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RESEARCH PAPER

2050 Projections of the Persian Gulf Economies

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Abstract

Projections of Persian Gulf Economies are obtained by forecasting their GDPs (constant 2010 US$) with spectral analysis until 2050. Persian Gulf Economies being oil-driven, the special relationship between oil price and Persian Gulf Economies is unfolded with Multiscale Principal Component Analysis and integrated into the forecasts. The GDPs are decomposed into clearer signals called approximations and details in the one-dimensional discrete wavelet analysis framework. The simplified signals are recomposed after the Burg extension. Spectral analysis forecasts are all bullish for the eight economies of the Persian Gulf. Two thousand fifty spectral analysis projections rank Iraq first with an annual growth rate of +2.37% and Iran second with +2.19%. The two laggers among the 2050 spectral analysis projections are Saudi Arabia (+1.37%) and Kuwait (-0.04%). Two thousand twenty-four spectral analysis projections rank Iran first with an annual growth rate compounded of +4.12% and Iraq second with +3.79%. In comparison, IMF projections rank Iraq first (+3.17%) and United Arab Emirates (+2.92%). The two laggers among the 2024 spectral analysis projections are Qatar (0.22%) and Kuwait (-3.74%), while the two laggers among the 2024 IMF projections are Saudi Arabia (+2.15%) and Iran (-0.30%). In 2020, the COVID-19 pandemic brutally hurt Persian Gulf Economies following a collapse in the global demand for oil and an oversupplied industry. The individual effect on these economies will depend on the response brought by their respective governments.
Keywords: GDP, Spectral Analysis, Forecasts, Multiscale Principal Component Analysis, Persian Gulf Economies.
JEL Classification: C01, C5, C53, E3, E17, E37.

Introduction

The purpose of this paper is to forecast with spectral analysis the GDPs (constant 2010 US$) of the 8 Persian Gulf economies until 2050. The projections of the economies are compared using the forecasted annual growth rates annually compounded of GDPs (constant 2010 US$) between 2019 and 2050. In order to test the reliability of the spectral analysis model, 2024 IMF GDPs projections are used as benchmarks. The Persian Gulf Economies being oil-driven, the special relationship between oil price and Persian Gulf Economies is unfolded with Multiscale Principal Component Analysis and integrated in the forecasts.

Persian Gulf countries are sharing coastlines on the Persian Gulf. They include the United Arab Emirates (UAE), the States of Bahrain, the Kingdom of Saudi Arabia, the Sultanate of Oman, the State of Qatar, the State of Kuwait, the Republic of Iraq and the Islamic Republic of Iran. COVID-19 virus has been in the air since the end of 2019 bringing a global pandemic that has hit the 5 continents and plunged the world economy into a severe recession in 2020.

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The global demand for oil collapsed and much of the world is nowadays, for the first time in history, oversupplied. On April 20, 2020, the WTI futures price for delivery in May 2020 has dropped to MINUS \$37.63 from \$18.27 (-300%!!!). That day, sellers of oil were essentially disposed to pay buyers to take delivery of their oil! (Ngai et al., 2020). In July 2020, WTI spot price was flirting with the \$40 line below the long-term average of \$44 (January 1986 - June 2020). Persian Gulf countries share about two-thirds of the world's crude oil reserves and about one-third of the world's natural gas reserves belongs to Qatar and Iran. In 2020, Persian Gulf countries have thus been the most hit by the pandemic crisis as well as USA, Russia, China and Canada, all belonging to the top-tier oil producing countries. In December 2014, Persian Gulf countries had a similar story and were affected by low oil price which dropped below the \$60-line which was able to recover above this line only in January 2018 following an extended supply cut from OPEC and Russia who started to withhold output a year before. Table 1 presents the proportions of Gross domestic product (GDP) and government revenues of the Persian Gulf countries represented by the oil and gas sector and their annual GDPs (constant 2010 US\$) growth rates between 2014 and 2018.

Table 1. Percentage of GDP and Government Revenues of the Persian Gulf Countries between 2014 and 2018

	% of GDP from the oil and gas sector*	**% of Government Revenues from the oil and gas sector***	**GDP (constant 2010 US\$) annual growth rates**				
			2014	**2015**	**2016**	**2017**	**2018**
UAE	30%	81%	4.40%	5.06%	2.99%	0.79%	1.42%
Bahrain	11%	70%	4.35%	2.86%	3.47%	3.80%	1.78%
KSA	42%	87%	3.65%	4.11%	1.67%	-0.74%	2.21%
Oman	39%	84%	2.75%	4.74%	4.98%	-0.93%	2.13%
Qatar	60%	70%	3.98%	3.66%	2.13%	1.58%	1.43%
Kuwait	50%	90%	0.50%	0.59%	2.93%	-3.48%	1.24%
Iraq	60%	90%	0.70%	2.48%	13.57%	-1.67%	0.63%
Iran	10%	60%	4.60%	-1.32%	13.40%	3.76%	-3.90%
Average	38%	79%	3.12%	2.77%	5.64%	0.39%	0.87%

Source: World Bank, CIA, Economy of Oman Webpage, Kuwait-oil and gas webpage, FRED webpage.
Note: (*) 2017 or 2018 estimates

The oil and gas sector represents 38% on average of GDPs of Persian Gulf countries and more than the double on average of the government revenues (i.e. 79%). The oil and gas sector is therefore the principal source of revenues of the Persian Gulf governments, which, with a tumbling oil price for the past 6 years, has brought their budget under severe turmoil. Urgent reforms have been implemented in order to invert the trend of the government budget deficit. One remedy has been to implement taxes: for the first time in history, six among the Persian Gulf countries (Saudi Arabia, Bahrain, Kuwait, Oman, Qatar and United Arab Emirates) have introduced 5% VAT (Value Added Tax) in January 2018. Saudi Arabia also cut energy subsidies in order to repair public finances. Regarding GDP (constant 2010 US\$) annual growth rates, 2017 was the worst year (+0.39% on average) followed by 2018 (+0.87%).

To confirm the tight relationship between Persian Gulf economies and WTI oil price, we compute the correlation matrix between the eight Persian Gulf annual GDPs (constant 2010 US\$) and the annual average WTI price.

Table 2. Correlation Matrix between the Eight Persian Gulf Annual GDPs (Constant 2010 US$) and the Annual Average WTI Price between 1960 and 2018 (Sample Size Varying for each Country)

	UAE	Bahrain	KSA	Oman	Qatar	Kuwait	Iraq	Iran	Annual Average WTI Price
UAE	100%								
Bahrain	99%	100%							
KSA	96%	97%	100%						
Oman	96%	98%	92%	100%					
Qatar	96%	98%	98%	98%	100%				
Kuwait	98%	96%	94%	92%	90%	100%			
Iraq	97%	97%	94%	95%	96%	91%	100%		
Iran	91%	98%	91%	87%	90%	96%	88%	100%	
Annual average WTI price	**80%**	**76%**	**81%**	**78%**	**53%**	**83%**	**80%**	**80%**	**100%**

Source: Research finding.

Table 2 shows that Gulf Economies are highly correlated. Regarding the relationship between crude oil price and the Gulf Economies, the correlation coefficient varies between 53% with Qatar and 83% with Kuwait. It suggests that Qatar is a more diversified economy than Kuwait. The average correlation of oil price with the eight Gulf Economies is 76% that shows the strong and positive relationship between oil price and these Economies. This strong relationship between oil price and GDP time series is captured by the forecasting model presented in this paper using Multiscale Principal Component Analysis (MPCA). The forecast of the Real GDP time series between 2019 and 2050 after MPCA is realized with wavelet analysis which expand functions in terms of wavelets generated in the form of translations and dilations of a fixed function called the mother wavelet. The resulting wavelets have special scaling properties, localized in time and frequency, permitting a closer connection between the represented function and their coefficients. IMF projections are used as benchmarks of spectral analysis forecasts between 2019 and 2024. The choice of the spectral forecasting model relates to the nature of GDP time series. GDPs, interest rates, exchange rates, volatility of asset returns, levels of employment or consumer spending propagate through time in waveforms. Waveforms are the shape and form of these economic signals. The modelization of economic variables based on time element, subject to uncertain, unexpected and irregular dynamics and where fluctuations occur, has challenged econometricians and forecasters in a quest for sophisticated models able to capture and predict the evolving behavior, frequency, rate of change, amplitude, shape and form of these economic variables through time. Many physical phenomena such as electrical, audio or seismic signals propagate through space in waveforms. The basic idea of this paper is to apply a model that captures dynamics in physics to dynamic economics. The concept of dynamics derived from Physics, referring to a state where there is a change such as movement. By analyzing the system of mechanics of signals, dynamics can be understood. Wavelet analysis has stirred interest for its ability to analyze changing transient physical signals (Lee and Yamamoto, 1994). 'Wavelet analysis expands functions in terms of wavelets generated in the form of translations and dilations of a fixed function called the mother wavelet. The resulting wavelets have special scaling properties, localized in time and frequency, permitting a closer connection between the represented function and their coefficients. Greater numerical stability in reconstruction and manipulation is ensured.' Extending the analysis to complex-behavior economic signals, the originality of this paper is to apply wavelet analysis to economic variables subject to common dynamics such as GDP time series of countries pertaining to the same economic zone, the Persian Gulf. Next section will present economic forecasting methods and make a tour of signal processing in the literature.

Literature Review

Traditional economic forecasting methods include causal methods (regression analysis, logit, probit), time series methods (moving average, exponential smoothing, trend and seasonal decomposition, Box-Jenkins ARIMA used as a benchmark in this paper) and qualitative methods (Delphi Method, Jury of Executive Opinion, Sales Force Composite, Consumer Market Survey) (FHI, 2019). Signal processing used in this paper to forecast GDPs of the Persian Gulf region belongs to time series methods. Signal processing is borrowed from Physics and focuses on the analysis, synthesis, and modification of signals. The basic assumption of this paper is that economic time series behave like signals propagating through time instead of propagating through space like physics phenomena such as audio, video, speech, geophysical, sonar, radar, medical or musical signals (IEEE, 2019). Wavelet analysis is a tool of signal processing. In Physics, wavelets have practical applications to model physical phenomena such as electrical, audio or seismic signals which propagate through space in waveforms. Wavelets mimic signals with specific properties that make them useful for signal processing. Signal processing focuses on the analysis, synthesis, and modification of signals. Spectral (or spectrum) analysis focuses on data analysis of signals. More specifically (Stoica and Moses, 2005), from a finite record of a stationary data sequence, spectral analysis estimates how the total power is distributed over frequency. In meteorology, astronomy and other fields, spectral analysis may reveal 'hidden periodicities' in data, which are to be associated with cyclic behavior or recurring processes.

Regarding wavelet analysis, forecasters have focused on the Discrete Wavelet Transform due to several not tractable properties of continuous wavelet transform (CWT) such as highly redundant wavelet coefficients (Valens, 1999), infinite number of wavelets in the wavelet transform and no analytical solutions found for most functions of the wavelet transforms. A wavelet-based forecasting method using redundant "à trous" wavelet transform and multiple resolution signal decomposition was presented in Renaud et al. (2002). Forecasting day-ahead electricity prices based on the wavelet transform and ARIMA models was a challenge detailed in Conejo et al. (2005). Schlüter and Deuschle (2010) were able to capture seasonalities with time-varying period and intensity, incorporated the wavelet transform to improve forecasting methods. Tan et al. (2010) proposed a price forecasting method based on wavelet transform combined with ARIMA and GARCH models. Kao et al. (2013) integrated wavelet transform, multivariate adaptive regression splines (MARS), and support vector regression (SVR called Wavelet-MARS-SVR) to address the problem of wavelet sub-series selection and to improve forecast accuracy. Ortega and Khashanah (2013) proposed a wavelet neural network model for the short-term forecast of stock returns from high-frequency financial data. Kriechbaumer et al. (2014) showed the cyclical behavior of metal prices. With wavelet analysis, they were able to capture the cyclicality by decomposing a time series into its frequency and time domain. They presented a wavelet-autoregressive integrated moving average (ARIMA) approach for forecasting monthly prices of aluminum, copper, lead and zinc. He et al. (2014) proposed an entropy optimized wavelet-based forecasting algorithm to forecast the exchange rate movement. Berger (2016) transformed financial return series into its frequency and time domain via wavelet decomposition to separate short-run noise from long-run trends and assess the relevance of each frequency to value-at-risk (VaR) forecast. Rostan and Rostan (2018a) illustrated with market data the versatility of wavelet analysis to the forecast of financial times series with distinctive properties. Rostan et al. (2015) appraised the financial sustainability of the Spanish pension system and Rostan et Rostan (2018b) of the Saudi pension system using spectral analysis. With a refined methodology using multiscale principal component analysis to take into account the co-dynamics of age groups, Rostan and Rostan (2017) forecasted European and Asian populations with signal processing which lead to original outcomes compare to more conformist population projections of the United Nations. In addition, Rostan and Rostan (2019) identified when European Muslim population will be majority. Rostan and Rostan applied wavelet analysis to the forecasts of Spanish (2018c), Greek (2018d), Saudi (2021) and Austrian (2020a) economies.

Section3 presents the methodology. Section4 gathers the results and section5 concludes.

Methodology

The objective of the paper is to identify with spectral analysis the economic winners and losers of the Persian Gulf region by forecasting their GDPs (constant 2010 US$) between 2019 and 2050. Figure 1 illustrates historical annual data of GDPs (constant 2010 US$) from 1960 to 2018 (58 data for the longest time series).

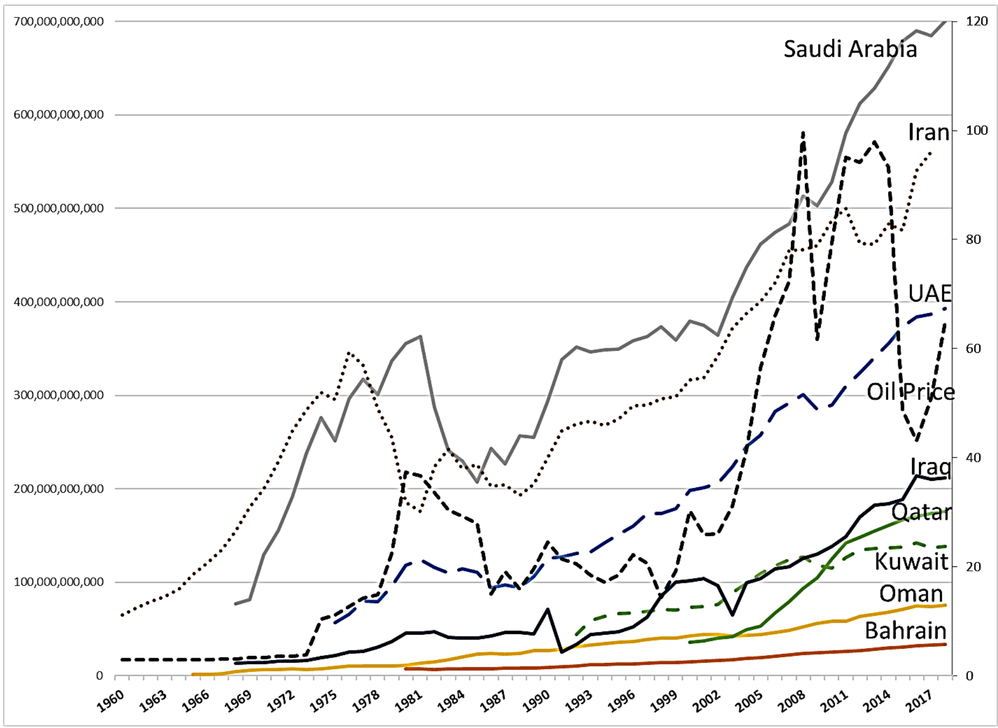

Figure 1. Gross Domestic Products from 1960 to 2018 and Annual Average WTI Price
Source: World Bank, OECD, and Federal Reserve Bank of St. Louis.

From Figure 1, three countries dominate the Persian Gulf region in terms of GDP constant 2010 US$: Saudi Arabia, Iran and UAE.

Left Axis is the Gross Domestic Products (constant 2010 US$), and its frequency is annual from 1960 to 2018 (58 annual data for the longest time series, Iran, 19 data for the shortest, Qatar). The right axis is annual average WTI price.

Step 1: Database

From the World Bank database, we retrieve GDP constant 2010 US$ of the 8 countries of the Persian Gulf region from 1960 to 2018. None of the countries have a full dataset of 59 years, the longest time series being Iran with 58 data, the shortest Qatar with 19 data, Saudi Arabia (51 data), UAE (44), Iraq (51), Kuwait (27), Oman (54), Bahrain (39). We do not extrapolate data and use the time series as they are since extrapolating data would bias the forecasts. Reduced time series however limit the number and the quality of the forecasts.

Step 2: De-noising and Compression of the First-order Difference of the 8-Time Series

We compute the first-order difference of the eight-time series (GDPs of United Arab Emirates, Bahrain, KSA, Oman, Qatar, Kuwait, Iraq and Iran) to transform non-stationary series into stationary series. We apply the Augmented Dickey-Fuller test to the 8 GDP time series before and after differentiation. All tests lead to the same conclusion: before differentiation, the 8 time-series are non-stationary (i.e. existence of a unit root) and after differentiation the 8 time-series are stationary (rejection of the existence of a unit root). The choice of this transformation relies on the fact that wavelet analysis presents a more accurate forecasting ability with stationary time series than non-stationary time series. Refer for example to Rostan and Rostan (2018a) for a demonstration.

We then de-noise each series using a one-dimensional de-noising and compression-oriented function using wavelets. The function is called 'wdencmp' in Matlab (Misiti et al., 2015). The underlying model for the noisy signal is of the form:

$$s(n) = f(n) + \sigma e(n) \tag{1}$$

where time *n* is equally spaced, *e(n)* is a Gaussian white noise *N(0,1)* and the noise level σ is supposed to be equal to 1. The de-noising objective is to suppress the noise part of the signal *s* and to recover *f*. The de-noising procedure proceeds in three steps: 1) Decomposition. We choose the wavelet *sym4*, and choose the level 2-decomposition. *Sym4* is a Symlets wavelet of order 4 used as the mother wavelet for decomposition and reconstruction. It is a nearly symmetrical wavelet belonging to the family of Symlets proposed by Daubechies (1994). We compute the wavelet decomposition of the signal *s* at level 2. 2) Detail coefficients thresholding. For each level from 1 to 2, we select a threshold and apply soft thresholding to the detail coefficients. 3) Reconstruction. We compute wavelet reconstruction based on the original approximation coefficients of level 2 and the modified detail coefficients of levels from 1 to 2.

Like de-noising, the compression procedure contains three steps:

1- Decomposition

2- Detail coefficient thresholding. For each level (1 or 2), a threshold is selected and hard thresholding is applied to the detail coefficients.

3- Reconstruction. The difference with the de-noising procedure is found in step2. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using a small number of approximation coefficients (at a suitably selected level) and some of the detail coefficients.

As an example, we illustrate in Figure 2 Oman’s GDP (constant 2010 US$, 54 years) before differentiation (top figure), after differentiation (middle) and after de-noising and compression (bottom).

Step 3: Wavelet Decomposition

We decompose the signals after being differentiated, de-noised and compressed. The signals, i.e. the time series of 8 GDPs transformed at step 2, are decomposed into decomposed signals *cAs* named approximations and *cDs* named details. The Discrete Wavelet Transform is a kind of decomposition scheme evaluated by passing the signal through low pass and high pass filters (Corinthios, 2009), dividing it into a lower frequency band and an upper band. Each band is subsequently divided into a second level lower and upper bands. The process is repeated, taking the form of a binary, or “dyadic” tree. The lower band is referred to as the approximation *cA* and the upper band as the detail *cD*. The two sequences *cA* and *cD* are down sampled. The down sampling is costly in terms of data: with multilevel decomposition, at each one-level of decomposition the sample size is reduced by half (in fact, slightly more than half the length of the original signal, since the filtering process is implemented by convolving the signal with a filter. The convolution “smears” the signal, introducing several extra samples into the result). Therefore, the decomposition can proceed only until the individual details consist of a single sample. Thus, the number of levels of decomposition will be limited by the initial number of data of the signal. With the example of Saudi Arabia, Figure 3 illustrates the 3rd-level decomposition of its transformed GDP (constant 2010 US$, after differentiation and de-noising/compression, 50 points). We observe in Figure 3 that details *cD*s are small and look like high-frequency noise, whereas the approximation *cA3* contains much less noise than does the initial signal (constant 2010 US$, after differentiation and de-noising/compression). In addition, the higher the level of decomposition, the lower the noise generated by details. For a better understanding of signal decomposition using discrete wavelet transform, refer to the methodology section of Rostan and Rostan (2018a).

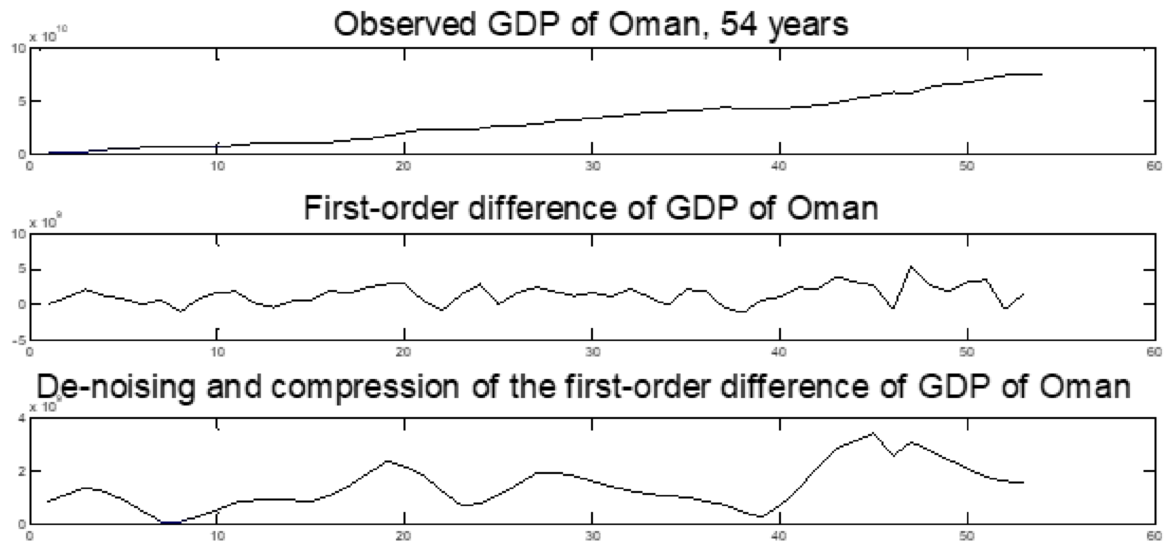

Figure 2. Observed Oman’s GDP from 1965 to 2018
Source: Research finding.

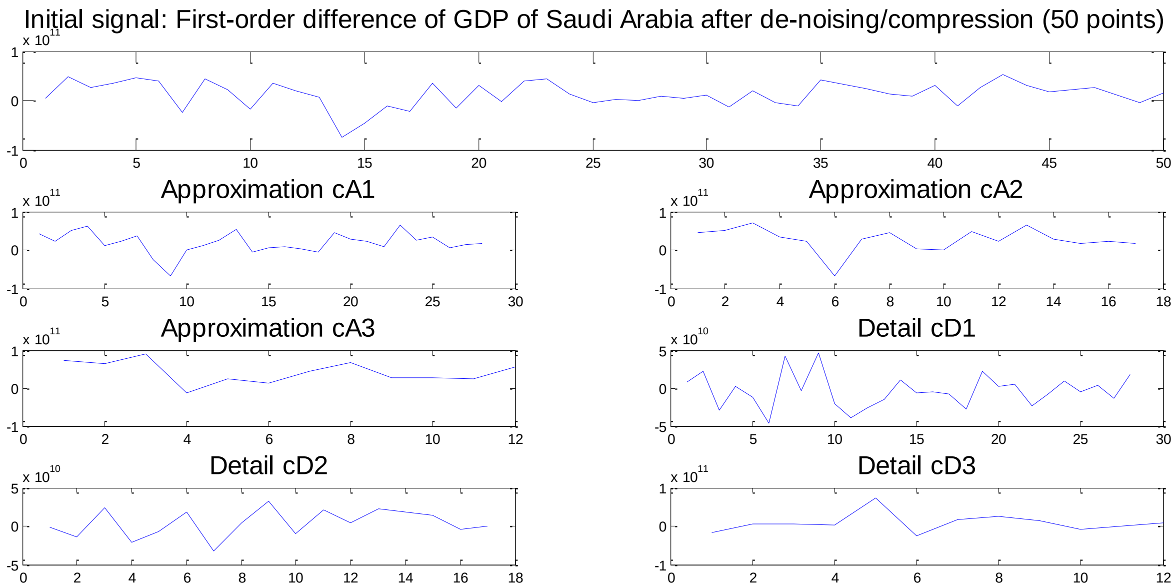

Figure 3. 3rd level Decomposition of the Transformed Saudi Arabia's GDP Using One-dimensional Discrete Wavelet Analysis
Source: Research finding.

Step 4: Burg extension of approximations and details

We apply Burg extension to c*A* and *cD* as presented in Figure 5. To run the Burg extension, we apply an autoregressive p^{th} order from historical data, in this paper we choose a p^{th} order equal to the longest available order when forecasting. For instance on 2018, when forecasting GDP (constant 2010 US$) of Saudi Arabia for the subsequent years, the longest p^{th} order available is 49 out of 51 data. Given *x* the decomposed signal (which is *cA* or *cD*), we generate a vector *a* of all-pole filter coefficients that model an input data sequence using the Levinson-Durbin algorithm (Levinson, 1946; Durbin, 1960). We use the Burg (1975) model to fit a p^{th} order autoregressive (AR) model to the input signal, *x*, by minimizing (least squares) the forward and backward prediction errors while constraining the *AR* parameters to satisfy the Levinson-Durbin recursion. *x* is assumed to be the output of an *AR* system driven by white noise. Vector *a* contains the normalized estimate of the *AR* system parameters, *A(z)*, in descending powers of *z*:

$$H(z) = \frac{\sqrt{e}}{A(z)} = \frac{\sqrt{e}}{1 + a_2 z^{-1} + \ldots + a_{(p+1)} z^{-p}} \qquad (2)$$

Since the method characterizes the input data using an all-pole model, the correct choice of the model order *p* is important. In Figure 4, the prediction error, *e(n)*, can be viewed as the output of the prediction error filter *A(z)*, where *H(z)* is the optimal linear predictor, *x(n)* is the input signal, and *(n)* is the predicted signal.

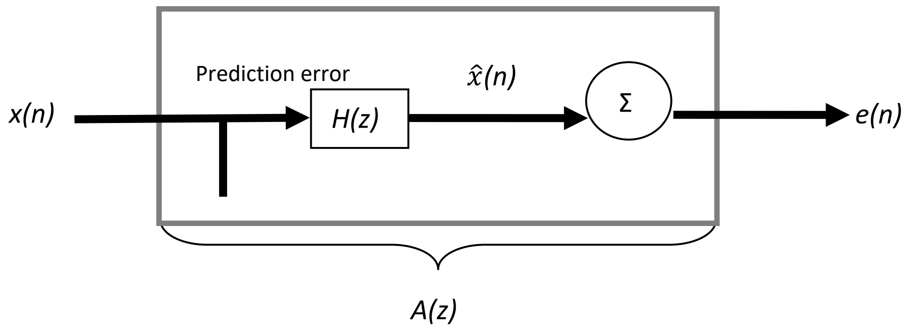

Figure 4. Prediction Error Filter to Run the Burg Extension
Source: Research finding.

In a last step, the Infinite Impulse Response (*IIR*) filter extrapolates the index values for each forecast horizon. *IIR* filters are digital filters with infinite impulse response. Unlike finite impulse response (*FIR*) filter, *IIR* filter has the feedback (a recursive part of a filter) and is also known as recursive digital filter.

Step 5: Wavelet Reconstruction

We recompose the forecasted signals after Burg extension using the methodology illustrated in Figure 5. We present the 3rd-level decomposition/reconstruction diagram. After reconstruction, we retransform the time series of the first-order difference of the GDPs (constant 2010 US$) into GDPs.

Step 6: Adjusting the Forecasts with the co-dynamics of the 8 Persian Gulf Economies and oil price with Multiscale Principal Component Analysis

Multiscale Principal Component Analysis (MPCA) tool belongs to the Wavelet Toolbox of Matlab to reconstruct a simplified multivariate signal, starting from a multivariate signal and using a simple representation at each resolution level. MPCA generalizes the Principal Component Analysis (PCA) of a multivariate signal represented as a matrix by simultaneously performing a PCA on the matrices of details of different levels. The correlation matrix presented in Table 2 reveals the tight relationship between oil price and the 8 Gulf Economies. Applying MPCA to the 32-year forecasts and to the 19 most recent years since 2000 adjusts the forecasts by integrating the co-dynamics of the 9 times series.

The forecast of the WTI oil price follows the same methodology that the one presented in the above 5 steps and has been inspired by the article of Rostan and Rostan (2020b) whose objective was to forecast fossil fuels prices.

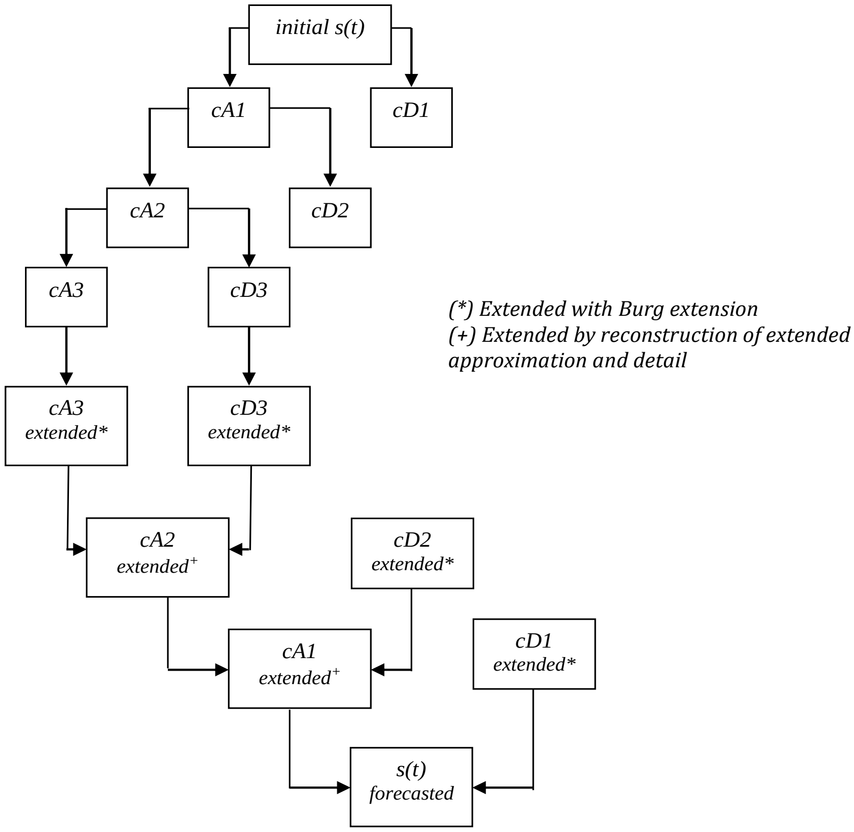

Figure 5. Diagram of a 3rd level Wavelet Decomposition/Reconstruction Tree to Forecast the Initial Signal s(t)
Source: Research finding.

Identifying the Optimal Level of Decomposition/Reconstruction

We focus in this section on identifying the optimal level of decomposition/ reconstruction of the spectral forecasting model. We divide the historical data into two in-samples: the 1st in-sample represents one-third of the historical data and it is used to forecast the 2nd in-sample which represents the last two-third of the historical data. We then compute the Root Mean Square Error between the forecasted values and the historical values of the 2nd in-sample. To generate forecasts, we apply steps 2 to 5 to the 1st in-sample making the level of decomposition/reconstruction varying from 1 to 7. We then measure the forecasting error over the 2nd in-sample of GDP data. Levels 1 and 2 return an error message. Level 3 also returns an error message for Qatar and Kuwait since their samples of historical data are small (19 and 27 data respectively). As an example, Figure 6 illustrates the RMSE computed on the last 26 in-sample years of the database (forecasts versus observed data) of the GDP (constant 2010 US$) of Bahrain.

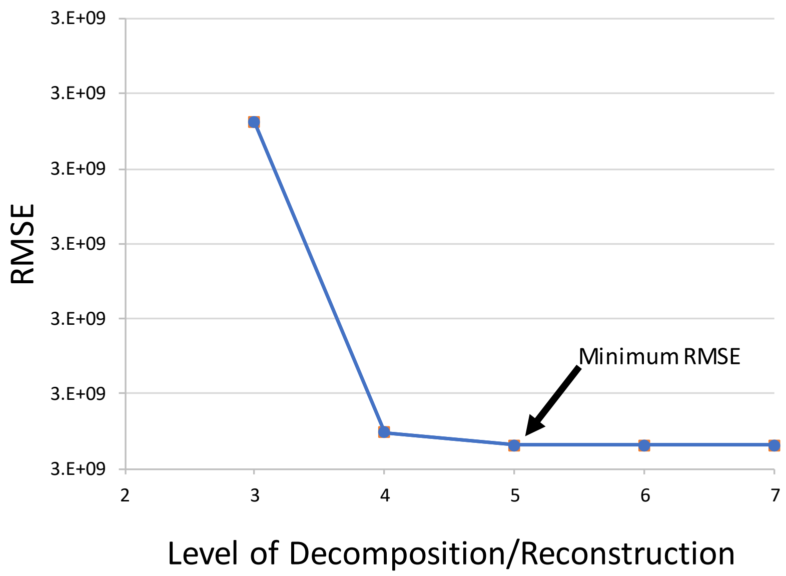

Figure 6. RMSE versus Level of Decomposition/Reconstruction of in-sample Annual GDP Forecasts of Bahrain from 1993 to 2018 (26 Data)
Source: Research finding.

At level 5-decomposition/reconstruction, the RMSE is at its minimum (i.e. 3,161,577,271). Level 5 is therefore the optimal level of decomposition/ reconstruction of annual GDP (constant 2010 US$) forecasts of Bahrain that we use to generate forecasts in the Results section. We repeat the step of identifying the optimal level of decomposition for the other variables under review. Table 3 gathers, based on in-sample data forecasts, the optimal level of decomposition/reconstruction for each variable.

Table 3. RMSE versus Level of Decomposition/Reconstruction Computed over the Forecasted in-sample Data for the 8 GDPs (Constant 2010 US$) of the Gulf Region and WTI Oil Price

Decomposition/ reconstruction:	**level 2**	**level 3**	**level 4**	**level 5**	**level 6**	**level 7**
p^{th}-order*	**M-2**	**M-2**	**M-2**	**M-2**	**M-2**	**M-2**
UAE	N/A	2.04E+11	**2.02E+11**	2.02E+11	2.02E+11	2.02E+11
Bahrain	N/A	3.18E+09	**3.16E+09**	3.16E+09	3.16E+09	3.16E+09
Saudi Arabia	N/A	**1.15E+12**	1.16E+12	1.16E+12	1.16E+12	1.16E+12
Oman	N/A	1.31E+10	1.28E+10	**1.28E+10**	1.28E+10	1.28E+10
Qatar*	N/A	N/A	**6.03E+10**	6.03E+10	6.03E+10	6.03E+10
Kuwait*	N/A	N/A	N/A	**3.38E+10**	3.38E+10	3.38E+10
Iraq	N/A	9.06E+10	**9.00E+10**	9.00E+10	9.00E+10	9.00E+10
Iran	N/A	**4.80E+11**	7.15E+11	7.19E+11	7.19E+11	7.19E+11
WTI oil price	N/A	**5.01E+01**	**5.05E+01**	**5.06E+01**	**5.06E+01**	**5.06E+01**

Source: Research finding.
Note: (*) For Qatar and Kuwait, p^{th} order = M-1 for all levels

RMSE Values in bold represent the lowest RMSE identifying the optimal level of decomposition/reconstruction applied in the Results section to the forecasts of the variables.

Results

Winners and losers of the 8 Persian Gulf Economies are identified by forecasting their GDPs (constant 2010 US$) with spectral analysis until 2050. In Figures 7 and 8, we illustrate 32-year forecasts from 2019 to 2050 located on the right-hand side of the vertical dotted line represented by year 2018. On the left-hand side are historical data observed from 1960 (for the longest time series) until 2018 (except Iran which ends in 2017). At the decomposition/ reconstruction step of the spectral forecasting model, we apply the fit best-level per country presented in Table 3. We finally apply Multiscale Principal Component Analysis (MPCA) to a window of 19 historical data and 32 forecasts to integrate the co-dynamics of the 8 Persian Gulf Economies and oil price to the forecasts.

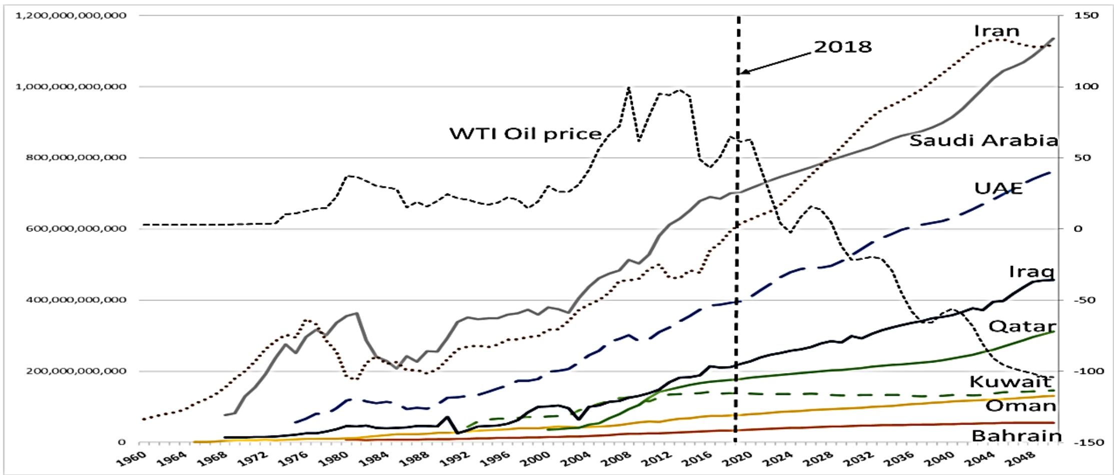

Figure 7. Before MPCA (1960 to 2018) and Forecasted (2019 to 2050) GDPs (constant 2010 US$) of the Persian Gulf
Source: World Bank and OECD, Federal Reserve Bank of St. Louis.

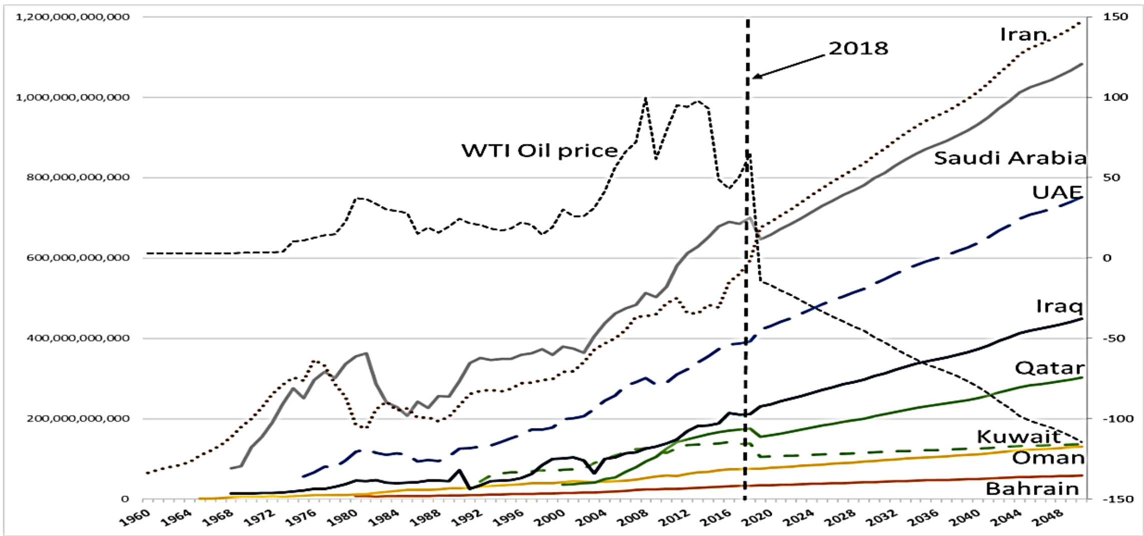

Figure 8. After MPCA (1960 to 2018) and Forecasted (2019 to 2050) GDPs (constant 2010 US$) of the Persian Gulf
Source: World Bank and OECD, Federal Reserve Bank of St. Louis.

GDPs (constant 2010 US$) projections obtained with spectral analysis and illustrated in Figure 7 on the right-hand side of the vertical dotted line increase steadily for all countries except Kuwait whose GDP is stagnant during the 32-year period. Table 4 illustrates the annual growth rates annually compounded between 2018 and 2050 of GDPs (constant 2010 US$) and the average annual growth rates between 2019 and 2024 benchmarked to IMF projections of Real GDP growth (Annual percent change).

Table 4. Forecasted Annual Growth Rates Annually Compounded of GDPs (constant 2010 US$) between 2019 and 2050 and Forecasted Annual Growth Rates Aannually Compounded between 2019 and 2024 Benchmarked to IMF Projections

	UAE	**Bahrain**	**Saudi Arabia**	**Oman**	**Qatar**	**Kuwait**	**Iraq**	**Iran**
2019-2050 Spectral analysis projections	2.05%	1.77%	1.37%	1.73%	1.71%	-0.04%	2.37%	2.19%
Ranking (spectral analysis)	3	4	7	5	6	8	1	2
2019-2024 Spectral analysis projections	3.17%	2.00%	0.35%	1.91%	0.22%	-3.74%	3.79%	4.12%
Ranking (spectral analysis)	3	4	6	5	7	8	2	1
(2019-2024) IMF projections*	2.92%	2.42%	2.15%	2.40%	2.85%	2.73%	3.17%	-0.30%
Ranking (IMF)	2	5	7	6	3	4	1	8

Source: IMF projections.

From Table 4, 2019-2050 spectral analysis projections rank Iraq first with an annual growth rate annually compounded of +2.37% and Iran second with +2.19%. The two laggers for the 2019-2050 period are Saudi Arabia (+1.37%) and Kuwait (-0.04%).

2019-2024 spectral analysis projections rank Iran first with an annual growth rate annually compounded of +4.12% and Iraq second with +3.79% when IMF projections rank Iraq first (+3.17%) and United Arab Emirates (+2.92%). The two laggers with spectral analysis between 2019 and 2024 are Qatar (+0.22%) and Kuwait (-3.74%) when the two laggers with IMF are Saudi Arabia (+2.15%) and Iran (-0.30%). Overall, 2019-2024 spectral analysis and IMF projections for the 8 countries average the forecasts of their average annual growth rates to +1.48% with spectral analysis versus +2.29% with IMF. We bring below additional information by country.

Kuwait

Based on spectral analysis forecasts, Kuwait is the worst performer among the 8 Persian economies over the 2019-2050 period with a negative annual growth rate of -0.04% and a creeping GDP. 'When Kuwait's Finance Minister warned in 2016 that it was time to cut spending and prepare for life after oil (MacDonald, 2020), he was mocked by a population raised on a seemingly endless flow of petrodollars'. In 2020, Kuwait is in an emergency situation having almost exhausted its liquid assets, leaving the country unable to cover a budget deficit expected to reach the equivalent of almost $46 billion in 2020. The sharp decline in energy prices has raised profound questions over how Gulf Arab states are run, Kuwait is an example.

Saudi Arabia

Saudi Arabia is the second worst performer over the 2019-2050 period among the 8 Persian economies with a forecasted annual growth rate of +1.37%. In 2016, the Saudi government unveiled a plan called Saudi Vision 2030 which has triggered structural economic reforms leading to an unprecedented strategy of transition from an oil-driven economy to a modern market economy. Rostan and Rostan (2021) forecasted economic indicators of the Saudi economy up to 2030 (GDP, government budget balance, current account balance in current prices, GDP by institutional sectors and population). Based on their paper, the 2030 economic indicators are all bearish. The authors mentioned that the effects of recent reforms have not yet been traced by historical data that they used to make the forecasts but unfortunately the occurrence of the COVID 19 pandemic should not help witnessing the positive effects of the Saudi Vision 2030 plan in a near future. Based on Figures 7 and 8, ignoring the pandemic effect on the economy, the Saudi GDP is expected to increase steadily until 2050 resulting very likely from the Saudi Vision 2030 plan whose objective is to make the economy less dependent on oil. FocusEconomics (2020a) sees the economy contracting 5.0% in 2020 and growing 3.5% in 2021.

Qatar

With 60% of Qatar GDP coming from the oil and gas sector and 70% of its government revenues coming from the oil and gas sector, compare to the average of its neighbors respectively equal to 38% and 79% (refer to Table 1), the economy of Qatar is highly dependent on the oil and gas sector and very sensitive to their prices. In the 2020 pandemic context of low oil prices, the economy of Qatar has been struggling like its neighbors. Qatar is ranked sixth in terms of forecasted annual growth rate over the 2019-2050 period with a rate of +1.71%; this rank may be explained by the lack of diversification of its economy. Not surprisingly, the Qatari economy should contract severely in 2020 with a 3.2% expected contraction in GDP before growing 3.1% in 2021. The lockdown will hit the tourism sector for the majority of 2020, while low energy prices will weigh heavily on government finances and the external sector (FocusEconomics 2020b).

Oman

Oman has about the size of the economies of Kuwait and Bahrain and ranks fifth in terms of forecasted annual growth rate over the 2019-2050 period with a rate of +1.73%. FocusEconomics projects the economy to shrink 5.0% in 2020, before growing 2.6% in 2021 (FocusEconomics, 2020c). 'Oman has recurrent fiscal and external deficits that should remain under strain due to low oil price. Rigid recurrent spending will keep public debt high, estimated to exceed 70% of GDP in 2020 and beyond. The real GDP growth has decelerated to 0.5% in 2019, down from a recovery of 1.8% in 2018. This was due to a decline in oil production that has been capped by an OPEC production deal. The non-oil economy has been downcast due to the slowdown in industrial activities and services sector' (World Bank, 2020). This outlook from the World Bank makes Oman a fragile economy with recurrent fiscal problems that may explain the sluggish growth forecasted until 2050 with spectral analysis.

Barhain

With +1.77% forecasted annual growth rate over the 2019-2050 period, Bahrain is the fourth top performer among the Persian Gulf economies. In 2020, its debt has been estimated to be equal to 105% of its GDP, even after it received a $10 billion bailout from its neighbors to avoid defaulting on a $750 million Islamic bond repayment in 2018 (Kullab and Qassim, 2020).

UAE

UAE will be the third top performer among the Persian Gulf economies with a forecasted annual growth rate of +2.05% over the 2019-2050 period. According to the IMF's World

Economic Outlook, the UAE's economy will contract 3.5 percent in 2020 amid the pandemic, but is expected to grow 3.3 percent in 2021 (Debusmann, 2020). 30% of U.A.E. GDP comes from the oil and gas sector and 81% of its government revenues come from the oil and gas sector, compare respectively to the average of 38% and 79% of its neighbors (refer to Table 1). Unlike most of its neighbors, the U.A.E. economy has diversified. This is a determinant factor that may help explain why the country should keep strengthening its economy once the pandemic is over.

Iran

With a +2.19% forecasted annual growth rate over the 2019-2050 period, Iran is the second top performer among the Persian Gulf economies. Iran has a large economy, second in size in the Gulf region after the one of Saudi Arabia. Only 10% of Iran GDP comes from the oil and gas sector and 60% of its government revenues come from the oil and gas sector, below the average of its neighbors which are respectively 38% and 79% (refer to Table 1). The fact that Iran has a more diversified economy, less dependent on oil, may explain the positive performance of Iran forecasted with spectral analysis over the 2019-2050 period. From Figure 7, Iran the main competitor of Saudi Arabia in terms of GDP, could overtake Saudi Arabia and become the economic leader of the region based on spectral projections. The political situation in the Persian Gulf region is linked to the performance of its economies. Becoming the economic leader of the region would be obviously bad news for Saudi Arabia who makes its position of economic and political leader of the region a priority. From Table 1, in 2016 Iran outperformed its neighbors (+13.40%) well above the regional average of +5.64%. This performance was the result of the relief of economic sanctions by the international community in January 2016 in exchange for Iran to end uranium enrichment program. The lifting of sanctions on Iran was expected to increase export from the oil sector and therefore government revenues, to increase foreign direct investment in different sectors (industry, oil, tourism, etc.), to make the access to financial services easier and to unfroze tens of billions of assets that would push public and private domestic investment (Stiftung, 2019). The result was immediate making Iran's GDP skyrocketing in 2016. By November 2016, Donald Trump was elected President of the United States. Willing to please Saudi Arabia and Israel, who were witnessing the economic rise of their arch-enemy, Iran, economic sanctions have been reestablished quickly. In May 2018, President Trump announced that the United States would withdraw from the Iran nuclear deal and reenact sanctions against Iran, that made Iran returning to limbo in 2018 (-3.90%, refer to Table 1). However, despite sanctions, Iran has proved to have a resilient economy, well diversified, and open to new trade partners. Defying the United States, China and Iran were near trade and military partnership in July 2020 (Fassihi and Myers, 2020). The rebalancing of the world economy may strengthen the position of Iran in a near future by developing lasting economic relationships with countries such as China and Russia.

Iraq

According to Table 4, spectral analysis projections make Iraq first in terms of forecasted annual growth rate over the 2019-2050 period relying on the momentum that has driven its economy since 1992 after reaching a low illustrated by Figures 7 and 8 (after MPCA). The reconstruction of the post-Saddam Hussein Iraq has been slow but from Table 1, Iraq outperformed its neighbors in 2016. In 2016, Iraq's economy recovered from a low base +0.70% in 2014 and +2.48% in 2015 growing at +13.57 % in 2016 (The World Bank, 2016). It was driven by the ramp-up in oil production, increase in oil-related FDI, structural reforms, implementation of the

IMF program, and a lessening of the incremental impact of the ISIS insurgency going forward. Unfortunately, Iraq was also hit by low oil price the subsequent years with -1.67% in 2017 and 0.63% in 2018, below the regional averages. In its draft 2020 budget (Kullab and Qassim, 2020), Iraq has relied on revenues from oil prices at $56 a barrel to fund badly needed development projects and the bloated public sector, costing nearly $45 billion in compensation and pensions. The Iraqi oil minister said that revenue from crude exports has dropped by 50% in the first quarter of 2020. The Iraq economy is still in a stage of fragile recovery and has been badly hit by the pandemic but the assumption of the authors is that least developed countries will be more resilient to cope with the pandemic than developed countries since they adjust more quickly to ordeals that have hit more often their economy. This assumption may explain the pole position of Iraq in terms of forecasted annual growth rate.

The Gulf Region

Saber-rattling has followed a sharp escalation of tensions in the Persian Gulf region since the announcement of United States' withdrawal from the Iran nuclear deal in 2018. The secretary of state Mike Pompeo made a nine-nation tour of the Middle East in 2019, which was aimed in large part at maintaining Arab solidarity against Iran. In May 2019, Riyadh accused Tehran of ordering drone strikes on two Saudi oil pumping stations, claimed by Yemen's Iran-aligned Houthi group. KSA's Minister of State for Foreign Affairs Adel al-Jubeir reaffirmed that in the event Tehran chooses war, KSA will respond with all force and determination (Rashad and Kalin, 2019). In July 2019, Iran's Revolutionary Guards seized a British oil tanker in the Strait of Hormuz (Kirkpatrick and Specia, 2019) in retaliation of the seizure earlier the same month of an Iranian tanker by the British Royal Marines off the coast of Gibraltar on suspicion it was breaking European sanctions and taking oil to Syria. These combined political maneuvers and wargames have however failed to lift WTI oil price as planned by political leaders. In addition, the COVID-19 pandemic has accelerated the collapse of WTI oil price that was flirting the $40-support line by September 2020, below the long-term historical average of $44 (January 1986 - June 2020). By plunging the world economy into a severe recession in 2020, the COVID-19 virus pandemic had a direct effect on the global demand for oil. Oil price projections with spectral analysis are very pessimistic for the next 30 years. The big losers will obviously be oil producing countries that have not succeeded in diversifying their economy away from the oil industry. The US oil industry that supplies 86% of its domestic demand is also at risk with an oil price far below the breakeven price of $50 required for the extraction of shale oil. The US shale oil industry is heavily indebted and companies will not be able to service the debt with a lower oil price (Singh, 2020). Saber-rattling involving war games in the Persian Gulf region, led by US and its allies, is therefore expected to be repeated in a near future to boost oil price.

Conclusion

The purpose of this paper is to forecast with spectral analysis the GDPs (constant 2010 US$) of the 8 Persian Gulf economies (United Arab Emirates, Bahrain, KSA, Oman, Qatar, Kuwait, Iraq and Iran) until 2050. The projections of the economies are ranked using the forecasted annual growth rates annually compounded of GDPs (constant 2010 US$) between 2019 and 2050: 1- Iraq (+2.37%) is first then 2- Iran (+2.19%); 3-UAE (+2.05%); 4-Bahrain (+1.77%); 5-Oman (+1.73%); 6-Qatar (+1.71%); 7-Saudi Arabia (+1.37%); 8- Kuwait (-0.04%).

Spectral analysis has stirred interest for its ability to analyze changing transient physical signals. Extending the analysis to complex-behavior economic signals, the originality of this paper is to apply spectral analysis to economic variables subject to common dynamics such as

GDP time series of countries pertaining to the same economic area, in this paper the Persian Gulf region. The forecasts cover 32 years from 2019 to 2050 and derivate from historical annual data extending from 1960 to 2018 (59 observed data for the longest time series, Iran, 19 data for the shortest, Qatar).

Spectral analysis methodology follows five steps that lead to GDPs (constant 2010 US$) forecasts: first, the observed GDP time series are transformed into stationary series which are denoised and compressed. Second, the series are decomposed in simpler signals called approximations and details in the framework of the one-dimensional discrete wavelet analysis. Third, the decomposed series are extended with the Burg (1975) model which fits a p^{th} order autoregressive (AR) model to the input signal by minimizing (least squares) the forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion. Fourth, the series are reconstructed and retransformed into non-stationary time series. The final step is to apply Multiscale Principal Component Analysis (MPCA) to the eight GDPs and oil price time series to integrate to the forecasts the co-dynamics of oil price and of the 8 oil-driven Persian Gulf Economies. Spectral analysis forecasts are bullish for 7 Gulf Economies and bearish for Kuwait (-0.04%). More specifically, 2050 spectral analysis projections rank Iraq first with an annual growth rate annually compounded of +2.37% and Iran second with +2.19%. The two laggers among the 2050 spectral analysis projections are Saudi Arabia (+1.37%) and Kuwait (-0.04%).

2024 spectral analysis projections rank Iran first with an annual growth rate annually compounded of +4.12% and Iraq second with +3.79% when IMF projections rank Iraq first (+3.17%) and United Arab Emirates (+2.92%). The two laggers among the 2024 spectral analysis projections are Qatar (0.22%) and Kuwait (-3.74%) when the two laggers among the 2024 IMF projections are Saudi Arabia (+2.15%) and Iran (-0.30%). Overall, 2019-2024 spectral analysis and IMF projections for the 8 countries average the forecasts of their average annual growth rates to +1.48% with spectral analysis versus +2.29% with IMF.

Finally, the COVID-19 pandemic has brutally hurt Persian Gulf Economies in 2020 following a collapse in the global demand for oil and an oversupplied industry. The individual impact on these economies will depend on the response brought by their respective governments.

Government policymakers, economists and investors should have with spectral analysis forecasts of Persian Gulf Economies a better insight, understanding and outlook of these economies.

Compliance With Ethical Standards

The authors declare that they have no conflict of interest and that their research paper does not involve Human Participants and/or Animals.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

Data derived from public domain resources. The data that support the findings of this study are available on the World Bank national accounts data and OECD National Accounts data files, which retrieved from
https://data.worldbank.org/indicator/ny.gdp.mktp.kd and on the IMF website: https://www.imf.org/external/datamapper/NGDP_RPCH@WEO/OEMDC/ADVEC/WEOWORLD

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