Journal of Engineering and Applied Sciences 15 (6): 1579-1588, 2020
ISSN: 1816-949X

South African Petrol Price and Consumption Cointegration Analysis

Matthew Femi Olayiwola and Solly Matshonisa Seeletse
Department of Statistics and Operations Research, Sefako Makgatho Health Sciences University,
1 Molotlegi Street, Ga-Rankuwa Township, 0204 Gauteng Province, South Africa

Abstract: In this study, the relationship between the quarterly data of consumption and price of petrol from 2005-2017 is considered. The two series are found to be integrated of the same order I(1) based on the ADF test. Though both variables do not have long-run equilibrium relationship based on Engle-Granger and Johansen tests but there exists a unidirectional causality from consumption to the retail price of petrol. The VAR Models estimated are found to be significant and stable and without any defects (i.e., no heteroskedasticity, no serial correlation and residuals of these VAR Models are found to be normally distributed).

Key words: VAR, augmented Dickey-Fuller, cointegration, significant, correlation

INTRODUCTION

Petrol is the quintessential commodity in the modern industrial economy. Although, the industrial revolution was initially powered by coal, since, the first commercial petrol well was drilled in Pennsylvania in 1859 petrol has gained increasing prominence in terms of its share of the world's primary energy supply. It now accounts for over 35%, the largest share. As an energy source petrol is used for electricity generation, heating and most importantly as a liquid fuel for transportation. The world's transport systems (including ships, trains, airplanes and road transport) depend on petrol for some 90% of their energy (Leggett, 2005). Consequently, the tourism sector in most countries is also highly reliant on petrol. Industrial agriculture depends heavily on petrol and natural gas for the production of fertilizers, herbicides and pesticides as well as to power mechanised farm machinery and transport products to markets.

The amount of fuel available is one of the influences of consumption and price. When an item is abundant, then the price tends to be cheaper and consumptions can also be high because of affordability. South Africa Yearbook (2008/09) reports that South Africa has limited oil reserves and that almost 95% of South Africa's crude oil requirements are imported from the Middle East and Africa. Thus, with only 5% being produced locally, there is an indication of scarcity and expectations of low consumption from consumers. Some several studies (Girma and Paulson, 1999; Gjolberg and Johnsen, 1999; Serlitis, 1994) have investigated the relationship between the prices of oil and refinery products. These studies have established the existence of long-run price relationships between crude oil and refined products. Insights to these relationships convey valuable information for forecasting in the oil industry. Interest has emerged that relationships be investigated between consumptions and prices of fuels. Recent several studies (Girma and Paulson, 1999; Gjolberg and Johnsen, 1999; Serlitis, 1994) have investigated the relationship between the prices of petrol and refinery products. These studies have established the existence of long-run price relationships between crude Petrol and refined products. Insights to these relationships convey valuable information for forecasting in the petrol industry. In this study, interest is to represent cointegration long term relationship of nonstationary petrol prices and consumption rates in South Africa using statistical methods.

Cointegration: The ADF test is used to test the null hypothesis that the series has a unit root against the alternative hypothesis of no unit root. This test is based on simple regression of series Y_t on series Y_{t-1} (that is the one period lagged value of Y_t) and check if the estimate of θ, the coefficient of Y_{t-1} as in Eq. 1 is equal to 1 or not:

$$Y_t = \theta Y_{t-1} + e_t \quad (1)$$

where e_t denotes a serially uncorrected white noise error term with a mean of zero and a constant variance. Reparametrising 1 from both sides becomes:

$$\Delta Y_t = \delta Y_{t-1} + e_t \quad (2)$$

where δ = (-1) and Δ is the first difference operator. In this study, we will estimate Eq. 2 and test for the null hypothesis of $\delta = 0$ against the alternative of $\delta \neq 0$. If $\delta = 0$, then $\theta = 1$ which implies that the series in question has a

Corresponding Author: Matthew Femi Olayiwola, Department of Statistics and Operations Research, Sefako Makgatho Health Sciences University, 1 Molotlegi Street, Ga-Rankuwa Township, 0204 Gauteng Province, South Africa

unit root (the series is nonstationary). According to Erdogdu (2007), it is important to note that the above null hypothesis, the t-value of the estimated coefficient of Y_{t-1} does not follow the t-distribution even if the sample size is large. This, implies that, this t-value does not have an asymptotic normal distribution. Thus, the decision rule now based on the Dickey-Fuller (DF) critical values of the τ (tau) statistic. But the DF test is based on an assumption that the residualsare not correlated.

However, in practice, the residuals in the DF test usually show evidence of serial correlation. In order to solve the resulting problem of serial correlation of the residuals, Dickey and Fuller came up with a test known as the Augmented Dickey-Fuller (ADF) test. In this test, the lags of the first difference are included in the regression equation, so as to make the residuals or error termswhite noise. Its regression equation is given below:

$$\Delta Y_t = \delta Y_{t-1}+\alpha_i \sum\nolimits_{i=1}^{m} \Delta Y_{t-1}+e_t \tag{3}$$

Including intercept and time, t, in Eq. 4 now yields:

$$\Delta Y_t = \beta_1+\beta_2 t+\delta Y_{t-1}+\alpha_i \sum\nolimits_{i=1}^{m} \Delta Y_{t-1}+e_t \tag{4}$$

The ADF unit root testing procedure uses this model:

$$\Delta y_t = \alpha+\beta t+\gamma Y_{yt-1}+\sum\nolimits_{j=1}^{\rho} \delta_j \Delta y_{t-j}+e_{it} \tag{5}$$

Where:

α	:	The intercept (a constant)
β	:	The coefficient time
t	:	The coefficient of y_{t-1}
ρ	:	The lag order of the autoregressive process
Δ_{yt}	:	The first difference of y_t
y_{t-1}	:	The one time period lag values
$y_t\Delta y_{t-j}$	:	The changes in lagged values
e_{it}	:	The white noise

In ADF Model, γ is now the parameter of interest. If $\gamma = 0$, then, the series y_t has unit root and therefore, it is integrated of order $d = 1$.

Choice of the appropriate number of lags has been a problem in the field of econometrics. The following six criteria; Langrange Multiplier (LM) test, Schwarz Information Criterion (SIC), the Hannan-Quinn Criterion (HQC), the general to specific sequential Likelihood Ratio test (SLR), Akaike Informatiion Criteria (AIC) and a small sample correction to test (SLR) were suggested for the selection of lag order in 2005 by Ivanov, Kilian *et al*. However, in this study, the number of lags is chosen based on SIC as it has been argued by many econometricians that the SIC should be applied to small sample and AIC to large sample. This study adopts the ADF test which is the most notable and commonly used among many unit root tests.

The VAR developed by Sims (1980) is regarded as an improvised multivariate model where each variable is regressed on its own lags and the lags of other variables in a finite-order system. And the objective of this approach is study the system dynamic response to innovations the system having to depend on restrictions embedded in the structural models. The VAR can thus be represented as below following the representation of Bernake and Blinder (1992):

$$\beta(y_t) = \theta(L)y_t+\delta(L)x_t+u_t \tag{6}$$

Where:

y_t	:	A (k×1) vector of endogenous variables
x_t	:	A q vector of exogenous variables
β, θ and δ	:	Matrices of the estimated coefficients
L	:	The lag operator
I	:	The lag order
u_t	:	The vector of innovations or shocks which are independently and identically distributed

The reduced form of Eq. 1 becomes:

$$y_t = \alpha(L)y_t+\varepsilon_t \tag{7}$$

where $(L) = \beta^{-1}\theta(L) = \alpha_1 L+\alpha_2 L^2+, ..., +\alpha_i L^i$, $\varepsilon_t = \beta^{-1}u_t$. And this can be written in the form of MA as:

$$y_t = \frac{1}{I-\alpha(L)}\varepsilon_t = K(L)\varepsilon_t \tag{8}$$

The impulse response functions and variance decomposition can be estimated for Eq. 8 when the estimated VAR is either stationary or not. Vector error correction model can be estimated if all the variables which are integrated of the same order are cointegrated and this can be used to estimate the impulse response functions and variance decomposition. Based on Eq. 4 the following three cases are discussed by Cochrane (2005):

$$\Delta y_t = \alpha(L)y_{t-1}-\sum\nolimits_{j=1}^{\infty} \alpha^* \Delta y_{t-j}+u_t \tag{9}$$

Case 1: We run a normal VAR in level if α(L) is full rank and any linear combination of y_{t-1} is stationary.

Case 2: We run VECM using Eq. 5 when the rank of α(L) lies between 0 and full rank and there exist some linear combinations of y_t that are stationary:

$$\Delta y_t = \alpha\beta' y_{t-1} - \sum_{j=1}^{\infty} \alpha^* \Delta y_{t-j} + u_t \qquad (10)$$

Case 3: We can run the normal VAR in first difference if the rank of α(L) is zero and Δy_t is stationary with no cointegration.

Lack of cointegration among variables leads to the estimation of unrestricted Vector Autoregressive Model (VAR). The most primary thing to consider before the estimation of VAR is the correct number of lag to use in the model. This is considered very important based on the study undertaken by Braun and Mittnik (1993) when they showed that the impulse response functions and variance decompositions of VAR estimates with different lag length as compared to the true lag length are inconsistent. It was indicated by Lutkepohl (1993) that autocorrelated errors are generated when the VAR lag length is underfitted while increase in the mean square forecast errors sets in as a results of overfitting the VAR lag length. Proper inference about the cointegration vector and rank is affected by the VAR order selection as indicated by Johansen (1991) and Gonzalo (1994). VAR models can be estimated either by using symmetric lags or asymmetric lags. By symmetric lags we mean the use of same lags for each variable in the model while asymmetric is the opposite. Interestingly, based on economic theory there is no compelling reason on whether to use symmetric or asymmetric lags. In this study, our choice of lag based on the lag number mostly chosen by the information criteria such as the AIC, LR, HQ and SIC.

MATERIALS AND METHODS

In South Africa, the official data collectors of Statistics for petrol prices and consumption are Statistics South Africa (Stats SA) and the Department of Energy. Also, the study can only depend on data collected over the past years since they are time series. Thus, secondary data on average monthly Retail Fuel Price (RFP) and quarterly Fuel Sales Volumes (FSV) were collected from the record of Department of Energy, Pretoria Head Office, South Africa for the period of 2000-2017 and 2005-2017, respectively. The accuracy of these data was verified using the data sets from Stats SA.

The two variables are pre-tested to determine their respective order of integration using augmented Dickey-Fuller test. After they are found to be integrated of the same order Johansen cointegration test was carried out to determine the existence of cointegrating relationship among the variables. VAR lag order selection method was used to determine the appropriate number of lag to use based on different criteria information. Causality among the variables was determined using Granger-causality test. Finally, the Impulse Response Function (IRF) and variance decomposition were estimated to further establish the relationship between petrol price and consumption. All analyses are carried out using Eviews 10.

RESULTS AND DISCUSSION

Graphical representation of the series: Figure 1 is the time series plot of both series. There is no cointegarting relationship between consumption and its retail fuel price. As shown in Fig. 1, both series seem to meander without any tendency to come together. However, we cannot conclusively say that there is no cointegration between the two variables until further analyses are carried out.

Figure 2 shows the scatter plot of the two variables. Since both series decline over time, there appears to be a negative relationship between the two.

Order of integration: The ADF test is used for the unit root testing of the two variables. And their p-values are reported in Table 1.

The results in Table 1 show that, the level series of each variable is not stationary while the first difference series of each variable is stationary. This implies that petrol price and consumption are integrated of the same order one. The VAR lag order selection criteria was used in determining the appropriate optimal lag to use in this study. Hannan-Quinin information criterion (HQ), sequential modified Likelihood Ratio test (LR) and Schwarz Information Criterion (SIC) indicated 2 lags as

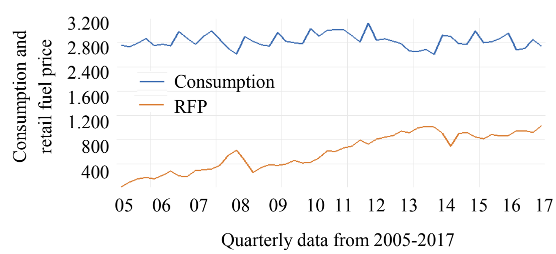

Fig. 1: Time series plot of consumption and retail fuel price

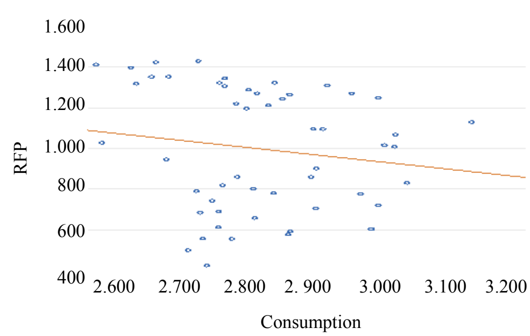

Fig. 2: Scatter plot of consumption and retail fuel price

Table 1: ADF results of level series of consumption of unit root testing

	Price		Consumption	
Series	p-values	Decision	p-values	Decision
Level series	0.6073	Do not reject H_0	0.9446	Do not reject H_0
First differenced series	0.0000	Reject H_0	0.0000	Reject H_0

Appendices II-V

Table 2: Results of trace statistic

Hypothesized No. of CE(s)	Trace statistic	Critical value at 5%	p-values	Decision
None	13.97203	15.49471	0.0837	Do not reject H_0
At most 1	2.395956	3.841466	0.1216	Do not reject H_0

Appendix VI

Table 3: Results of max-eigen statistic

Hypothesized No. of CE(s)	Max-eigen statistic	Critical value at 5%	p-values	Decision
None	11.57608	14.26460	0.1276	Do not reject H_0
At most 1	2.3959561	3.841466	0.1216	Do not reject H_0

Appendix VI

the optimal lag length to use while only Akaike Information Criterion (AIC) suggested 4 lags (see appendix I).

Cointegration test: The Johansen cointegration test becomes necessary on the basis that both consumption and RFP are integrated of order one, I(1). Since, it is established above that the series are integrated of the same order and are I(1).

The results in both Table 2 and 3 indicate that the null hypothesis of no cointegrating equation and at most 1 cointegrating equation are not rejected with both trace and maximum-eigen statistic. Meaning there exists no cointegration relationship among the two variables. In other words consumption and RFP do not have long-run relationship. And this leads to the estimation of unrestricted Vector Autoregressive Model (VAR).

VAR estimation: Lack of cointegration among the two variables necessitates the estimation of the vector autoregressive model. *The vector autoregressive equations with consumption being the dependent variable is given below in Eq. 11:

$$\begin{aligned}\Delta Cons_t &= -4932008-0.625822\Delta Cons_{t-1}-0.364727\Delta Cons_{t-2}- \\ &226206.30\Delta REP_{t-1}+471029.90\Delta REFP_{t-2}\end{aligned} \quad (11)$$

In Eq. 11, the dependent variable, consumption is a function of its lagged values and the lagged values of retail fuel price. The change of RFP for first-order lag has positive effect on the consumption at current period while its second-lag has a positive impact on consumption at the current period but its positive impact is greater than the negative ceteris paribus. For the consumption itself, its one and two-lagged period have negative influence on current period ceteris paribus. The coefficients and their corresponding p-values reported in appendix VIII show that the variables that significantly explain consumption at 5% significance level are the first lagged and second lagged of consumption itself. This model R^2 value shows that 34.29% variations are accounted for by the lagged variables and this model is significant with p-value of 0.0008 (see appendix VIII).

Also, the vector autoregressive equations with Retail Fuel Price (RFP) being the dependent variable is given in Eq. 12 below:

$$\begin{aligned}\Delta RFP_t &= 20.03639-3.84\times10^{-08}\Delta Cons_{t-1}+ \\ &2.36\times10^{-07}\Delta Cons_{t-2}+0.074490\Delta RFP_{t-1}- \\ &0.164305\Delta RFP_{t-2}\end{aligned} \quad (12)$$

In Eq. 12, the dependent variable, RFP is a function of its lagged values and the lagged values of consumption. One-lagged period of consumption is negatively related the current period of RFP while the consumption two-lagged period is positively related to the RFP which is greater than the former ceteris paribus. The change of RFP for first-order lag has positive effect on itself at current period while its second-lag has a negative impact on itself at the current period ceteris paribus. The coefficients and the corresponding p-values of Eq. 12 reported in appendix IX show that two-period of consumption is the only variable that is significant enough to explain retail fuel price at 5% significance level. The R^2 value of Eq. 11 shows that 26.81% variations are accounted for by the lagged variables and this model is significant with p-value of 0.0072 (see appendix IX).

Granger-causality test: Granger-causality test is performed to determine if the two variables Granger-cause each other or not and the results of this test are given in Table 4.

The Granger-causality test results show that, the null hypothesis of retail fuel price does not Granger-cause

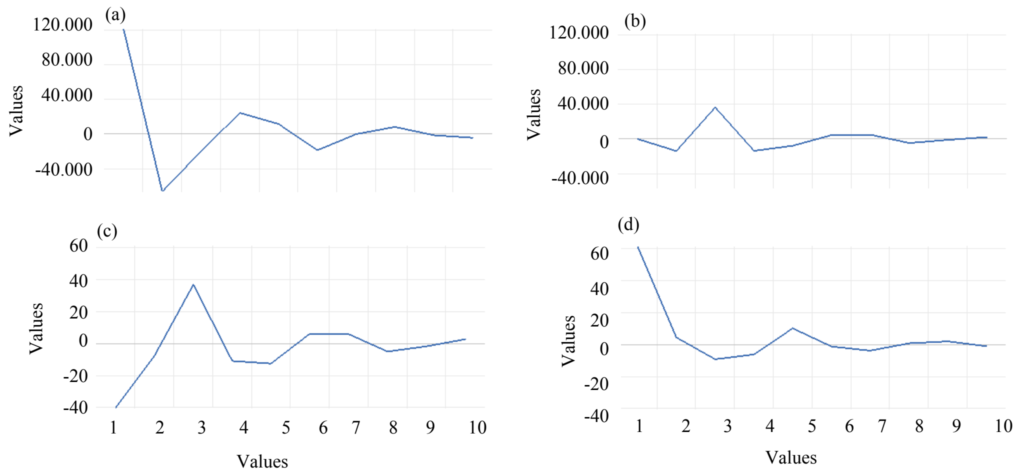

Fig. 3(a-d): Stability graph of retail fuel price model; Response to Cholesky one SD (df adjusted) innovations, (a) Response of D(CONS) to D(CONS), (b) Response of D(CONS) to D(RFP), (c) Response of D(RFP) to D(CONS) and (d) Response of D(RFP) to D(RFP)

Table 4: Results of Pairwise Granger-causality test

Null hypothesis	F-statistic	p-values	Decision
RFP does not Granger cause CONS	0.38942	0.6797	Do not reject H_0
Cons does not Granger cause RFP	11.5387	9×10^{-05}	Reject H_0

Appendix X

consumption is not rejected and the null hypothesis of consumption does not Granger-cause retail fuel price is rejected. This implies that, there is a unidirectional (or one-way) causality from consumption to retail fuel price.

IRF and variance decomposition: The IRF which is an essential tool in empirical causal analysis and policy effectiveness analysis is estimated below in order to explain the reaction of endogenous variable to one of the innovations(or shocks) and describes the evolution of the variable of interest along a specified time horizon after a shock in a given moment. It is estimated with the interest to further assess the tendencies of significant Granger-causality results given above in section 4.5. And variance decomposition is also estimated to determine the quantity of information a variable contributes to the other in each VAR Models above. The graph of the IRF is shown in Fig. 3.

Consumption starts by decreasing and later increases when a shock is received by the retail fuel price, this instability movement continues until period 8 (i.e., quarter 8) then stability is reached as consumption continues to increase. Also, a shock received in consumption has negative and positive impact on the retail fuel price which rises and falls from period one through 8, thereafter stability is reached as the retail fuel price continue rising.

Table 5: Variance decomposition of D(CONS)

Period	SE	D(CONS)	D(RFP)
1	1.20E+08	100.0000	0.000000
2	1.38E+08	98.99327	1.006727
3	1.44E+08	92.66950	7.330502
4	1.47E+08	92.08361	7.916394
5	1.48E+08	91.87740	8.122604
6	1.49E+08	91.91456	8.085436
7	1.49E+08	91.81124	8.188762
8	1.49E+08	91.75299	8.247006
9	1.49E+08	91.74976	8.250240
10	1.49E+08	91.73692	8.263085

Table 6: Variance decomposition of D(RFP)

Period	SE	D(CONS)	D(RFP)
1	73.20581	29.92248	70.07752
2	73.74121	30.55337	69.44663
3	82.99530	43.94872	56.05128
4	83.92814	44.65845	55.34152
5	85.45414	45.19624	54.80376
6	85.68542	45.47406	54.52594
7	85.97605	45.64968	54.35032
8	86.12228	45.82531	54.17469
9	86.16192	45.81964	54.18036
10	86.20979	45.86621	54.13379

Variance decomposition: The results of variance decomposition are shown in Table 5 and its graphs are attached in appendix XI.

In Table 5, the contribution of retail fuel price to consumption increases slightly from 0% to maximum of 8.26% in period 10. In both the short-term and long-term, almost 8.26% forecast error variance in consumption is explained by the retail fuel price while the remaining percentage is explained by consumption itself. This means that, retail fuel price does not have strong influence on consumption. In other words, retail fuel price has strong exogenous impact on consumption in both short-term and long-term.

In Table 6, the contribution of retail fuel price to decreases throughout the ten period and reaches a minimum of 54.13% in the long-run. Right from the short-run period into the future, consumption accounts for almost 45.87% forecast error variance in retail fuel price. In the long-run, consumption is a strong influencer of retail fuel price. In other words, consumption has strong endogenous impact on retail fuel price.

CONCLUSION

The retail fuel price and its consumption are integrated of order one I(I) but they do not have long-run equilibrium relationship. Thus, unrestricted VAR Models are estimated to study the relationship between the two variables. And there exists a one-way Granger-causality among the two variables and this runs from consumption to the retail fuel price. The two VAR Models are homoskedastic, normally distributed do not have serial correlation, significant and stable. It can be seen from the IRF and variance decomposition of the two variables that, the shock to the retail fuel is mainly caused by the consumption that is consumption is seen to have a strong endogenous impact on the retail fuel price. But retail fuel price has a strong exogenous influence on the consumption, meaning its own lagged values have strong impact on itself. Since, the lagged period of consumption significantly impacts the retail fuel price in South Africa, the policy makers are encouraged to focus on this when determining the future price of petrol. Also they need to take into consideration as they plan for future in order to prevent the drastic increase in the retail fuel price of petrol bearing in mind that the consumption of petrol will not drop except in the case of natural disaster such as war, terrorism, famine, earthquake, etc. Otherwise, if this is not prevented, it would lead to increase in the price of almost everything (i.e., cost of living) which may later result into high inflation rate.

APPENDIX

Appendix I: Lag selection criterion; VAR lag order selection criteria; Endogenous variables: CONS RFP; Exogenous variables: C; Date: 11/17/18; Time: 10:21; Sample: 2005Q1 2017Q4; Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1073.342	NA	7.69e+20	53.76709	53.85154	53.79763
1	-1028.623	82.72967	1.00e+20	51.73116	51.98449	51.82275
2	-1018.557	17.61508*	7.43e+19*	51.42787	51.85009*	51.58053*
3	-1015.989	4.238194	8.02e+19	51.49944	52.09055	51.71316
4	-1010.340	8.755360	7.45e+19	51.41701*	52.17700	51.69180
5	-1007.669	3.873566	8.07e+19	51.48344	52.41232	51.81929
6	-1005.699	2.658939	9.11e+19	51.58496	52.68273	51.98188
7	-1004.235	1.830461	1.06e+20	51.71174	52.97840	52.16972
8	-1000.588	4.193918	1.12e+20	51.72939	53.16494	52.24844
9	-997.7181	3.013241	1.25e+20	51.78591	53.39034	52.36602
10	-997.0283	0.655323	1.58e+20	51.95142	53.72474	52.59259
11	-991.8075	4.437717	1.62e+20	51.89037	53.83259	52.59262
12	-987.5495	3.193462	1.79e+20	51.87748	53.98858	52.64078

* 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

Appendix II: ADF results of level series consumption; Null hypothesis: CONS has a unit root; Exogenous: none; Lag length: 2 (Automatic-based on SIC, maxlag = 2)

Augmented Dickey-Fuller test statistic	t-statistic
Test critical values (Level%):	-0.081940
1	-2.613010
5	-1.947665
10	-1.612573

*MacKinnon (1996) one-sided p-values; Augmented Dickey-Fuller test equation; Dependent variable: D(CONS); Method: least squares; Date: 11/28/18; Time: 19:48; Sample (adjusted): 2005Q4 2017Q4; Included observations: 49 after adjustments

Variable	Coefficient	SE	t-statistic	Prob*
CONS(-1)	-0.000511	0.006232	-0.081940	0.9351
D(CONS(-1))	-0.509278	0.135366	-3.762244	0.0005
D(CONS(-2))	-0.402596	0.136706	-2.944975	0.0051
R^2	0.271572	Mean dependent var	-938302.4	
Adjusted R^2	0.239902	SD dependent var	1.42E+08	
SE of regression	1.24E+08	Akaike info criterion	40.16865	
Sum squared resid	7.07E+17	Schwarz criterion	40.28447	
Log likelihood	-981.1319	Hannan-Quinn criter.	40.21259	
Durbin-Watson stat	2.289301			

Null hypothesis: CONS has a unit root; Exogenous: constant; Lag length: 0 (automatic-based on SIC, maxlag = 4)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-5.252907	0.0001
Test critical values (Level%):		
1	-3.565430	
5	-2.919952	
10	-2.597905	

*MacKinnon (1996) one-sided p-values

Appendix III: ADF results of first difference series consumption; Null hypothesis: D(CONS) has a unit root; Exogenous: None; Lag length: 2 (Automatic-based on SIC, maxlag = 2)

Test	t-statistic	Prob.*
Augmented Dickey-Fuller test statistic	-7.779045	0.0000
Test critical values (Level%):		
1	-2.614029	
5	-1.947816	
10	-1.612492	

*MacKinnon (1996) one-sided p-values; Augmented Dickey-Fuller test equation; Dependent variable: D(CONS,2); Method: least squares; Date: 11/28/18 Time: 19:51; Sample (adjusted): 2006Q1 2017Q4; Included observations: 48 after adjustments

Variables	Coefficient	SE	t-statistic	Prob.
D(CONS(-1))	-2.622089	0.337071	-7.779045	0.0000
D(CONS(-1),2)	0.961271	0.245597	3.914022	0.0003
D(CONS(-2),2)	0.371369	0.139408	2.663902	0.0107
R^2	0.771861	Mean dependent var		-3801201
Adjusted R^2	0.761722	SD dependent var		2.37E+08
SE of regression	1.16E+08	Akaike info criterion		40.03184
Sum squared resid	6.03E+17	Schwarz criterion		40.14879
Log likelihood	-957.7642	Hannan-Quinn criter		40.07604
Durbin-Watson stat	1.791839			

Appendix IV: ADF results of level series retail fuel price; Null Hypothesis: RFP has a unit root; Exogenous: None; Lag length: 0 (Automatic-based on SIC, maxlag = 2)

Variables	t-statistic	Prob.*
Augmented Dickey-Fuller test statistic	1.252198	0.9446
Test critical values (Level%):		
1	-2.611094	
5	-1.947381	
10	-1.612725	

*MacKinnon (1996) one-sided p-values; Augmented Dickey-Fuller test equation; Dependent variable: D(RFP); Method: least squares; Date: 11/28/18 Time: 19:12; Sample (adjusted): 2005Q2 2017Q4; Included observations: 51 after adjustments

Variable	Coefficient	SE	t-statistic	Prob.
RFP(-1)	0.013937	0.011130	1.252198	0.2163
R^2	-0.028322	Mean dependent var	19.69922	
Adjusted R^2	-0.028322	SD dependent var	80.83894	
SE of regression	81.97570	Akaike info criterion	11.67014	
Sum squared resid	336000.7	Schwarz criterion	11.70801	
Log likelihood	-296.5885	Hannan-Quinn criter	11.68461	
Durbin-Watson stat	1.972576			

Appendix V: ADF results of first difference series retail fuel price; Null hypothesis: D(RFP) has a unit root; Exogenous: none; Lag length: 1 (Automatic-based on SIC, maxlag = 2)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.483925	0.0000
Test critical values (Level%):		
1	-2.613010	
5	-1.947665	
10	-1.612573	

*MacKinnon (1996) one-sided p-values; Augmented Dickey-Fuller test equation; Dependent variable: D(RFP,2); Method: least squares; Date: 11/28/18; Time: 19:43; Sample (adjusted): 2005Q4 2017Q4; Included observations: 49 after adjustments

Variable	Coefficient	Std. Error	t-statistic	Prob.
D(RFP(-1))	-1.262001	0.194635	-6.483925	0.0000
D(RFP(-1),2)	0.296237	0.140215	2.112730	0.0400
R^2	0.528003	Mean dependent var		1.033878
Adjusted R^2	0.517961	SD dependent var		116.6593

SE of regression	80.99545	Akaike info criterion	11.66662
Sum squared resid	308332.3	Schwarz criterion	11.74384
Log likelihood	-283.8323	Hannan-Quinn criter	11.69592
Durbin-Watson stat	1.942085		

Appendix VI: Johansen cointegration test; Date: 11/19/18; Time: 19:04; Sample (adjusted): 2005Q4 2017Q4; Included observations: 49 after adjustments; Trend assumption: Linear deterministic trend; Series: CONS RFP ; Lags interval (in first differences): 1 to 2

Unrestricted cointegration rank test (trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Prob.**
None	0.210414	13.97203	15.49471	0.0837
At most 1	0.047721	2.395956	3.841466	0.1216

Trace test indicates no cointegration at the 0.05 level; * Denotes rejection of the hypothesis at the 0.05 level; **MacKinnon-Haug-Michelis (1999) p-values

Unrestricted cointegration rank test (maximum eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen statistic	0.05 critical value	Prob.**
None	0.210414	11.57608	14.26460	0.1276
At most 1	0.047721	2.395956	3.841466	0.1216

Max-eigenvalue test indicates no cointegration at the 0.05 level; * denotes rejection of the hypothesis at the 0.05 level; **MacKinnon-Haug-Michelis (1999) p-values

Unrestricted cointegrating coefficients (normalized by b'*S11*b = I):

CONS	RFP	
-1.34E-08	-7.56E-05	
-4.61E-10	-0.003711	
Unrestricted adjustment coefficients (alpha):		
D(CONS)	45154339	12607180
D(RFP)	-28.48854	6.751161
1 Cointegrating equation(s): Log likelihood	-1241.370	
Normalized cointegrating coefficients (standard error in parentheses)		
CONS	RFP	
1.000000	5665.152	
	(82001.1)	
Adjustment coefficients (standard error in parentheses)		
D(CONS)	-0.602965	
	(0.21340)	
D(RFP)	3.80E-07	
	(1.3E-07)	

Appendix VII: Vector autoregressive model; Vector autoregression estimates; Date: 11/19/18; Time: 19:41; Sample (adjusted): 2005Q4 2017Q4 Included observations: 49 after adjustments; Standard errors in ( ) and t-statistics in [ ]

Variables	D(CONS)	D(RFP)
D(CONS(-1))	-0.625822	-3.84E-08
	(0.17054)	(1.0E-07)
	[-3.66959]	[-0.37031]
D(CONS(-2))	-0.364727	2.36E-07
	(0.17584)	(1.1E-07)
	[-2.07415]	[2.20613]
D(RFP(-1))	-226206.3	0.074490
	(295571.)	(0.17969)
	[-0.76532]	[0.41455]
D(RFP(-2))	471029.9	-0.164305
	(242602.)	(0.14749)
	[1.94157]	[-1.11404]
C	-4932008	20.03639
	(1.9E+07)	(11.3426)
	[-0.26434]	[1.76647]
R^2	0.342871	0.268127
Adj. R^2	0.283132	0.201593
Sum sq. resids	6.38E+17	235800.0
SE equation	1.20E+08	73.20581
F-statistic	5.739487	4.029920
Log likelihood	-978.6082	-277.2615

Akaike AIC	40.14727	11.52088
Schwarz SC	40.34031	11.71392
Mean dependent	-938302.4	17.82980
SD dependent	1.42E+08	81.92817
Determinant resid covariance (dof adj.)	5.45E+19	
Determinant resid covariance	4.39E+19	
Log likelihood	-1247.158	
Akaike information criterion	51.31258	
Schwarz criterion	51.69867	
Number of coefficients	10	

Appendix VIII: Vector autoregression estimates of consumption; Dependent variable: D(CONS); Method: least squares (Gauss-Newton/Marquardt steps); Date: 11/19/18; Time: 19:44; Sample (adjusted): 2005Q4 2017Q4; Included observations: 49 after adjustments; D(CONS) = C(1)*D(CONS(-1)) + C(2)*D(CONS(-2)) + C(3)*D(RFP(-1)) +C(4)*D(RFP(-2))+C(5)

Variables	Coefficient	SE	t-statistic	Prob.
C(1)	-0.625822	0.170543	-3.669593	0.0007
C(2)	-0.364727	0.175844	-2.074149	0.0439
C(3)	-226206.3	295570.7	-0.765321	0.4482
C(4)	471029.9	242602.1	1.941574	0.0586
C(5)	-4932008	18657601	-0.264343	0.7927
R^2	0.342871	Mean dependent var	-938302.4	
Adjusted R^2	0.283132	SD dependent var	1.42E+08	
SE of regression	1.20E+08	Akaike info criterion	40.14727	
Sum squared resid	6.38E+17	Schwarz criterion	40.34031	
Log likelihood	-978.6082	Hannan-Quinn criter	40.22051	
F-statistic	5.739487	Durbin-Watson stat	2.020728	
Prob(F-statistic)	0.000832			

Appendix IX: Vector autoregression estimates of retail fuel price; Dependent variable: D(RFP); Method: least squares (Gauss-Newton/Marquardt steps); Date: 11/19/18; Time: 19:49; Sample (adjusted): 2005Q4 2017Q4; Included observations: 49 after adjustments; D(RFP) = C(6)*D(CONS(-1)) +C(7)*D(CONS(-2))+C(8)*D(RFP(-1))+C(9); *D(RFP(-2)) + C(10)

Variables	Coefficient	Std. Error	t-Statistic	Prob.
C(6)	-3.84E-08	1.04E-07	-0.370309	0.7129
C(7)	2.36E-07	1.07E-07	2.206126	0.0326
C(8)	0.074490	0.179688	0.414550	0.6805
C(9)	-0.164305	0.147486	-1.114035	0.2713
C(10)	20.03639	11.34262	1.766470	0.0843
R^2	0.268127	Mean dependent var	17.82980	
Adjusted R^2	0.201593	SD dependent var	81.92817	
SE of regression	73.20581	Akaike info criterion	11.52088	
Sum squared resid	235800.0	Schwarz criterion	11.71392	
Log likelihood	-277.2615	Hannan-Quinn criter	11.59412	
F-statistic	4.029920	Durbin-Watson stat	2.067076	
Prob(F-statistic)	0.007184			

Appendix X: Granger-causality test; Pairwise granger causality tests; Date: 11/24/18; Time: 12:47; Sample: 2005Q1 2017Q4; Lags: 2

Null hypothesis:	Obs	F-Statistic	Prob.
RFP does not Granger cause CONS	50	0.38942	0.6797
CONS does not Granger cause RFP		11.5387	9.E-05

Appendix XI: Variance decomposition

Variance decomposition of D(CONS):

Period	SE	D(CONS)	D(RFP)
1	1.20E+08	100.0000	0.000000
2	1.38E+08	98.99327	1.006727
3	1.44E+08	92.66950	7.330502
4	1.47E+08	92.08361	7.916394
5	1.48E+08	91.87740	8.122604
6	1.49E+08	91.91456	8.085436
7	1.49E+08	91.81124	8.188762
8	1.49E+08	91.75299	8.247006
9	1.49E+08	91.74976	8.250240
10	1.49E+08	91.73692	8.263085
Variance decomposition of D(RFP):			
1	73.20581	29.92248	70.07752
2	73.74131	30.55337	69.44663

3	82.99530	43.94872	56.05128
4	83.92814	44.65848	55.34152
5	85.45414	45.19624	54.80376
6	85.68542	45.47406	54.52594
7	85.97605	45.64968	54.35032
8	86.12228	45.82531	54.17469
9	86.16192	45.81964	54.18036
10	86.20979	45.86621	54.13379

Cholesky Ordering: D(CONS) D(RFP)

REFERENCES

Bernanke, B.S. and A.S. Blinder, 1992. The federal funds rate and channels of monetary transmission. Am. Econ. Rev., 82: 901-921.

Braun, P.A. and S. Mittnik, 1993. Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions. J. Econom., 59: 319-341.

Cochrane, J.H., 2005. Time Series for Macroeconomics and Finance. University of Chicago, Chicago, Illinois,.

Erdogdu, E., 2007. Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey. Energy Policy, 35: 1129-1146.

Girma, P.B. and A.S. Paulson, 1999. Risk arbitrage opportunities in petroleum futures spreads. J. Future. Markets, 19: 931-955.

Gjolberg, O. and T. Johnsen, 1999. Risk management in the oil industry: Can information on long-run equilibrium prices be utilized?. Energy Econ., 21: 517-527.

Gonzalo, J., 1994. Five alternative methods of estimating long-run equilibrium relationships. J. Econ., 60: 203-233.

Johansen, S., 1991. Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. Econometrica, 59: 1551-1580.

Leggett, J.K., 2005. Half Gone: Oil, Gas, Hot Air and the Global Energy Crisis. Portobello Books, London, England, UK., ISBN: 9781846270048, Pages: 312.

Lutkepohl, H., 1993. Introduction to Multiple Time Series Analysis. 2nd Edn., Springer, New York, USA., ISBN: 9780387569406, Pages: 545.

Serletis, A., 1994. A cointegration analysis of petroleum futures prices. Energy Econ., 16: 93-97.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica, 48: 1-48.