The Role of Oil Prices in Forecasting Economic Growth in Oil Exporting Countries: Evidence from the Kingdom of Saudi Arabia and the United Arab Emirates

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Contents

Abstract

This paper aims at forecasting economic growth for the Kingdom of Saudi Arabia (KSA) and the United Arab Emirates (UAE), where the GDP of the two countries, together, made about 43 percent of the GDP of the Arab countries, over the last five years (2015-2019). For this, we use a vector error correction model, augmented by two to three exogenous variables (VECM-X). The first is oil price changes that capture the foreign shocks most affecting the economies of Saudi Arabia and the UAE, the second is government expenditure, as an external fiscal policy variable that represents the fiscal policy stance in these countries. The third exogenous variable, the primary fiscal balance as percent of GDP, is also added, instead of the second variable or jointly with it, to consider the expenditure and revenue side. The results showed that the two models provide good quality forecasts for both countries, particularly for GDP growth, according to a set of statistical tests assessing the accuracy of the forecasts.

The study used VECM-X models to predict economic growth over the period 2021-2023, based on the assumptions expecting exogenous variables, during the period 2021-2023, issued by some international institutions for oil price forecasts, as well as based on budget forecasts ,from national or international sources, for government expenditures and the primary fiscal balance. Three assumptions were tested for oil price expectations, and two cases of restrictive and expansionary fiscal policy of about 2.5 per cent per year of government expenditures growth. To check the robustness of the results, two models were examined. The first includes all variables without restrictions (short term and long term), while the second model restricts the impact of the inflation rate and/or the current account balance to the short term only.

On average, according to the Saudi Arabia model, an economic growth rate of about 2 percent is expected in 2021, 5.5 percent in 2022, and 4.4 percent in 2023. Similarly, the model predicted for the United Arab Emirates that the growth rate of GDP is about 2.3 percent in 2021, about 4 percent in 2022, and 4.1 percent in 2023. In general, our forecasts are, to some extent, in line with those produced by other national and international organizations.

Nevertheless, these expected performances could be challenged by uncertainty especially with the emergence of new mutations of the Covid-19 virus such as the current "Omicron" variant, adding more doubts about oil prices expectations, which is likely to reduce the pace of economic growth. In addition, these models cannot, in any case, replace the structural macroeconomic models and the general equilibrium models that describe all interconnections and sectoral relationships as well as the behavior of all the economic variables. Therefore, their results should be considered with caution and used as a valuable and helpful tool in economic forecasts.

Key Words: Current Account Balance, Economic growth, Exogenous shocks, Quality of Prediction, Error Correction Model, Theil Criterion.

ملخص:

تهدف هذه الورقة إلى توقع النمو الاقتصادي للمملكة العربية السعودية والإمارات العربية المتحدة، حيث يشكل إجمالي الناتج المحلي للدولتين معاً حوالي 43 في المائة من إجمالي الناتج المحلي الإجمالي للدول العربية، على مدى السنوات الخمس الأخيرة (2015-2019). تم استخدام نموذج تصحيح الخطأ المتجه، مدعوماً بمتغيرين خارجيين (VECM-X)، يتمثل الأول في تغيرات أسعار النفط التي تلتقط الصدمات الخارجية الأكثر تأثيراً على اقتصاد المملكة العربية السعودية والإمارات العربية المتحدة، والثاني يتعلق بالاستهلاك الحكومي و/أو رصيد ميزان المالية العامة الأولي كمتغير خارجي يعكس السياسة المالية في هاتين الدولتين. أظهرت النتائج أن النموذجين يقدمان تنبؤات ذات نوعية جيدة لكلا الدولتين، لا سيما لنمو الناتج المحلي الإجمالي، وفقًا للاختبارات الإحصائية التي تقيم دقة التوقعات.

استخدمت الدراسة نماذج (VECM-X) للتنبؤ بالنمو الاقتصادي خلال الفترة 2021-2023، بناءً على فرضيات توقع المتغيرات الخارجية، خلال الفترة 2021-2023، الصادرة عن بعض المؤسسات الدولية فيما يتعلق بتوقعات أسعار النفط، وكذلك على أساس توقعات الميزانية من مصادر وطنية أو دولية، بالنسبة للنفقات الحكومية ورصيد المالية العامة الأولي. تم اختبار ثلاث فرضيات لتوقعات أسعار النفط، وحالتين من السياسة المالية التقييدية والتوسعية بنحو 2.5 في المائة سنوياً لنمو النفقات الحكومية. للتحقق من متانة النتائج، تم اختبار نموذجين. الأول يشمل جميع المتغيرات دون قيود، والثاني تقتصر فيه القيود على وجود تأثير لمعدل التضخم و/أو رصيد الحساب الجاري على المدى القصير فقط.

في المتوسط ، ووفقَ نموذج المملكة العربية السعودية، من المتوقع تحقيق معدل نمو اقتصادي بحوالي 2 في المائة في عام 2021 و5.5 في المائة في عام2022 و4.4 في المائة في 2023. بالمثل، توقع النموذج بالنسبة لدولة الإمارات العربية المتحدة أن يبلغ معدل نمو الناتج المحلي الإجمالي حوالي 2.3 في المائة في عام 2021، وحوالي 4 في المائة في 2022، و4.1 في المائة في عام 2023. بشكل عام، تتماشى توقعاتنا، إلى حدٍ ما، مع تلك التي تنتجها المنظمات الوطنية والدولية الأخرى.

بالرغم من ذلك، تبقى هذه النتائج رهينة تحديات عدم اليقين خاصةً مع ظهور طفرات جديدة لفيروس كوفيد -19 مثل متغير "أوميكرون" الحالي، مما يضيف المزيد من الشكوك حول توقعات أسعار النفط، والتي يُرجح أن تحد من وتيرة النمو الاقتصادي. إضافةً إلى ذلك، لا يمكن لهذه النماذج أن تعوض بأي حال من الأحوال، النماذج الهيكلية ونماذج التوازن الكلية التي تصف كل العلاقات التشابكية بين جميع القطاعات، وسلوك كل المتغيرات الاقتصادية. لذا، يلزم أخذ نتائجها بحذر واستخدامها كأداة قيمة ومساعدة في التوقعات الاقتصادية.

الكلمات الدالة: ميزان الحساب الجاري، النمو الاقتصادي، الصدمات الخارجية، جودة التنبؤ، نموذج تصحيح الخطأ، معيار "Theil".

1. Introduction

To produce economic forecasts, economists use a handful of methods. In the first case, some prefer setting economic theory-based models that describe well the evolving behaviours of economic agents and their interactions in the formalized economy (example: macroeconomic structural models). Second, some could appeal to statistical models (time series models) benefitting from their ability to project the future using solely the history of the time series based on the properties of the Data Generating Process (DGP). Third, in certain cases, others may rely on the experts' good knowledge allowing to draw information from an implicit diagram, they have in mind, for the studied economy (called experts-judgment). An average mix of different previous sources of forecasts (called consensus forecast) is also used to enhance the accuracy of forecast, particularly when the issued forecast from some methods (models) is likely to be underestimated while oppositely, in other methods, is overestimated.

Regardless of their ineluctable utility, models are subject to some criticism. For example, structural macroeconomic models are pointed by some economists to offer too much maneuver to theoretical expectations. This rigorous theoretical exigency along with its complications and reliability to be applied leads the opponents of this type of models preferring the usage of time series models, particularly the Vector Autoregressive (VAR) models where theoretical requirements and economic expectations are less embodied. Thus, VAR models appeared in the early 80s as an alternative following the criticism of the methodology underlying the construction and the use of structural models (Sims, 1980) and following the famous Lucas's critic to structural models (Lucas, 1976). At the same time, the development of the econometric times series analysis and regressions, such as cointegration concepts and error correction models, as well as the advancement of econometric software led to the enhancement of the VAR usage integrating such evolving technics (example: VECM).

Despite their utility in forecasting, VAR models have also their drawbacks in that they cannot describe the whole economy as the degrees of freedom (the data range freely available for their estimation) decrease with the number of parameters and variables in the VAR. Therefore, a part the aforementioned differences, the tradeoff between the use of one type over the other is dictated by the cost of time, data, and human resources for structural models over an incomplete description of the whole economy for the VAR specifications. Therefore, VAR models can be useful once we target a small number of equations to study limited relationships between a handful of variables.

The next section presents the literature review. The third section describes a VECM approach enriched by purely exogenous variables as well as a set of statistical criteria for the evaluation of the prediction accuracy. The fourth section displays data and some preliminary analysis particularly the oil prices developments. The fifth one shows results and the sixth concludes.

2. Literature review

2.1. From structural Keynesian models to VAR and VECM models

Historically, structural macro econometric modeling flourished since the late 1950s to the early 1970s under a research program developed in the early 1940s within the Cowles Commission for which simultaneous equation models constitute the core. The first generation of the structural models adopts a Keynesian theoretical framework as reference centered around the IS-LM model of Modigliani (1944). The first published operational models in the literature are developed by Klein (1955) and Klein and Goldberger (1955) based on the business cycle theory analysis of Jan Tinbergen at the end of 1930s period. Since these models, concerns about the empirical validation of the theoretical model and the disaggregation of its equations have been much emphasized in the Cowles Commission discussions, leading to adjustments in the original theoretical equations. Most of these concerns were raised in the debate between monetarists and Keynesians in the 1960s and 1970s periods and was related to linkages already embodied in the IS-LM model. The existence of large gaps between the estimated relationships and the theoretical model favoured the new synthesis models which seeks to restrain the importance of the theoretical gap between Keynesians and Monetarists shifting the debate to the empirical ground. Sims (1980) criticizes the structural models of the Cowles Commission for having too many theoretical assumptions that have not been empirically tested, thus, suggesting exposing the hypotheses of exogeneity to direct and accurate econometric tests. Moreover, the development of the Error Correction Models and cointegrated VAR has made it possible to renew the analysis.[1]

In practice, the advantages of a type over the other depend on the constraints related to the availability of information as well as the ability to capture agents' economic behaviors. The advantage of VAR models, for example, is that their estimate is flexible and less demanding in information and time easily allowing the integration of new data. But the VAR models have also their drawbacks: The most important one is that standard VAR models are assimilated to "black boxes" because they lack description and economic explanation of the linkages between variables as they do not refer to any economic theory framework. These weaknesses make such models an additional tool of forecasting and cannot totally substitute the structural models. Structural models require the development of an economic theory and an accounting framework. This allows explaining linkages between variables thus providing forecasts accompanied by economic explanations. Their difficulties are related to the significant efforts of their designs and updates.

Besides, some studies confirmed the utility of the VARs and their derivatives in terms of forecasting (Sargent, 1979; 1984; Learner, 1985; Litterman, 1982; 1984; Bentour, 2015). Moreover, Bentour (2013, 2015) constructed a set of VAR models to forecast the GDP for the

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[1] Along with the problem of identification, the Lucas (1976) critics constitutes the second fundamental critic faced by structural models.

Moroccan economy, from which, a cointegrated VAR model enriched by two exogenous variables representing the shocks of oil prices on the current account balance[2] and the rainfall metrics as purely exogenous variable representing periods of droughts which negatively affect the Moroccan agricultural supply side (Bentour, 2013).

Regardless of the weaknesses that could surround all these types of models, they remain vital in economic decision, especially in an evolving world relying on systems that are increasingly complicated. Therefore, their output in terms of economic forecasting, despite induced errors and uncertainties, remains very useful to policymakers.

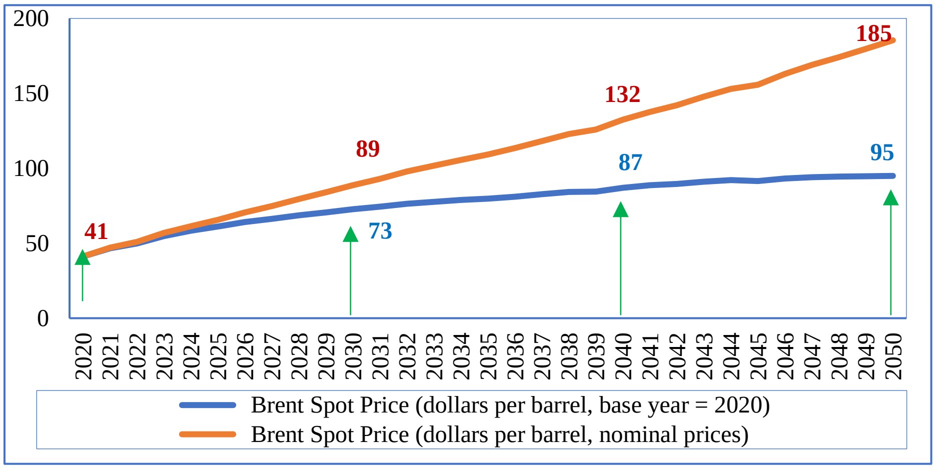
2.2. Oil prices developments and GDP forecasting

Oil is the most important international commodity for which the price, determined and exchanged in Dollar, is determined following a variety of factors of demand and supply as well as geopolitical factors leading to oil prices behaving with high volatilities and fluctuations, particularly in recent years. Bentour (2021) listed four types of factors behind the oil prices: "*First, supply production surges/disruptions driven by refining capacities expansion, OPEC or major oil producing decisions, climate disasters, as well as the rhythm of oil exploration. Second, demand factors driven by world GDP as well as population growth rates. Third, international macroeconomic environment through the exchange rates system and interest rates. Fourth, speculations due to uncertainty factors and future contracts in the oil markets. Bentour, 2021; page 6*".

Besides, the multiplicity of these factors increase uncertainty, rending the outlook of oil prices very complicated to forecast in the short and long run as well. For example, figure (1) presents a long run projection of oil prices from the Energy Information Administration (EIA) which show a relatively smooth linear trend of nominal oil prices, and a relatively logarithmic apparent trend of deflated oil prices over 2020-2050.

[2] Before the subsidy reform of energy prices that started in 2013, the current account balance was highly impacted by oil prices fluctuations as Morocco imports all its energy needs.

Figure 1. Oil Brent spot prices projections over long term period: 2020-2050



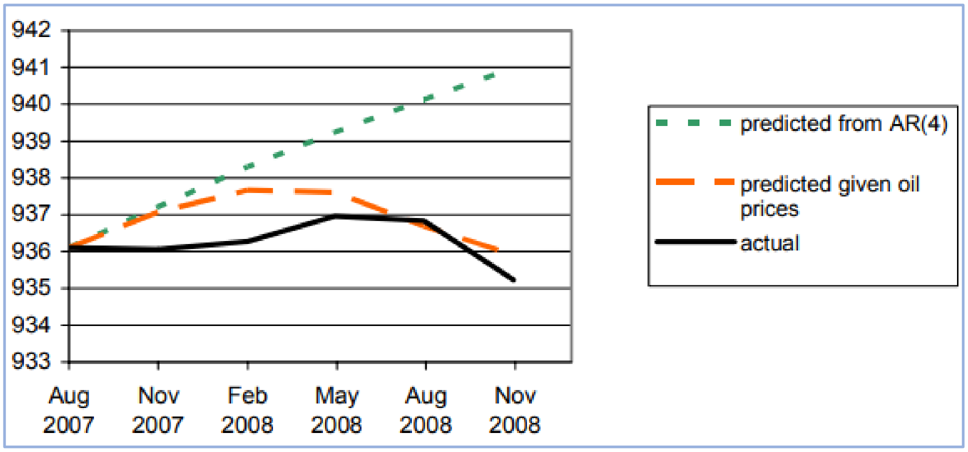
Source: Constructed from data of the United States Energy Information Administration (https://www.eia.gov/outlooks/aeo/), Annual Energy Outlook, 2021.

There is an abundant literature assessing the impact of oil prices variations and volatility on the economic activity, in developed and developing countries as well, whether oil-importing or oil-exporting countries.[3] A large part of this literature uses times series models, particularly VAR models and their derivatives (Bayesian VAR, BVAR; Structural VAR, SVAR; Vector Error Correction Models, VECM; etc.), taking particularly the advantage of the impulse responses functions and variance decomposition allowed by this type of modelling approach. In this regard, Bentour (2020) assessed the oil price variations on the fiscal policy outcomes showing fiscal multipliers sensitivity to oil price swings, for 18 Arab countries. similarly, Bentour (2021) showed the effect of oil prices on the real economic sectors for 9 oil exporting countries.

However, in forecasting, very few studies were interested in taking the advantage of the oil price influence on the economic activities to predict its main economic aggregates such as GDP growth. This is the case for some well-known papers trying to forecast the United States GDP from oil prices effects as in Hamilton (2009). The later, based on an earlier model he developed (Hamilton, 2003), showed how oil prices drops in 2008 economic recession helped predict well the United States Quarterly GDP, compared to a univariate time series model (autoregressive, AR (4)) as illustrated in figure (2).

[3] Examples of research on the effects of oil prices on economic growth are: Tatum (1987), Kilian (2009), Peersman and Van Robays (2012), Baumeister and Peersman (2013), Cashin and others (2014), and Van de Ven and Fouquet 2017). On inflation and consumption patterns: Gelos and Ustyugova (2012) and Bentour (2016). On the financial markets returns: Kang and others (2014) and Salisu and Gupta (2021). On international commodities' prices: Demirer and others (2020). On the exchange rate: Arezki and Blanchard (2015). On companies' profitability and productivity: Hesse and Poghosyan (2009).

Figure 2. United States quarterly GDP forecast in 2008 economic crisis, with and without oil price.



Source: Hamilton (2009).

As formerly mentioned, some researchers studied the possibility of oil prices volatility to forecast the economic growth in some advanced countries. However, despite evolving literature on the impact of oil prices on the economic activity in the Arab countries, to our best knowledge, no study has undertaken the opportunity to forecast the economic growth, based particularly on the oil price exogenous fluctuations, in the Arab region. This paper fills the gap in the literature for this region, particularly for oil exporting countries, and is of high relevancy given the importance of the oil sector in these economies and economic growth vulnerabilities to oil prices shocks.

The Kingdom of Saudi Arabia and the United Arab Emirates control important oil reserves. According to the Organization of the Petroleum Exporting Countries (OPEC) statistical bulletin released in 2021, the two countries have about 30 percent of the total OPEC's reserves and about 24 percent of the World Proven reserves. In 2020, OPEC reported about 262 billion barrels of proven reserves for KSA and 107 billion barrels for the UAE, making a share of the total OPEC proven reserves of respectively, 21 percent and 9 percent for KSA and UAE (OPEC, 2021).

In terms of GDP, the two countries make together around 43 percent of the total Arab countries' GDP.[4] The Oil sector is the main driver of these economies that have helped the two countries to grow faster and reach very high human development levels as well as modernizing the non-oil sectors activities. Besides, the dependency to oil sector makes these economies also vulnerable to the oil prices volatility. The GDP in level, as well as its growth rate, is highly correlated with oil prices in levels and their growth rate respectively, particularly in the period of 2001-2010 and 2011-2020 (Table 1). This fact is also emphasized by figure (3) which shows that economic growth in both countries, are more correlated and behave approximately in the same direction in recent periods than previously. Although, correlation does not mean causation, this leads to presumably

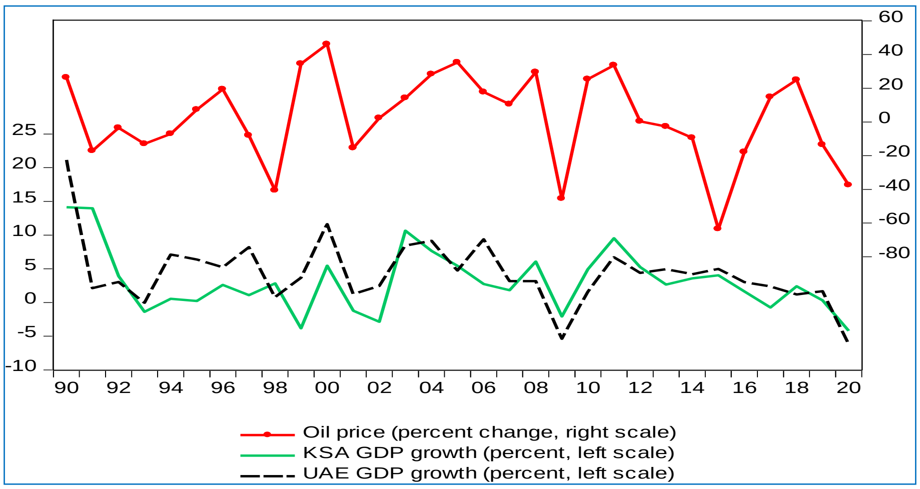
[4] Source: Calculated share from AMF database over the period 2015-2019.

conclude that the two countries are likely sharing similar important foreign shocks, particularly the oil price shocks.

Table 1. KSA and UAE GDP and economic growth correlations with oil prices

	1980-1990		1991-2000		2001-2010		2011-2020		1980-2020	
Correlation between:	KSA	UAE	KSA	UAE	KSA	UAE	KSA	UAE	KSA	UAE
Oil prices and GDP in levels	60%	81%	33%	38%	93%	95%	-86%	-87%	72%	74%
Oil prices and GDP in growth rate	18%	67%	-19%	61%	71%	67%	46%	32%	20%	59%

Figure 3. Oil prices and GDP growth in the KSA and UAE evolution over 1990-2020



3. VAR and VECM methodology with purely exogenous variables

3.1. Definition and specification of a VAR model

The autoregressive vector is commonly used to make predictions of interrelated time series systems and to analyze the dynamic impact of random disturbances on the system of variables. VAR models are proposed as an option to simultaneous and structural equation models. The latter has been subject to much criticism from Granger (1969), Lucas (1976) and Sims (1980). Empirically, the main criticisms formulated against these structural models concern the simultaneity of relations and the notion of exogenous variable. When we are dealing with a linear multiple equations model, it often happens that an endogenous variable of one equation appears as an explanatory variable of another equation. This double status of certain variables results in a bias in the estimates of the coefficients when we use the ordinary least squares method, equation by equation. The VAR representation, a generalization of univariate autoregressive (AR) models, provides a statistical answer to the exogeneity issue. In this representation, all the endogenous

VAR elements are explained by their lags which are considered exogenous, thus, avoiding the above-mentioned problem of simultaneity. VAR methodology allows to model each endogenous variable in the system as a function of the lagged values of all the endogenous variables in the system. A VAR with p lags[5] can be specified as: $Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \zeta t$

Where, Y_t is the vector of endogenous variables, $A_1, \ldots, A_p$ are matrices of the associated coefficients to be estimated and ζt is a vector of innovations. The terms of the vector ζt can be correlated with each other for current values (time t) but are uncorrelated to their past values and are uncorrelated to all the other variables of the right-hand side of the VAR equation system. The VAR models could also be built to include purely exogenous variables other than the usually lagged elements of the exogenous variables. This is simply done by adding such exogenous variables and could be specified as: $Yt = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + BX_t + \zeta_t$. Where, X_t is the vector of exogenous variables, and B is the matrix of the coefficients associated with the purely exogenous variables. Since only lagged values of endogenous variables appear on the right side of each equation, there is no simultaneity problem and OLS is a suitable estimation technique.

3.2. Definition and specification of a VEC model (VECM)

A Vector Error Correction Model (VECM) is a VAR model that includes cointegrating relationships. Thus, a VECM is designed from non-stationary series which validate the cointegration conditions. The VEC specification restricts the long-term behavior of endogenous variables to converge towards their cointegrating relationships while allowing short-term dynamics. Cointegration captures the idea that two or more series evolve together over time and generate a long-term equilibrium. In the short term, such variables can evolve in different directions. But if they continue to evolve away from each other, in the long run, economic forces such as a market mechanism or public intervention, will begin to pull them back to be closer to each other. For example, consumption and income are more likely cointegrated. Otherwise, it would mean that in the long run consumption would move above or below income, so that consumers would spend irrationally.

According to Engle and Granger (1987), a linear combination of two or more variables can be stationary ($I(0)$). If such a stationary combination exists, then the non-stationary variables ($I(1)$) are said to be cointegrated. The stationary linear combination is called the cointegration equation and can be interpreted as a long-term relationship between the variables. Cointegration could exist also at a higher order of integration d>1. In this case, two series are said to be cointegrated at order d, noted $CI(d)$, if they are first: nonstationary at order d, noted $I(d)$ and, second, if it exists a linear combination of the two series that is integrated at an inferior order $d-1$ ($I(d-1)$).

[5] A set of statistical criteria are used to determine the order of the VAR (the number of lags p), particularly, Akaike Information Criterion (AIC) and Schwartz Criterion (SC).

The concept of cointegration was developed as a solution to “Spurious regressions”.[6] In this regard, regressions between cointegrated series are better written in the form of an error correction model which encompasses long run trend equilibrium while keeping short run dynamics. For the purpose of illustration, we simplify by considering a VAR with two variables with one cointegrating equation. The cointegrated relationship (called also long-term relationship) is simply given by: $Y_t = \lambda X_t$, and the error correction vector model is written as:

$$\begin{cases} \Delta X_t = \lambda_1 (Y_{t-1} - \lambda X_{t-1}) + \sum_{i=1}^{p} \alpha_{Y,i} \Delta Y_{t-i} + \sum_{i=1}^{p} \beta_{X,i} \Delta X_{t-i} + \varepsilon_{1,t} \\ \Delta Y_t = \lambda_2 (Y_{t-1} - \lambda X_{t-1}) + \sum_{i=1}^{p} \alpha_{X,i} \Delta X_{t-i} + \sum_{i=1}^{p} \beta_{Y,i} \Delta Y_{t-i} + \varepsilon_{2,t} \end{cases}$$

With, $(\varepsilon_{1,t}, \varepsilon_{2,t})' = \epsilon_t$ is the associated vector of innovations. The two first terms on the right-hand side of the equations are the error correction terms corresponding to two VECM components in this example. The summation terms are representing short dynamics associated with lagged terms to the degree p. The coefficients λ_1 and λ_2, which must be negative for a cointegrated vector of variables, measure the speed of adjustment or convergence to the equilibrium. Thus, each coefficient acts as a restoring force to bring the relationship between the two variables (the explanatory and the explained) to its equilibrium.

In case the endogenous variables of a VAR are not necessarily all cointegrated, restrictions on long run relationships could be imposed, in formulating a VECM. For example, considering income, consumption, and inflation, showing that only income and consumption are cointegrated, while inflation has no long run relationship with the two other variables, restrictions in the inflation equation in the VECM could then be imposed to consider this issue. Restrictions could also be dictated by assumptions from economic theory.

3.3. Hybrid VECM-X models to forecast economic growth: Variables’ Selection

We construct for each country, a vector error correction model including four endogenous variables and two purely exogenous variables. Endogenous variables are, Real Gross Domestic Product (GDP), the private consumption, the current account balance as percent of GDP and the inflation. Endogenous variables are selected to reflect some behaviors grounded in the economic theory particularly between income and household consumption. Therefore, two endogenous variables that are GDP and Household consumption are chosen to be cointegrated to take account

[6] Since early developments in econometrics, researchers start to realize that correlations and regressions between time series should be cautionary considered, avoiding what Engle and Newbold (1974) called as “Spurious Regressions”. These regressions are characterized by R^2 tending to 1 and Durbin Watson (DW) values near 0, which distorts the use of "Student" tests as indicators of statistical inference.

of the long run equilibrium and short run dynamics as previously explained. Moreover, inflation is introduced as this one is more likely impacting the household consumption patterns by eroding their purchasing power. The choice of the current account balance as the fourth endogenous variable is to link it particularly to the important foreign shocks playing the role of direct passthrough form which these shocks affect GDP. Such important foreign shocks are most likely coming from the oil price fluctuations which is the first exogenous variable considered to capture important shocks that highly affect oil exporting countries such as Saudi Arabia and the UAE. The exogenous character of this variable is driven by international determinant factors as explained in section (2.2). The second is government expenditure, as an exogenous fiscal policy variable representing the fiscal policy stance in these countries.[7] We also tested the fiscal primary fiscal balance as exogenous variable which improved the performance of the UAE model. Fiscal variables (particularly expenditures) are also considered exogenous in the literature of the macroeconomic modelling as they are generally determined in the budget law of each country.

3.4. Measuring the quality of prediction

To compare the forecasts issued for future values of an economic variable, economists as well as policymakers may often produce or have access to different forecasts, either from models they have created themselves or from forecasts got from external sources. Once confronted with competing forecasts from different models and/or sources, it may be hard to choose the accurate "best" forecast in terms of accuracy and precision. Thus, for the purpose of assessing the quality of the prediction, economists developed a set of statistical criteria. Evaluation of the quality of a forecast requires comparing the forecast values to actual values of the forecasted variables over a defined period.

In forecasting, the conventional paradigm for a best model is the one that can well reproduce the historical observations of data. Accordingly, a set of statistical criteria are developed to choose the best model in terms of forecasting, centered around the forecast errors. The approach is to rank models over a period, according to the rule that the best model is the one on which such criteria are minimized. The rank is done over a period of forecasts, precisely over the horizon of in-sample forecasting, which may be extended to the whole sample of data. Among statistical measures, Theil's formula is the best proposed criterion in the literature of forecasting evaluation overcoming the shortcoming of other proposed measures.

Defining for an endogenously determined variable y, the forecast error $f_{i,t}^{e}$, as the difference between the predicted (simulated) value $\hat{y}_{i,t}$ by a model "i" at time "t" and the observed value y_t (hence; $f_{i,t}^{e} = y_t - \hat{y}_{i,t}$), statistical criteria are calculated to compare models based on the average of forecast errors over the whole common history of simulated and observed data, or on a limited given period of forecasting. Precisely, for a given variable, criteria measure how distant is each

[7] A set of econometric tests on the variables' observed data has been undertaken to complete the characteristics of the VEC models for the studied countries for which results are displayed in the data section (section 4)

model's forecast from the actual observations. Assuming a horizon of forecasting time h, the time points of forecasting an endogenous variable in time t is in the sample interval $[T+1, T+h]$ $(t \in \{T+1, T+2, \dots, T+h\})$. Table (1) reported a set of forecast evaluation criteria based on the mean forecast errors and their properties over this horizon of time.[8]

Furthermore, another test developed by Diebold and Mariano (1995) and emphasized in Diebold (2015), uses almost similar approach, based on the forecasting errors series (whether squared or in absolute values) to compare whether two rival forecasts have the same accuracy.[9] Besides, other economic methods (although not very popularized compared to the statistical criteria) may provide a comparison, especially based on the content of economic information by the produced forecast. The economic criteria are indeed necessary especially when two forecasted values could not be separated by statistical criteria. Examples of such methods are Fair and Shiller (1989)[10], as well as a combination of tests of Chong and Hendry (1986) and Timmermann (2006), that assesses whether combined individual forecasts can perform better than the individual forecasts themselves.

The concept of all these methods is, whether an individual forecast encompasses all information contained in the other individual forecasts, this forecast will be just as good as a consensus of all the forecasts. These tests are fundamentally based on hypothesis testing on coefficients, between the single forecast error over the horizon of forecasts $t+h$ from the source or model i ($f^{e}_{i,t+h}$) as previously defined, explained by the other sources or models of forecasts j, in the following regression model: $f^{e}_{i,t+h} = \beta_0 + \sum_{j \neq i}^{N} \beta_j y_{j,t+h}$. The null hypothesis is: $H_0: \beta_j = 0;\ \forall\ (j \neq i)$, in which case, rejection signify that it exists at least one model j (different from i) for which forecasts contribute to explaining the i model's forecasts. This means that the i model should be introduced in the combination or consensus forecasts.

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[8] Such properties are relatively detailed and summarized in Bentour (2015).

[9] Whereas Diebold and Mariano (1995) run several n-step tests, EViews delivers just the one-step version.

[10] Refer to Bentour (2015) for a detailed description and application of this method.

Table 1. Statistical criteria formulae for forecast evaluation

Label	Specification Formula	Some properties
Mean of the Errors (ME)	$ME = \sum_{t=T+1}^{T+h} f_{i,t}^{e}/h$	Used as starting point but is useless in selecting the best model, as negative errors could be cancelled by positive ones.
Mean of the Absolute Errors (MAE/MAPE)	$MAE = \sum_{t=T+1}^{T+h} \lvert f_{i,t}^{e}\rvert/h$ or in percentage: MAPE=MAE*100	The mean of the absolute errors handles the previous mean of the errors disadvantage. This is also expressed in percentage in some software (EViews for example) thus named as MAPE
The Root of the Mean of Squared Errors (RMSE)	$RMSE = \sqrt{\sum_{t=T+1}^{T+h}\left(f_{i,t}^{e}\right)^{2}/h}$	The penalty associated with the forecast error increases squarely and significant errors are penalized more than smaller ones. RMSE can be inefficient when the measuring unit of data is different.
Theil Coefficients (U1 and U2)	$U1 = \frac{\sqrt{\sum_{t=T+1}^{T+h}\left(f_{i,t}^{e}\right)^{2}/h}}{\sqrt{\sum_{t=T+1}^{T+h} y_t^2/h}+\sqrt{\sum_{t=T+1}^{T+h} \hat{y}_{i,t}^2/h}}$ $U2 = \frac{\sqrt{\sum_{t=T+1}^{T+h}\left(f_{i,t}^{e}\right)^{2}/h}}{\sqrt{\sum_{t=T+1}^{T+h} y_t^2/h}}$	Theil formulae, U1, is the previous measure, RMSE, scaled either by the sum of the squared root of the average squared of actual and predicted values over the horizon of forecasting.[11] The more Theil value is approaching zero, the more the model is accurate in forecasting. Another formula is the RMSE scaled by the root of the mean squared observation. Note that U1 ranges between 0 and 1 while U2 is bounded by 0 and unbounded for upper values.

4. Data sources, descriptive statistics, and econometric tests results

Many sources are examined for data of real variables (in constant prices), either for the observed data or the outlook of the exogenous variables, particularly that constant prices data are missing or very short in published national sources for the variables of government and household consumptions. For the two countries (KSA and UAE), data for variables in constant prices (in real terms) and in national currencies are mainly obtained for World Development Indicators (WDI)

[11] Another formula of Theil criterion is to compare the RMSE to the one issued from a "naïve model", which assumes adaptative expectations: that is, a model assuming the forecast of a variable to be only its previous actual value (see, Bentour, 2015 for more details).

of the World Bank database, and the IMF World Economic Outlook (WEO) database. Data from these sources are obtained for the four endogenous variables that are Gross domestic products in constant prices, final household consumption in constant prices, current account balance as percent of GDP and inflation. The government expenditures in real terms are also obtained from the WDI source and the IMF source, while the fiscal primary balance as percent of GDP is from IMF.

The data, in constant prices, for the general government expenditures as well as the household final consumption have data starting only in 2000 for the KSA and 2001 for the UAE. For more degrees of freedom for the models, data on real terms are available for these real variables going back to 1970 until 2019, from the UNCTAD source, but in United States Dollar. Therefore, we also browsed these data as a check and validation in addition to used it for the missing range after converting it to national currencies and comparing trends over the common available periods.

Other sources are also used particularly for the outlook of the exogenous variables such as the budget law statement for 2022 and 2023 (for the KSA)[12] for the government expenditures, as well as IMF outlook for primary fiscal balance. For the oil prices, data are obtained from the Energy Information Administration, which displays average annual crude oil prices in United States Dollars per barrel, in nominal and constant prices as well.[13] We present in the Appendix figures for the set of endogenous variables and exogenous variables, as well as their descriptive statistics (Table A1).

To choose the appropriate specification of the VECM model, we run for all the considered variables of each country and the oil price variable, a variety of econometric tests related to time series stationarity, lag determination tests, and cointegration tests. For stationary tests, we use Augmented Dickey Fuller tests; for the lag determination, we use set of statistical criteria to determine the order of the VAR (the number of lags p), particularly, Akaike Information Criterion (AIC) and Schwartz Criterion (SC). For the cointegration tests, usually single cointegrated relationships are tested by the Engle and Granger (1987) while, we use the Johansen cointegration approach that is suitable for the multivariate systems (i.e., VEC models).

Results are summarized in the Appendix where tables A2 to A5 present respectively, the Augmented Dickey Fuller tests for stationarity, the lag determination criteria, the cointegration summary tests and the Johansen cointegration tests. The results show that all the variables are integrated of order 1, the VAR lags is set to 1, and confirm cointegration relationships particularly between GDP and the household final consumption. Furthermore, single relationship cointegrations between the four endogenous variables shows that we could impose some restrictions on the VECM to consider the absence of cointegration between inflation and the three other variables and the current account balance and the three remaining variables, while keeping the cointegration relationships between GDP and the consumption.

[12] For the UAE, information is only available for the federal budget (see section 6.2).

[13] https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

5. Estimations and backward simulations: Model Selection

Based on the test of single cointegration relationship, only consumption and GDP are strongly revealed cointegrated to order one. Therefore, we test a variety of models where some restrictions are imposed. This exercise also constitutes a kind of robustness check for to select the suitable model for our forecasts based on the forecast evaluation criteria and tests. We particularly restrict the cointegration relationships of the VEC to only consumption and GDP variables while the current account balance and inflation rate are restricted to the short-term dynamics only. We then have four cases delivering four models:

- Model 1 is the unrestricted model where all the variables are introduced without any restrictions on any of the variables' coefficients.
- Model 2 is a model where the inflation effects is restricted to only short-term dynamics.
- Model 3 is a model where coefficients of the current account balance as percent of GDP are restricted to only short-term.
- Model 4 is a model where both coefficients of the inflation and the current account balance as percent of GDP are restricted to only short-term.

We produce in-sample forecasts over the period 2005-2020 for the four cases for each country and use statistical criteria described in the section (3.4) to rank these models in terms of forecasting performances.

5.1. Model Selection based on Forecast Evaluation for the KSA

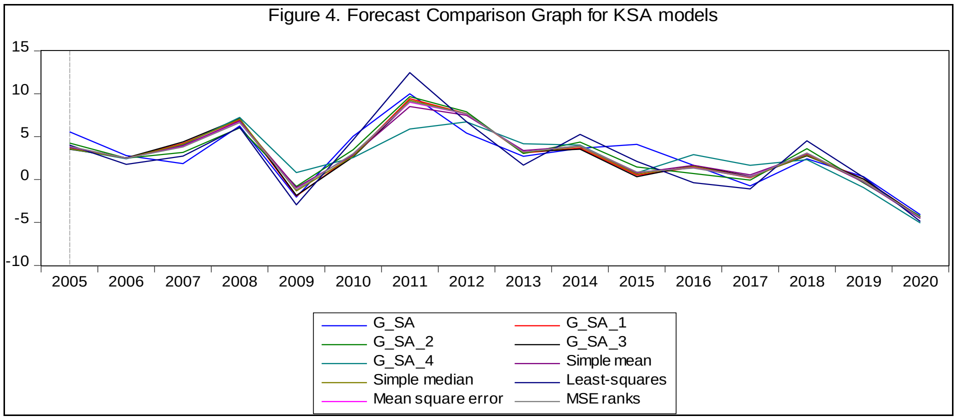
Applying the combination inference test (Timmermann, 2006), table 2 shows that we reject the null hypothesis at 5 percent for the model 4 and at 10 percent for model 3, which means that each model, separately used, do not include enough information contained in the other concurrent models. Besides, looking at the associated probabilities (F-prob), model 2 is the one that contains more information and the first one comes second. This is confirmed also by evaluation statistics table where three criteria (RSME, MAE and Theil U1) are minimal for model 2 overcoming all the other models. The models are also compared by other methods generated by the software EViews and this model is only overcome by least squares method according to MAPE and SMAPE and by the MSE ranks method according to Theil U2.

Despite some differences that may arise between the statistical criteria, Theil criterion U1 is the most reliable as other methods suffers from some shortcoming as explained in the section 3.4. Figure 4 presents the simulate GDP growth rate for the KSA over the period 2005-2020 for all the compared models and methods. Furthermore, generating forecast over the period 2005-2017 show models 2 overcome all the other models as well as all other calculated methods according to all the 6 criteria (Appendix, Table A6).

Table 2. Forecast Evaluation for the GDP growth rate of the KSA

Sample: 2005 2020						
Combination tests[14]						
Null hypothesis: Forecast ***i*** includes all information contained in others						
Forecast	F-stat	F-prob				
Model 1	2.327127	0.1263				
Model 2	0.622125	0.6141				
Model 3	2.656716	0.0959				
Model 4	12.35612	0.0006				
Evaluation statistics						
Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Model 1	1.479495	1.052606	40.19639	50.78084	0.170561	0.144159
Model 2	1.246690	1.012856	47.84505	54.76734	0.143341	0.144311
Model 3	1.564262	1.120862	42.42172	52.35119	0.181054	0.150856
Model 4	2.031067	1.716533	87.11593	72.10291	0.243982	0.260190
Simple mean	1.474344	1.172167	51.70806	56.48403	0.172669	0.158105
Simple median	1.481456	1.116603	46.34554	55.32475	0.171295	0.144301
Least-squares	1.366516	1.165237	40.12892	43.31754	0.148506	0.258465
Mean square error	1.396474	1.099081	47.83618	55.22433	0.162394	0.145059
MSE ranks	1.382645	1.084984	47.13575	55.03127	0.160557	0.143238

Figure 4. Forecast Comparison Graph for KSA models



Note: G_SA_X is the forecasted growth rate of GDP for Saudi Arabia (G_SA) by the model $X \in \{1,2,3,4\}$.

5.2. Model Selection based on Forecast Evaluation for the UAE

Applying the combination inference test (Timmermann, 2006), table 3 shows that we reject the null hypothesis at 5 percent for the model 1, model 3 and model 4 with a high rejection probability of the latter. This means that each model of these three models, separately used, include enough information contained in the other concurrent models. Moreover, looking at the associated probabilities (F-prob), model 3 is the one that contains more information, which is further confirmed by evaluation statistics table where criteria (RSME, MAE, SMAPE, Theil U1 and Theil

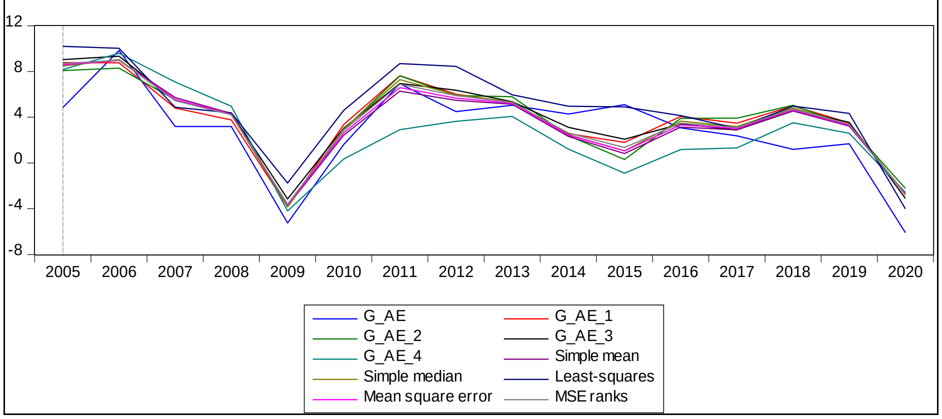
[14] Test of Chong and Hendry (1986), refined by Timmermann (2006). Refer to section 3.4 "Measuring the quality of prediction" for the methodology of this test, as well as for the definitions of the other statistical criteria for which statistics are displayed in this table.

U2) are minimal for model 2 overcoming all the other models. Figure 5 presents the simulated GDP growth rate for the UAE over the period 2005-2020 for all the compared models and methods.

Table 3. Forecast Evaluation for the GDP growth rate of the UAE

Sample: 2005 2020						
Combination tests						
Null hypothesis: Forecast i includes all information contained in others						
Forecast	F-stat	F-prob				
Model 1	1.713995	0.2171				
Model 2	2.915680	0.0778				
Model 3	1.033764	0.4125				
Model 4	2.374705	0.1213				
Evaluation statistics						
Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Model 1	2.123944	1.805210	63.26221	46.90998	0.214156	0.486177
Model 2	2.346556	2.006086	66.57546	54.76376	0.238500	0.528467
Model 3	2.092212	1.707346	59.48777	44.03899	0.209668	0.459828
Model 4	2.724809	2.262330	65.49871	70.67704	0.294406	0.597169
Simple mean	2.151738	1.712431	56.08670	46.29919	0.222461	0.471882
Simple median	2.165202	1.796172	61.52440	48.30497	0.219259	0.483323
Least-squares	2.519353	2.043293	73.85465	48.02483	0.232243	0.534702
Mean square error	2.133679	1.724867	57.73639	46.36567	0.219049	0.471283
MSE ranks	2.119872	1.732045	59.20456	46.12652	0.215884	0.471303

Figure 5. Forecast Comparison Graph for UAE models



Note: G_AE_X is the forecasted growth rate of GDP for UAE (G_AE) by the model $X \in \{1,2,3,4\}$.

6. Assumptions on the Exogenous Variables

In order to forecasts the GDP over the period 2021-2023, we must adopt suitable scenarios on the two exogenous variables that are likely to reflect the oil price forecasts and the government expenditures of the two studied countries. For the 2021 year, observed data for oil prices and the government consumption execution in the public budget available for the three quarters could help making a plausible assumption for the entire year. For the years 2022 and 2023, assumptions on the oil prices could be based on some international institutions' outlook such as the EIA.

Once the model is tested on the history of the data, providing exogenous variables future values in a highly uncertain and volatile economic environment is probably the last difficult challenge before running the model to produce endogenous variables forecasts. Our models have two important determinant exogenous variables that are oil prices and Government expenditures. The primary fiscal balance is also tested as exogenous variables and help enhance forecast for the UAE but not for the KSA.

6.1. Assumptions and scenarios on the outlook of oil prices:

First, the oil prices outlook, highly uncertain, is projected by some institutions, like the United States Energy Information Administration (EIA). The EIA long term outlook released on May 2021, forecasts nominal Brent spot prices at $47.1 in 2021, $50.9 in 2022 and $56.9 in 2023, that is approximately an increase by $5 over the forecasted years. However, in its short-term outlook of November 2021, it reported an updated monthly outlook going until December 2022, with an annual average forecast of $71.6 for 2021 and $71.9 for 2022. The IMF, in its World Economic Outlook report of October 2021, reported on average, forecasts of oil prices of $65.7 for 2021 and $64.5 for 2022. However, recent prognostics, released in December 2, 2021, from JP Morgan expect high peaks of oil prices of around $125 in 2022 and $150 in 2023.[15] For the medium-term period 2021-2023 we adopt for our forecasting, the EIA projected oil prices, in nominal term, for 2021 at $71.6,[16] while, faced with high uncertainty and differences in the outlook of the oil prices between forecasters, we adopt three scenarios for the period 2022-2023, particularly considering the likely pace of gradual recovery as the vaccination process is advancing in the World:

- The first scenario is based on the levels of the oil prices forecasted by the EIA for 2021 and 2022, with an increasing trend by $5 in 2023, in line with the EIA long-term outlook,[17] as well as the gradual expected ***moderate pace of recovery*** from the pandemic as an advancement of the vaccination process.
- The second scenario adopt a relatively continuous higher increase by $10 each year starting from 2022, in conformity with ***relatively high pace of recovery*** with the value of 2021 kept as in the first and second scenario.
- The third scenario keeps the same forecasted values for 2021-2022 by the EIA and adopt a decreasing trend of oil prices by $5 in 2023, in conformity with the monthly observed

[15] https://www.reuters.com/business/energy/jp-morgan-sees-oil-prices-hitting-125-2022-150bbl-2023-2021-12-02/
[16] This value is not far from the average observed oil prices of $68 for the 11 months of the year 2021.
[17] Long term EIA outlook for oil prices going until 2050 year is accessible through the link: https://iea.blob.core.windows.net/assets/888004cf-1a38-4716-9e0c-3b0e3fdbf609/WorldEnergyOutlook2021.pdf

decreasing trend of oil prices in 2022 as reported in the EIA short term outlook.[18] Table (4) summarizes these scenarios.

Table 4. summary of oil prices scenarios adjusted for inflation over 2021-2023

		2021	2022	2023
	Projected Oil prices inflation (%)[19]	1.2	1.3	1.5
Scenario 1	Oil Prices (U.S. $ per Barrel)	71.6	76.6	81.9
	Real Oil prices (U.S. $ per Barrel)	70.8	75.6	80.7
Scenario 2	Oil Prices (U.S. $ per Barrel)	71.6	81.6	91.6
	Real Oil prices (U.S. $ per Barrel)	70.8	80.6	90.2
Scenario 3	Oil Prices (U.S. $ per Barrel)	71.6	71.9	66.9
	Real Oil prices (U.S. $ per Barrel)	70.8	71.0	65.9

6.2. Assumptions and scenarios on the fiscal variables

For the Kingdom of Saudi Arabia, we adopted projections on government expenditure for the Saudi Arabia figures on government consumption assumptions and inflation (to be used for the calculation of the real counterpart the government consumption) from the pre-budget statement for year 2022, released on September 30, 2021.20 Total expenditures are set to 1076 billion of Riyals in 2021, 1015 billion in 2022 and 955 billion in 2023. These figures indicate a moderate restrictive fiscal policy by almost 6 percent in nominal terms in 2021 and 2022 and 1.5 percent in 2023. This goes in line with the authorities' objectives aiming at rationalizing expenditures and increasing their efficiency without altering the big projects adopted in the Saudi Vision 2030. Besides, alternative expansive fiscal policy of 2.5 percent increase of expenditures is also considered starting from 2022 along with the scenario of expected increase in oil prices (scenarios 2 and 3).

For the UAE, we have information on the expenditures for the federal budgeted projects only amounting AED 58.113 billion for 2021 from the open data website of the Ministry of Finance.[21] The UAE general federal budget over the period 2022-2026 was approved in early October 2021, with an amount of AED 290 billion, allocating AED 58.931 billion for 2022. In the absence of the budget assumptions for the UAE, we adopt a first scenario of a restrictive fiscal policy as for the

[18] For further reasons and details explaining the monthly oil prices decreasing trend in 2022, the short term EIA outlook is accessed through the link: https://www.eia.gov/outlooks/steo/pdf/steo_full.pdf .

[19] Oil price inflation is calculated from EIA energy outlook report (https://www.eia.gov/outlooks/aeo/) and used to deduce the adjusted oil prices for inflation over the forecasted years.

[20] The English version of the report is available at : https://mof.gov.sa/en/Documents/BTM-Bud_En_2022.pdf, and the Arabic version at: https://www.mof.gov.sa/Documents/BTM-Bud_2022.pdf.

[21] https://www.mof.gov.ae/en/media/materials/News/Pages/131020215.aspx

KSA by about 2.5 percent yearly in the average. Besides, the IMF projected government expenditures for the UAE in his outlook of October 2021, assuming an expansive fiscal policy by around 2.5 percent yearly over the period 2021-2023 (2.7 percent in 2021, 2.3 percent in 2022 and 2.4 percent in 2023). We adopt this scenario as a second scenario. This also goes with scenarios expected of oil prices recovery after the pandemic. For the third exogenous variable whenever used, the primary fiscal balance as percent of GDP, we adopt the projected values by the IMF outlook. Table 5 summarizes outlook scenarios of fiscal exogenous variables over 2021-2023:

Table 5. Government expenditures assumptions over 2021-2023 for the KSA and the UAE

	Source		2021	2022	2023
Kingdom of Saudi Arabia	MoF [22]	Inflation expectations (percent change)[23]	3.3	1.3	2.0
	IMF	Primary Fiscal Balance (percent of GDP)	-5.3	-3.2	-1.9
	Restrictive Fiscal Policy (RFP)	Government Expenditure (percent change)	-5.7	-5.9	-1.5
	Expansive Fiscal Policy (EFP)	Government Expenditure (percent change)	2.5	2.5	2.5
United Arab Emirates	IMF	Inflation expectations (percent change)	2.0	2.2	2.1
	IMF	Primary Fiscal Balance (percent of GDP)	-4.4	-3.0	-2.2
	Restrictive Fiscal Policy (RFP)	Government Expenditure (percent change)	-2.5	-2.5	-2.5
	Expansive Fiscal Policy (EFP)	Government Expenditure (percent change)	2.7	2.3	2.4

7. Forecasting GDP for the KSA and UAE over 2021-2023: Results and discussion

This section presents forecasted GDP growth rates for different oil prices scenarios as well as scenarios of expected fiscal policies stance, for both countries in the medium term (2021-2023).

7.1. GDP forecasts for the KSA

7.1.1. Summary of the scenarios results

Table 6 summarizes the results for the GDP growth for two models, according to the three previously described oil prices scenarios and the scenarios of fiscal policies (restrictive versus expansive). In this regard, Model 1 (the unrestricted model) projected for 2021 an economic growth around 2.4 percent under restrictive fiscal policy and 2 percent under expansive fiscal policy.[24] For 2022, the model predicts, for the first scenario, about 4.4 and 4.1 percent under restrictive and expansive fiscal policies respectively. For the second scenario, it projects 4.8 and 4.4 per cent under respectively restrictive and expansive fiscal policies. In 2023, under restrictive

[22] https://mof.gov.sa/en/Documents/BTM-Bud_En_2022.pdf

[23] Inflation expectations is not an exogenous variable but is used to deduce the real government expenditures over the horizon forecasts.

[24] The growth rate is not different across scenarios as we adopted the same oil price outlook for the 2021, for the three scenarios, $71 per barrel, as the most likely value as we are approaching the end of this year.

fiscal policy, the model reported 3.7 per cent for the first scenario, 4 percent for the scenario 2 and 2.9 percent for scenario 3. Under expansive fiscal policy, growth rate, across each scenario, is slightly reduced by almost 0.25 percentage point compared to restrictive fiscal policy case.

For the model 2, the forecasts are slightly lower for the 2021 year while seem slightly higher than for the first model for the 2022-2023 period. On average across scenarios, model 2 predicts around 1.7 under restrictive fiscal policy and to 2.1 percent under expansive fiscal policy. In 2022, the growth rate is expected, depending on the fiscal policy scenarios to be between 5.5 and 5.8 percent, while for 2023, it is forecasted to be between 4.3 and 4.4 percent. We draw the two models results accordingly with the different scenarios in figures (6 and 7).

Table 6. Forecasted GDP growth rate for the Kingdom of Saudi Arabia (%)

Model 1	Scenario 1		Scenario 2		Scenario 3		Average RFP	Average EFP	Average All cases
	RFP1	EFP1	RFP2	EFP2	RFP3	EFP3			
2021	2.375	1.994	2.375	1.994	2.375	1.994	2.4	2.0	2.2
2022	4.446	4.124	4.750	4.427	4.149	3.828	4.4	4.1	4.3
2023	3.671	3.409	4.016	3.753	2.897	2.637	3.5	3.3	3.4
Model 2	Scenario 1		Scenario 2		Scenario 3		Average RFP	Average EFP	Average All cases
	RFP1	EFP1	RFP2	EFP2	RFP3	EFP3			
2021	1.730	2.072	1.730	2.072	1.730	2.072	1.7	2.1	1.9
2022	5.486	5.762	5.780	6.056	5.200	5.475	5.5	5.8	5.6
2023	4.426	4.566	4.771	4.912	3.668	3.807	4.3	4.4	4.4
Average of model 1 and model 2									
2021	2.052	2.033	2.052	2.033	2.052	2.033	2.1	2.0	2.0
2022	4.966	4.943	5.265	5.242	4.674	4.651	5.0	4.9	5.0
2023	4.049	3.987	4.394	4.332	3.283	3.222	3.9	3.8	3.9

Figure 6. Forecated GDP growth for the Kingdom of Saudi Arabia by Model 1 (%)

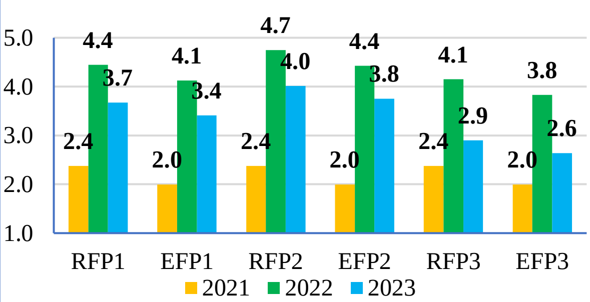
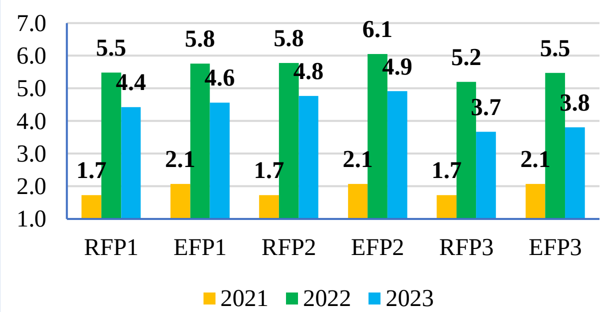


Figure 7. Forecasted GDP growth for the Kingdom of Saudi Arabia by Model 2 (%)



Moreover, according to the evaluation forecast criteria on predicting the endogenous variables (Table 7), the model, in its current specification, is good at forecasting the real GDP growth rate and to some extend the private consumption but not the two other endogenous variables (inflation and current account balance). Indeed, Theil criterion is minimized for the real GDP and the real private consumption.

Table 7. Evaluation forecast for the KSA model forecasted variables

Sample: 2000 2023

Variable	Inc. obs.	RMSE	MAE	MAPE	Theil
CABS_SAU	21	15.33288	12.41695	52.85380	0.371913
INFR_SAU	21	5.626661	5.040232	351.1379	0.808277
RFC_SAU	21	1.75E+11	1.40E+11	25.20522	0.151627
RGDP_SAU	21	2.15E+11	1.66E+11	7.989968	0.053211

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
Theil: Theil inequality coefficient

7.1.2. Comparison with other sources forecasts

Our results are compared to the other national and international sources producing forecasted economic growth. These are the Saudi Arabia Ministry of Economy and Finance (MoF), the International Monetary Fund (IMF), the World Bank (WB), and the United Nations Department of Economic and Social Affairs (UNDESA). The first two sources produced forecasts for 2021 and 2022 while the two others forecasted GDP also for 2023 (Table 8):

- On September 30, 2021, The KSA Ministry of Finance released the pre-statement of the public budget for 2022 expecting the economy to grow this year by 2.6 percent, by 7.5 percent in 2022 and by 3.6 percent in 2023.
- The IMF, in the WEO of October 2021, projected the KSA economy to grow by 2.8 percent in 2021, 4.8 percent in 2022 and 2.8 percent in 2023.
- The World Bank in its Global Economic Prospects of June 2021 predicted the KSA economy to grow by 2.4 percent in 2021 and 3.3 percent in 2022.
- The World Economic Situation and Prospects report of 2021, produced by the UNDESA, forecasted the KSA economy to grow by 3.2 percent in 2021 and 2.2 percent in 2022.

Based on the results of the model 2, for 2021, our GDP forecasts is in the range of what is forecasted for the KSA GDP growth rate by other institutions including the national source. For the 2022, our forecast is bounded by the IMF forecasts (4.8 percent) and the KSA Ministry of Finance forecast (7.5 percent). For 2023, our forecasts scenarios are slightly higher than the two forecasts produced by the MoF and the IMF.

Table 8. Forecasted GDP growth for the KSA by other sources and our model's scenarios

	National and International Sources				Model 2 forecasts								
					Scenario 1		Scenario 2		Scenario 3		Averages		
	MoF	IMF	WB	UN	RFP1	EFP1	RFP2	EFP2	RFP3	EFP3	RFP	EFP	All cases
2021	2.6	2.8	2.4	3.2	1.730	2.072	1.730	2.072	1.730	2.072	1.7	2.1	1.9
2022	7.5	4.8	3.3	2.2	5.486	5.762	5.780	6.056	5.200	5.475	5.5	5.8	5.6
2023	3.6	2.8	NA	NA	4.426	4.566	4.771	4.912	3.668	3.807	4.3	4.4	4.4

7.2. GDP forecasts for the UAE

7.2.1. Summary of the scenarios results

Table 9 presents the results for the UAE for different scenarios for oil prices and fiscal policies as described in tables 2 and 3. The unrestricted model (Model 1) projected, that economic growth will be around 1.8 percent in 2021 under restrictive fiscal policy and 2 percent under expansive fiscal policy, 3.5 percent in 2022 and 3.6 percent in 2023. Model 2 forecasts 1.8 per cent for GDP growth for 2021. For 2022, model 2 predicts around 2.6 percent, while in 2023, it projects 3.3 to 3.6 per cent depending on scenarios and fiscal policy stance. All the scenarios are illustrated in figures 8 and 9.

Table 9. Forecasted GDP growth rate for the United Arab Emirates (%)

Model 1	Scenario 1		Scenario 2		Scenario 3		Average RFP	Average EFP	Average All cases
	RFP1	EFP1	RFP2	EFP2	RFP3	EFP3			
2021	1.806	2.014	1.806	2.014	1.806	2.014	1.8	2.0	1.9
2022	3.468	3.638	3.324	3.481	3.610	3.793	3.5	3.6	3.6
2023	3.086	3.129	2.891	2.929	3.488	3.555	3.2	3.2	3.2
Model 3	Scenario 1		Scenario 2		Scenario 3		Average RFP	Average EFP	Average All cases
	RFP1	EFP1	RFP2	EFP2	RFP3	EFP3			
2021	2.305	2.255	2.305	2.255	2.305	2.255	2.3	2.3	2.3
2022	3.958	4.166	3.997	4.222	3.921	4.111	4.0	4.2	4.1
2023	4.201	4.131	4.295	4.248	4.055	3.935	4.2	4.1	4.1
Average of model 1 and model 3									
2021	2.056	2.134	2.056	2.134	2.056	2.134	2.1	2.1	2.1
2022	3.713	3.902	3.660	3.851	3.766	3.952	3.7	3.9	3.8
2023	3.644	3.630	3.593	3.589	3.771	3.745	3.7	3.7	3.7

Figure 8. Forecasted GDP growth for the United Arab Emirates by Model 1 (%)

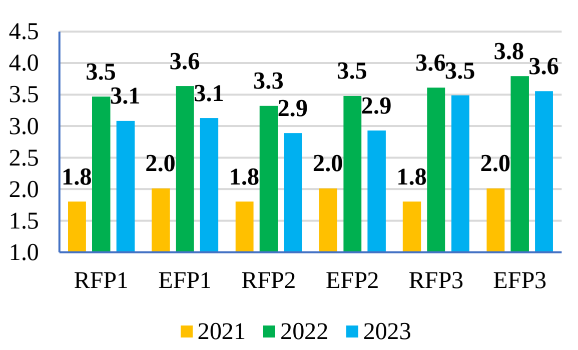
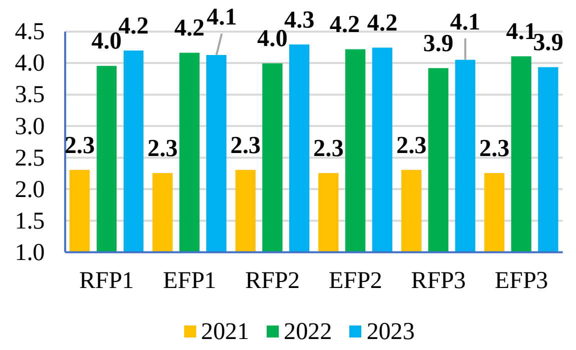


Figure 9. Forecasted GDP growth for the United Arab Emirates by Model 2 (%)



Besides, according to the evaluation forecast criteria on predicting the endogenous variables (Table 10), the model, in its current specification, is good at forecasting the real GDP growth rate and to some extend the private consumption but not the two other endogenous variables (inflation and current account balance). Indeed, Theil criterion is minimized for the real GDP and the real private consumption.

Table 10. Evaluation forecast for the UAE model forecasted variables

Sample: 2000 2023

Variable	Inc. obs.	RMSE	MAE	MAPE	Theil
CABS_ARE	21	4.816444	3.957223	119.2599	0.223090
INFR_AE	21	2.743678	2.296852	128.0632	0.321744
RFC_ARE	21	1.15E+11	1.02E+11	17.45908	0.102602
RGDP_ARE	21	5.19E+10	4.49E+10	4.366631	0.022795

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
Theil: Theil inequality coefficient

7.2.2. Comparison with other sources forecasts:

- The Central Bank of the United Arab Emirates (CBUAE), in its second Quarterly Economic Review released September 22, expected the UAE economy to grow by 2.1 percent in 2021 and 4.2 percent in 2022. This slightly represents a small adjustment of the annual growth which was expected at 2.4 and 3.8 percent respectively in 2021 and 2022 in its first Quarterly Economic Review released in July 2021.
- The IMF, in the WEO of October 2021, projected growth rate for 2021 by 2.2 percent and 3 percent for 2022 and 2023.
- The World Bank in its Global Economic Prospects of June 2021 predicted the UAE to grow by 1.2 percent in 2021 and 2.5 percent in 2022.

- The World Economic Situation and Prospects report of 2021, produced by the United Nations Department of Economic and Social Affairs (UN DESA), forecasted the UAE economy to grow by 3.7 percent in 2021 and 2.8 percent in 2022.

Based on model 3 results, we assume for the comparison, the case of an expansive fiscal policy in conformity with the continuous support of the authorities for the recovery. In comparison to our forecasts, GDP growth is in the range of what is forecasted by the UAE Central Bank and the IMF forecasts in 2021. In 2022, our forecast almost what is reported by the Central Bank particularly for the model 3 while is higher than the other international sources by more than 1 point . For 2023, our forecast reported an economic growth that is higher than the IMF forecast, the only source available for this year, by about 1.1 percentage point.

Table 11. Forecasted GDP growth for the UAE by other sources and our model's scenarios

	CBUAE	IMF	WB	UN DESA	Scenario 1 (EFP1)	Scenario 2 (EFP2)	Scenario 3 (EFP3)	Scenarios average
2021	2.1	2.2	1.2	3.7	2.3	2.3	2.3	2.3
2022	4.2	3.0	2.5	2.8	4.2	4.2	4.1	4.2
2023	NA	3.0	NA	NA	4.1	4.3	3.9	4.1

8. Conclusion

We constructed a Vector Error Correction model in this paper to forecasts the GDP growth for the Kingdom of Saudi Arabia and the United Arab Emirates. The impact of the oil price on these economies in shaping the trajectory of many fiscal and economic variables behaviours made it possible also to produce GDP forecasts, by times series models particularly the VECM models. In particular, the VECM model is augmented by exogenous variables of, first, oil price changes that capture the foreign shocks most affecting the economies of Saudi Arabia and the UAE, second is government expenditure, as an external fiscal policy variable that represents the fiscal policy stance in these countries. The third exogenous variable, the primary fiscal balance as percent of GDP, is also added in some cases, instead of the second variable or jointly with it, to consider the expenditure and revenue side. Simulating historical data, the results show that the two models provide good quality "in-sample" forecasts for both countries, particularly for GDP growth, according to statistical tests that assess the accuracy of forecasts.

Therefore, based on projected scenarios of the exogenous variables, particularly real international oil prices and real Government expenditures in each country, over the period 2021-2023, the constructed models are used to forecast economic growth over the medium term of 2021-2023. The produced GDP forecasts by these models are in the range of what is produced by international and national sources that may appeal to complete structural models.

These models could be enriched to include other sectors' variables such as the monetary and financial sectors, subject to the availability of the real data (in constant prices). Indeed, many challenges, raised in this study, particularly related to the availability of long time series data in real terms (constant prices) which are mandatory for the modelling purposes. This pushed us to look for data in many sources. As the number of variables increases, the number of coefficients increases which reduces the degrees of freedom for estimations.

Finally, it is worth mentioning that these results do not consider the uncertainty related to the path of the pandemic, particularly the emergence of new virus mutations which may affect scenarios of oil prices, hence, economic growth outlook, in oil exporting countries. In addition, these models cannot, in any case, replace the structural macroeconomic models and the general equilibrium models that describe all interconnections and sectoral relationships as well as the behavior of all the economic variables. Therefore, their results should be considered with caution and used as a valuable and helpful tool in economic forecasts.

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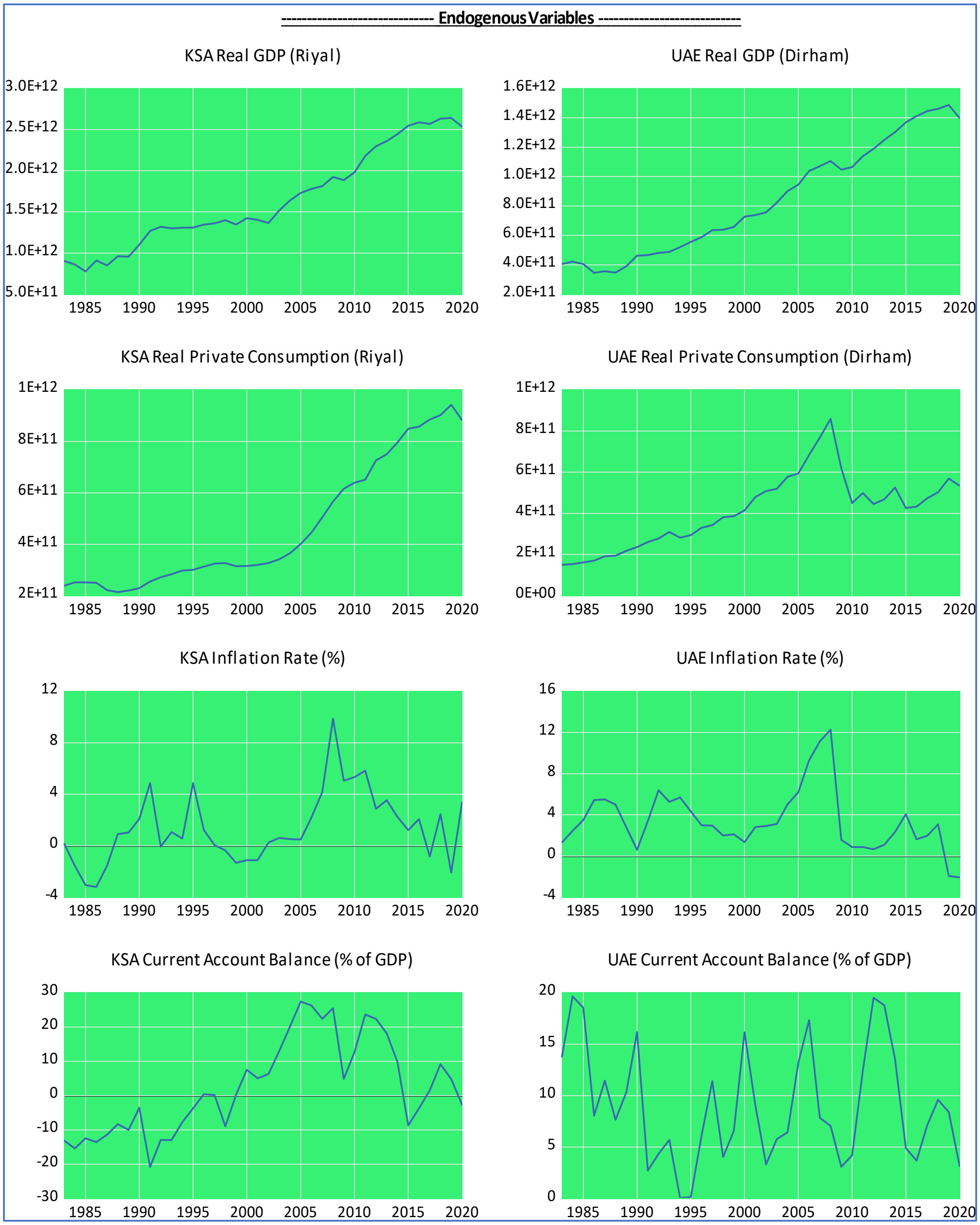
10. Appendix: Data description, Descriptive Statistics, and Tests



---------------------------- Exogenous Variables ----------------------------------

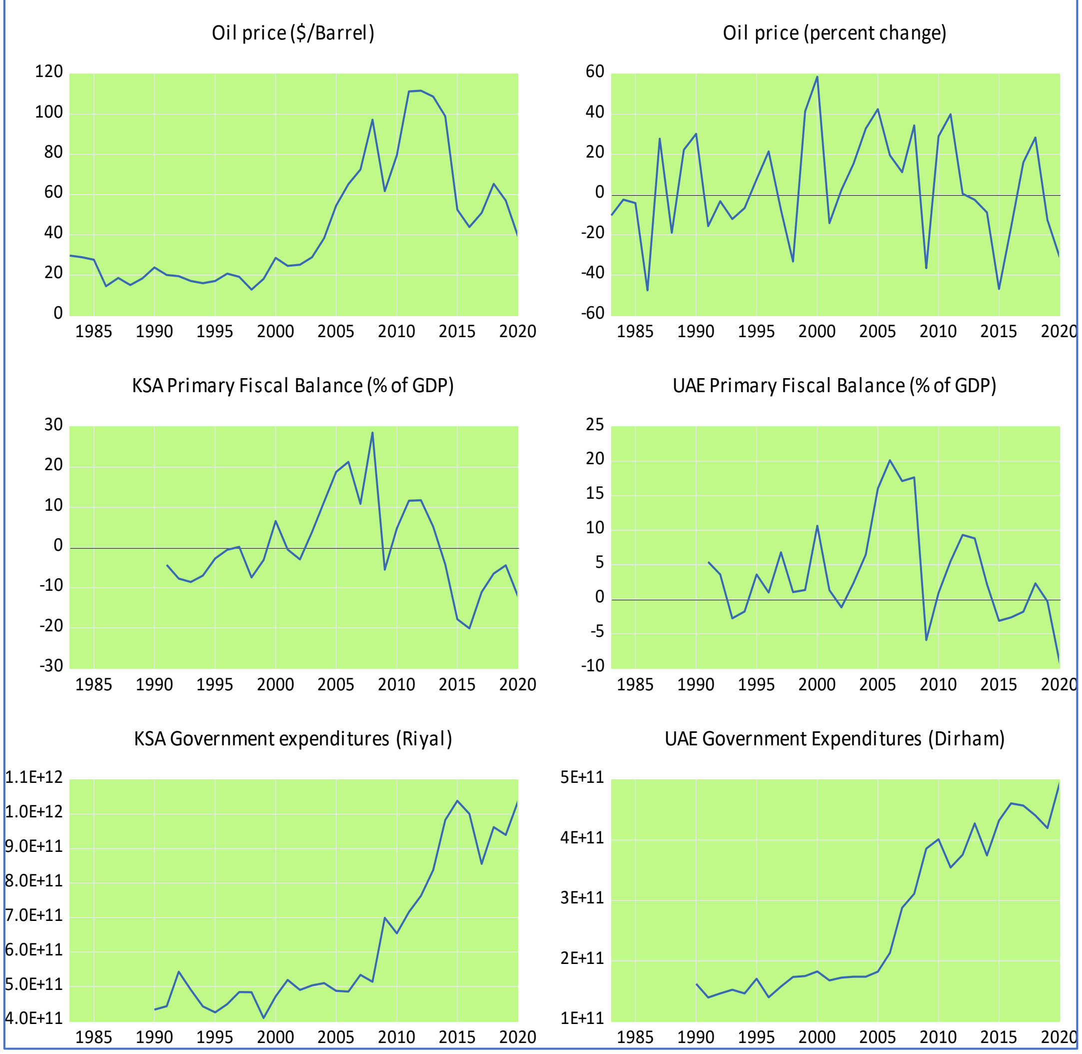


Table A1. Descriptive statistics

	Kingdom of Saudi Arabia						OPAI
	RGDP	RFC	CABS	INF	RGC	PFB	
Mean	1.65E+12	4.64E+11	2.404	1.385	6.32E+11	0.240	43.412
Median	1.41E+12	3.27E+11	0.341	0.970	5.14E+11	-2.882	28.805
Maximum	2.64E+12	9.42E+11	27.398	9.870	1.04E+12	28.569	111.670
Minimum	7.78E+11	2.14E+11	-20.805	-3.203	4.08E+11	-20.166	12.720
Std. Dev.	5.90E+11	2.44E+11	13.672	2.729	2.15E+11	11.205	30.529
Skewness	0.370	0.752	0.351	0.787	0.807	0.592	1.026
Kurtosis	1.881	1.997	1.985	3.859	2.069	3.092	2.839
Jarque-Bera	2.847	5.174	2.411	5.091	4.487	1.761	6.711
Probability	0.241	0.075	0.300	0.078	0.106	0.415	0.035
Sum	6.25E+13	1.76E+13	91.36567	52.64758	1.96E+13	7.2	1649.7
Sum Sq. Dev.	1.29E+25	2.20E+24	6916.5	275.5	1.38E+24	3640.9	34484.1
Observations	38	38	38	38	31	30	38
	United Arab Emirates						
	RGDP	RFC	CABS	INF	RGC	PFB	
Mean	8.38E+11	4.13E+11	8.979	3.419	2.72E+11	3.811	
Median	7.47E+11	4.29E+11	7.754	2.942	1.82E+11	2.227	
Maximum	1.49E+12	8.59E+11	19.636	12.272	4.95E+11	20.151	
Minimum	3.45E+11	1.50E+11	0.050	-2.074	1.39E+11	-9.271	
Std. Dev.	3.80E+11	1.74E+11	5.538	2.986	1.26E+11	7.093	
Skewness	0.296867	0.373657	0.476	1.025	0.406389	0.702	
Kurtosis	1.682	2.748	2.205	4.583	1.456	3.007	
Jarque-Bera	3.310	0.984	2.433	10.624	3.932	2.463	
Probability	0.191	0.611	0.296	0.005	0.140	0.292	
Sum	3.18E+13	1.57E+13	341.2	129.9	8.44E+12	114.3	
Sum Sq. Dev.	5.35E+24	1.12E+24	1134.7	329.8	4.77E+23	1459.1	
Observations	38	38	38	38	31	30	

Notes: RGDP is real domestic product, RFC is real final consumption, CABS is current account share to GDP, INF is inflation, RGC is real government consumption, PFB is primary fiscal balance as percent of GDP and OPAI is crude Brent oil price adjusted for inflation.

Table A2. Augmented Dickey Fuller test results.

	Endogenous variables							
	RGDP		Dlog(RGDP)		RFC		Dlog(RFC)	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
KSA	-0.2843	0.9180	-5.1274	0.0001	0.0113	0.9538	-3.0221	0.0418
UAE	0.6049	0.9880	-3.7052	0.0079	-1.5296	0.5080	-5.1048	0.0002
	CABS		D(CABS)		INF		D(INF)	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
KSA	-0.5894	0.8627	-3.0761	0.0358	0.1494	0.9661	-3.7477	0.0065
UAE	2.3508	0.9999	-4.985	0.0000	-0.6376	0.8517	-4.283	0.0001
	Exogenous variables							
	RGC		Dlog(RGC)		PFB		D(PFB)	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
KSA	-0.0583	0.9453	-5.9870	0.0000	-2.3646	0.1600	-6.8841	0.0000
UAE	0.17277	0.96610	-5.5982	0.0001	-2.4942	0.1272	-5.4771	0.0001
	OPAI				Dlog(OPAI)			
	t-Statistic		Prob.*		t-Statistic		Prob.*	
	-1.4267		0.5591		-5.4018		0.0001	

Notes: Dlog(X) stands for the first differenced log linearized variable X and D(X) stands for fist differences of X.
* Probabilities are calculated based on MacKinnon (1996) one-sided p-values. The obtained ADF t-Statistics to compare to critical references for a test including a constant term at 1% (-3.69), 5% (-2.96) and 10% (-2.62), for 38 observations. These critical values are slightly increased for shorter times series sample of less than 30 observations.

Table A3. VAR Lag Order Selection Criteria

Sample: 1983 2020

	Lag	LogL	LR	FPE	AIC	SC	HQ
KSA	0	-74.25836	NA	0.003076	5.565056	6.120148	5.746002
	1	-2.150453	111.6510*	8.48E-05	1.945191	3.240405*	2.367398*
	2	15.61817	22.92725	8.34e-05*	1.831086	3.866423	2.494555
	3	31.8653	16.77124	0.000103	1.815142*	4.590601	2.719872
UAE	0	-122.5711	NA	0.069455	8.682007	9.237099	8.862953
	1	-39.83373	128.1095*	0.000965*	4.376370*	5.671584*	4.798577*
	2	-28.66058	14.41697	0.001452	4.687779	6.723116	5.351248
	3	-12.37093	16.81512	0.001784	4.669092	7.444551	5.573823

* Indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table A4. Summary of Cointegration tests

KSA

Sample: 1991 2020
Included observations: 30
Series: LOG(RFCLC_SAU) LOG(RGDP_SAU) INFR_SAU CABS_SAU
Exogenous series: DLOG(OP2) DLOG(GFC2_SAU)
Warning: Rank Test critical values derived assuming no exogenous series
Lags interval: 1 to 1
Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	1	1	1	1
Max-Eig	0	1	1	1	1

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
Log Likelihood by Rank (rows) and Model (columns)					
0	-20.538	-20.538	-18.013	-18.013	-17.681
1	-11.135	2.963	5.284	6.581	6.906
2	-4.495	11.090	13.384	15.478	15.646
3	-3.331	17.449	18.327	21.753	21.921
4	-3.173	18.584	18.584	22.257	22.257
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	2.436	2.436	2.534	2.534	2.779
1	2.342	1.469*	1.514	1.495	1.673
2	2.433	1.527	1.508	1.501	1.624
3	2.889	1.703	1.712	1.683	1.739
4	3.412	2.228	2.228	2.250	2.250
Schwarz Criteria by Rank (rows) and Model (columns)					
0	3.183	3.183	3.468	3.468	3.900
1	3.463	2.6368*	2.822	2.849	3.168
2	3.928	3.115	3.189	3.276	3.492
3	4.757	3.712	3.767	3.878	3.981
4	5.653	4.656	4.656	4.865	4.865

UAE

Sample: 1991 2020
Included observations: 30
Series: LOG(RFCLC_ARE) LOG(RGDP_ARE) INFR_AE CABS_ARE
Exogenous series: DLOG(OP1) DLOG(GFC2_ARE) PFB_ARE
Warning: Rank Test critical values derived assuming no exogenous series
Lags interval: 1 to 1
Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	2	2	1	1	1
Max-Eig	2	2	1	1	1

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
Log Likelihood by Rank (rows) and Model (columns)					
0	-51.334	-51.334	-40.828	-40.828	-39.010
1	-28.524	-28.501	-19.108	-17.025	-15.243
2	-15.474	-15.199	-10.368	-8.286	-6.515
3	-11.517	-8.621	-8.244	-4.228	-4.216
4	-10.611	-7.245	-7.245	-3.114	-3.114
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	4.489	4.489	4.055	4.055	4.201
1	3.502	3.567	3.141	3.068*	3.150
2	3.165	3.280	3.091	3.086	3.101
3	3.434	3.441	3.483	3.415	3.481
4	3.907	3.950	3.950	3.941	3.941
Schwarz Criteria by Rank (rows) and Model (columns)					
0	5.236	5.236	4.989	4.989	5.322
1	4.623	4.734	4.448	4.42283*	4.644
2	4.660	4.868	4.773	4.861	4.969
3	5.303	5.450	5.538	5.610	5.723
4	6.149	6.378	6.378	6.556	6.556

Table A5. Johansen Cointegration test for linear deterministic trend

KSA					UAE				
Sample (adjusted): 1991 2020					Sample (adjusted): 1991 2020				
Included observations: 30 after adjustments					Included observations: 30 after adjustments				
Trend assumption: Linear deterministic trend					Trend assumption: Linear deterministic trend				
Series: LOG(RFC) LOG(RGDP) INFR CABS					Series: LOG(RFC) LOG(RGDP) INFR CABS				
Exogenous series: DLOG(OPAI) DLOG(GFC)					Exogenous series: DLOG(OPAI) DLOG(GFC) PFB				
Critical values assume no exogenous series					Critical values assume no exogenous series				
Lags interval (in first differences): 1 to 1					Lags interval (in first differences): 1 to 1				
Unrestricted Cointegration Rank Test (Trace)					Unrestricted Cointegration Rank Test (Trace)				
Hypothesized		Trace	0.05		Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Crit. Value	Prob.*	No. of CE(s)	Eigenvalue	Statistic	Crit. Value	Prob.**
None *	0.788	73.193	47.856	0.000	None *	0.765	67.166	47.856	0.000
At most 1	0.417	26.599	29.797	0.112	At most 1	0.442	23.726	29.797	0.212
At most 2	0.281	10.399	15.495	0.251	At most 2	0.132	6.248	15.495	0.666
At most 3	0.017	0.513	3.841	0.474	At most 3	0.064	1.999	3.841	0.157
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level					Trace test indicates 1 cointegrating eqn(s) at the 0.05 level				
* Denotes rejection of the hypothesis at the 0.05 level					* Denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values					**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)					Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized		Max-Eigen	0.05		Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Crit. Value	Prob.*	No. of CE(s)	Eigenvalue	Statistic	Crit. Value	Prob.**
None *	0.788	46.594	27.584	0.000	None *	0.765	43.440	27.584	0.000
At most 1	0.417	16.200	21.132	0.213	At most 1	0.442	17.478	21.132	0.151
At most 2	0.281	9.886	14.265	0.220	At most 2	0.132	4.248	14.265	0.832
At most 3	0.017	0.513	3.841	0.474	At most 3	0.064	1.999	3.841	0.157
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level					Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level				
* Denotes rejection of the hypothesis at the 0.05 level					* Denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values					**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):					Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):				
LOG(RFC)	LOG(GDP)	INFR	CABS		LOG(RFC)	LOG(GDP)	INFR	CABS	
24.279	-38.779	-0.634	0.004		0.733	-0.698	0.348	0.256	
-4.492	9.301	-0.241	-0.092		1.890	0.335	0.126	-0.248	
-6.032	8.930	-0.307	0.069		3.594	-4.756	-0.145	-0.010	
-2.598	0.064	0.089	0.007		6.737	-2.925	-0.444	-0.062	
Unrestricted Adjustment Coefficients (alpha):					Unrestricted Adjustment Coefficients (alpha):				
LOG(RFC)	-0.009	-0.011	0.005	0.002	LOG(RFC)	-0.016	-0.028	-0.009	-0.016
LOG(RGDP)	0.014	-0.012	-0.005	0.003	LOG(RGDP)	-0.011	-0.003	0.009	0.000
INFR	1.416	0.223	0.676	0.052	INFR	-0.681	-1.213	0.005	0.098
CABS	-0.782	2.150	-0.954	0.143	CABS	-2.587	1.453	-0.038	0.103
1 Cointegrating Equation(s):		Log likelihood		5.2842	1 Cointegrating Equation(s):		Log likelihood		-19.107
Normalized cointegrating coefficients (standard error in parentheses)					Normalized cointegrating coefficients (standard error in parentheses)				
LOG(RFC)	LOG(RGD)	INFR	CABS		LOG(RFC)	LOG(RGDP)	INFR	CABS	
1.000	-1.597	-0.026	0.000		1.000	-0.953	0.474	0.350	
	(-0.02117)	(-0.00255)	(-0.00053)			(-0.52764)	(-0.07537)	(-0.05778)	
Adjustment coefficients (standard error in parentheses)					Adjustment coefficients (standard error in parentheses)				
LOG(RFC)	-0.227	(-0.137)			LOG(RFC)	-0.012	(-0.01296)		
LOG(RGDP)	0.336	(-0.17219)			LOG(RGDP)	-0.008	(-0.00404)		
INFR	34.386	(-8.09461)			INFR	-0.499	(-0.30452)		
CABS	-18.988	(-20.5059)			CABS	-1.896	(-0.42349)		

Table A6. Forecast Evaluation for the simulated Growth rate of KSA

Sample: 2005 2017

Combination tests: Null hypothesis: Forecast *i* includes all information contained in others

Forecast	F-stat	F-prob
Model 1	3.176196	0.0778
Model 2	1.134166	0.3862
Model 3	3.613869	0.0584
Model 4	13.36732	0.0012

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Model 1	1.631544	1.212884	40.70558	48.85913	0.177190	0.379325
Model 2	1.328319	1.087163	38.12521	48.70500	0.144316	0.270999
Model 3	1.729044	1.308356	43.79498	50.69384	0.188459	0.411211
Model 4	2.209211	1.931239	75.49863	71.33744	0.252148	0.517318
Simple mean	1.616229	1.323866	46.42401	52.01111	0.178811	0.378174
Simple median	1.631393	1.280683	43.41091	50.96347	0.177689	0.383439
Least-squares	1.651767	1.390065	49.06083	50.70389	0.166189	0.293118
Mean square error	1.529935	1.241438	43.32264	50.42500	0.168130	0.349416
MSE ranks	1.512031	1.216373	42.30325	49.90980	0.165734	0.342939

*Trimmed mean could not be calculated due to insufficient data