Journal of Advances in Economics and Finance, Vol. 3, No. 4, November 2018
https://dx.doi.org/10.22606/jaef.2018.34001

Saudi Arabia's Crude Awakening

Mona El Shazly

Division of Business, Mathematics and Science, Columbia College, Columbia S.C., United States
Email: melshazly@columbiasc.edu

Abstract. The dual effect of weakening oil prices coupled with rising levels of government expenditures have translated into significant budget deficits for Saudi Arabia. Between 2014- 16, a fiscal balance surplus of SAR180 billion turned into SAR 366 billion deficit. This abrupt swing served as a "crude awakening "to the Saudi government pushing for the implementation of sweeping reforms. This research advocates adding to these initiatives an exchange rate system that is jointly pegged to oil and the U.S. dollar, allowing the SAR to be devalued when oil prices decline. The weights of the joint peg are determined and optimized by designing a hybrid model that combines artificial neural networks with a genetic training algorithm. In so doing, petro dollar revenues would be secured while domestic expenditures denominated in a devalued SAR will cut domestic expenditures providing the needed tail wind to balance the budget.

Keywords: Saudi Arabia, oil price, currency peg, artificial neural networks

1 Background

Though oil price volatility is nothing new to Saudi Arabia, the 2014 -16 collapse of oil prices did serve as a "crude awakening "to the government calling for rapid and drastic intervention measures to combat fiscal imbalances that proved to be endemic to the system. Within this two year span, Saudi Arabia saw its budget surplus of SAR 180 billion turn to a deficit of SAR 366 billion. As a result, fiscal reforms towards achieving a balanced budget by 2020 became an integral component of Saudi Arabia's vision 2030 plan.

While oil, economic growth, and politics have always been intertwined in the region, the trajectory for Saudi Arabia's future development had to be reset. What was initially thought of as a temporary price decline, became a somber realization of a paradigm shift in the oil industry. Prolonged sharp price drops and increased uncertainty resulting from non-conventional shale production exerted additional pressure on the government's struggle to meet competing internal demands while maintaining a regional geopolitical leadership role.

Driven by the realization of a new norm of oil prices around $50-60 per barrel band, it became clear that sweeping reform measures were necessary. Economic, institutional and social initiatives became integral in the design of the blueprint for future viable economic growth. The social contract had to be rewritten as it became unsustainable under the lower band of oil prices.

The austerity plan announced by the Saudi government however, though necessary, is not sufficient to remedy the current fiscal deficit. By cutting back spending, the government risks contracting the economy and increasing the levels of unemployment thereby intensifying the prospect of civilian unrest. Internally, pressures percolating from high unemployment amongst Saudi citizens together with the external forces of contagion from neighboring Arab Spring countries, a war that is being fought on the borders with Yemen, and heightened tensions with Iran and Qatar all are all adding tension to the system. To diffuse some of the pressure that is building up, this paper advocates adopting a new exchange rate policy.

Rather than totally abandoning the dollar peg and risking major disruptions, the proposed system would have a built in shock absorber that would partially shield the economy from external disruptions offering protection rather than exposure to outside shocks transmitted from either oil or the dollar. The exchange rate system would peg the Saudi Arabian Riyal (SAR) to both the U.S. dollar and oil. In so doing, Saudi Arabia will continue receiving petro dollar revenues, while denominating its expenditures in a cheaper SAR. This would make reforms more palatable as expenditure in riyals would not need to be severely cut albeit they would be worth less. Recognizing that this adjustment will make its way through inflation, the economy can still continue to grow and the deficit can be eradicated.

Copyright © 2018 Isaac Scientific Publishing

To determine the relative weights of the exchange rate composition of the dual peg, the paper relies on an architectural model design that combines artificial neural networks (ANNs) with a genetic training optimizer (GTO) to further enhance the results.

The paper is divided into five sections. Section 2 presents recent trends of fiscal expenditures and revenues. Section 3 lays out the roadmap to the future highlighting the fiscal reforms towards a 2020 balanced budget. The model architectural design is discussed in Section 4, and concludes in section 5 with a discussion of the results and their policy implications.

2 Recent Trends

The fiscal imbalances experienced in 2016 that followed the sharp declines in oil revenues called for swift actions on the part of the government. Reforms were quickly put in place in an effort to circumvent what could have turned into a chronical imbalance. These reforms while aiming at diversifying government revenue sources, incorporated a number of measures directed towards cutting government spending programs, the objective being moving towards a balanced budget by the year 2020 (Vision 2030).

Government revenues that are primarily dependent on oil, translate to increased fiscal budgetary exposure. The connection strength of the pulse transmitted from the oil market to the Saudi Arabian economy is weighty (El Shazly and Lou, 2016). When oil prices decline, revenues shrink, deficits increase and reserves are depleted. Likewise when oil prices are high, revenues increase, surpluses are generated, reserves accumulate, and the government is allowed to pay down its debts.

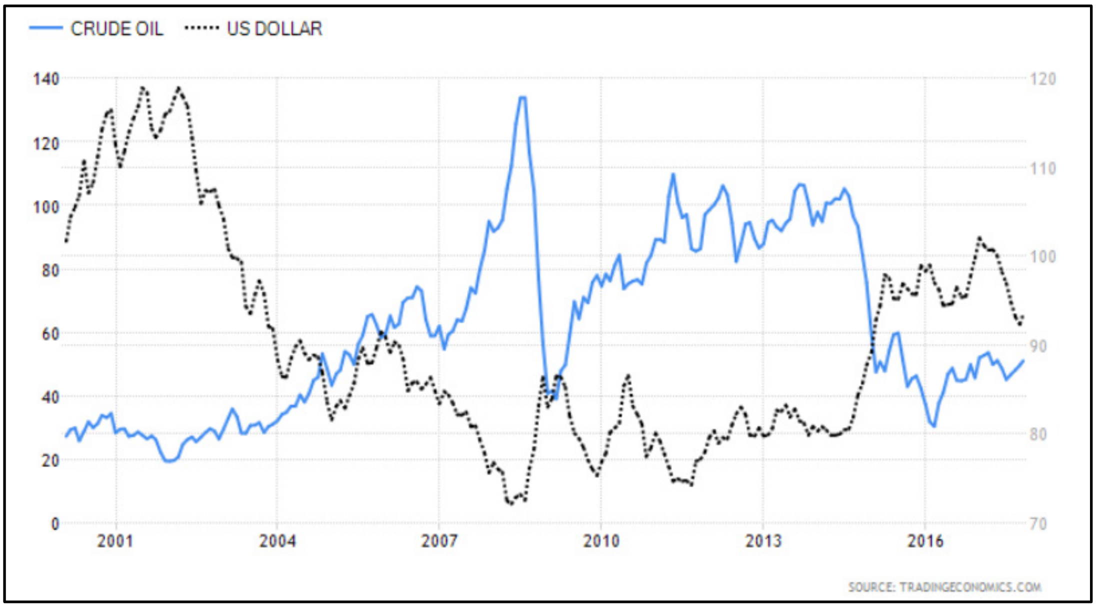

Figure 1. Oil and U.S. Dollar Prices

Figure 1 tracks the more recent price movements of oil and the dollar. Since the two markets are driven by different fundamentals, the task of identifying structural relationships between the two would be hard to ascertain. However, what can be affirmed is that their impact on the budget is significant providing support for a joint currency and commodity peg as a way to alleviate budgetary pressures. Depending on the directional and proportional change in the oil and dollar prices, the net cumulative effect on the budget may be exasperated, nullified or dampened.

Saudi Arabia has experienced five recent sharp drops in oil prices since the 1980's (Fiscal Balance Program 2020). Each episode triggered a response from the government aimed at implementing austerity measures to reduce the deficit. Between 1981-86 price of oil declined by 52%. The sharp price drop in the eighties focused on reducing government expenditures to decrease the budget deficit. Some of the

 Copyright © 2018 Isaac Scientific Publishing

government cutbacks included reductions in capital expenditures, allowances, bonuses, per diems, and overtime compensations.

In the decade to follow, two price drops occurred, the first a 24% drop in 1992-94 and the second a 17% drop between 1997- 99. In the early nineties, following the Gulf War, in face of the 24% oil price drop, the government again cut back capital spending from SAR 77 billion in 1992 to only SAR2 billion in 1994. The late 1990s response included in addition to the cutbacks in capital expenditures, a reduction in operational expenses of 10% and saw the beginning of a discussion on creating initiatives to diversify revenue sources away from oil. Steps taken towards revenue diversification however did not take hold as price of oil between 2002-14 rose and the government revenues increased from SAR 213 billion in 2002 to SAR 1247 billion in 2014 (Fiscal Balance Program).

Although the most recent price decline in 2014-16, was not a new occurrence, it differed from previous episodes in at least two dimensions: amplitude and duration. As such, additional measures needed to be undertaken to remedy the problems associated with the adverse shocks oil transmits, and to insulate the economy from its extreme price swings.

Historically, Saudi Arabia's prosperity led to generous spending by the government with little budgetary planning and discipline. Expenditure overruns were common as seen in Appendix 1, Figure 2. These overruns translate to a depletion of reserves during periods of declining oil prices and to rising fiscal deficits that hamper economic growth. In contrast with previous downturns, the latest episode of declining oil prices has altered the trajectory for future growth and development. Driven by the recognition that lower oil prices will be the new norm and that the environment surrounding it has increased in complexity and uncertainty, new reform plans were implemented.

3 Roadmap to the Future

The blueprint for sustainable non-oil growth is multidimensional and presents challenges that are tempered by the need to maintain a delicate balance between social, economic and political objectives. Achieving a balanced budget by 2020 requires diversifying revenue sources away from oil in addition to generating additional revenues and reducing government expenditures.

Though oil revenues continue to be the largest revenue component of the budget, the share of oil has been declining since 2012 from 93% to 62% in 2016 as seen in Appendix 1, Figure 3. Non-oil revenues since 2010 saw significant increases (Figures 4 and 5) from sources such as SAMA returns, custom tariffs, fees, taxes and royalties (Albilad Capital).

In addition, the government is gradually removing subsidies on fuel, electricity, gas and water so as to streamline consumption spending. By providing energy products at a discounted price, the domestic consumer has been enjoying the benefits while the government was absorbing the opportunity cost measured as the price differential between world and domestic price of a barrel of oil. Of the total subsidies provided in 2015, energy and water benefits accounted for roughly 80% of the total value which was estimated at SAR 300 billion. (Fiscal Balance Program 2020).

Table 1. Budget Allocation 2017

Budget Item	**SAR Billion**	**Percentage share**
Education	200	23
Military	191	21
Health and Social Development	120	14
Public Programs Unit	108	12
Security and Regional Administration	97	11
Infrastructure and Transport	52	6
Municipality Services	48	5
Economic Resources	47	5
Public Administration	27	3
Total	**890**	**100**

Copyright © 2018 Isaac Scientific Publishing

Furthermore, by rationalizing capital and operational expenditures, the government aims at strengthening the foundations that promote economic growth. Prioritization and selection of projects will be closely aligned with Vision 2020 and will be carefully scrutinized and reviewed. Budget allocations for 2017 following the specified guidelines have education, military and health topping the list as shown in the Table 1 (Albilad Capital).

As the government forges ahead with the re-writing of the social contract, public angst over the proposed spending cuts has to be carefully factored in. The road towards market reforms is anything but smooth, many obstacles have to be overcome and should be approached with care. Internally, public discourse may switch from excitement to discontent if financial hardships prove to be too much of a burden on citizens that regard the privileges they were granted as inherent rights that they are owed.

One sector that requires careful management and cannot be ignored is employment. Recognizing that public sector employment at inflated salaries could not be sustained even at a price of $100 /barrel of oil, pressure mounted to shift sectorial employment away from public into the private sector. This transition adds to the anguish of a young workforce that now has to compete with labor immigrants both in terms of salaries and productivity.

Though a single currency peg worked well for Saudi Arabia in the 1980s and 1990s, the more recent extreme swings in prices pointed to the need for rethinking the current exchange rate system by replacing it with an arrangement that subdues rather than fuels economic trends. This research advocates switching away from a single currency peg to a joint peg that includes currency and commodity. The commodity is oil, the primary export and revenue source, the currency is the U.S. dollar, the principal transactional currency. While linkage to the U.S. dollar will provide the SAR with the confidence and stability that it needs, the oil component will act as an automatic built in stabilizer. When oil prices rise, the currency will be allowed to appreciate thereby dampening the inflow of money and inflationary pressures from building in the economy, and when oil prices fall, the currency can depreciate relieving the budgetary pressures off the government. The exchange rate mechanism proposed would alleviate economic pressures and provide for more leveled economic growth enabling Saudi Arabia to achieve the planned Vision 2030 without having to undertake extreme fiscal expenditure measures that could derail them from achieving a balanced budget by 2020.

The joint oil-dollar peg would allow the SAR while benefiting from the stability of a fixed rate system and provide some flexibility to offset economic fluctuations transmitted by the oil price volatility. Rather than the currency being pro-cyclical, it would be counter cyclical dampening instead of exacerbating economic fluctuations (Frankel, 2017).

The proposed exchange rate regime is designed to safeguard against the volatility transmitted from oil price instability so that the government would not have to take on extreme budgetary reactions. The basic idea of switching from a dollar peg to a basket that consists of currency plus commodity has been presented by Frankel in 2008 and 2017. The blueprint of implementation however left the question of determining the weights of the basket components unanswered. This research aims at designing the model that generates the weight distribution of the variables determining the SAR‘s valuation.

4 Architectural Model Design

The basic network architecture is developed using the **Brainmaker Software** by California Scientific, and is that of the multi-layer perceptron (MLP) which is the most commonly used. The Artificial Neural Network (ANN) applied has a number of attractive features which include:

1. Versatility: allows for changes, adjusts on the inputs that it is being fed
2. Adaptability: the architectural design can be customized to include any number of components
3. Simplicity: no priori model specifications or assumptions are needed

Moreover, it is dynamic, capable of processing incomplete noisy facts and to formulate relationships that are data driven. Artificial Neural Networks (ANNs), provide inductive powers by using examples and are good at pattern recognition. Through a process of training, they are able to learn by association. ANNs estimations have often been criticized as a “black box”. Questions related to the network design, parameter selections, number of neurons and hidden layers selected and the fundamental theory on which it rests, are common critisisms that have been voiced (McNelis, 2005). The black box criticism stems from the need to tie down the empirical estimation to an economic theory whose agents act

 Copyright © 2018 Isaac Scientific Publishing

rationally in an environment that they are familiar with under a set of rules that guide them towards optimal decisions. This very criticism can be turned around and responded to by saying that agents must learn from their environments through an ongoing process by adapting and adjusting to complex interactions of variables affecting them.

There are many types of ANN models, they all however can be described in terms of their individual neurons, their connections or topology, and their learning rule. The neurons, or nodes, have connections to one another allowing for the transmission of information. Each neuron receives signals from other neurons, calculates its own output by determining the weighted sum of of its inputs and generates an activation level that is then passed to the output or transfer function (Lawrence, 1993). The connection strength between two neurons is called the weight. The weight can be thought of as a measure of the strength of the pulse of transmission and is presented by rows and columns in the form of a weight matrix.

Neurons are located in three layers: input, hidden and output. Input nodes are fed in the data that they then send to the hidden layer neurons. The hidden layer neurons' are those that connect the input with the output neurons. The output neurons in turn provide us with the response to the input data. The basic network architecture is shown in Appendix 2, Figure 6. While the connections between neurons determine the way processing will take place, the learning process itself is what sets the weights and adjustments.

According to the backpropagation algorithm, each neuron takes inputs from the layer preceding it and sends outputs only to the inputs of neurons in the next layer. If we think of each layer as a vector of neuron outputs, then the connection strengths between any two layers constitute the elements of a real-valued matrix. We call this matrix **W**. W_{ji} represents the weights from neuron *j* (in some layer) to neuron *i (*in the next higher layer). The weights are the values that are modified by the training algorithm.

Given **N** input/output pairs that need to be learned, these pairs may be indexed with the letter 'p', where the value of p runs from 1 to N. We designate the pth input as $Input_{p,}$ and the corresponding desired output as $Pattern_p$. The weights are made to change in such a way as to ultimately achieve a state in which the network maps $Input_p$ to $Pattern_p$ for all values of p. The neural network architecture design used in this paper is that of supervised learning. Under this class of learning, the network's output target is known during training. The difference between the desired target and the actual output, which is the error, is fed back to the network to improve its performance and from hence the name backpropagation is derived (Azoff, 1994).

Training the network to associate the input/output patterns can be thought of as a minimization problem, where the quantity to be minimized is E, the total error on all patterns. The square of the error for neuron *i* is:

$$\left(d_i - o_i\right)^2 = d_i^2 + o_i^2 - \left(2 * d_i * o_i\right) \tag{1}$$

where d_i is the desired output of the neuron, and o_i is the actual output. In adapting the weights, we are trying to minimize the mean square error. The mean square error is:

$$\frac{\sum_{i=1}^{n}\left(d_i - o_i\right)^2}{N} \tag{2}$$

The objective is to force the weights to change in such a way as to ultimately achieve a state in which the network maps $Input_p$ to $Pattern_p$ for all values of p. If we designate the output of any individual neuron with index *I* as $Output_{i.}$ Similarly the activation of neuron "i" is $A_{i.}$ There is a transfer function, TF, which must be continuous and differentiable, such that $Output_i = TF(A_i)$. The transfer function TF that is used is a logistic sigmoid function.

$Pattern_{pi}$ will represent the target output for the i^{th} neuron in the output layer of the network, on the p^{th} input/output pair. $Output_{pi}$ will be the actual output for that neuron. $Output_{pi}$ initially will not be equal to $Pattern_{pi}$ because the network starts out untrained. We can define the error, on pattern p, of the i^{th} output neuron as:

$$Error_{pi} = \tfrac{1}{2}\,(Pattern_{pi} - Output_{pi})^2 \tag{3}$$

The squaring insures that all errors are positive, and the factor of ½ is for simplifying the math. The total error on pattern p is now:

$$\text{Error}_{\text{p}} = ½ \sum_i(\text{Pattern}_{\text{p}i} - \text{Output}_{\text{p}i})^2 \quad (4)$$

The total error for all patterns is the sum of the errors on each pattern over all p:

$$\text{Error} = \sum_{\text{p}} \text{Error} = ½ \sum_{\text{p}} \sum_i(\text{Pattern}_{\text{p}i} - \text{Output}_{\text{p}i})^2 \quad (5)$$

The training process of the network is shown in Appendix 2, Figure 7 panels 1-4. In panel 1, the input layer transmits the data of facts to the hidden nodes in the second layer, which through a transfer function calculates a weighted sum of inputs. The hidden nodes in panel 2 broadcast the results to the output node. The output node then calculates a weighted sum and passes it through the same transfer function to calculate actual results. The results generated are then compared to the desired output or pattern, and an output error is computed in panel 3. Lastly, the errors are propagated back to the hidden layer so that the weighted sum of error derivative is computed in order to determine its contribution to the output. Weights are then adjusted according to a pre-specified rule such as minimizing the model's sum squared errors. The process continues until the desired accuracy level is achieved (Hammerstrom, 1993).

Finding the coefficient values for a neural network is not easy in a complex nonlinear system. There may be multiple optimal local solutions, to find the global optimum on a nonlinear surface we may apply alternate approaches of which genetic algorithms is one.

The basic ANN applied in this paper relies on back propagation which is a system of supervised learning. The network is initially trained by presenting it with inputs and output pairs. Weights are changed by feeding back error signals to minimize their occurrence. The transfer function that defines the activation value of the output is the sigmoid function which is well suited for the purpose of this work. Once training is complete, the network is tested using new out-of- sample data. Those networks that are identified as being "good" are then further enhanced by subjecting them to a genetic training algorithm.

Genetic algorithms are a class of probabilistic research techniques based on biological evolution (Davis, 1991; Goldberg, 1989). Their search is based on computationally simulated version of "survival of the fittest". In search for the optimal solution, the algorithm mimics the process of natural selection by testing the fitness of the individuals (networks) to determine if they will be allowed to reproduce. The genes of the "good" or "fit" network are mutated to create another "parent" network. The two networks are then crossed over to create to create a new "child" network. If the child network outperforms one or both parents, it is saved and used for reproducing even better generations of future networks (Kingdon, 1997).

The process of genetic evolution is initiated by randomly selecting a population and evaluating each of its members. Three operators are then applied to all candid solutions: reproduction, crossover and mutation evolution. Reproduction allows relatively fit networks to survive and procreate. The process is asexual with the hopes that it could improve on the fitness levels. Crossover represents a way of moving through the space of possible solutions based on information gained from existing solutions. As an operator, crossover is described in terms of exploitation of information in good individuals, and is similar to "artificial mating" and requires taking neurons from each parent to produce the child network. Mutation is the random adjustment of the individual's genetic structure. As an operator, mutation is described as the exploration of the search space, it requires one parent, and is conducted by a random modification of the neuron weights (Kingdom, 1997).

Figure 8 in Appendix 2, shows how the process of genetic evolution is applied to the networks. Unlike traditional techniques, GAs seek to identify optimal solutions by searching entire populations of candid solutions in parallel. An appealing feature of GAs is that their performance is largely unaffected by initial conditions enabling them of finding relationships between inputs and outputs even when patterns are ill defined.

5 Model Results

The data set was trained and tested for the complete period 1985-2016 using annual data obtained from Public Finance Statistics for Saudi Arabia. The model has 5 input nodes: oil prices in U.S. dollars, Oil Revenues in SAR, Other Revenues in SAR, Expenditures in SAR and U.S. Dollar index. The output node is the Budget in SAR.

 Copyright © 2018 Isaac Scientific Publishing

The outputs generated from the genetic training optimizer GTO are described in the STA, ANZ and NET files. The STA file contains statistics on the number of runs, the total number of facts that have been considered, the number of good and bad facts for the run and the error measurements. All the statistics reported are calculated using internal, normalized data representation and are offset and scaled to be between zero and one. The coefficient of determination of 0.972 for R^2 is also reported.

GTO STA File

Run	TotFacts	Good	Bad	BadOutputs	TotalBad	Learn	Tolerance	AvgError	RMSError	hh:mm:ss	Rý:SARbudget	Bad:SARbudget
1000	3	2	1	1	1	1.0000	0.1000	0.1020	0.1227	00:00:10	0.9789	1

The complete data set is divided into a training and testing set. The network's input layer contains five nodes: Oil price, oil revenues, other revenues, total expenditures and the dollar index value. The hidden layer has ten nodes and the output layer one node being the budget. During training and testing the tolerance level was set at 0.10, the transfer function between input and hidden, and hidden and output layers is the sigmoid transfer function which exhibits many desirable properties and works well with back propagation. The sigmoid transfer function is one in which the output is a continuous monotonic function of the input. Both the function and its derivatives are continuous everywhere.

Model specifications for the GTO are reported in NET file below.

GTO 001 NET File

input number 1 5 output number 1 1 hidden 10 filename trainfacts GTOFACT.FCT filename testfacts C:\SA\ANN1.fct

filename runfacts C:\SA\ANN1.in filename teststats C:\SA\GTOCHLD.STA checkpoint 8 CHECKPT.NET

learnrate 1.0000 constant learnlayer 1.0000 1.0000 smoothing 0.9000 traintol 0.1000 testtol 0.1000

stoptraining maxruns 100 function hidden1 sigmoid 0.0000 1.0000 0.0000 1.0000

function output sigmoid 0.0000 1.0000 0.0000 1.0000

dictionary input $oilPrice SARoilRev SARotherRev SARtExp $index

dictionary output SARbudget display input thermom 5 1 5 1 1 display output thermom 5 19 1 1

display pattern thermom 6 19 1 1 display color bold 5 19 1 10 display string 4 1 $oilPrice SARbudget

display string 5 15 Out: display string 6 1 SARoilRev Ptn: display string 7 1 display string 8 1 SARotherR

display string 9 1 display string 10 1 SARtExp display string 11 1 display string 12 1 $index

outputfile C:\SA\GTO001.out number none number none none 1 0 1 always

displayon

scale input minimum

11.576 42464. 33486. 137422 0.4398 scale input maximum 109.46 1.144Y 185749 1.109Y 1.2476

scale output minimum -362229 scale output maximum 580924 statistics 2929 558 101 stathistory 101

0.1213 0.1172 0.1159 0.1192 0.1176 0.1146 0.1164 0.1186 0.1170 0.1155 0.1177 0.1162 0.1156 0.1178 0.1161
0.1161 0.1184 0.1174 0.1150 0.1165 0.1193 0.1160 0.1160 0.1188 0.1167 0.1168 0.1169 0.1163 0.1166 0.1173
0.1160 0.1163 0.1172 0.1169 0.1164 0.1172 0.1160 0.1163 0.1174 0.1160 0.1162 0.1169 0.1167 0.1162 0.1171
0.1156 0.1162 0.1185 0.1154 0.1149 0.1189 0.1171 0.1143 0.1171 0.1197 0.1165 0.1151 0.1189 0.1181 0.1157
0.1173 0.1187 0.1157 0.1150 0.1191 0.1171 0.1155 0.1178 0.1168 0.1149 0.1172 0.1184 0.1154 0.1163 0.1191
0.1155 0.1166 0.1195 0.1160 0.1166 0.1192 0.1156 0.1168 0.1194 0.1160 0.1167 0.1192 0.1158 0.1167 0.1193
0.1158 0.1166 0.1192 0.1157 0.1166 0.1193 0.1157 0.1167 0.1193 0.1156 0.1166

weights 3 1 5 10 1

Copyright © 2018 Isaac Scientific Publishing

3.7716	2.9052	0.1054	2.6674	0.6912	-2.9604					
3.3500	-1.9596	-2.3426	0.3844	-2.1240	-1.5344					
0.8640	0.5740	-2.6536	-1.5602	-2.8282	-0.3906					
0.5142	-1.6930	0.5532	2.4682	-2.8032	-1.1472					
4.4276	1.6340	-0.2536	1.8254	1.9736	4.7386					
-3.5642	-0.6810	4.8152	-1.7172	2.3850	-3.3634					
-0.5186	-3.0576	-1.8420	0.3640	1.1890	-1.0784					
-0.0184	-2.6852	1.3096	-0.3820	1.2940	1.5090					
1.3222	-2.2306	2.9534	1.9396	-3.4540	-1.9362					
2.7770	5.1772	-1.2772	-2.4972	1.6260	6.6326					
2.2510	1.4872	-1.5976	-1.5884	-2.7486	-3.5382	0.2880	2.3874	-2.7774	0.0864	0.3156

The weights 3 1 5 10 1 define the network as having 3 layers with 1 threshold neuron, 5 input neurons, 10 neurons in the hidden layer and 1 neuron in the output layer. The values reported show the weight matrices produced for all the runs. The file contains two parts, the first part of the report shows the general relationships between each of the inputs and output over all the facts. The inputs are sorted and shown in order of the mean sensitivity from most positive to most negative. The second part has one line for the output that reflects the average change of output neuron over all the facts when each of the inputs is varied by +/- 10%.

GTO 001 ANZ

Output #1 (SARbudget):	AbsMin	AbsMax	Mean	AbsMean	SDev
Input #1 ($oilPrice)	0.0112	0.1616	0.1079	0.1079	0.0396
Input #4 (SARtExp)	0.000	0.0876	0.0456	0.0463	0.0270
Input #2 (SARoilRev)	0.0002	0.1213	0.0311	0.0317	0.0336
Input #5 ($index)	0.0012	0.1127	0.0224	0.0360	0.0437
Input #3 (SARotherRev)	0.0190	0.1882	0.0977	0.0977	0.0375

Mean:	OilPrice	Oil Rev	Other Revenues	Expenditures	US Dollar Index Value
Budget	0.1079	0.0311	0.0977	0.0456	0.0224

The ANZ file shows the relationship between each of the inputs and output over all the facts. Inputs are sorted in the order of their mean sensitivities. Absolute minimum shows the smallest amount of change the input has on the output, while absolute maximum shows the largest and the mean is the average amout of change the input has over all the facts.

Based on the results reported in the ANZ file, oil prices have the largest impact on the Saudi Arabian budget with 0.1079 while the dollar price index‘s relationship is only 0.0224. Based on the weights generated by the network results, a composite basket can be formulated with weights distributed according to the relative importance of the input to the output. Changes in oil prices would be reflected in the currency valuation allowing the SAR to be devalued when oil prices fall thereby providing the budget with the needed buffer. By releasing budgetary pressures, the government may be able to circumvent the need to adopt radical expenditure cuts and avert serious negative consequences.

To confirm the network results for the most recent oil price bust of 2014-2016, an implied exchange rate SAR* is computed. Appendix 3 provides a detailed description for computing the implied exchange rate that has been modeled Frankel (2017). In Frankel's computational formula the assumption is that weights are equally distributed amongst two currencies (Euro and USD) and one commodity (oil). In this paper the weights for the composite basket consisting of one commodity (oil) and one currency

 Copyright © 2018 Isaac Scientific Publishing

(USD) for the SAR valuation are generated by the neural network results. All values reported in the table are in millions.

Table 2. Empirical Results

YEAR	OIL PRICE USD/BARL	SAR/USD	TR USD	TE USD	BUDGET DEFICIT/SURPLUS USD	BUDGET DEFICIT/SURPLUS SAR
2013	106	3.75	308363	260270	48093	180348
2014	96	3.75	278498	295974	-17476	-65535
2015	49	3.75	164243	260837	-57227	-214601
2016	40	3.75	138519	221470	-82951	-311066
		SAR*/USD	**TR USD**	**TE* USD**	**Budget Deficit/Surplus USD**	
2013	106	3.83	308363	254833	53530	
2014	96	4.03	278498	275410	3088	
2015	49	6.41	164243	152595	11648	
2016	40	4.13	138519	201092	-62573	

The above table provides the results of the proposed joint peg. The top portion shows the budgetary impact under the current pegged system during the most recent price drop from $106/barrel in 2013 to $40/barrel in 2016. As seen in the table the surplus of 180348 million SAR in 2013 turned into a 311066 million deficit by 2016.

The lower part of the table reports the results under the proposed joint peg for the same time period. This drastic reversal in the budget position under the proposed joint peg is significantly subdued as seen from the reported values in the lower part of the table above. The joint basket peg SAR* links the SAR value to both the USD as well as oil prices. As oil prices fall SAR* weakens. With revenues generated in USD, and assuming that government expenditures are unchanged, a weaker SAR* will help alleviate the pressure on fiscal imbalances. By comparing the budgetary position over the 2013-16 period, the findings show that the proposed exchange rate system provides the needed tailwind that would support a balanced budget as initially projected.

The research findings highlight the extreme volatility of energy prices and the vulnerability and toll which oil exporting countries have to absorb. Though the budgetary pressures are nothing new to those countries, policies have to be adopted to safeguard against collapses such as those experienced in Venezuela and Nigeria. Saudi Arabia's position is different as it is able to manage its budget accounts by borrowing from local banks and by accessing global financial markets.

In terms of policy implications, this paper advocates the need for policy reforms that are economic, social and structural. Proposed measures on the economic front are revenue diversification, taxation and rationalization of expenditures. Structural reforms should focus on employment issues that deal with salaries and benefits as well as growing the private sector employment to alleviate the burden off of public sector hiring.

While this research supports the reforms and vision that Saudi Arabia has laid out for its future growth path and acknowledges the urgency of adoption, it does so with a sense of trepidation. As such the proposed approach to currency valuation is one that helps ease some of the anxiety that builds up when drastic budgetary cuts are enforced. The economic, political, social and psychological state of Saudi Arabia and the region at large is currently highly charged. Steps taken to implement changes in norms and expectations have to be carefully treaded and measured to safeguard against any backlash that may occur.

References

1. Albilad Capital, *Saudi Public Budget for FY 17,* December 26, 2016.

2. E.M. Azoff, *Neural Network Time Series Forecasting of Financial Markets,* New York, Wiley, 1994.

3. R.Bhatia, “Saudi Arabia Budget 2017”, *The Gulf International Bank,* February, 2017.
4. Conference Report, “Petro Diplomacy: Challenges in the New Energy World”, *The Arab Gulf States Institute in Washington*, December 16, 2016.
5. Conference Report, “Petro Diplomacy: Navigating the New Oil Era”, *The Arab Gulf States Institute in Washington,* September 25, 2017.
6. L.Davis, *Handbook of Genetic Algorithms,* New York: Van Nostrand Reinhold, 1991.
7. M.El Shazly and A. Lou, “Measuring Contagion Between Oil Prices and Stock Markets in the GCC Countries Using a Hybrid Artificial Neural Network”, *International Journal of Trade, Economics and Finance,* Vol.7, No. 4, August 2016.
8. J.Frankel, “The Currency-Plus-Commodity Basket: A Proposal for Exchange Rates in Oil-Exporting Countries to Accommodate Trade Shocks Automatically”, CID Working Paper No.33, *Center for International Development at Harvard University*, March 2017.
9. J.Frankel, “Currency-Plus-Commodity Basket: A Proposal for a New Exchange Rate Arrangement for Gulf Oil-Exporting Countries”, *Economic Research Forum*, Policy Brief No. 26, June 2017.
10. D.E.Goldberg, *Genetic Algorithms in Search, Optimisation, and Machine Learning*, Addison-Wesley, Reading, MA, 1989.
11. D.Hammerstrom,” Neural Networks at Work”*, IEEE Spectrum,* June 1993, pp.26-32.
12. J.Kingdon, *Intelligent Systems and Financial Forecasting*, Springler-Verlag Publishers, London, U.K.1997.
13. J.Lawrence, *Introduction to Neural Networks: Design, Theory and Applications,* California Scientific Press, 1993.
14. https://tradingeconomics.com/commodity/crude-oil
15. https://www.belfercenter.org/publication/uae-and-other-gulf-countries-urged-switch-currency-peg-dollar-basket-includes-oil
16. P.McNelis, *Neural Networks in Finance*, Elsevier Academic Press, 2005, pp.55-56.

 Copyright © 2018 Isaac Scientific Publishing

Appendix 1. Saudi Arabia's Revenues and Expenditure

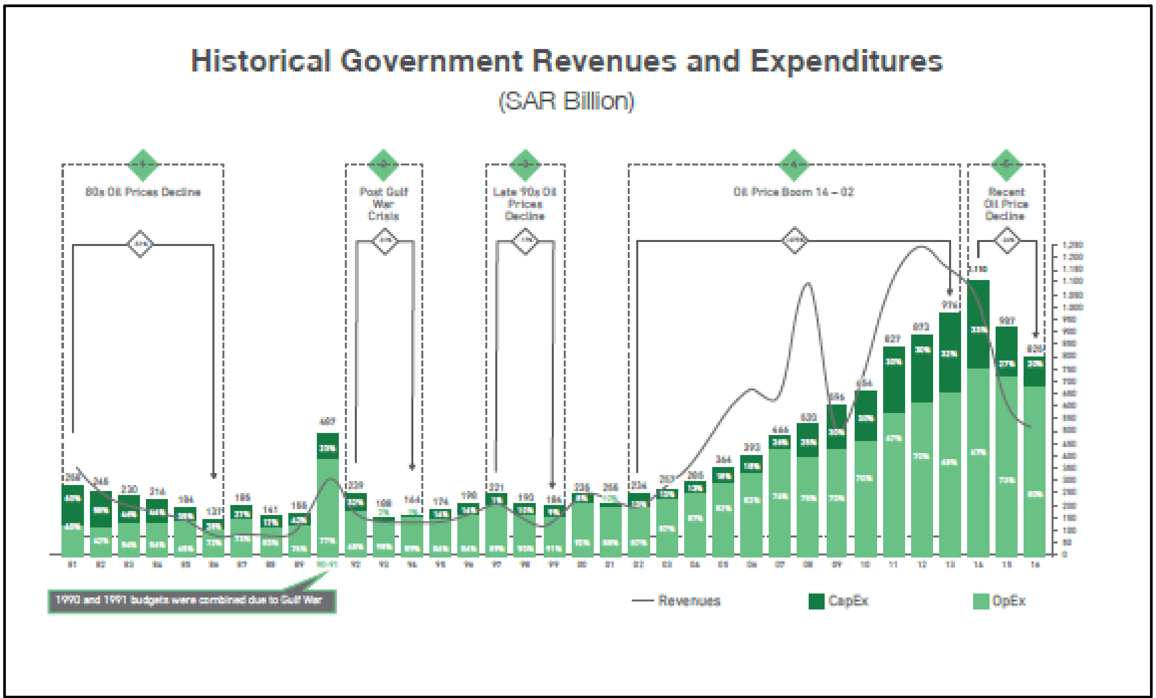

Figure 1

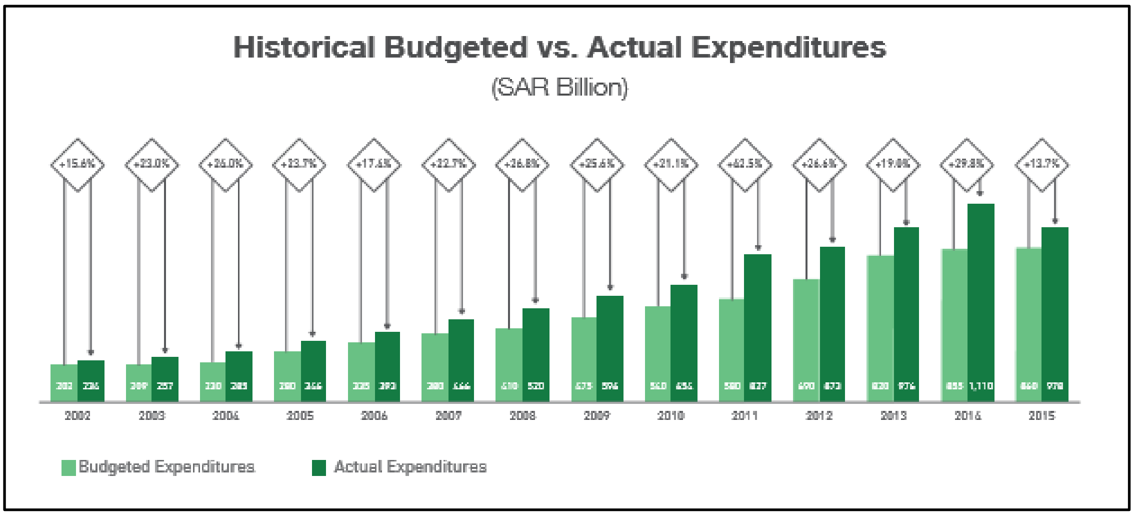

Figure 2

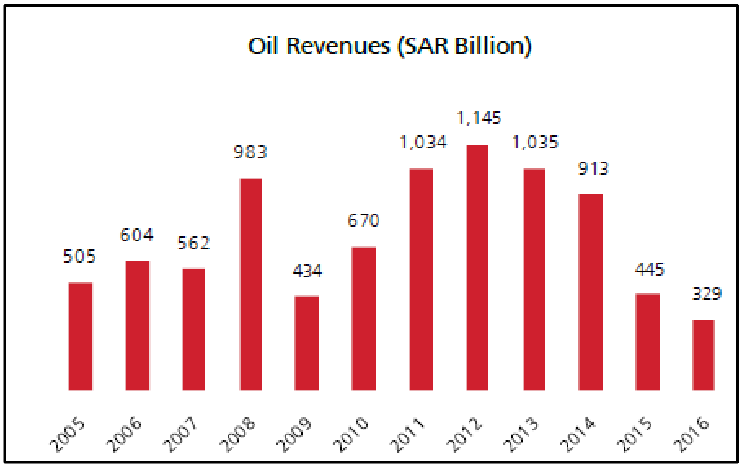

Figure 3

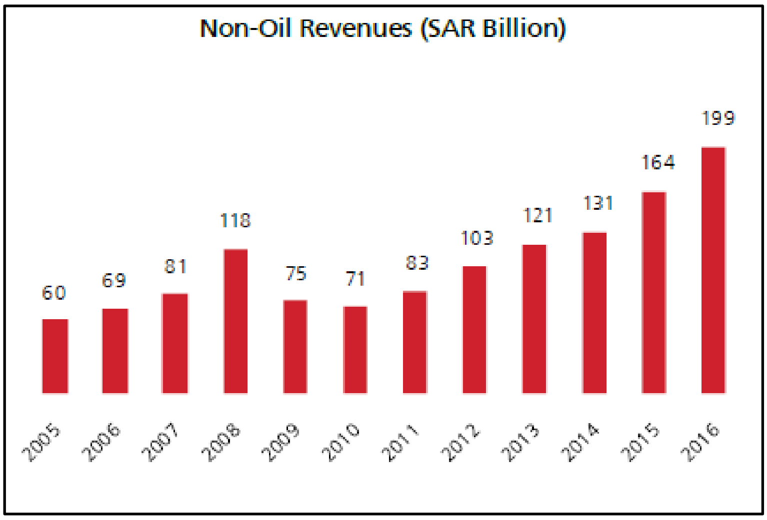

Figure 4

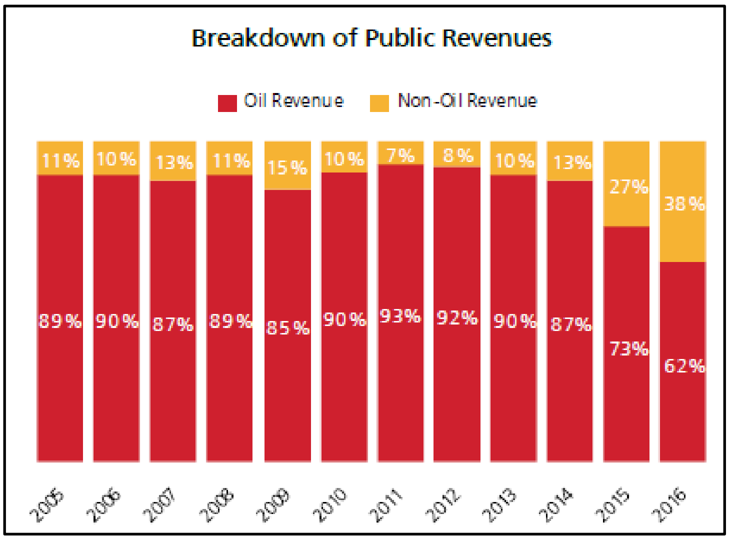

Figure 5

 Copyright © 2018 Isaac Scientific Publishing

Table 1: Non-Oil Revenues

Non-Oil Revenues– SAR billion	2015 A	2016 E	Growth
Custom Tariffs	25.9	20.8	(19.8%)
SAMA Returns	35.4	62.2	75.7%
Sales of Goods and Services	15.1	14.1	(6.6%)
Oil Product Fees	16.2	15.5	(4.3%)
Public Investment Fund Returns	15.0	15.0	0.0%
Taxes on Income, Profits and Gains	14.6	14.5	(0.7%)
Fines, Penalties and Confiscations	9.2	7.5	(18.5%)
Visa Taxes	7.1	7.9	11.3%
Telecom Royalty	3.7	4.8	29.7%
Tobacco Tariffs	0.1	4.8	7900.0%
Radio Spectrum Fees	0.5	0.5	0.0%
Uncategorized Miscellaneous Revenues	8.5	1.8	(78.7%)
Mining Fees	0.6	0.6	9.1%
Realized Returns from Other Sources	0.0	15.0	-
Selective Taxes (Energy Drinks,Carbonated Beverages)	0.0	0.0	-
Zakat	14.1	14.0	(0.7%)
Total non-oil revenues	**165.9**	**199.0**	**19.95%**

Appendix 2. Artificial Neural Network Design

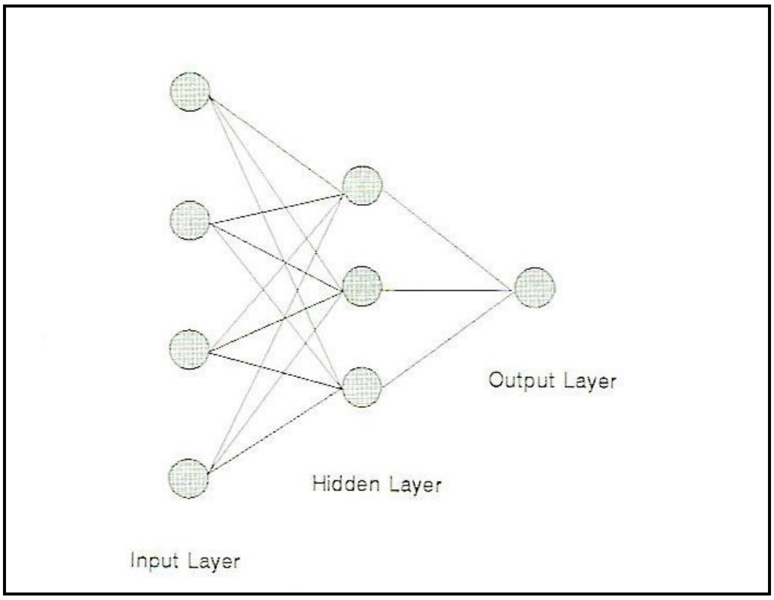

Figure 6. Basic Neural Network

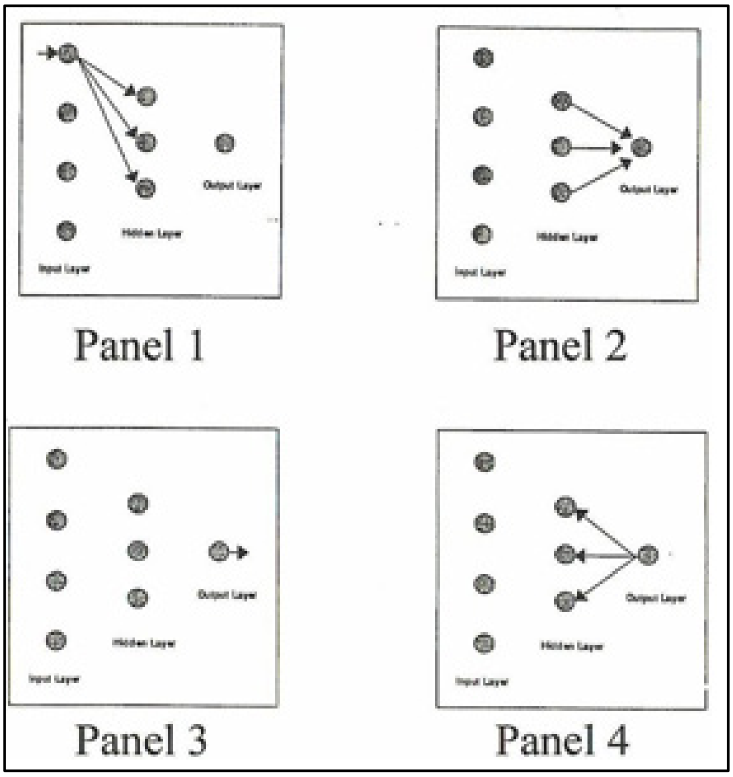

Figure 7. Neural Network Training

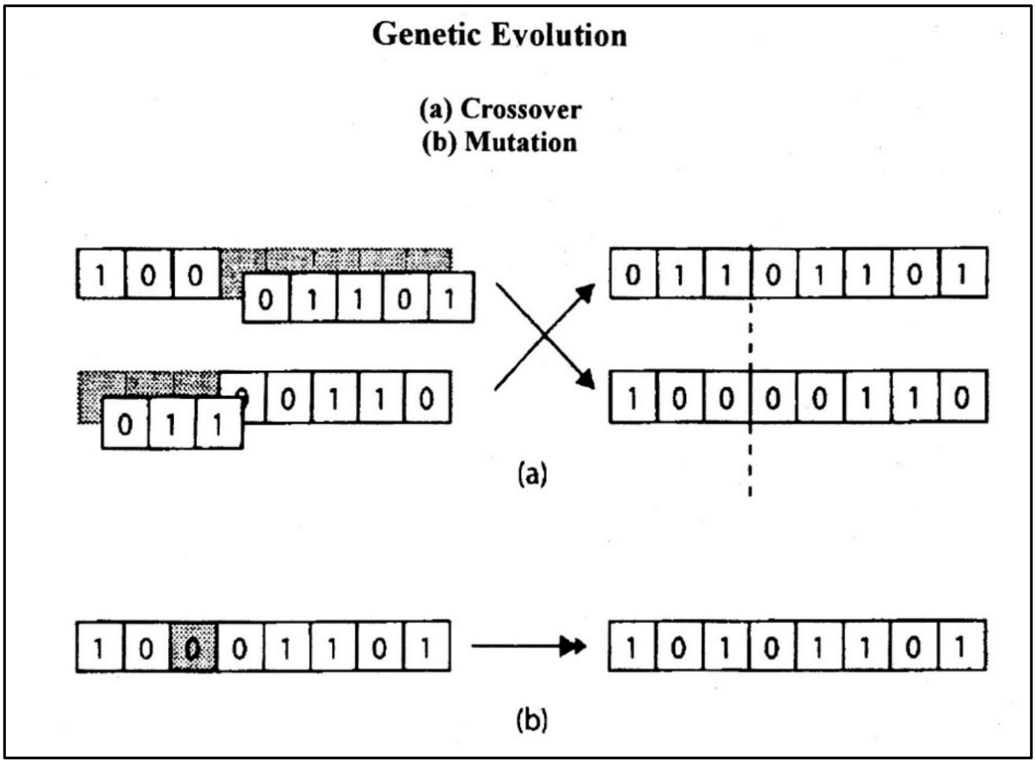

Figure 8

 Copyright © 2018 Isaac Scientific Publishing

Appendix 3. Frankel's Computational Formula for Currency Plus Commodity Basket

	Date on which determined	US dollar	euro	Barrel of oil (Brent)	Value of local currency
1. Weights	1-Jul-16	0.3333	0.3333	0.3333	1
2. Value of unit in dollars on benchmark day	Dec. 31, 2016	1	$1.0517	56.8200	
3. Relative coefficient in basket formula = (1)/(2)	For daily setting of the $ exchange rate during the coming year	0.3333	$0.3169	0.0059	
4. To take the example of Kuwait, $ value of dinar on benchmark date	Dec. 31, 2016				$3.2755
5. Absolute coefficient in basket formula, assuming no discrete devaluation or revaluation at date of implementation = (3)*(4)	Dec. 31, 2016	**1.0918**	**1.0382**	**0.0192**	
6. Check value of formula on benchmark day (i) observed rates = (2)	Dec. 31, 2016	1	1.0517	56.82	
(ii) exchange rate on benchmark day implied by basket formula = (5)*(6), then summed.		$1.092	$1.092	$1.092	$3.276
7. Example i) observed rates at time t,	e.g., *t* = March 1, 2017	$1.000	$1.088	$55.720	$3.282
ii) exchange rate at time t implied by basket formula = (5)*(7), then summed	*t* = March 1, 2017	$1.092	$1.129	$1.071	$3.292

Copyright © 2018 Isaac Scientific Publishing