THE JOURNAL OF ENERGY AND DEVELOPMENT

Nourah AlYousef and Mohammed A. Aljarrah,

"The Demand for Oil Products in Saudi Arabia,"

Volume 36, Number 2

THE DEMAND FOR OIL PRODUCTS IN SAUDI ARABIA

*Nourah AlYousef and Mohammed A. Aljarrah**

Introduction

Saudi Arabia has long been recognized as one of the major global oil producers and exporters. The nation possesses the largest proven crude oil reserves in the world, estimated to be 266.5 billion barrels in 2009.[1] The consumption of petroleum products in Saudi Arabia has increased significantly in the last three decades (1980 to 2010), making it one of the fastest growing consumers of oil internationally. One possible factor contributing to the high demand for oil products in the country is that these products are sold in the domestic markets at subsidized prices. Other factors include high population growth and increasing demand by the

---

*Nourah AlYousef, Associate Professor of Economics at King Saud University (Riyadh, Saudi Arabia), earned a B.A. in business administration and an M.B.A. from the University of Bellarmine (Kentucky), a master's degree in economics from King Saud University, and a Ph.D. in economics from Surrey University (United Kingdom). She conducted postdoctoral research at the Oxford Energy Institute. The author's professional positions have included Vice Chair of the Economics Department and as an Advisor to the Saudi Arabian Ministry of Petroleum and Mineral Resources, to the Gulf Cooperation Secretariat, and to the "Majuls Alshura" (Saudi Arabian Parliament). Dr. AlYousef's areas of research concentration are in the fields of energy economics and econometric applications.

Mohammed A. Aljarrah, Professor and Chair of the Economics Department at King Saud University, holds a Ph.D. in economics from the University of Nebraska-Lincoln and a master's degree in economics from Michigan State University. The author's areas of academic interest are international economics, quantitative analysis, and econometrics. Dr. Aljarrah has published numerous papers in Arabic and English in the areas of macroeconomics, trade, and finance, a book on international finance and investment, and co-authored a text on principles of macroeconomics (in Arabic).

The Journal of Energy and Development, Vol. 36, Nos. 1 and 2

industrial sector. This development in domestic consumption has significant implications for global oil supply. With increased domestic consumption, less oil will be available for exports. This paper seeks to estimate income and price elasticities for oil derivatives consumption in Saudi Arabia for the period of 1980 to 2010. Obtaining these elasticities is essential in forecasting the future demand for oil products and for drafting the appropriate plans for capacity building to meet the growing internal demand.

The study starts with a historical overview of rising demand for petroleum products. Variables of the study include the consumption of gasoline, diesel oil, kerosine, fuel oil, real gross domestic product (GDP), and the products' prices. The sources for the data used here were obtained from the Ministry of Petroleum and Minerals of Saudi Arabia and the Saudi Arabian Monetary Agency (SAMA) and cover the period 1980 to 2010.

Historical Overview

As the world's largest producer and exporter of crude oil, the Saudi economy remains heavily dependent on oil and petroleum-related industries, including petrochemicals and refining. Oil export revenues have accounted for around 90 percent of total Saudi export earnings and state revenues and above 40 percent of the country's GDP.

Saudi Arabia is the largest oil-consuming nation in the Middle East, and the seventh largest consumer in the world, as seen in table 1. In 2010, Saudi Arabia consumed approximately 2.643 million barrels per day (b/d) of oil, up 72 percent since 2000, from 1.54 million b/d with a yearly average of 5.8 percent growth due to strong economic and industrial growth accompanied by subsidized prices. Figure 1 shows the difference between the real price of gasoline and the Saudi subsidized price.

Since 1982, Saudi oil product consumption has risen faster than production, mainly due to the low price of oil products, which is determined by the government. Figure 2 depicts the rapid rise in Saudi Arabia's consumption of total oil products from 1980 through 2010. On some occasions, the government imported oil products in order to meet the excess demand. Although the prices of the imported products were higher, the imported products were sold locally at the lower domestic prices. Consequently, government expenditures increased and potential revenues, which would have been obtained by more exports of crude oil and products, decreased. Beginning in 1983, the Saudi government started to implement a policy of gradually increasing the nominal gasoline price, as can be seen in figure 1. Nominal prices were dropped briefly for the time period between 1992 through 1994; in 1995 the nominal price was increased once more, creating a trend lasting until 2006 when the price was decreased.

Table 1
TOP WORLD TOTAL OIL PRODUCERS AND CONSUMERS, 2010
(in thousands of barrels per day)

Rank	Country	Production	Rank	Country	Consumption
1	Saudi Arabia	10,521	1	United States	19,148
2	Russia	10,146	2	China	9,189
3	United States	9,688	3	Japan	4,423
4	China	4,273	4	India	3,182
5	Iran	4,252	5	Russia	2,937
6	Canada	3,483	6	Brazil	2,654
7	Mexico	2,983	7	Saudi Arabia	2,643
8	United Arab Emirates	2,813	8	Germany	2,489
9	Brazil	2,678	9	South Korea	2,249
10	Nigeria	2,458	10	Canada	2,237

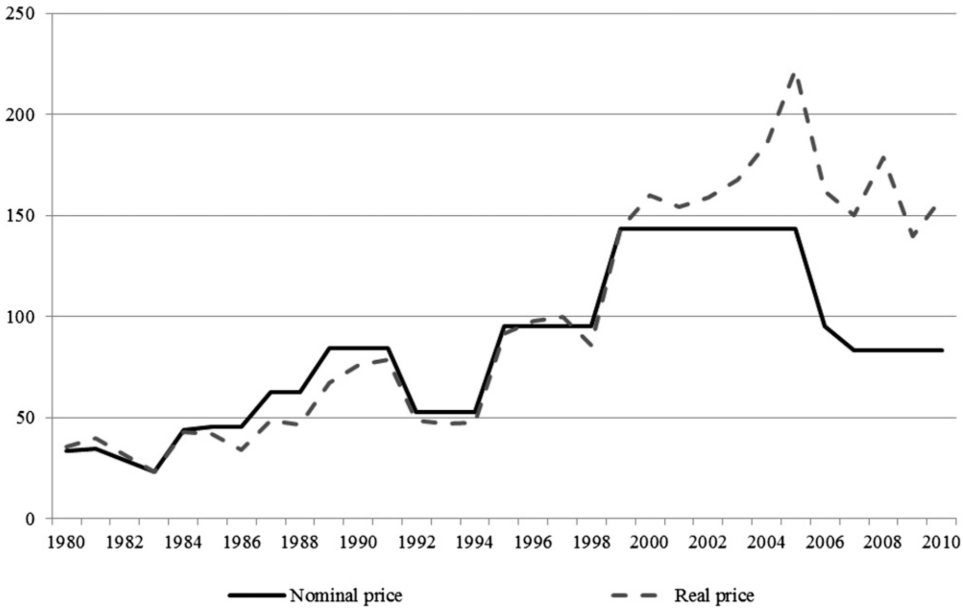
Source: U.S. Energy Information Administration (EIA), International Energy Statistics, available at http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=5&pid=53&aid=1.

Review of the Literature

Many studies have focused on the causality between energy consumption and GDP. Establishing the causality direction between these two variables has important policy implications for economic growth. G. Hondroyiannis et al. examined the link among energy consumption, GDP, and the consumer price index (CPI) for Greece over the period of 1960 to 1996.[2] They found a bi-directional causality between total and industry energy consumption and GDP, but no causality was found between residential use of energy and GDP. For a group of 16 developed and newly developed countries, U. Soytas and R. Sari found only one country (Argentina) with a bi-directional causality between energy consumption and GDP.[3] The remaining countries showed a uni-directional causality, which ran either from GDP to energy consumption or vice versa. N. Odhiambo examined the causal relationship between energy consumption and economic growth in Tanzania during the period of 1971 to 2006.[4] The results support the hypothesis of uni-directional causal flow from energy consumption to economic growth.

However, there are studies that have attempted to analyze price and income elasticities of energy demand. P. Narayan and R. Smyth estimated long-term income and price elasticities for oil in 12 Middle East countries.[5] Using panel unit root and panel cointegration techniques, the authors found that the demand for oil in the Middle East tends to be more price inelastic and less income elastic. Their results suggest that the demand for oil in these countries is affected basically by economic growth, whereas consumers appeared less sensitive to price changes. Similar results were obtained by N. Al-Mutairi and M. N. Eltony, who estimated the income and price elasticities of energy demand for Kuwait over the period of 1965 to 1989.[6]

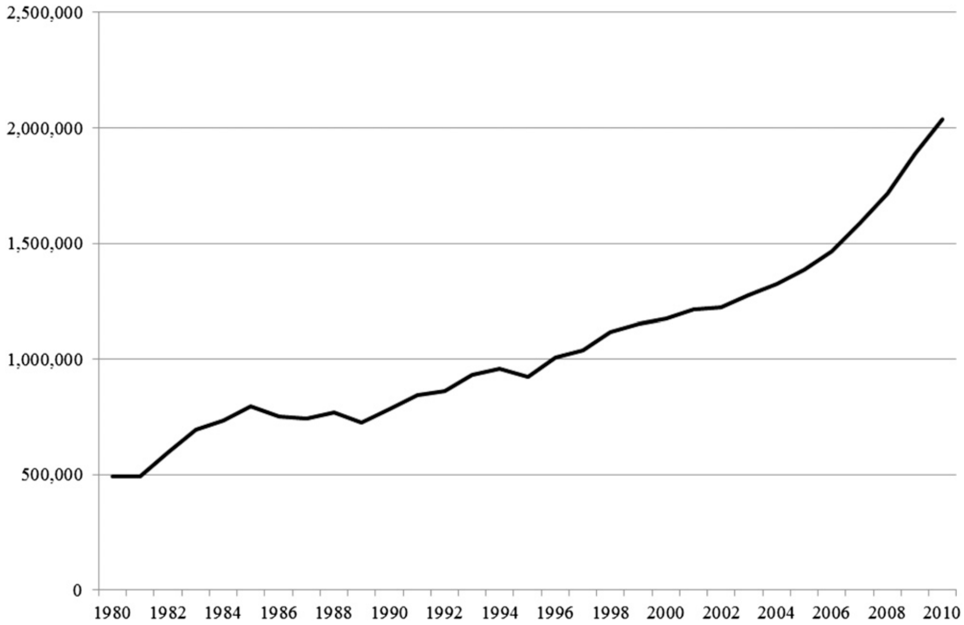
Figure 1
SAUDI ARABIA: GASOLINE PRICES, 1980 TO 2010
(in Saudi riyals per barrel)



They found that energy demand was price inelastic over the long and short run, while income was elastic over the long run but inelastic over the short term.

S. Bhattacharyya and A. Blake analyzed the domestic demand for petroleum products in the Middle East and in North African (MENA) countries for the period of 1982 through 2005.[7] The authors did not find strong evidence that price or income is elastic in the MENA group. They suggested that price or income may not be the most important demand drivers of petroleum products in the region, but that other factors, such as socioeconomic variables and the lack of price policies of the MENA governments, might play a more salient role. The authors also pointed out that the subsidization of oil products in the domestic market has led to the rapid increase in energy use. M. N. Eltony and Y. Mohammad and M. N. Eltony estimated the elasticities of demand for energy consumption in the member countries of the Gulf Cooperation Council (GCC) using data from the 1970s and 1980s and found that income and price are inelastic over the long and short run.[8] A. Al-Faris reached the same conclusion on price and income elasticities in the GCC countries over the short run.[9] He used a partial adjustment model for the period of 1970 through 1991 and found the price to be inelastic. In another article, A. Al-Faris estimated income and price elasticity of gasoline demand for member states of the Organization of Arab Petroleum Exporting Countries (OAPEC).[10]

Figure 2
SAUDI ARABIA: TOTAL OIL PRODUCTS CONSUMPTION, 1980 TO 2010
(in barrels per day)



M. Belhaj estimated short- and long-run prices and income elasticities of demand for gasoline in Morocco over the period of 1970 to 1996.[11] He found that, in the short run, price elasticity ranges between –0.29 and –0.09 and income elasticity ranges between 0.27 and 0.09. In the long term, the elasticities were generally equal to 0.6 in absolute values. Applying cointegration techniques and vector autoregression (VAR) analysis, M. Polemis examined transportation energy demand in Greece for the period of 1978 to 2003.[12] His results indicated that the long-run gasoline energy demand appears to be price and income inelastic, while diesel demand appears to be price inelastic and income elastic.

Method of Analysis

The demand equation to be estimated in this study is

$$Q_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 P_{it} + \beta_3 T + u_t \qquad (1)$$

where Q_{it} is the per-capita petroleum product consumption for product i (i.e., gasoline, kerosine, diesel and fuel oil) in year t, Y_{it} is the real gross domestic product (GDP) for Saudi Arabia in year t, and P_{it} is the real retail price of oil product i. The estimation was carried out using a natural logarithm of the variables

and, hence, each coefficient is estimated as an elasticity. To determine the appropriate model, a test for the constant and time trend was performed using ordinary least squares (OLS), which indicated that the model has constant and does exhibit a time trend.

$$lnq_{it} = \beta_1 lny_{it} + \beta_2 lnp_{it} + \beta_3 T + u_t$$

The approach of testing for the existence of relationships between variables, taking into account the stationary nature of the time series and applying cointegration techniques, has dominated the economic literature in recent years. Various cointegration methods have been used to carry out such tests. Among the most familiar methods are the approach of R. Engle and C. W. Granger, S. Johansen and K. Jueslius, and S. Johansen.[13] Other, less frequently used techniques include those of P. Phillip and B. Hansen, Y. Shin, and J. Stock and M. Watson.[14] All of these approaches require that the underlying time series be integrated in the same order, or, specifically, of order one. See M. Pesaran et al. and C. Cavanagh et al. for studies that introduce difficulties in performing cointegration analysis.[15]

The methodology used here is derived from that developed in the studies by M. Persaran et al. and is based on an autoregressive distributed lag (ARDL) framework.[16] The advantage of using the ARDL approach is that it does not require the levels of integration to be equal. Furthermore, it can be applied to cases in which the value of the regressors is purely I(0), purely I(1), or mutually cointegrated. Hence, the testing for stationarity is no longer essential.

The procedure tests the significance of lagged levels of the variables under consideration in a conditional, unrestricted equilibrium correction model using the Wald or F-statistic in a generalized Dickey-Fuller regression.[17] The estimates obtained from the ARDL method of cointegration analysis are unbiased and efficient. The choice of the ARDL method in this study is based on the reasons stated by M. Pesaran et al., which include the following: (a) the method can be applied to studies with a small sample, (b) the method estimates the long- and short-run components of the model simultaneously, removing issues associated with omitted variables and autocorrelations, and (c) the method can distinguish between dependent and explanatory variables.[18]

The cointegration test consists of two stages. In the first stage, if the theory predicts that there is a long-run relationship among the variables y, x, and z, assuming no prior information about the direction of the long-run relationship among variables, the following three unrestricted error-correction (EC) regressions are estimated in which each variable is considered in turn as a dependent variable:

$$\Delta y_t = \alpha_{0y} + \sum\nolimits_{t=1}^{n} b_{ty}\, \Delta y_{t-j} + \sum\nolimits_{i=1}^{n} c_{iy}\, \Delta x_{t-j} + \sum\nolimits_{i=1}^{n} d_{iy} \Delta z_{t-j} + \gamma_{1,y} y_{t-j} + \gamma_{2,y} x_{t-j} + \gamma_{3,y} z_{t-j} + v_{1t} \tag{2a}$$

$$\Delta x_t = \alpha_{0x} + \sum_{t=1}^{n} b_{tx}\Delta y_{t-j} + \sum_{i=1}^{n} c_{ix}\Delta x_{t-j} + \sum_{i=1}^{n} d_{ix}\Delta z_{t-j} + \gamma_{1,x}y_{t-j} + \gamma_{2,x}x_{t-j} + \gamma_{3,x}z_{t-j} + v_{2t} \tag{2b}$$

$$\Delta z_t = \alpha_{0z} + \sum_{t=1}^{n} b_{tz}\Delta y_{t-j} + \sum_{i=1}^{n} c_{iz}\Delta x_{t-j} + \sum_{i=1}^{n} d_{iz}\Delta z_{t-j} + \gamma_{1,z}y_{t-j} + \gamma_{2,z}x_{t-j} + \gamma_{3,z}z_{t-j} + v_{3it}. \tag{2c}$$

The F-tests are used to test for the existence of long-run relationships. When such relationships are found to exist, the F-tests dictate which variables should be normalized. The null hypothesis for testing the "nonexistence" of the first "long-run relationship" is as follows:

$$H_0 : \gamma_{1y} = \gamma_{2y} = \gamma_{3y} = 0 \qquad \textit{the test} \qquad F_y(y/x,z) \qquad \textit{for} \qquad (2a)$$
$$H_0 : \gamma_{1x} = \gamma_{2x} = \gamma_{3x} = 0 \qquad \textit{the test} \qquad F_x(x/y,z) \qquad \textit{for} \qquad (2b)$$
$$H_0 : \gamma_{1z} = \gamma_{2z} = \gamma_{3z} = 0 \qquad \textit{the test} \qquad F_z(z/y,x) \qquad \textit{for} \qquad (2c)$$

The F-test has a non-standard distribution, which depends upon the following: (a) whether variables included in the ARDL model are I(0) or I(1), (b) the number of regressors, and (c) whether the ARDL model contains an intercept and/or a trend. Two sets of critical values reported in M. Pesaran and B. Pesaran provide critical value bounds for all classifications of the regressors into purely I(l), purely I(0), or mutually cointegrated.[19] Next, the F-statistic computed in the second step is compared with the upper and lower 90, 95, or 99 percent critical value bounds (FU and FL). As a result, three cases may emerge. If F > FU, then $\gamma_1 = \gamma_2 = \gamma_3 = 0$ is rejected; hence, it can be concluded that there is a long-term relationship between y and the vector of the x values. However, if F < FL, then $\gamma_1 = \gamma_2 = \gamma_3 = 0$ cannot be rejected, and it is concluded that a long-run relationship does not exist. Finally, if FL < F < FU, the inference is regarded as inconclusive, and the order of integration of the underlying variables must be investigated more deeply.

Once a long-run relationship has been established, a subsequent two-step procedure to estimate the model is carried out in the second stage. First, the orders of the lags in the ARDL model are selected using appropriate lag selection criteria, such as the Schwarz Bayesian Criteria (SBC). Second, the selected model is estimated by the ordinary least squares technique. Equation (1), shown earlier, is estimated using the following ARDL (m, n, p) model:

$$lnq_{it} = \beta_0 + \sum_{p=1}^{m} \beta_1 lnq_{it-p} + \sum_{p=0}^{n} \beta_2 lny_{t-p} + \sum_{p=0}^{p} \beta_3 lnp_{it-p} + u_t \tag{3}$$

M. Pesaran and Y. Shin demonstrate for the ARDL model that the SBC method is superior with respect to the Akaike Information Criterion (AIC) method for this reason; therefore, we used the SBC in the lag selection.[20] When using annual data,

M. Pesaran and Y. Shin recommend choosing a maximum of two lags and, proceeding with analysis, ARDL lags will be selected that minimize the SBC.[21]

In the presence of cointegration, short-run elasticities also can be derived by constructing an error-correction model of the following form:

$$\Delta lnq_{it} = \alpha_0 + \sum_{i=1}^{k=4} \alpha_1 \Delta lnq_{it-k} + \sum_{i=0}^{k=4} \alpha_2 \Delta lny_{it-k} + \sum_{i=0}^{k=k} \alpha_3 \Delta lnp_{it-1} + \lambda ECM_{it-1} + e_i \tag{4}$$

where ECM_{it-1} is the error-correction term, defined as

$$ECM_{it} = q_{it} - \beta_0 - \sum_{p=1}^{m} \beta_1 q_{it-p} - \sum_{p=0}^{n} \beta_2 y_{it-p} - \sum_{p=0}^{p} \beta_3 p_{it-p} \tag{5}$$

Here, Δ is the first difference operator, α's are the coefficients relating to the short-run dynamics of the model's convergence to equilibrium, and λ measures the speed of adjustment.

Empirical Results

In the first step of estimating equation (3), equations (2a) to (2c) are estimated to examine the long-run relationship. Because the observations are annual, for the maximum order of lags in the ARDL we choose an order of two and use the SBC to select the appropriate lags. The estimation is conducted for the years 1980 to 2010. The calculated F-statistics for all of the four oil products, gasoline kerosine, diesel, and fuel oil, are reported in table 2.

For gasoline, kerosine, and diesel, the F-values are higher than the upper bound critical value of 5.5018 at the 5-percent level and 4.5458 at the 1-percent level. The above results imply that the null hypothesis of no cointegration cannot be accepted for gasoline, kerosine, and diesel, which indicates that there is, indeed, a cointegration relationship among the variables in equations (2a) and (2b). For fuel oil, we cannot reject the null hypothesis of no cointegration at the levels of 5 percent and 1 percent. Therefore, we will proceed with the estimation for the long-run and short-run relationship for gasoline, diesel, and kerosine only.

The empirical results of the long-run gasoline, kerosine, diesel, and total product demand models are presented in equations (6) through (9). All of the variables appear with the correct sign. Clearly, the income is influential in determining the consumption of all products (gasoline, kerosine, and diesel). The magnitudes of the estimated income elasticities vary from one product to another with gasoline consumption recording the highest value (1.88), followed by diesel (1.40), and lastly kerosine (0.91). Consumption, on the other hand, reacts negatively to an increase in price in all estimated equations. The outcomes also show

Table 2
F-STATISTICS FOR COINTEGRATION RELATIONSHIP

Oil Product	F-Value	Critical Value Bounds of the F-Statistics with Intercept and No Trend (k = 2) 90 Percent I(0)	90 Percent I(1)	95 Percent I(0)	95 Percent I(1)
Gasoline	10.7395				
Kerosine	6.7994	3.5141	4.5458	4.3592	5.5018
Diesel	5.4933				
Fuel oil	3.4570				
Total products	18.3693	4.3323	5.1720	5.4830	6.4727

Source: Critical value bounds are from M. H. Pesaran and B. Pesaran, *Microfit 5.0* (Oxford: Oxford University Press, 2010).

that, with a 1-percent increase in price, consumption would fall by 0.07 percent for gasoline, 0.17 percent for kerosine, and 0.06 percent for diesel. The absence of reliable public transport could be an explanation for the low elasticity estimates for gasoline and diesel. It is worth noting that the equation for the demand for kerosine includes a dummy variable for the Gulf War of 1991:[22]

$$lnq_t^{Gasoline} = 0.79 + 1.88\, lny_t - 0.07\, lnp_t + e_t \quad (6)$$

$$t = 0.79[0.559] \quad 6.69[0.000] \; -0.77[0.445]$$

$$lnq_t^{Kerosine} = 6.70 + 0.91 lny_t - 0.17\, lnp_t - 90D + e_t \quad (7)$$

$$t = 5.11[0.000] \quad 3.46[0.002] \; -1.94[0.066] \quad 3.29[0.004]$$

$$lnq_t^{Diesel} = 4.14 + 1.40 lny_t - 0.06\, lnp_t + e_t \quad (8)$$

$$t = 3.17[0.004] \quad 5.74[0.000] \; -0.81[0.422]$$

$$lnq_t^{Total} = 4.01 + 1.56 lny_t + e_t \quad (9)$$

$$t = 5.58[0.000] \quad 13.48[0.000] \; -0.81[0.422]$$

Since the price is published for each product and no average price was calculated for the total, we will use the income only. These results imply that a 1-percent increase in income will lead to a 1.56-percent increase in total products consumption.

Using long-run coefficient estimates from equations (6), (7), (8), and (9), we form the error-correction term *ECM*. After replacing the lagged level variables with ECM_{t-1}, we re-estimate the model at the same optimum lags used on the cointegration test. From tables 3 and 4, it is evident that the significantly negative

coefficient obtained for the lagged error-correction term supports the adjustment toward equilibrium. The speed of the adjustment itself, which is 26 percent for gasoline, 52 percent for kerosine, 30 percent for diesel, and 31 percent for total products, indicates a moderate rate of convergence to equilibrium for gasoline, diesel, and total products, and a high rate of convergence for kerosine. The larger the error-correction coefficient, the faster the economy returns to its equilibrium level after being shocked. The tables also show the results of the three other diagnostic tests. The Lagrange Multiplier (LM) test statistic for the presence of autocorrelation, the Ramsey's RESET statistic tests for functional specification, and a statistic to test for the normality of the residuals also are included. For all three of the statistics, the p-values are higher than the level of significance of 5 percent for Lagrange multipliers, which means that we have a correctly specified model that is autocorrelation-free. For the other tests only diesel has normally distributed residuals. Lastly, the CUSUM and CUSUMSQ tests were applied to the residuals of the estimated error-correction model to test for the stability of both the short-run and long-run coefficient estimates. The CUSUM tests reveal that the estimated coefficients are stable because neither statistic crosses the critical values represented by the two straight lines.

The diagnostic tests and the stability tests indicate that the models are good and can be used for forecasting. Hence, in the next section, we will use the model for forecasting for the log of the level of consumption per capita for gasoline and fuel oil, and we will transform the logarithm to the value of consumption per capita and, later, to the aggregate consumption.

Forecasting

The objective of the final section is to forecast demand for the three oil products (gasoline, kerosine, and diesel). In doing so, assumptions regarding the real GDP for the years 2011 to 2016 were obtained from the International Monetary Fund's *2011 World Economic Outlook*.[23] The error-correction model is used in forecasting the level of consumption, which is conditioned by the current and past changes in real income and price. First we turn our attention to the results of the dynamic forecasts for the level of the log of consumption per capita of gasoline based on 29 observations from 1982 to 2010 (table 5). In the dynamic forecasts presented in table 5, the ARDL (1,1,0) model was selected using the Schwarz Bayesian Criterion with the dependent variable being the log of the consumption of gasoline with a lag of 2. As seen in table 5, the consumption of gasoline will experience a steep increase from the year 2011 onwards to reach a level of 631,782 b/d in 2016, which amounts to an average increase of 7.16 percent per year.

Next, we look at the dynamic forecasts for the level of the log for kerosine consumption (table 6). This is based upon 29 observations from 1982 to 2010 and

Table 3
ERROR CORRECTION REPRESENTATION FOR THE SELECTED AUTOREGRESSIVE DISTRIBUTED LAG (1,0,0) MODEL BASED ON THE SCHWARZ BAYESIAN CRITERION FOR GASOLINE, KEROSINE, AND DIESEL

	Gasoline		Kerosine		Diesel	
	Coefficient	**T-Value**	**Coefficient**	**T-Value**	**Coefficient**	**T-Value**
Intercept	–0.002	–.13[.894]	0.24	3.98[.001]	0.002	0.19[.850]
$*\Delta l_{t-1}$	–0.10	–.78[.443]			0.20	1.40[.173]
Δly_t	0.02	.11[.910]	0.62	2.53[.019]	0.39	2.12[.044]
Δly_{t-1}			–0.72	–3.10[.005]		
Δlp_t	–.006	–.26[.795]	–0.03	–.64[.530]	–0.08	–3.10[.005]
D			–.25	–4.2[.000]		
ECM_{t-1}	–.26	–5.10[.000]	–0.52	–8.89[.000]	–0.30	–4.81[.000]
	$\bar{R}^2 = .64$		$\bar{R}^2 = .80$		$\bar{R}^2 = .63$	
	$F_{4,24} = 13.78$ [.000]		$F_{5,2} = 23.62$ [.000]		$F_{3,25} = 12.93$[.001]	
	DW = 2.32		DW = 1.67		DW = 2.13	
	$dh = 1.18$[.246]				$dh = .557$[.577]	
	$LM = \chi_1^2 = 3.18$[0.079]		$LM = \chi_1^2 = 0.72$[0.396]		$LM = \chi_1^2 = 0.537$[0.464]	
	$RESET = \chi_1^2 =$ 6.74[0.009]		$RESET = \chi_1^2 =$ 11.57[0.001]		$RESET = \chi_1^2 =$ 3.10[0.078]	
	$Normality = \chi_2^2 =$ 17.71[.000]		$Normality = \chi_2^2 =$ 18.33[.000]		$Normality = \chi_2^2 =$ 4.54[.108]	

Table 4
ERROR CORRECTION REPRESENTATION FOR THE SELECTED AUTOREGRESSIVE DISTRIBUTED LAG (1,2) MODEL BASED ON THE SCHWARZ BAYESIAN CRITERION FOR TOTAL PRODUCTS

	Total Products	
	Coefficient	**T-Value**
Intercept		
$*\Delta l_{t-1}$	–.038	–.33 [.737]
Δly_t	.23	1.66 [.108]
Δly_{t-1}	–.42	–2.71 [.012]
ECM_{t-1}	–.31	–8.25 [.000]
	$\bar{R}^2 = .67$	
	$F_{3,25} = 16.12$ [.000]	
	DW = 2.31	
	$dh = –.134$[.727]	
	$LM = \chi_1^2 = 0.27$[0.603]	
	$RESET = \chi_1^2 = 0.24$[0.627]	
	$Normality = \chi_2^2 = 1.35$[.508]	

Table 5
DYANIMC FORECASTS FOR THE LEVEL OF THE LOG OF CONSUMPTION PER CAPITA OF GASOLINE[a]

Year	**Prediction of Log**	**Prediction Value of Aggregate Consumption of Gasoline (in barrels per day)**
2011	13.0107	447,172.63
2012	13.0811	479,788.18
2013	13.1480	512,984.03
2014	13.2136	547,764.10
2015	13.2832	587,246.53
2016	13.3563	631,782.20

[a] Based upon 29 observations from 1982 to 2010 with the autoregressive distributed lag (1,1,0) model selected using the Schwarz Bayesian Criterion. The dependent variable in this model is the log of the consumption of gasoline, included with a lag of 2.

Table 6
DYANIMC FORECASTS FOR THE LEVEL OF THE LOG OF CONSUMPTION OF KEROSINE[a]

Year	**Prediction of Log**	**Prediction Value of Aggregate Consumption of Kerosine (in barrels per day)**
2011	11.0986	66,078.59
2012	11.1074	66,662.64
2013	11.1433	69,099.31
2014	11.1808	71,739.73
2015	11.2135	74,124.40
2016	11.2485	76,764.69

[a] Based upon 29 observations from 1982 to 2010 with the autoregressive distributed lag (1,2,0,2) model selected using the Schwarz Bayesian Criterion. The dependent variable in this model is the log of the consumption of kerosine, included with a lag of 2.

employs the ARDL model (1,2,0,2) selected using the Schwarz Bayesian Criterion. The dependent variable in the ARDL model is the log of consumption of kerosine, included with a lag of 2. Table 6 shows that the consumption of kerosine increases by an average of 3.05 percent a year, reaching a level of 76,764.7 b/d in 2016.

Table 7 provides us with the dynamic forecast for the level of the log of diesel consumption. Again, this is based on 29 observations from 1982 to 2010 and employs an ARDL model (2,1,0) selected using the Schwarz Bayesian Criterion. The dependent variable in the ARDL model is the log of the consumption of diesel, included with a lag of 2. The table shows that the consumption of diesel continues to increase and reaches 853,840.8 b/d in 2016.

Table 7
DYANIMC FORECASTS FOR THE LEVEL OF THE LOG OF CONSUMPTION OF DIESEL[a]

Year	Prediction of Log	Prediction Value of Aggregate Consumption of Diesel (in barrels per day)
2011	13.3868	651,348.43
2012	13.4334	682,419.60
2013	13.4838	717,695.02
2014	13.5381	757,743.34
2015	13.5960	802,911.68
2016	13.6575	853,840.77

[a] Based upon 29 observations from 1982 to 2010 with the autoregressive distributed lag (2,1,0) model selected using the Schwarz Bayesian Criterion. The dependent variable in this model is the log of the consumption of diesel, included with a lag of 2.

Table 8
DYANIMC FORECASTS FOR THE LEVEL OF THE LOG OF TOTAL PRODUCTS CONSUMPTION[a]

Year	Prediction of Log	Prediction Value of Total Products Consumption (in barrels per day)
2011	14.5621	2,109,792.16
2012	14.5973	2,185,379.38
2013	14.6539	2,312,639.34
2014	14.7102	2,446,575.87
2015	14.7664	2,588,010.52
2016	14.8274	2,750,793.57

[a] Based upon 29 observations from 1982 to 2010 with the autoregressive distributed lag (1,2) model selected using the Schwarz Bayesian Criterion. The dependent variable in this model is the log of the total products consumption with a lag of 1.

Last, we examine the dynamic forecast for the level of the log of total products consumption. Table 8 provides us with the forecast results, based on the same number of observations over the same period, employing an ARDL model (1,2) selected using the Schwarz Bayesian Criterion. The dependent variable in the ARDL model is the log of consumption of total products with a lag of 1. We see a similar upward consumption trend that pushes total products consumption to around 2.750 million b/d by the year 2016. Greater details on the dynamic forecasts and summary statistics for the residuals and forecast errors can be found in the appendix tables.

Conclusion

This paper investigates the long-run relationship between the consumption of refined products, per-capita income, and domestic prices for Saudi Arabia over the period of 1980 to 2010 using the recently developed autoregressive distributed lag (ARDL) approach, also known as a "bounds testing" procedure. It is found that a long-running relationship exists between gasoline and fuel oil. The results of the analysis show that gasoline, kerosine, and diesel demand are likely to increase significantly for a given increase in the gross domestic product. Gasoline, kerosine, and diesel demand are relatively inelastic to price changes over the long and short run. The error-correction model shows that gasoline, kerosine, and diesel demand adjust to the long-run equilibrium at a relatively moderate rate. Finally, the ARDL model is used to forecast petroleum product consumption for the years 2011 through 2016.

These findings indicate that policy makers should raise the price of refined products to influence consumption. The subsidized product prices affect the consumption of said products. If Saudi Arabia is to continue such pricing policies, it should build more refineries to meet the increasing consumption.

NOTES

[1]U.S. Energy Information Administration (EIA), *Saudi Arabia Country Analysis Briefing* (Washington, D.C.: EIA, 2010), available at www.eia.doe.gov.

[2]G. Hondroyiannis, S. Lolos, and E. Papapetrou, "Energy Consumption and Economic Growth: Assessing the Evidence from Greece," *Energy Economics*, vol. 24, no. 4 (2002), pp. 319–36.

[3]U. Soytas and R. Sari, "Energy Consumption and GDP: Causality Relationship in G7 Countries and Emerging Markets," *Energy Economics*, vol. 25, no. 1 (2003), pp. 33–7.

[4]Nicholas M. Odhiambo, "Energy Consumption and Economic Growth Nexus in Tanzania: An ARDL Bounds Testing Approach," *Energy Policy*, vol. 37, no. 2 (2009), pp. 617–22.

[5]P. K. Narayan and R. Smyth, "A Panel Cointegration Analysis of the Demand for Oil in the Middle East," *Energy Policy*, vol. 35, no. 12 (2007), pp. 6258–265.

[6]M. N. Eltony and N. H. Al-Mutairi, "Demand for Gasoline in Kuwait—An Empirical Analysis Using Cointegration Techniques," *Energy Economics*, vol. 17, no. 3 (1995), pp. 249–53.

[7]S. C. Bhattacharyya and A. Blake, "Domestic Demand for Petroleum Products in MENA Countries," *Energy Policy*, vol. 37, no. 4 (2009), pp. 1552–560.

[8]M. N. Eltony, "Demand for Gasoline in the GCC: An Application of Pooling and Testing Procedures," *Energy Economics*, vol. 18, no. 3 (1996), pp. 203–209, and Y. H. Mohammad and M. N. Eltony, "The Demand for Natural Gas in the Gulf Cooperation Council (GCC) States," *Middle East Business and Economic Review*, vol. 8 (1996), pp. 41–8.

[9]Abdul-razak F. Al-Faris, "Demand for Oil Products in the GCC Countries," *Energy Policy*, vol. 25, no 1 (1997), pp. 55–61.

[10]Abdul-razak F. Al-Faris, "Income and Price Elasticity of Gasoline Demand in the Organization of Arab Petroleum Exporting Countries," *Journal of Energy and Development*, vol. 17, no. 2 (spring 1992), pp. 209–23.

[11]Mohammed Belhaj, "Vehicle and Fuel Demand in Morocco," *Energy Policy*, vol. 30, no. 13 (2002), pp. 1163–171.

[12]M. L. Polemis, "Empirical Assessment of the Determinants of Road Energy Demand in Greece," *Energy Econ*omics, vol. 28, no. 3 (2006), pp. 385–403.

[13]R. Engle and C. W. Granger, "Cointegration and Error-Correction: Representation Estimation and Testing" *Econometrica*, vol. 55, no. 2 (1987), pp. 251–76; S. Johansen and K. Jueslius, "Maximum Likelihood Estimation and Inference on Cointegration with Application to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, vol. 52, no. 2 (1990), pp. 169–209; S. Johansen, "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control*, vol. 12, nos. 2–3 (1988), pp. 231–54; and S. Johansen, "Estimating and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," *Econometrica*, vol. 59, no. 6 (1991), pp. 1551–589.

[14]P. C. B. Phillips and B. E. Hansen, "Statistical Inference with I(1) Processes," *Review of Economic Studies*, vol. 57 (1990), pp. 99–124; Y. Shin, "A Residual Based Test of the Null of Cointegration Against the Alternative of No Cointegration," *Econometric Theory*, vol. 10, no. 1 (1994), pp. 91–115; and J. H. Stock and M. W. Watson, "Testing for Common Trends," *Journal of the American Statistical Association*, vol. 83, no. 404 (1988), pp. 1097–1107.

[15]M. H. Pesaran, Y. Shin, and R. Smith, "Testing the Existence of a Long-Run Relationship," DAE Working Paper Series no. 9622, Department of Applied Economics, University of Cambridge, United Kingdom, 1996; M. H. Pesaran, Y. Shin, and R. Smith,"Bounds Testing Approaches to the Analysis of Level Relationships," *Journal of Applied Econometrics*, vol. 16, no. 3 (2001), pp. 289–326; and C. L. Cavanagh, G. Elliott, and J. H. Stock, "Inference in Models with Nearly Integrated Regressors," *Econometric Theory*, vol. 11, no. 5 (1995), pp. 1131–114.

[16]M. H. Pesaran and Y. Shin, "Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis," DAE Working Paper Series no. 9514, Department of Applied Economics, University of Cambridge, United Kingdom, 1995; M. H. Pesaran, Y. Shin, and R. Smith, "Testing the Existence of a Long-Run Relationship;" M. H. Pesaran, "The Role of Economic Theory in Modeling the Long-Run," *Economic Journal*, vol. 107 (January 1997), pp. 178–91; M. H. Pesaran and Y. Shin, "An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis," in *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium,* ed. S. Storm (Cambridge, United Kingdom: Cambridge University Press, 1999); and M. H. Pesaran, Y. Shin, and R. Smith, "Bounds Testing Approaches to the Analysis of Level Relationships."

[17]M. H. Pesaran, Y. Shin, and R. Smith, "Bounds Testing Approaches to the Analysis of Level Relationships," p. 1.

[18]Ibid.

[19]M. H. Pesaran and B. Pesaran, *Microfit 5.0* (Oxford: Oxford University Press, 2010), and M. H. Pesaran, Y. Shin, and R. Smith, "Bounds Testing Approaches to the Analysis of Level Relationships."

[20]M. H. Pesaran and Y. Shin, "An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis."

[21]Ibid.

[22]Today (2012), the single largest use of kerosine is jet fuel, which is basically kerosine. As the Gulf War of 1991 depended on airplane fighting, the use of jet fuel increased dramatically between January 1991 to end of February 1991.

[23]International Monetary Fund (IMF), *2011 World Economic Outlook* (Washington, D.C.: IMF, 2011).

Appendix 1

EVALUATION OF THE FORECASTING FOR GASOLINE, KEROSINE, AND DIESEL

Table A1
DYNAMIC FORECASTS FOR THE LEVEL OF LOG(GASOLINE) WITH AUTOREGRESSIVE DISTRIBUTED LAG MODEL (1,1,0)

Year	**Prediction**	**Actual**	**Error**
2008	12.8162	12.8327	.016524
2009	12.8791	12.8953	.016143
2010	12.9272	12.9611	.033903

[a] Based upon 26 observations from 1982 to 2007 with this model selected using the Schwarz Bayesian Criterion.

Table A2
SUMMARY STATISTICS FOR RESIDUALS AND FORECAST ERRORS FOR LOG(GASOLINE)

	Estimation Period to 2007	**Forecast Period 2008 to 2010**
Mean	–.0000	–.13907
Mean absolute	.020310	.13907
Mean sum squares	.8592E-3	.024928
Root mean sum squares	.029312	.15789

Table A3
DYNAMIC FORECASTS FOR THE LEVEL OF LOG(KEROSINE) WITH AUTOREGRESSIVE DISTRIBUTED LAG MODEL (1,2,0,2)

Year	**Prediction**	**Actual**	**Error**
2008	11.0122	11.0339	.021720
2009	11.0369	11.0590	.022100
2010	11.0790	11.0601	–.018885

[a] Based upon 26 observations from 1982 to 2007 with this model selected using the Schwarz Bayesian Criterion.

Appendix 1 (continued)

Table A4
SUMMARY STATISTICS FOR RESIDUALS AND FORECAST ERRORS FOR LOG(KEROSINE)

	Estimation Period to 2007	**Forecast Period 2008 to 2010**
Mean	–.0000	.0083115
Mean absolute	.024160	.020902
Mean sum squares	.0010183	.4389E-3
Root mean sum squares	.031911	.020951

Table A5
DYNAMIC FORECASTS FOR THE LEVEL OF LOG(DIESEL) WITH AUTOREGRESSIVE DISTRIBUTED LAG MODEL (1,2,0,2)

Year	**Prediction**	**Actual**	**Error**
2008	13.2280	13.2836	.055596
2009	13.2684	13.3126	.044220
2010	13.2880	13.3513	.063338

[a] Based upon 26 observations from 1982 to 2007 with this model selected using the Schwarz Bayesian Criterion.

Table A6
SUMMARY STATISTICS FOR RESIDUALS AND FORECAST ERRORS FOR LOG(DIESEL)

	Estimation Period to 2007	**Forecast Period 2008 to 2010**
Mean	–.0000	.054385
Mean absolute	.022284	.054385
Mean sum squares	.8582E-3	.0030193
Root mean sum squares	.029294	.054948