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Forecasting GDP of OPEC: The role of oil price

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Abstract

In this paper, we examine the role of oil in GDP forecast of selected OPEC member countries using the Autoregressive Distributed Lag Mixed Data Sampling (ADL-MIDAS) approach. Both the in-sample and out-of-sample forecasts of this approach are evaluated and compared with some competing models namely AR(1), ARFIMA, ARIMA and ARDL models. We find that allowing for high frequency oil price data in the predictive model of GDP will enhance its forecast performance. The ADL-MIDAS is found to out-perform all the competing models for both the in-sample and out-of-sample forecast. In addition, we find that the higher the data frequency of oil price, the better the forecast performance. These results are robust to different data frequencies, multiple forecast horizons, and alternative proxies for oil price and measures of forecast performance.

Keywords: Oil price; GDP, ADL-MIDAS; Linear time series models; Forecast evaluation
JEL Classification: C12, C22, Q42, Q43, Q47

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1.0 Introduction

Accurate economic information, for example those offered by GDP data or its growth are germane for targeting economy-wide policies effectively given its role as an indicator of the aggregate situation of the economy. At the individual level, information on the present and predicted (future) values of GDP growth guide rational economic agents' investment decisions with knowledge of current and likely future situation of the macroeconomy, knowledge of sectoral efficiencies as well as glimpse of future expectations. At the aggregate level, the knowledge of present and future GDP growth provides glimpse of future stand of the economy relevant for policy administration (policy decisions and assessment). Hence, the necessity for GDP forecasting cannot be overemphasized. Several factors have been considered in forecasting GDP growth in the literature. One of the prominent (pioneered by Hamilton, 1983) and yet relevant factor in modern economies is the oil price as a strategic commodity for the global economy even as oil still accounts for substantial proportion (put at 40.6%) of the global energy supply (Gokmenoglu et al., 2015; Al-sasi et al., 2017).

Given the importance of the oil industry, the continued high correlation between oil prices and economic growth and in line with the seminal paper of Hamilton (1983), a number of empirical studies have examined the oil price – GDP nexus with divergent ideas and outcomes (see for example, Hamilton, 1983; Loungani, 1986; Burbidge and Gisser and Goodwin, 1986; Finn, 2000; Hamilton, 2009; Kilian and Vigfusson, 2011; Edirneligil and Mucuk, 2014; Ftiti, et al. 2016; Benramdane, 2017). These papers are informed by such theoretical positions in the extant literature linking oil price fluctuations to the macroeconomy through a number of channels; indirect impacts through inflation, monetary policy, investment and consumption consequences (see for example, Bruno and Sachs, 1982; Lee and Ni, 2002; Farzanegan and Markwardt, 2009;

Tang et al. 2010; and Wei and Guo, 2016) and direct relationship between oil prices and output where the nexus has been shown in recent years to be different for oil-importing and oil-exporting economies (see Hamilton, 1983, 1996, 2003; Mork, 1989; Lee et al., 1995; Brown and Yücel, 1999; Jimnez-Rodrıguez, 2005, 2009; Moshiri and Banihashem, 2012; Nusair, 2016; Taghizadeh-Hesary et al., 2016; Maji et al., 2017).

The foregoing theoretical and empirical exercises motivate our interest to probe further the oil price – GDP nexus. To do this, we are motivated by two major issues. First, is the availability of high frequency data for oil price and the interest here is to see whether we can exploit useful information for this frequency in order to produce better accurate GDP forecasts. The second motivation is the peculiar nature of the economy of oil exporting countries in OPEC where oil serves as the mainstay for most of them and therefore we hypothesize that future trends in GDP can be significantly influence by the future expectations about oil price. Moreover, our focus on OPEC countries, preceded by related studies (for example Chai et al., 2011; Ftiti et al., 2016; Nusair, 2016) is reinforced given: one, the strategic role of the cartel overtime as a market phenomenon; two, the significance of the oil sector to the member countries' economy as a huge share of GDP, major source of export earnings and government revenues; and three, the importance of oil price as an important statistic on the basis of which budgets are drawn especially in most of these oil-exporting countries. These intuitive realities inform our choice of OPEC member countries whereby the peculiarities corroborate the earlier convictions that oil price fluctuations ought to be an important phenomenon in forecasting economic growth in these nations.

Our paper is the first to adopt the Mixed Data Sampling (MIDAS) framework to simultaneously estimate and forecast the oil-output nexus. The choice of this methodology is underscored by its ability to accommodate both high and low frequencies in the predictive model for the oil-GDP nexus. The only related paper that has also adopted the MIDAS approach, to the best of our knowledge, is the recent study by Valadkhani and Smyth (2017). However, they only capture the in-sample analysis of daily changes in oil prices in US monthly industrial output. We depart from this study in the following ways. First, our forecast evaluation involves both the in-sample and out-of-sample forecasts and we also offer some comparative analyses with prominently used time series models for GDP forecast. This enables us to draw meaningful conclusions about the superiority or otherwise of the ADL-MIDAS approach over other competing models whether for in-sample or out-of-sample forecast. Secondly, while the Valadkhani and Smyth (2017) involve a net oil importer (US), we focus on oil exporting countries that are more likely to be influenced by oil price given the structure of the economy of most of the oil exporting countries where oil revenue accounts for over 80 percent of their total revenue. Thus, our conclusions further complement those of the Valadkhani and Smyth (2017) as to whether the nature of the economy has a role to play in producing accurate GDP forecasts.

The choice of the MIDAS approach is further motivated by recent findings suggesting possible superior forecast performance of this approach over other competing models (see for example, Alper et al., 2008; Bai et al., 2009; Andreou et al., 2013; Ghysels and Ozkan, 2015; Barsoum and Stankiewicz, 2015; Jung, 2017 for arguments in support of the MIDAS modelling structure). There are many variants of the MIDAS regression in the literature such as the GARCH-MIDAS, its multivariate counterpart, the DCC-MIDAS model, MIDAS Quantile regression, and the ADL-MIDAS regression models. However, the ADL-MIDAS approach is more suitable for our study since we are dealing with low frequency regressand (in this case, GDP) and high frequency regressor (oil price).

The application of the ADL-MIDAS framework is increasingly gaining recognition in the literature (see Ghysels et al., 2009; Andreou et al., 2013; Albu et al., 2015; Salisu and Ogbonna, 2017; Valadkhani and Smyth, 2017 for further evidence in support of the ADL-MIDAS framework). Nonetheless, this paper is the first to demonstrate its application to oil-output nexus involving both the in-sample and out-of-sample forecast evaluation for a panel of oil exporting countries. For completeness, we compare the forecast performance of the ADL-MIDAS with uniform frequency time series models such as ARMA, ARIMA and ARFIMA as well as the ARDL model. For robustness checks, we consider different data frequencies, multiple forecast horizons, and alternative proxies for oil price and measures of forecast performance.

The rest of the paper is structured as follows. The next section evaluates the theoretical intricacies of the oil – GDP nexus. Section 3.0 describes the methodology and the forecast model evaluation criteria. Section 4.0 presents and discusses the results including descriptive statistics and robustness tests. Section 6.0 concludes the paper.

2.0 The underlying theory for the oil-GDP nexus

The theoretical linkage of oil, as a natural resource, with economic output can be traced back to the Malthusian postulation of 1883. Malthus noted that such exhaustible scarce resource poses a limit to growth by starving the population through economic stagnation at a later date due to exponential population growth (Merz, 2016). In more recent times, the linkage between oil (being a source of energy, revenue and input to production) and economic growth has been associated with four testable hypotheses: the growth hypothesis; the conservation hypothesis; the feedback hypothesis and the neutrality hypothesis. Of particular relevance are the growth and feedback hypotheses where oil serves as a catalyst for economic growth. In essence, positive changes to energy consumption, say through favourable energy policy is expected to be beneficial to economic growth because energy consumption represents a fundamental factor of economic growth and not just its result (see Alper and Oguz, 2016; Brinia et al. 2017; Mehmet and Alper 2017).

Now as a financial variable, the theoretical underpinning of the oil price – GDP nexus can be viewed from microeconomics and macroeconomics perspectives. The microeconomics viewpoint proposes supply and demand-side channels of transmission of oil price fluctuations to real economic activity (see among others, Brown and Yucel, 1999; Abel and Bernanke, 2001; Jiménez-Rodríguez and Sánchez, 2005, 2009). In the supply side, given the role of oil as a basic input to production, higher oil prices tend to raise production costs that induce firms to lower output in other non-energy sectors. On the demand side, the wealth effect of rise in oil price, for instance, affects consumption via negative relation with disposable income, and by extension, aggregate demand.

On the macroeconomics standpoint, the proposition depends on whether the underlying economy is an oil-importing or an oil-exporting economy (see Jimenez-Rodriguez and Sanchez, 2005; Lardic and Mignon, 2006; Moshiri and Banihashem, 2012; Balcilar and Ozdemir, 2013; and Nusair, 2016). For instance, a positive oil price shock is expected to foster growth in an oil exporting country. This is so because the resultant increase in the country's income further encourages increased expenditure and investments, leading to greater productivity. This view is further buttressed from arguments that such increase in oil price represents a wealth transfer from oil-importing countries to oil-exporting economies leading to rise in the purchasing power of firms and households in the latter countries to further raise aggregate demand levels. On the other hand, for net oil importer, an increase in oil price may lead to higher costs of production which may lower productivity at least in the short run. Thus, based on the foregoing theoretical construct, a distinct analysis of the role of oil price in the GDP forecast of oil exporting countries will further enhance our knowledge as to how much of information can be exploited from oil price to produce better forecasts for the GDP of these oil-based economies.

3.0 Methodology

3.1 The Model and forecast evaluation procedure

The underlying framework for the oil-GDP nexus is theoretically motivated by the energy-growth hypothesis suggesting that energy consumption can actually serve as a good predictor for economic growth and can therefore improve growth forecast (see for example, Ucan et al., 2014; Rafindadi, 2015; Rafindadi and Ozturk, 2015, 2017; Alam et al., 2016; Chiou-Wei et al., 2016; Pinzon, 2017). A stronger motivation lies in the structure of the economy of most of the OPEC member countries particularly those considered in this study. These countries essentially rely on proceeds from oil and thus, any shock to oil whether it is demand-oriented or supply-oriented influences the macro-economy. Since oil is a major driver of their economy, including oil in the growth model is more likely to enhance its forecasts.

In line with the foregoing, we can write the predictive model for oil-GDP nexus as follows:

$$\ln GDP_t = \alpha + \beta \ln Oil_{t-1} + \varepsilon_t \qquad (1)$$

where $\ln GDP_t$ is the log of GDP and $\ln Oil_t$ is the log of oil price while ε_t is the error term, all expressed at a given period *t*. The underlying null hypothesis for testing the predictability of oil price for GDP is that $H_0 : \beta = 0$ and therefore, a rejection of H_0 implies the significance of oil in the predictive model for GDP; otherwise, it is redundant in the model. One of the limitations of equation (1) is that it requires uniform frequency even when it well known that oil price is available at high frequency. Thus, we favour the MIDAS framework that exploits probable useful information in the high frequency oil price variable to produce more accurate forecasts for GDP.[2] Although, there are different variants of the MIDAS regression models ranging from the Flat weight aggregation approach which involves equal weights for the aggregation of the high frequency; the Unrestricted MIDAS (U-MIDAS) which does not require the aggregation of high frequency observations in order to convert to low frequency and the ADL-MIDAS model proposed by Ghysels et al. (2007) which does not require any assumption on the weights for aggregation of high frequency variables. The latter forms

[2] See (Alper et al. 2008; Bai et al. 2009; Barsoum and Stankiewicz 2015; Jung 2017) for arguments in support of such modelling structure that allows the predictor and predicted variables to be sampled at different data frequencies.

the basis for the oil-GDP forecast owing to its flexibility. In addition, it also helps to circumvent the problem of parameter proliferation inherent in the U-MIDAS. Among the competing variants of the ADL-MIDAS, the exponential Almon lag polynomial proposed by Ghysels et al. (2007) which allows for more general weighting scheme compared to others and can assume different shapes, is preferred. Consequently, we specify below the ADL-MIDAS model for oil-GDP predictability with lag structure $(p_{GDP}^{A}, q_{Oil}^{M})$:[3]

$$\ln GDP_{t+1}^{A} = \lambda + \sum_{i=0}^{p_{GDP}^{A}-1} \alpha_i \ln GDP_{t-i}^{A} + \beta \sum_{i=0}^{q_{Oil}^{M}-1} \cdot \sum_{j=0}^{N_M-1} w_{i+j*N_M}(\phi^M) \ln Oil_{N_M-j,t-i}^{M} + \varepsilon_{t+1} \tag{2}$$

where p_{GDP}^{A} and q_{Oil}^{M} denote the number of lags of the annual (low) and monthly (high) frequency variables, respectively. More specifically, p is the lag length for the predicted (GDP) while q is the lag length for the predictor (oil price). The superscripts on the lags denote the data frequencies for the series. Also, the $w_i(\phi^H)$ is a weighting structure of a two-parameter exponential Almon lag polynomial expressed as:

$$w_i(\phi^H) = w_i(\phi_1, \phi_2) = \frac{e^{(\phi_1 i + \phi_2 i^2)}}{\sum_{i=0}^{k} e^{(\phi_1 i + \phi_2 i^2)}} \tag{3}$$

For completeness, the forecast performance of the ADL-MIDAS is compared with the ARDL model that requires uniform frequency. Like the ADL-MIDAS, a typical ARDL(*p*,*q*)] model can be specified as:

$$\Delta \ln GDP_t = \alpha + \beta_1 \ln GDP_{t-1} + \beta_2 \ln Oil_{t-1} + \sum_{i=1}^{p-1} \beta_{3i} \Delta \ln GDP_{t-i} + \sum_{i=0}^{q-1} \beta_{4i} \Delta \ln Oil_{t-i} + + \xi_t \tag{4}$$

The optimal lags are determined on the basis of the Schwartz Information Criterion (AIC) where the model with the least SIC is considered parsimonious and the corresponding lag structure producing such model is considered the optimal lag and is therefore used for the in-sample and out-of-sample forecasts.

[3] The specification is also in line with Albu et al. (2015).

As customary for forecast evaluation involving time series, we also consider a number of univariate time series models such as the first order autoregressive, ARIMA and ARFIMA models and their forecast results are also compared with the ADL-MIDAS. We test the validity of our forecast models for both in-sample and out-of-sample predictability on the basis of various forecast evaluation criteria. We use the 75 percent of the total observations for the forecast evaluation and the rolling window approach is employed to produce the forecast results in order to allow for some time variations in the regression coefficients. Four complementary forecast measures are considered namely the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), the Campbell-Thompson (CT) test and the Diebold and Mariano (DM) statistics. Smaller values of RMSE and MAE statistics and particularly those that are close to zero are preferred. Unlike the RMSE and the MAE, the CT test and DM test are considered as pairwise tests as the forecasts from two predictive models are simultaneously compared in order to determine the one with a better forecast accuracy. The CT test is computed as $1-\left(M\widehat{S}E_{UR} / M\widehat{S}E_{R}\right)$ where the $M\widehat{S}E_{UR}$ and $M\widehat{S}E_{R}$ are the mean square error (MSE) of the prediction from the unrestricted and restricted models, respectively. While a positive CT statistic implies the superiority of the unrestricted model over the restricted version; the reverse is the case if the CT statistic is negative. However, it is hard to establish if the difference between the two forecasts is statistically different from zero using the CT test. This is the motivation for the DM test which is essentially used to test for the equality of forecast accuracy of two competing models at a time. The test statistic is specified as:

$$\text{D-M stat} = \frac{\bar{d}}{\sqrt{\frac{1}{T}V\left(d\right)}} \sim N\left(0,1\right) \tag{5}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T}\left[g\left(\xi_{it}\right)-g\left(\xi_{jt}\right)\right]$ is the sample mean loss differential and $V\left(d\right)$ is the unconditional variance of d. The $\left\{\xi_{it}\right\}_{t=1}^{T}$ and $\left\{\xi_{jt}\right\}_{t=1}^{T}$ are the forecast errors associated with the two forecasts say $\left\{\hat{y}_{it}\right\}_{t=1}^{T}$ and $\left\{\hat{y}_{jt}\right\}_{t=1}^{T}$ respectively. The $g\left(\xi_{it}\right)$ and $g\left(\xi_{jt}\right)$ are the loss functions associated with these two forecasts while $d_t \equiv g\left(\xi_{it}\right) - g\left(\xi_{jt}\right)$ is the loss differential. The null hypothesis of equal forecast accuracy for the two forecasts is that $E\left[d_t\right] = 0$. Thus, the forecast accuracy of two competing models is considered relatively equal if the null hypothesis of the DM test is not rejected; otherwise, it is not (see Salisu et al., 2018).

4.0 Discussion of results

4.1 Data and preliminary analyses

For the purpose of empirical analyses, we utilize annual GDP data of selected OPEC member countries while the oil price variables are collected over three data frequencies namely annual, quarterly and monthly data frequencies. The selected countries are Kuwait, Nigeria, Oman, Qatar and United Arab Emirates (UAE) and they are chosen based on data availability. The use of annual frequency for GDP of OPEC is underscored by paucity of high frequency data. In fact, this is one of the motivations for the consideration of the ADL-MIDAS approach in this study. Thus, for the ARDL model involving uniform frequency, the estimation and forecast analyses utilize annual frequency for both GDP and oil price. Similarly, the annual frequency is used for the ARIMA and ARFIMA models since the estimation only requires data on GDP. In the case of the ADL-MIDAS, we utilize monthly and quarterly frequencies for oil price variables and annual data for GDP. The two frequencies for oil prices are considered for robustness purpose. In addition, we also test whether the ADL-MIDAS results are not sensitive to the choice of oil price proxy by using two oil price variables (Brent and West Texas Intermediate oil prices) and the results are compared using the forecast criteria previously mentioned. The GDP data are sourced from the International Financial Statistics of the International Monetary Fund while those of oil prices are obtained from the US Energy Information Administration (US EIA). Table 1 below offers basic descriptive statistics for the relevant variables including the data scope. The UAE records the highest GDP figure on average over the period under consideration and it also exhibits the highest volatility judging by the standard deviation. Next to UAE is Nigeria both in terms of the mean and standard deviation values of GDP. All the countries exhibit positive skewness and leptokurtic distribution, which further attest to the non-normal behaviour of GDP series in these countries. The oil price variables also exhibit similar features as the GDP series both in terms of skewness and kurtosis while the Brent oil price has a higher mean value and therefore tends to be more volatile than the WTI.

Table 1: Descriptive statistics

	Mean	Std. Dev.	Skewness	Kurtosis	Start Date	End Date	Freq.	Obs.
GDP by Countries (Billion USD)								
Kuwait	29.60	19.30	2.36	8.59	1975	2017	Annual	42
Nigeria	43.60	27.70	2.13	7.59	1975	2017	Annual	42
Oman	12.60	8.16	1.14	4.29	1975	2017	Annual	42
Qatar	12.10	12.50	2.57	9.41	1975	2017	Annual	42
UAE	67.80	47.40	1.64	5.41	1975	2017	Annual	42
Global Oil Price (USD/Barrel)								
WTI	25.44	12.15	1.67	5.95	1975	2017	Monthly	384
BRENT	31.34	20.05	1.76	5.60	1980	2017	Monthly	360

Note: The ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

4.2 The results

The focus of this study centres on improving the predictability of GDP of selected oil exporting countries (Kuwait, Nigeria, Oman, Qatar and United Arab Emirates) on the basis of oil price. Essentially, the aim is to provide evidence-based arguments, not only on the importance of oil price in the prediction of selected countries' GDP, but also to add to the extant literature the benefits of incorporating the mixed data sampling methodology in output prediction. Firstly, we attempt to examine the in-sample predictability of oil the predictive model of output. Secondly, we compare the (in-sample and out-of-sample) forecast performance of the competing models in order to determine the most preferred model for predicting output of the selected countries, using four different forecast accuracy tests – root mean square error (RMSE), mean absolute error (MAE), Campbell-Thompson (CT) and Diebold & Mariano (DM). On the basis of data frequency, we consider uniform frequency theoretical model (ARDL), time-series models [AR(1), ARFIMA and ARIMA] and a mixed data sampling (MIDAS)-based theoretic model (ADL-MIDAS). For the purpose of robustness, we use both monthly and quarterly frequencies for ADL-MIDAS and two oil price proxies for all the models. Subsequent sections provide detailed discussion of the results.

4.2.1 In-Sample predictability

Here, we examine the in-sample predictability of oil price for output using the ADL-MIDAS, which incorporates the mixed data sampling methodology, as our reference model. This is also because it provides an avenue to vary the frequency of the independent variable (in this case, monthly and quarterly oil price). Table 2 shows the parameter estimates for both frequencies employed with much similarity in both. As hypothesized, oil price significantly influences the prediction of the output of the five selected oil exporting countries. This supports the argument in favour of the inclusion of oil price in the predictive model for output (see also Chontanawat et al., 2006; Ucan et al., 2014; Rafindadi, 2015; Rafindadi and Ozturk, 2015, 2017; Alper and Oguz, 2016; Brinia et al., 2017; Valadkhani and Smyth, 2017). However, virtually all these papers follow a different methodology. The only exception is the Valadkhani and Smyth (2017) paper although the analysis is restricted to in-sample (impact) evaluation. Thus, regardless of the methodology, oil price seems to play significant role in the predictive model of output. Since both the monthly and quarterly frequencies produce similar results particularly in terms of sign and statistical significance, it then suggests that the predictability results of the ADL-MIDAS-based oil-GDP nexus are robust to alternative data frequencies. Having established the in-sample predictability, we proceed to evaluate in the forecast performances of all the competing models.

Table 2: In-sample predictability using WTI oil price (ADL-MIDAS Model)

Country	Monthly			Quarterly		
	$lgdp_{t-1}$	$lwti1$	$lwti2$	$lgdp_{t-1}$	$lwti1$	$lwti2$
Kuwait	0.9810***	0.1690**	-5.7100	0.9828***	0.1505*	-0.6516
Nigeria	0.9692***	0.2525**	-6.9916	0.9718***	0.2315**	-7.5514
Oman	0.9719***	0.2318***	0.5345	0.9717***	0.2323***	-5.4481
Qatar	0.9753***	0.2101*	-4.8934	0.9757***	0.2060**	-6.0425
UAE	0.9859***	0.1368**	-2.4004	0.9857***	0.1375**	-6.4863

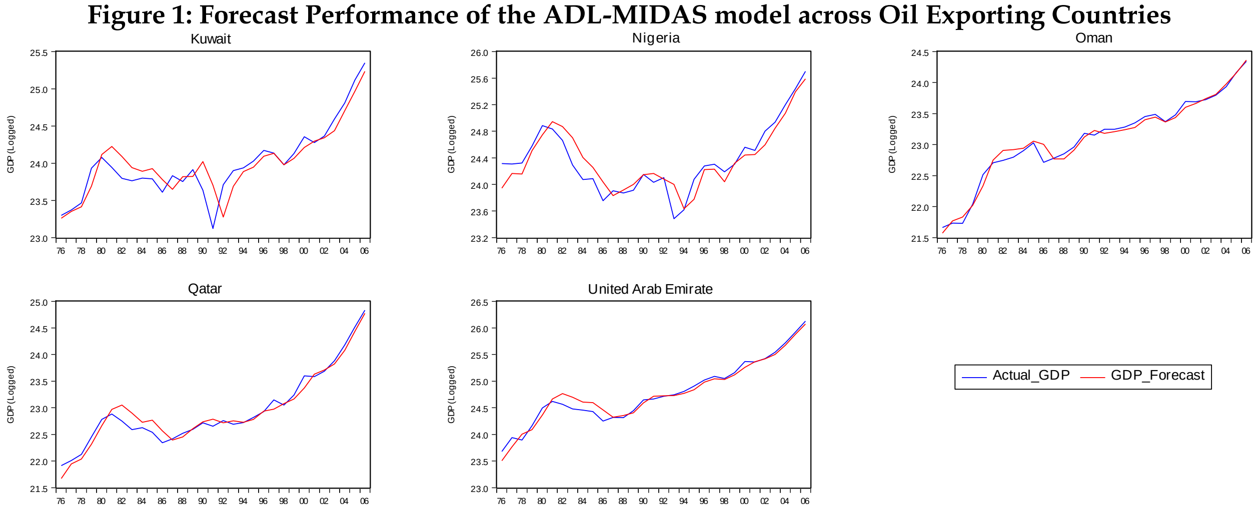
Note: Statistical significance of parameter estimates at 1%, 5% and 10% are indicated by ***, ** and *, respectively. The $lgdp$ and $lwti$ denote the natural logarithm of GDP and WTI oil price, respectively.

4.2.2 In-Sample forecast evaluation

Using the WTI oil price, we evaluate the in-sample forecast performance of the various competing models on the basis of their RMSE (see Table 3), MAE (see Table 4), Campbell-Thompson (see Table 5) and Diebold & Mariano (see Table 6). The first two forecast accuracy measures (RMSE and MAE) are based on the individual forecast performance of each model, such that the closer the values to zero, the better the model of interest. On the other hand, CT and DM are based on a pairwise comparison, with positive CT values and negative and statistically significant DM values indicating preference for the reference/benchmark model. In this study, we set our reference model to be ADL-MIDAS owing to its characteristic feature of incorporating a mixture of data frequencies in one regression model, thus providing more information necessary to improve model performance. These performances are observed across two different oil price frequencies using 75% of full data sample for five selected oil exporting countries.

Table 3 reveals the superior performance of ADL-MIDAS (on the basis of the least RMSE values) over all the other competing models in the in-sample for all the countries except Oman, where ARDL outperformed all the other competing models including ADL-MIDAS. This performance is also observed to be replicated across the two frequencies considered, which suggests that the results are not sensitive to the choice of data frequency used in the ADL-MIDAS model. A comparison of the RMSE results for our reference model, ADL-MIDAS, when both quarterly and monthly oil price data are used reveals that the higher the frequency of the independent variable, the lower the forecast error. This is consistently observed across the five countries as the ADL-MIDAS model with monthly oil price produced lower RMSE values compared to the ADL-MIDAS model with quarterly oil price. A similar feat of outperformance of the ADL-MIDAS model is observed with the MAE results (Table 4). We further show the forecast performance for each country graphically and observed that the forecasts closely track the actual series (see Figure 1).

Figure 1: Forecast Performance of the ADL-MIDAS model across Oil Exporting Countries



Let us now turn to the pairwise forecast measures using the Campbell-Thompson (CT) test (see Table 5) and Diebold & Mariano (DM) test (see Table 6), which compares model on a pair-wise basis. For all the countries considered with the exception of Oman, positive CT values and significantly negative DM values are observed when ADL-MIDAS is compared with ARDL model. In the case of Oman, the DM test values are positive and not significant, which suggest that although the ARDL model seems to perform better than the ADL-MIDAS model, this observed difference is not significant.

Generally, ADL-MIDAS outperformed all the other competing models across different oil price frequencies in the in-sample.

Table 3: RMSE results using WTI Oil Price

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
				Monthly					
	AR(1)			*ARFIMA*			*ARIMA*		
Kuwait	0.5095	0.5015	0.4959	19.2146	22.5223	26.4089	0.5249	0.5187	0.5175
Nigeria	0.8242	0.8112	0.7984	0.7285	0.7228	0.7230	0.7240	0.7189	0.7199
Oman	0.2438	0.2437	0.2606	1.3090	1.3968	1.5056	0.2553	0.2556	0.2732
Qatar	0.4020	0.4063	0.4179	2.5777	2.9209	3.3086	0.4096	0.4049	0.3990
UAE	0.3308	0.3262	0.3242	0.9273	0.9998	1.0783	0.2817	0.2775	0.2731
	ARDL			*ADL-MIDAS*					
Kuwait	0.3084	0.3128	0.3200	0.2046	0.2015	0.1983			
Nigeria	0.3627	0.3712	0.3792	0.2026	0.2001	0.1981			
Oman	0.0844	0.0838	0.0827	0.0940	0.0963	0.0957			
Qatar	0.3159	0.3377	0.3646	0.1280	0.1260	0.1258			
UAE	0.1359	0.1348	0.1345	0.0999	0.0986	0.0975			
				Quarterly					
	AR(1)			*ARFIMA*			*ARIMA*		
Kuwait	0.5095	0.5015	0.4959	19.2146	22.5223	26.4089	0.5249	0.5187	0.5175
Nigeria	0.8242	0.8112	0.7984	0.7285	0.7228	0.7230	0.7240	0.7189	0.7199
Oman	0.2438	0.2437	0.2606	1.3090	1.3968	1.5056	0.2553	0.2556	0.2732
Qatar	0.4020	0.4063	0.4179	2.5777	2.9209	3.3086	0.4096	0.4049	0.3990
UAE	0.3308	0.3262	0.3242	0.9273	0.9998	1.0783	0.2817	0.2775	0.2731
	ARDL			*ADL-MIDAS*					
Kuwait	0.3084	0.3128	0.3200	0.2069	0.2039	0.2007			
Nigeria	0.3627	0.3712	0.3792	0.2068	0.2042	0.2019			
Oman	0.0844	0.0838	0.0827	0.0945	0.0965	0.0951			
Qatar	0.3159	0.3377	0.3646	0.1300	0.1279	0.1287			
UAE	0.1359	0.1348	0.1345	0.1002	0.0988	0.0974			

Table 4: MAE results for WTI oil price

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
				Monthly					
	AR(1)			***ARFIMA***			***ARIMA***		
Kuwait	0.4240	0.4132	0.4087	11.7848	13.6041	15.7164	0.4389	0.4335	0.4349
Nigeria	0.7349	0.7156	0.6937	0.6205	0.6174	0.6210	0.6165	0.6142	0.6184
Oman	0.2251	0.2257	0.2366	1.0948	1.1567	1.2290	0.2384	0.2392	0.2505
Qatar	0.2920	0.2994	0.3114	1.7505	1.9544	2.1828	0.3488	0.3448	0.3373
UAE	0.3046	0.2988	0.2974	0.7426	0.7922	0.8453	0.2575	0.2518	0.2441
	ARDL			***ADL-MIDAS***					
Kuwait	0.2347	0.2408	0.2487	0.1501	0.1472	0.1430			
Nigeria	0.2915	0.3005	0.3091	0.1456	0.1440	0.1434			
Oman	0.0701	0.0698	0.0688	0.0668	0.0695	0.0696			
Qatar	0.3003	0.3144	0.3310	0.0979	0.0954	0.0961			
UAE	0.1232	0.1223	0.1224	0.0718	0.0710	0.0705			
				Quarterly					
	AR(1)			***ARFIMA***			***ARIMA***		
Kuwait	0.4240	0.4132	0.4087	11.7848	13.6041	15.7164	0.4389	0.4335	0.4349
Nigeria	0.7349	0.7156	0.6937	0.6205	0.6174	0.6210	0.6165	0.6142	0.6184
Oman	0.2251	0.2257	0.2366	1.0948	1.1567	1.2290	0.2384	0.2392	0.2505
Qatar	0.2920	0.2994	0.3114	1.7505	1.9544	2.1828	0.3488	0.3448	0.3373
UAE	0.3046	0.2988	0.2974	0.7426	0.7922	0.8453	0.2575	0.2518	0.2441
	ARDL			***ADL-MIDAS***					
Kuwait	0.2347	0.2408	0.2487	0.1536	0.1509	0.1467			
Nigeria	0.2915	0.3005	0.3091	0.1492	0.1476	0.1463			
Oman	0.0701	0.0698	0.0688	0.0677	0.0702	0.0689			
Qatar	0.3003	0.3144	0.3310	0.1020	0.0995	0.1011			
UAE	0.1232	0.1223	0.1224	0.0723	0.0713	0.0700			

4.2.3 Out-of-sample forecast evaluation

Having examined the in-sample performance of all the competing models used in this study, we proceed to examine their out-of-sample forecast performance using the forecast accuracy measures as in the case of the in-sample (see Tables 3 - 6). The forecast horizon is defined in terms of the data frequency of the regressand as one-year [$h=1$] and two-year [$h=2$] ahead forecast. This is necessitated by the need to confirm that the results hold even for the out-of-sample case. Results confirm the previous stance observed in the in-sample case, with regard to the performance of each model as we find ADL-MIDAS to outperform all the other competing models consistently irrespective of the forecast measure (whether RMSE, MAE, CT or DM test) and forecast horizon. The confirmation lends support to the preference of the ADL-MIDAS model over other competing models regardless of the data frequencies. In other words, the ADL-MIDAS approach is superior to time series models as well as ARDL when forecasting GDP with oil price. This also validates the need to exploit the inherent useful information in high frequency regressor(s) when forecasting low frequency regressand.

Table 5: Campbell-Thompson Results

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
	AR(1) Model			*ARFIMA Model*			*ARIMA*			*ARDL Model*		
						Monthly						
Kuwait	0.8388	0.8386	0.8400	0.9999	0.9999	0.9999	0.8481	0.8491	0.8531	0.5600	0.5852	0.6158
Nigeria	0.9396	0.9392	0.9384	0.9227	0.9234	0.9249	0.9217	0.9226	0.9243	0.6881	0.7095	0.7271
Oman	0.8512	0.8437	0.8652	0.9948	0.9952	0.9960	0.8644	0.8579	0.8773	-0.2407	-0.3234	-0.3391
Qatar	0.8986	0.9039	0.9094	0.9975	0.9981	0.9986	0.9023	0.9032	0.9006	0.8358	0.8609	0.8810
UAE	0.9089	0.9086	0.9095	0.9884	0.9903	0.9918	0.8743	0.8737	0.8724	0.4601	0.4650	0.4744
						Quarterly						
Kuwait	0.8351	0.8347	0.8362	0.9999	0.9999	0.9999	0.8447	0.8454	0.8495	0.5499	0.5751	0.6065
Nigeria	0.9371	0.9366	0.9361	0.9194	0.9202	0.9221	0.9184	0.9193	0.9214	0.6751	0.6973	0.7166
Oman	0.8497	0.8432	0.8669	0.9948	0.9952	0.9960	0.8630	0.8575	0.8788	-0.2533	-0.3273	-0.3227
Qatar	0.8955	0.9009	0.9051	0.9975	0.9981	0.9985	0.8993	0.9002	0.8959	0.8307	0.8565	0.8753
UAE	0.9083	0.9083	0.9098	0.9883	0.9902	0.9918	0.8736	0.8732	0.8729	0.4569	0.4629	0.4763

Table 6: Diebold and Mariano Result

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
	AR(1) Model			*ARFIMA Model*			*ARIMA*			*ARDL Model*		
							Monthly					
Kuwait	-4.6476***	-4.6008***	-4.6327***	-2.6174**	-2.6134**	-2.6084**	-4.5719***	-4.5947***	-4.7456***	-1.8739*	-2.0616**	-2.2916**
Nigeria	-5.9862***	-5.8800***	-5.7704***	-5.1882***	-5.2684***	-5.4536***	-5.1714***	-5.2633***	-5.4597***	-3.5789***	-3.8321***	-4.0811***
Oman	-5.7022***	-5.8325***	-4.8959***	-4.6239***	-4.5346***	-4.3309***	-6.0063***	-6.1725***	-5.0806***	0.4206	0.5696	0.6011
Qatar	-3.0809***	-3.2609***	-3.503***	-2.9534***	-2.9604***	-2.9651***	-4.9948***	-5.021***	-4.9534***	-5.9885***	-4.9074***	-4.3254***
UAE	-6.4769***	-6.3984***	-6.5181***	-4.0577***	-4.0201***	-3.9903***	-5.9598***	-5.8748***	-5.757***	-2.3346**	-2.3999**	-2.5172**
							Quarterly					
Kuwait	-4.6810***	-4.6311***	-4.6633***	-2.6174**	-2.6134**	-2.6084**	-4.5979***	-4.6192***	-4.7715***	-1.8746*	-2.0636**	-2.2962**
Nigeria	-6.0072***	-5.8994***	-5.7913***	-5.2046***	-5.2851***	-5.4727***	-5.1878***	-5.2801***	-5.479***	-3.5650***	-3.8177***	-4.0657***
Oman	-5.7312***	-5.8714***	-4.881***	-4.6236***	-4.5342***	-4.3302***	-6.0277***	-6.2025***	-5.0616***	0.4503	0.5877	0.5831
Qatar	-3.0741***	-3.2542***	-3.4948***	-2.9531***	-2.9602***	-2.965***	-4.9837***	-5.0099***	-4.9259***	-5.9576***	-4.8828***	-4.3257***
UAE	-6.4926***	-6.4161***	-6.5432***	-4.0571***	-4.0196***	-3.9896***	-5.9549***	-5.8733***	-5.769***	-2.3264**	-2.3971**	-2.5333**

Note: The values in the table represent the DM test values comparing the forecast error of the ADL-MIDAS model with the listed competing models. Negative and significant values indicate preference in favour of the ADL-MIDAS model. The statistical significance at 1%, 5% and 10% are represented by ***, ** and *, respectively.

4.2.4 Robustness checks

Up to this point, the analyses involve the use of the West Texas Intermediate oil price as a proxy for oil price. We are also interested in determining the sensitivity, or otherwise, of the preferred model not only to the different data frequencies and alternative measures of forecast performance but also to alternative proxies of oil price. Consequently, we consider another global oil price proxy, which is the Brent crude oil price and the analyses are replicated for both in-sample and out-of-sample forecasts using the same forecast measures as the WTI price. In other words, we examine the forecast performance of the competing models on the basis of four different forecast accuracy measures – RMSE, MAE, CT and DM tests (see Tables 7 - 10). The superior performance of the ADL-MIDAS model in comparison with the other models is upheld even when an alternative proxy of oil price (the Brent oil price) is used. Thus, the conclusion remains the same regardless of the forecast measures, data frequencies and oil price proxies. We therefore convincingly state here that the ADL-MIDAS model, which incorporates mixed data frequencies and provides additional information, is the most preferred model with respect to the output prediction of the five selected countries considered in the study.

5.0 Conclusion

We set out in this study to examine the predictability of oil price in GDP forecast. Most Previous studies have approached the link using uniform frequencies, which we find to be too conservative. While we acknowledge that GDP is largely available at a low frequency, our interest is to demonstrate that allowing for high frequency data for oil price will produce better forecast results than those involving uniform frequencies. This is achieved by incorporating a MIDAS-based regression (ADL-MIDAS) model (see Ghysels et al., 2002; Ghysels et al., 2007; Clements and Galavao, 2009; Andreou et al., 2013), which we set as our reference model in this study. In the light of this, we attempt to predict annual GDP using monthly and quarterly oil prices in the ADL-MIDAS construct. First, we examine the in-sample predictability of oil price for GDP using our reference model and find oil price to be an important predictor (whether measured monthly or quarterly). Consequently, we proceed to examine the forecast performance of the reference model relative to some competing models [AR(1), ARFIMA, ARIMA and ARDL].

On the forecast performance, both in-sample and out-of-sample, we find the outperformance of the ADL-MIDAS model over all the others competing models to be consistent across chosen oil price frequencies, sample intervals and forecast horizons. While we observe the performance of the ADL-MIDAS model to be insensitive to the choice of oil price used and consequent robustness of emanating estimates, we find interestingly too, that the higher the data frequency of the oil price proxy employed, the better the forecast performance. We thus have shown conclusively that model incorporating a mixture of data frequency in the prediction of output tends to be superior to models that are based on uniform frequencies.

Table 7: RMSE Result (Monthly Brent Oil Price)

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
				Monthly					
		AR(1)			***ARFIMA***			***ARIMA***	
Kuwait	1.3591	1.3781	1.4262	0.7920	0.8932	1.0729	3.2570	3.7098	4.2912
Nigeria	1.4388	1.4197	1.4089	4.6477	5.0278	5.4803	2.6739	2.7806	2.9206
Oman	0.1665	0.1682	0.1672	0.1079	0.1345	0.1327	0.1714	0.1682	0.1812
Qatar	3.5191	3.9336	4.4569	6.7357	7.5157	8.4446	6.8828	7.7414	8.7688
UAE	0.6036	0.6415	0.7189	0.8710	0.9338	1.0388	0.7717	0.8168	0.8999
		ARDL			***ADL-MIDAS***				
Kuwait	0.3433	0.3423	0.3379	0.2046	0.2012	0.2166			
Nigeria	0.4062	0.4079	0.4134	0.2151	0.2112	0.2323			
Oman	0.0621	0.0677	0.0667	0.0837	0.0862	0.1094			
Qatar	0.5129	0.5614	0.6399	0.1313	0.1303	0.1461			
UAE	0.1007	0.1006	0.1132	0.0836	0.0821	0.1124			
				Quarterly					
		AR(1)			***ARFIMA***			***ARIMA***	
Kuwait	1.3591	1.3781	1.4262	0.7920	0.8932	1.0729	3.2570	3.7098	4.2912
Nigeria	1.4388	1.4197	1.4089	4.6477	5.0278	5.4803	2.6739	2.7806	2.9206
Oman	0.1665	0.1682	0.1672	0.1079	0.1345	0.1327	0.1714	0.1682	0.1812
Qatar	3.5191	3.9336	4.4569	6.7357	7.5157	8.4446	6.8828	7.7414	8.7688
UAE	0.6036	0.6415	0.7189	0.8710	0.9338	1.0388	0.7717	0.8168	0.8999
		ARDL			***ADL-MIDAS***				
Kuwait	0.3433	0.3423	0.3379	0.2032	0.1997	0.2137			
Nigeria	0.4062	0.4079	0.4134	0.2150	0.2110	0.2243			
Oman	0.0621	0.0677	0.0667	0.0792	0.0832	0.0956			
Qatar	0.5129	0.5614	0.6399	0.1255	0.1246	0.1375			
UAE	0.1007	0.1006	0.1132	0.0811	0.0797	0.1042			

Table 8: MAE Result (Monthly Brent Oil Price)

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
				Monthly					
	AR(1)			***ARFIMA***			***ARIMA***		
Kuwait	1.2678	1.2876	1.3267	0.5690	0.6326	0.7268	2.3036	2.5807	2.9171
Nigeria	1.3845	1.3618	1.3517	3.7503	4.0186	4.3247	2.3697	2.4590	2.5671
Oman	0.1394	0.1420	0.1417	0.0922	0.1048	0.1035	0.1400	0.1351	0.1444
Qatar	2.6482	2.9126	3.2288	5.0032	5.5063	6.0853	5.0235	5.5655	6.1927
UAE	0.5239	0.5519	0.5976	0.7451	0.7899	0.8539	0.6786	0.7124	0.7640
	ARDL			***ADL-MIDAS***					
Kuwait	0.2788	0.2803	0.2767	0.1542	0.1509	0.1623			
Nigeria	0.3503	0.3540	0.3606	0.1660	0.1612	0.1752			
Oman	0.0475	0.0514	0.0505	0.0586	0.0615	0.0724			
Qatar	0.4052	0.4380	0.4838	0.1021	0.1020	0.1117			
UAE	0.0837	0.0842	0.0916	0.0666	0.0647	0.0772			
				Quarterly					
	AR(1)			***ARFIMA***			***ARIMA***		
Kuwait	1.2678	1.2876	1.3267	0.5690	0.6326	0.7268	2.3036	2.5807	2.9171
Nigeria	1.3845	1.3618	1.3517	3.7503	4.0186	4.3247	2.3697	2.4590	2.5671
Oman	0.1394	0.1420	0.1417	0.0922	0.1048	0.1035	0.1400	0.1351	0.1444
Qatar	2.6482	2.9126	3.2288	5.0032	5.5063	6.0853	5.0235	5.5655	6.1927
UAE	0.5239	0.5519	0.5976	0.7451	0.7899	0.8539	0.6786	0.7124	0.7640
	ARDL			***ADL-MIDAS***					
Kuwait	0.2788	0.2803	0.2767	0.1542	0.1506	0.1612			
Nigeria	0.3503	0.3540	0.3606	0.1631	0.1571	0.1677			
Oman	0.0475	0.0514	0.0505	0.0586	0.0622	0.0693			
Qatar	0.4052	0.4380	0.4838	0.1044	0.1042	0.1124			
UAE	0.0837	0.0842	0.0916	0.0678	0.0664	0.0770			

Table 9: Campbell- Thompson Result (Monthly Brent)

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
	AR(1) Model			*ARFIMA Model*			*ARIMA*			*ARDL Model*		
						Monthly						
Kuwait	0.9773	0.9787	0.9769	0.9332	0.9493	0.9592	0.9961	0.9971	0.9975	0.6446	0.6545	0.5890
Nigeria	0.9776	0.9779	0.9728	0.9979	0.9982	0.9982	0.9935	0.9942	0.9937	0.7195	0.7319	0.6841
Oman	0.7473	0.7375	0.5715	0.3978	0.5892	0.3201	0.7615	0.7374	0.6353	-0.8157	-0.6212	-1.6943
Qatar	0.9986	0.9989	0.9989	0.9996	0.9997	0.9997	0.9996	0.9997	0.9997	0.9345	0.9462	0.9479
UAE	0.9808	0.9836	0.9755	0.9908	0.9923	0.9883	0.9883	0.9899	0.9844	0.3109	0.3341	0.0125
						Quarterly						
Kuwait	0.9776	0.9790	0.9775	0.9342	0.9500	0.9603	0.9961	0.9971	0.9975	0.6495	0.6596	0.6000
Nigeria	0.9777	0.9779	0.9747	0.9979	0.9982	0.9983	0.9935	0.9942	0.9941	0.7199	0.7326	0.7056
Oman	0.7739	0.7553	0.6732	0.4613	0.6171	0.4814	0.7867	0.7552	0.7218	-0.6242	-0.5112	-1.0551
Qatar	0.9987	0.9990	0.9990	0.9997	0.9997	0.9997	0.9997	0.9997	0.9998	0.9402	0.9507	0.9538
UAE	0.9820	0.9845	0.9790	0.9913	0.9927	0.9899	0.9890	0.9905	0.9866	0.3522	0.3715	0.1517

Note: Positive values indicate preference in favour of ADL-MIDAS model over the listed models.

Table 10: Diebold and Mariano Test Results (Brent oil Price)

	In-Sample	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$	*In-Sample*	$h=1$	$h=2$
	AR(1) Model			*ARFIMA Model*			*ARIMA*			*ARDL Model*		
							Monthly					
Kuwait	-7.6463***	-7.9636***	-7.6725***	-3.0615***	-3.0074***	-2.6081**	-3.0026***	-2.9645***	-2.8521***	-2.2347**	-2.3447**	-2.0435*
Nigeria	-9.9755***	-9.7437***	-9.7063***	-4.0236***	-3.9845***	-3.8779***	-5.8253***	-5.8659***	-5.6928***	-4.0282***	-4.2698***	-4.1866***
Oman	-2.7161**	-2.8432***	-1.8553*	-1.3007	-1.5371	-0.6741	-3.3475***	-3.1585***	-3.2753***	0.8725	0.8172	1.3069
Qatar	-3.2984***	-3.2542***	-3.1300***	-3.2843***	-3.2595***	-3.1934***	-3.1589***	-3.1327***	-3.0694***	-3.3298***	-3.3784***	-3.1361***
UAE	-4.7258***	-4.6587***	-3.8805***	-4.4306***	-4.3516***	-3.8377***	-4.9806***	-4.9094***	-4.2316***	-1.0915	-1.2117	-0.0381
							Quarterly					
Kuwait	-7.6507***	-7.968***	-7.6689***	-3.0637***	-3.0093***	-2.6076**	-3.0026***	-2.9646***	-2.8521***	-2.3301**	-2.445**	-2.1609**
Nigeria	-10.038***	-9.8014***	-9.8136***	-4.0236***	-3.9845***	-3.8773***	-5.8263***	-5.8666***	-5.6885***	-4.1539***	-4.4022***	-4.5126***
Oman	-3.0218***	-3.1285***	-2.6613**	-1.8992*	-1.7438*	-1.2596	-3.5803***	-3.3122***	-3.5699***	0.8990	0.9084	1.3720
Qatar	-3.2987***	-3.2545***	-3.1300***	-3.2844***	-3.2596***	-3.1934***	-3.159***	-3.1328***	-3.0694***	-3.3497***	-3.3958***	-3.1377***
UAE	-4.7374***	-4.6684***	-3.8641***	-4.4351***	-4.3554***	-3.8308***	-4.9883***	-4.9159***	-4.2197***	-1.3440	-1.4657	-0.6333

Note: The values in the table represent the DM test values comparing the forecast error of the ADL-MIDAS model with the listed competing models. Negative and significant values indicate preference in favour of the ADL-MIDAS model. The statistical significance at 1%, 5% and 10% are represented by ***, ** and *, respectively.

References

Abel, A. and B. Bernanke, B. (2001). Macroeconomics (4th ed.). Addison-Wesley, Boston, 2001.

Alam, M., Murad, W., Nomanc, A. and Ozturk, I. (2016). Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecological Indicators, 70, 466–479.

Albu, L.L., RaduLupu, R .R. and Calin, A.C. (2015). Stock market asymmetric volatility and macroeconomic dynamics in Central and Eastern Europe. Procedia Economics and Finance, 22, 560 – 567

Alper A and Oguz O. (2016). The role of renewable energy consumption in economic growth: Evidence from asymmetric causality. Renewable and Sustainable Energy Reviews, 60, 953–959.

Alper, C.E., Fendoglu, S. and Saltoglu, B. (2008). Forecasting Stock Market Volatilities Using MIDAS Regression: An Application to the Emerging Markets. MPRA Paper No. 7460.

Al-sasi, B. O., Taylan, O. and Demirbas, A. (2017). The impact of oil price volatility on economic growth. Energy Sources, Part B: Economics, Planning, and Policy, 12, 847-852.

Andreou, E., Ghysels, E. and Kourtellos, A. (2013). Should macroeconomic forecasters look at daily financial data? Journal of Business and Economic Statistics, 31, 240 - 251.

Bai, J., Ghysels, E. and Wright, J. (2009). State space models and MIDAS regression. Working Paper, NY Fed, UNC and John Hopkins.

Balcilar, M. and Ozdemir, Z. 2013. The causal nexus between oil prices and equity market in the U.S.: A regime switching model. Energy Economics, 39: 271-282

Barsoum, F. and Stankiewicz, S. (2015). Forecasting GDP growth using mixed-frequency models with switching regimes. International Journal of Forecasting, 31, 33–50

Benramdane, A. (2017). Oil price volatility and economic growth in Algeria. Energy Sources, Part B: Economics, Planning, and Policy, 12, 338-343.

Brinia R, Amara M and Jemmali H. (2017). Renewable energy consumption, International trade, oil price and economic growth inter-linkages: The case of Tunisia. Renewable and Sustainable Energy Reviews, 76, 620–627

Brown, S. and M. Yucel (1999). Oil prices and US aggregate economic activity: A question of neutrality. Economic and Financial Review-Federal Reserve Bank of Dallas, 16–23.

Brown, S. and Yucel, M. 2000. Energy prices and aggregate economic activity: An interpretative survey. The Quarterly Review of Economics and Finance, 42(2), 193–208.

Bruno, M. and J. Sachs (1982). Input price shocks and the slowdown in economic growth: The case of UK manufacturing. The Review of Economic Studies 49: (5), 679–705.

Burbidge, J. and A. Harrison (1984). Testing for the effects of oil-price rises using vector autoregressions. International Economic Review 25 (2), 459–484.

Chai, J., J.-E.Guo, J.E., L. Meng, L. and S.-Y.Wang, S.Y. (2011). Exploring the core factors and its dynamic effects on oil price: An application on path analysis and BVAR-TVP model. Energy Policy, 39: (12), 8022–8036.

Chiou-Wei, S., Zhu, Z., Chen, S. and Hsueh, S. (2016). Controlling for relevant variables: Energy consumption and economic growth nexus revisited in an EGARCH-M (Exponential GARCH-in-Mean) model. Energy Economics, 109, 391-399.

Chontanawat J, Hunt LC and Pierse, R (2006). Causality between energy consumption and GDP: evidence from 30 OECD and 78 non-OECD countries. Surrey Energy Economics Centre (SEEC), School of Economics Discussion Papers (SEEDS) 113, University of Surrey.

Clements, M. P. and Galvão, A. B. (2009). Forecasting US output growth using leading indicators: an appraisal using MIDAS models. Journal of Applied Econometrics, 24:, 7, 1187-1206.

Edirneligil, A. and M. Mucuk, M. (2014). The effects of oil price on Turkish economic growth. Proceedings of International Academic Conferences, 2014. International Institute of Social and Economic Sciences.

Farzanegan, M.R. and G. Markwardt, G. (2009). The effects of oil price shocks on the Iranian economy. Energy Economics, 31:(1,): 134-151.

Finn, Mary. G. (2000). Perfect Competition and the Effects of Energy Price Increases on Economic Activity. Journal of Money, Credit, and Banking, 32, pp. 400-416.

Ftiti, Z., K. Guesmi, K., F. Teulon, F. and S. Chouachi, S. (2016). Relationship between crude oil prices and economic growth in selected OPEC countries. Journal of Applied Business Research, 32:(11,): 11-22.

Ghysels, E. and Ozkan, N. (2015). Real-time forecasting of the US federal government budget: A simple mixed frequency data regression approach. International Journal of Forecasting, 31:(4), 1009-1020.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2002). The MIDAS touch: Mixed Data Sampling Regression. Working Paper UNC and UCLA.

Ghysels, E., Sinko, A. and Valkanov, R. (2006). MIDAS regression: Further results and new directions. Econometric Reviews, 26, 53-90.Ghysels, E., Sinko, A., and Valkanov, R. 2007. MIDAS regressions: Further results and new directions. Econometric Reviews, 26, 53–90.

Ghysels, E., Sinko, A. and Valkanov, R. (2009). Granger Causality Tests with Mixed Data Frequencies. UNC Discussion Paper.

Gisser, M. and, Goodwin T. (1986). Crude Oil and the Macroeconomy: Tests of Some Popular Notions. Journal of Money, Credit, and Banking 18, 95-103.

Gokmenoglu, K., Azin, V. and Taspinar, N. (2015). The Relationship between Industrial Production, GDP, Inflation and Oil Price: The Case of Turkey. Procedia Economics and Finance, 25, 497 – 503.

Hamilton J. D. (1983). Oil and the Macroeconomy Since since World War II. Journal of Political Economy 91, 228-248.

Hamilton J. D. (2009). Causes and consequences of the oil shock of 2007-08. Brooking papers on Economic Activity, springSpring, 215- 261.

Hamilton, J. D. (1996). This is What Happened to the Oil Price–Macroeconomy Relationship. Journal of Monetary Economics, 38, 215–220.

Hamilton, J. D. (2003). What is an Oil Shock? Journal of Econometrics, 113, 363–398.

Jiménez-Rodríguez, R. and Sánchez, M. (2005). Oil price shocks and real GDP growth: empirical evidence for some OECD countries. Applied Economics, 37:2, 201-228.

Jiménez-Rodríguez, R. and Sánchez, M. (2009). Oil shocks and the macro-economy: a comparison across high oil price periods. Applied Economics Letters, 16:16, 1633-1638.

Jung, A. (2017). Forecasting broad money velocity. North American Journal of Economics and Finance, 42, 421–432

Karaki, M.B. 2017. Nonlinearities in the response of real GDP to oil price shocks. Economics Letters, 161, 146-148

Kilian, L., and R.J. Vigfusson, R.J. (2011a). Nonlinearities in the oil price-output relationship. Macroeconomic Dynamics, 15, 337-363.

Lardic, S. and Mignon, V. (2006). The impact of oil prices on GDP in European countries: An empirical investigation based on asymmetric cointegration. Energy Policy, 34, 3910-3915

Lee, K., S. Ni, S. and R. Ratti, R.. 1995. Oil shocks and the macroeconomy: The role of price variability. The Energy Journal, (4), 39–56.

Lee, K.iseok, and Shawn Ni, S. (2002). On the Dynamic Effects of Oil Price Shocks: A Study Using Industry Level Data. Journal of Monetary Economics, 49, 823-852.

Loungani, P. 1986. Oil price shocks and the dispersion hypothesis. Review of Economics and Statistics, 58: (3), 536–539.

Maji, I.K., Saari, M.Y., Habibullah, M.S. and Utit, C. (2017). Measuring the economic impacts of recent oil price shocks on oil-dependent economy: evidence from Malaysia, Policy Studies, 38, 375-391.

Mehmet, A.D and Alper, A. (2017). Renewable and non-renewable energy consumption and economic growth in emerging economies Evidence from bootstrap panel causality. Renewable Energy, 111, 757-763

Merz, M. (2016). An introduction to economic growth theory and the oil market: Scarce Natural Resources, Recycling, Innovation and Growth. Springer: GablerVerlag, (pp.3-9).

Mork, K. (1989). Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results. The Journal of Political Economy 97: (3), 740– 744.

Moshiri, S. and A. Banihashem, A. (2012). Asymmetric effects of oil price shocks on economic growth of oil-exporting countries. 1- 33. Available from SSRN 2006763.

Nusair, S.A. (2016). The effects of oil price shocks on the economies of the Gulf Co-operation Council countries: Nonlinear analysis. Energy Policy, 91, 256–267.

Pinzon, K. (2017). Dynamics between energy consumption and economic growth in Ecuador: A granger causality analysis. Economic Analysis and Policy, In press

Rafindadi, A.A. (2015). Econometric prediction on the effects of financial development and trade openness on the German energy consumption: a startling revelation from the data set. International Journal of Energy & Economic Policy; 5:1, 182–196.

Rafindadi, A.A. and Ozturk, I. (2015). Natural gas consumption and economic growth nexus: is the 10th Malaysian plan attainable within the limits of its resource? Renewable & Sustainable Energy Review, 49, 1221–1232.

Rafindadi, A.A. and Ozturk, I. (2017.) Impacts of renewable energy consumption on the German economic growth: Evidence from combined cointegration test. Renewable and Sustainable Energy Reviews, 75, 1130-1141.

Salisu, A. A, Ademuyiwa, I. and Isah, K. (2018). Revisiting the forecasting accuracy of Phillips curve: the role of oil price. Energy Economics, DOI: 10.1016/j.eneco.2018.01.018.

Salisu, A. A. and Ogbonna, A. E. (2017). Forecasting GDP with energy series: ADL-MIDAS vs. Linear Time Series Models. Centre for Econometric and Allied Research, University of Ibadan Working Papers Series, CWPS 0035.

Taghizadeh-Hesary, F., Yoshino, N. Abadi, M.M.H. and Farboudmanesh, R. (2016). Response of macro variables of emerging and developed oil importers to oil price movements. Journal of the Asia Pacific Economy, 21, 91-102.

Tang, W., L. Wu, and Z. Zhang (2010). Oil price shocks and their short-and long-term effects on the chinese economy. Energy Economics 32, S3–S14.

Ucan, O., Aricioglu, E. and Yucel, F. (2014). Energy consumption and economic growth nexus: Evidence from developed countries in Europe. International Journal of Energy Economics and Policy, 45:(3), 411–419.

Valadkhani, A. and Smyth, R. (2017). How do daily changes in oil prices affect US monthly industrial output? Energy Economics, doi:10.1016/j.eneco.2017.08.0.

Wei, Y. and X. Guo, X. (2016). An empirical analysis of the relationship between oil prices and the Chinese macro-economy. Energy Economics, 56:(C):, 88-100.