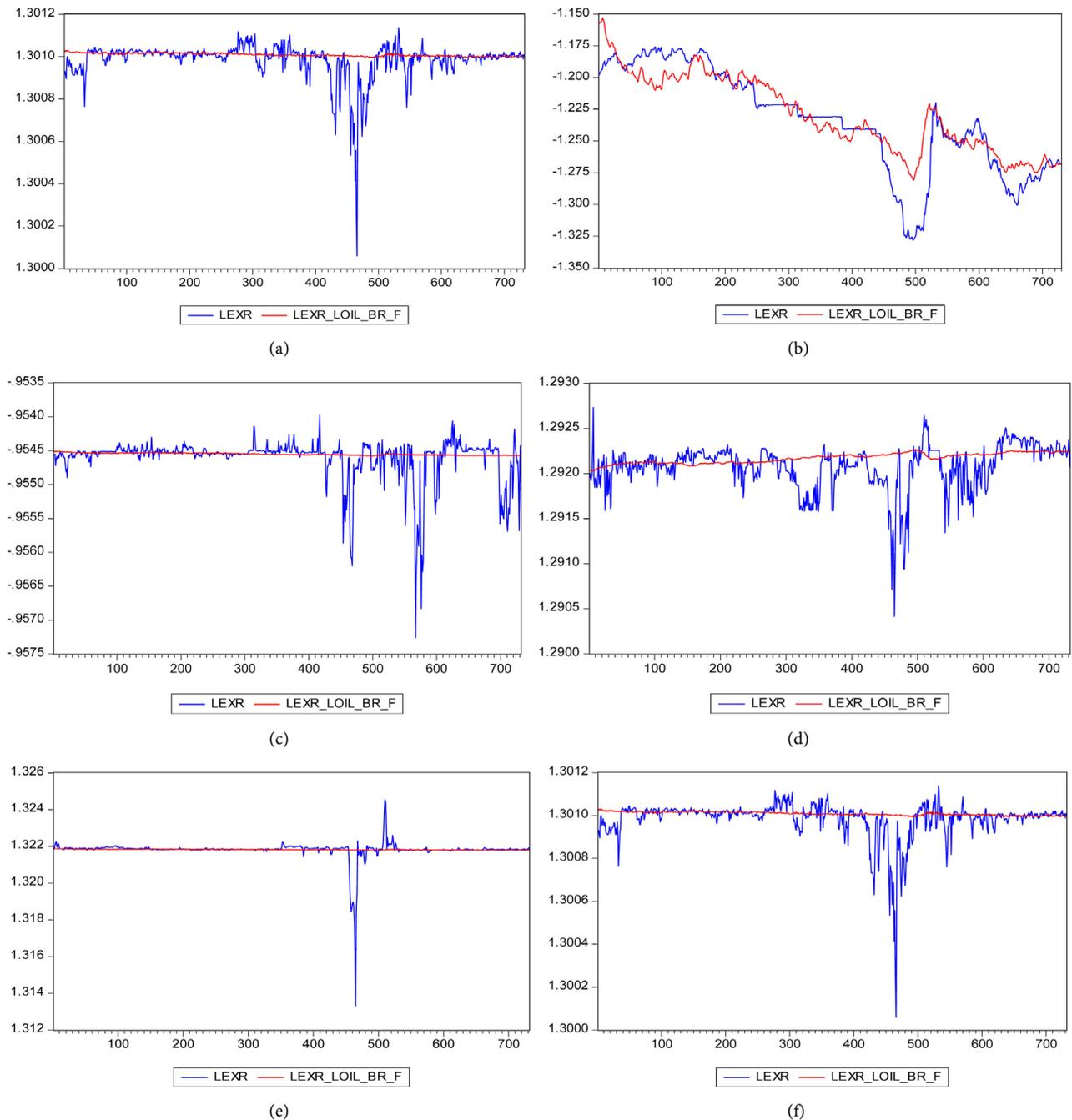
**Figure 2.** Predictability Graphs for oil-based exchange rate models (Brent price). (a) Oil-based exchange rate model for Bahrain; (b) Oil-based exchange rate model for Kuwait; (c) Oil-based exchange rate model for Oman; (d) Oil-based exchange rate model for Qatar; (e) Oil-based exchange rate model for Saudi Arabia; (f) Oil-based exchange rate model for UAE.

in the region, and as noted by Amin [14], the inability of the GCC nominal exchange rates, which are pegged completely or partially to the US dollar, to adjust to the oil price shocks through appreciation or depreciation means that the impact would be transferred to the GCC economies in the form of domestic inflation and higher prices relative to the foreign prices, with a large resultant effect on the GCC real exchange rates.

## 6. Conclusions

We offer new evidence on the predictability of exchange rates using crude oil prices, namely Brent and WTI prices, across the six GCC countries comprising Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirate. Driven by the need to account for some salient features usually present in high frequency time-series data, we employ the estimator proposed by Lewellen [20] and Westerlund, *et al.* [1] [2] in order to account for possible persistence, endogeneity, serial correlation, and conditional heteroscedasticity effects in our predictors (which in this case, are crude oil prices). Our results show the presence of significant serial dependence, conditional heteroscedasticity and persistence effects in the predictors; while we at the same time establish the absence of endogeneity bias in the same predictors (that is, crude oil prices) across the GCC countries, save Kuwait.

Further, our results show the presence of significant in-sample predictability of exchange rates using crude oil prices (Brent and WTI prices) across the GCC countries. The results of forecast evaluation based on the root mean square error (RMSE), Campbell-Thompson (C-T) statistic and Diebold-Mariano (D-M) statistic are rather mixed. We obtain greater forecast performance in favour of our predictive exchange rate model in the cases of Kuwait and Saudi Arabia, while we establish a superior forecast accuracy of time-series models (AR, ARMA, and ARFIMA) in the contexts of Bahrain, Qatar, and the United Arab Emirate. The forecast performance of our predictive exchange rate model and time-series model is highly sensitive to the choice of benchmark time-series models: while AR and ARMA models predict the dollar exchange rate better than our predictive model, the reverse is the case for the ARFIMA model using both in-sample and out-of-sample periods. We, however, conclude the overwhelming forecast performance of time-series models (namely, AR, ARMA, and ARFIMA) over our oil-based exchange rate model in predicting exchange rates across the GCC region.

Meanwhile, some policy implications can be highlighted from the results of this study. The significance of oil price in influencing the exchange rate behavior of some GCC countries will be useful to financial analysts and investors who rely on such information for investment decisions and to policy makers when making policy decisions. Notwithstanding the usefulness of the research findings of the study, a number of areas can still be explored to improve the paper and are therefore suggested for future research. The first area relates to the choice of countries; future research can conduct same for other countries particularly net oil importers and non-OPEC net oil exporters. The latter is also important to see if the results of the giant members of OPEC can be generalized for the non-members in terms of the predictive power of oil price in forecasting stock returns. The second area relates to other statistical properties underlying exchange rate which are not captured in the current study. These properties include structural breaks and asymmetries. We therefore suggest that further studies

investigate if accounting for structural breaks and asymmetries in oil-exchange rate nexus would improve the predictability of exchange rates using crude oil prices. A considerable attention can also be drawn towards the use of real exchange rate, which is a measure of a country's international competitiveness in the foreign market.

## Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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# Appendix

Predictability Graphs for oil-based exchange rate models (WTI price).
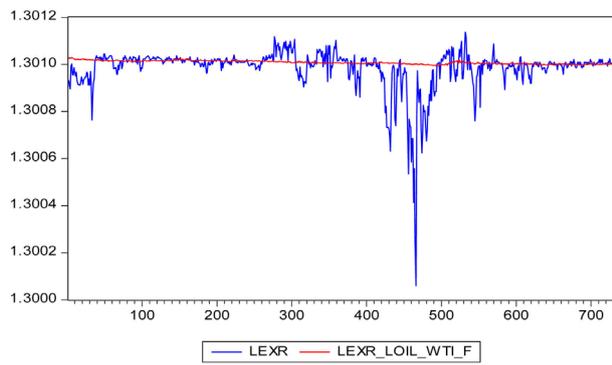


Bahrain
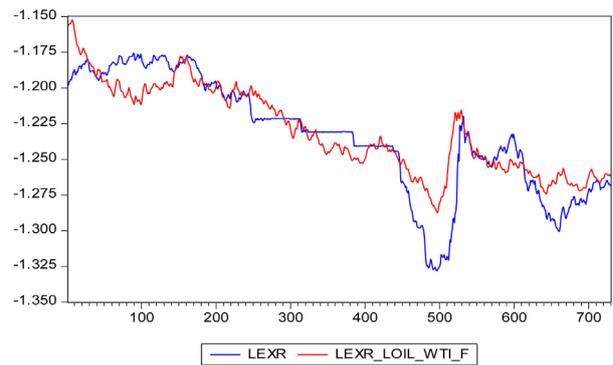
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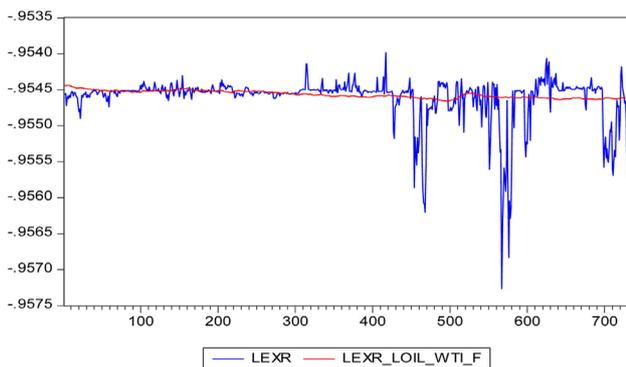
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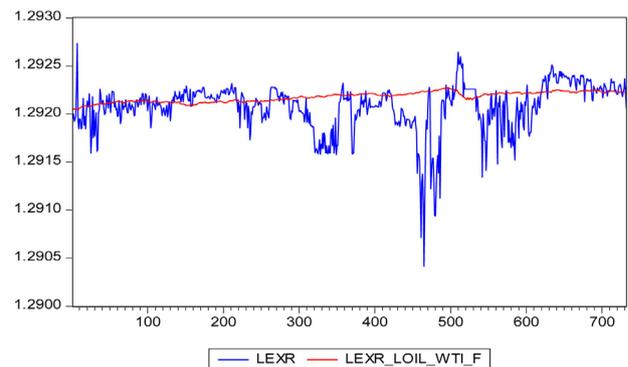
Qatar

Saudi Arabia

United Arab Emirate