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# Multivariate Time Series Modelling Of Ex-Pump Prices Of Petroleum Products In Ghana

## Chapter 4: Results and Discussions

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## Objective

The purpose of the study is to obtain a suitable model for the ex-pump prices of petroleum products in Ghana.

To examines how changes in the prices of one product cause changes in the price of others in both the short and long run.

Data spanning January, 2007 to June, 2015 are obtained from the National Petroleum Authority of Ghana, covering four petroleum products; Gasoline, Gasoil, Kerosene, and Liquefied Petroleum Gas (LPG) .



# Chapter 4: Result And Discussion

This chapter analyses and discusses the results. It presents results of the association between the prices of the products considered, namely;

- Gasoil

- Gasolin

- Kerosene

- Liquefied Petroleum Gas (LPG)

All associated tests and models are generated with R



## Start Up

- ◇ Plotting and Descriptive Statistics
- ◇ Stationarity Test
- ◇ Differencing If Not Stationary
- ◇ Plotting of ACF and PACF



## Estimation Of Model

- ◇ Lag Length Selection (LLS)
- ◇ Cointegration Test
- ◇ Long Run Equilibrium
- ◇ Short Run Equilibrium
- ◇ Estimation of VEC Model (If There is cointegration)
- ◇ Model Validation
- ◇ Forecast of Ex-Pump prices of Products





# Descriptive Statistics

In all, 204 observations are used (January, 2007 to June, 2015 ).

Training data of 144 observations (January 2007 to December 2012) for modelling

Testing data of 60 data points (January 2013 to June 2015) for model validations.

The descriptive statistics of the products are shown in Table 1 on page 8



# Summary Statistics

Table: 1 Summary Statistics

| Statistics             | GASOIL  | GASOLINE | KEROSENE | LPG     |
|------------------------|---------|----------|----------|---------|
| Mean                   | 122.445 | 123.570  | 82.989   | 94.766  |
| Maximum                | 175.480 | 177.090  | 120.420  | 136.190 |
| Minimum                | 11.600  | 49.170   | 6.470    | 58.500  |
| Standard Deviation     | 32.306  | 31.817   | 27.186   | 20.609  |
| Skewness               | -0.201  | 0.1307   | -1.988   | 0.413   |
| Kurtosis               | 3.374   | 2.123    | 6.293    | 2.292   |
| Number of Observations | 144     | 144      | 144      | 144     |



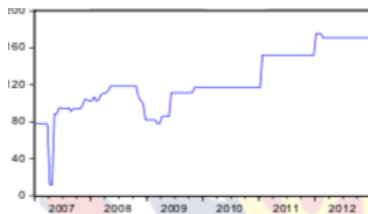
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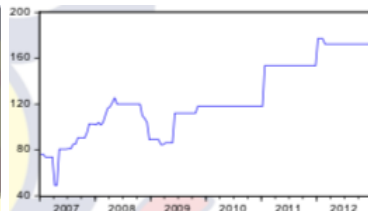
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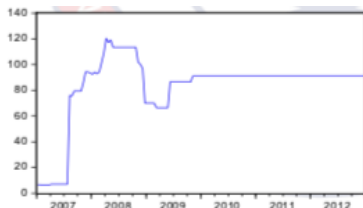
# Plot of Original Series



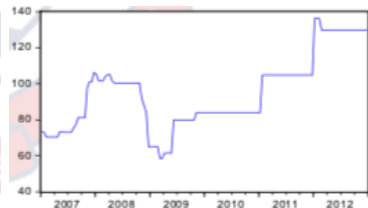
(a) GASOLINE



(b) GASOIL



(c) KEROSENE



(d) LPG

Figure: 1 Time Series Plot of the Original Series



# Stationarity Test

We have numerous ways of testing for the presence of a unit root. We have chosen to apply

## Augmented Dickey-Fuller Test

$H_0$  : The series is not stationary

$H_1$  : The series is stationary.

## Phillips-Perron Unit Root Test

$H_0$  : The series is not stationary

$H_1$  : The series is stationary.

## KPSS Test for Level Stationarity

$H_0$  : The series is stationary

$H_1$  : The series is not stationary.

# Stationarity of Original Series

Table: 2 Univariate URTs of the Original Series

| Series   | Lag Order | (Test Statistics) |       | (P-Values) |       |
|----------|-----------|-------------------|-------|------------|-------|
|          |           | ADF               | KPSS  | ADF        | KPSS  |
| GASOLINE | 5         | -2.738            | 2.370 | 0.269      | 0.010 |
| GASOIL   | 5         | -2.450            | 2.437 | 0.389      | 0.010 |
| KEROSENE | 5         | -3.106            | 0.709 | 0.166      | 0.010 |
| LPG      | 5         | -1.975            | 1.497 | 0.587      | 0.010 |

## Is Stationary ?

It is observed that for ADF, all the p-values of the series are greater than 0.05 and this indicates non stationarity. The KPSS test also showed the same results. We now difference the series since the series are not stationary.

## First Difference

Since all the series (Gasoline, Gasoil, Kerosene, LPG) are not stationary we perform 1st differencing in order to achieve stationarity; The figure 2 below is a plot after the first differencing .



# Plot of First Differenced Series

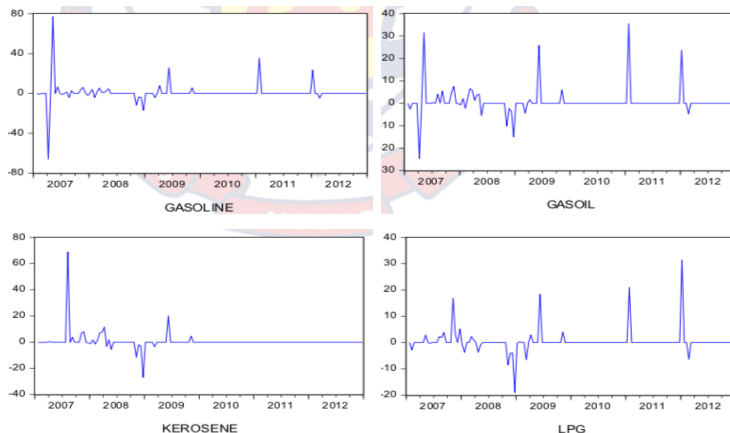


Figure: 2 Time Series Plot of the Original Series



# Stationarity of First Differenced Series

Table: 3 Univariate URTs of the Differenced Series

| Series   | Lag Order | (Test Statistics) |       | (P-Values) |      |
|----------|-----------|-------------------|-------|------------|------|
|          |           | ADF               | KPSS  | ADF        | KPSS |
| GASOLINE | 5         | -7.781            | 0.031 | 0.010      | 0.10 |
| GASOIL   | 5         | -5.537            | 0.045 | 0.010      | 0.10 |
| KEROSENE | 5         | -4.493            | 0.263 | 0.010      | 0.10 |
| LPG      | 5         | -4.473            | 0.063 | 0.010      | 0.10 |

## Is Stationary ?

It is observed that for ADF, all the p-values of the series are less than 0.05 and this indicates the stationarity. The KPSS test also showed the same results. We now estimate the models since the series have attained stationarity.



# ACF Plot of First Differenced Series

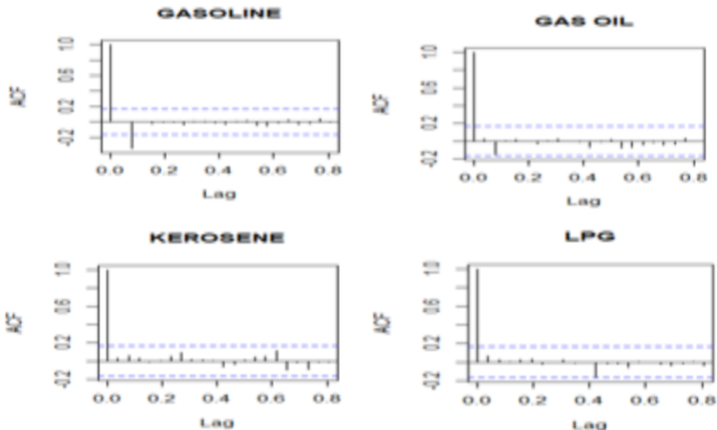


Figure: 3 ACF of the Differenced Series



# PACF Plot of First Differenced Series

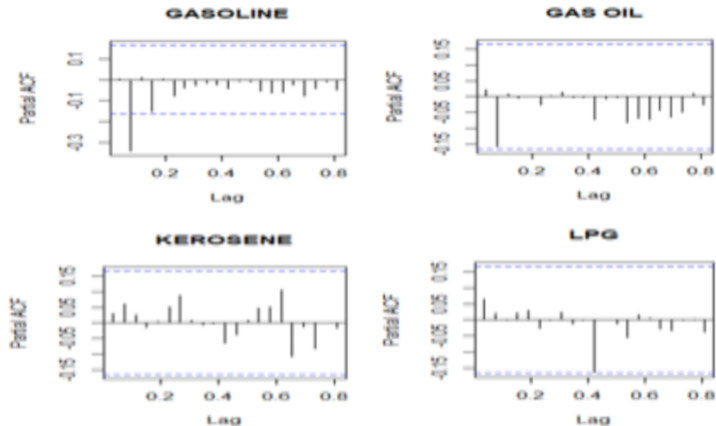


Figure: 4 PACF of the Differenced Series



# What Next After Series is Stationary ?

## Estimation of VAR/ VEC Models

- ◇ Lag Length Selection (LLS)
- ◇ Cointegration Test
- ◇ Long Run Equilibrium
- ◇ Short Run Equilibrium
- ◇ Estimation of VEC Model (If There is cointegration)
- ◇ Model Validation
- ◇ Forecast of Ex-Pump prices of Products



# Estimation of VAR/ VEC Models

Estimating parameters of **Vector Autorelation** (VAR) or **Vector Error Correction** (VEC) models require that variables are covariance stationary

VAR for instance cannot be used if the variables are not stationary. Also, if the data is non-stationary, the forecast cannot be done because **VAR assumes stationarity**

We then test for the long run relationship using **Johansens cointegration test**.

That is if the result confirms that there is a long-run relationship among the variables, we can proceed to the VEC model.

The first step involved in estimating is to first determine the lag Length or order.

# Lag Length Selection (LLS) Criteria

LLS is significant for VAR/VEC models since selecting too few intervals to result in a cointegrated error and selecting too many intervals may lead to unnecessary loss of degrees of freedom

Three of the LLS criteria are used, namely ;

FPE (Final Prediction Error)

AIC (Akaike Information Criterion)

BIC (Bayesian Information Criterion), aka SC (Schwarz Criterion)

FPE, AIC, and BIC support the inclusion of lag 1 as italicized, and starred in Table 4.



Table: 4 Lag Length Selection Criteria

| Lag | FPE                | AIC     | BIC     |
|-----|--------------------|---------|---------|
| 0   | $1.03 \times 10^9$ | 32.107  | 32.192  |
| 1*  | 117944.1*          | 23.029* | 23.454* |
| 2   | 127300.7           | 23.105  | 23.869  |
| 3   | 142926.7           | 23.219  | 24.3224 |
| 4   | 149122.0           | 23.259  | 24.701  |
| 5   | 169942.3           | 23.385  | 25.167  |
| 6   | 156708.8           | 23.297  | 25.419  |

From Table 4, we can rely on information criteria as only one of these three tests; FPE, AIC, and BIC obtained minimum values at the indicated lag. The test displays **lag 1** as the optimum. Thus, the lag length for the estimation is 1.

# What Next After Lag Length Selection

Once the unit roots and lag length selections are determined for a time series data, the next step is to inspect whether there exists a **Cointegration (Long run relationship)** among the variables or not.



# Cointegration : Long Run Relationship

Cointegration analysis is important because, if two or more non-stationary variables are cointegrated, a VAR model in the first difference is mis-specified due to the effects of a common trend. The cointegration test determines the type of the regression model to be applied i.e. VAR or VEC

## Cointegration Test

$H_0$  : There is no cointegration equation.

$H_1$  : There is a cointegration equation





Table: 5 Determining the Number of Cointegrated Equations

| Number of EC | Eigenvalues | Trace Statistic | P-Value | Max-Eigen Statistic | P-Value |
|--------------|-------------|-----------------|---------|---------------------|---------|
| None*        | 0.358       | 79.102          | 0.000   | 62.959              | 0.000   |
| At most 1    | 0.070       | 16.143          | 0.702   | 10.258              | 0.720   |
| At most 2    | 0.033       | 5.885           | 0.709   | 4.778               | 0.769   |
| At most 3    | 0.008       | 1.107           | 0.293   | 1.107               | 0.293   |

## Conclusion

Remarkably, the Trace test and max-Eigen statistics suggest the existence of a cointegrated equation (CE).

We shall take into account this fact at the next step.

Since all the series are  $I(1)$  and cointegrated, the products ought to be modelled as a VEC model

As a result, a cointegration relationship is obtained. This throws more light on the long run relationships among the products. Consequently, the products; **GASOLINE, GASOIL, KEROSENE, and LPG** prices are linked by a long run equation.

Once the unit roots and lag length selections are determined for a time series data, the next step is to inspect whether there exists a long-run equilibrium relationship among the variables or not.



# Long Run Relationship

The cointegrating (long-run) relationship is estimated to be;

$$\text{GASOLINE} = -0.0221 \text{ GASOIL} + 0.027 \text{ KEROSENE} - 0.580 \text{ LPG}$$

Thus, with GASOLINE price as the endogenous variable, the long-run relationship indicates that the ex-pump prices of the other products have long run effects.

Specifically, the results indicate that the other products have a negative relation with GASOLINE price in the long run (except KEROSENE), all things being equal.



# Log Run Equilibrium

The coefficients of the error correction terms (ECT) [Table 6, 7, 8, 9] show the speed of adjustments of disequilibrium in the period under study.

The negative sign associated with the error term is simply a departure in one direction. These are satisfying as they imply convergence in the long run. That is, deviation from the long run is corrected



Table: 6 Gasoline Model

| Parameters                | Coefficient | S.E   | t-satistics |
|---------------------------|-------------|-------|-------------|
| <b>GASOLINE Model</b>     |             |       |             |
| $(\text{Gasoline})_{t-1}$ | 0.691       | 0.189 | 3.650*      |
| $(\text{Gasoil})_{t-1}$   | -0.0221     | 0.386 | -1.561*     |
| $(\text{Kerosene})_{t-1}$ | 0.027       | 0.091 | 0.294       |
| $(\text{LPG})_{t-1}$      | -0.580      | 0.262 | -2.211      |
| Constant                  | 0.006       | 0.805 | 0.007       |
| ECT                       | -0.613      | 0.145 | -11.118*    |

The negative coefficients of the error term for GASOLINE prices indicate dynamic stability, suggesting rapid adjustment speeds.

The magnitude of the correction of the imbalances suggest that , 61.3% of the imbalances in GASOLINE prices are corrected.

Table: 7 Gasoil Model

| Parameters                | Coefficient | S.E   | t-statistics |
|---------------------------|-------------|-------|--------------|
| <b>GASOIL Model</b>       |             |       |              |
| $(\text{Gasoline})_{t-1}$ | 0.524       | 0.126 | 4.165*       |
| $(\text{Gasoil})_{t-1}$   | -0.783      | 0.256 | -3.059*      |
| $(\text{Kerosene})_{t-1}$ | -0.002      | 0.060 | -0.030       |
| $(\text{LPG})_{t-1}$      | -0.214      | 0.174 | -1.227       |
| Constant                  | 0.017       | 0.535 | 0.032        |
| ECT                       | -0.695      | 0.096 | -7.215*      |

Concerning GASOIL prices, it indicates 69.5% of shocks in its prices (imbalance) are corrected every two weeks.



Table: 8 Kerosene Model

| Parameters                | Coefficient | S.E    | t-statistics |
|---------------------------|-------------|--------|--------------|
| <b>KEROSENE Model</b>     |             |        |              |
| (Gasoline) <sub>t-1</sub> | 0.058       | 0.163  | 0.359        |
| (Gasoil) <sub>t-1</sub>   | -0.002      | -0.085 | -0.256       |
| (Kerosene) <sub>t-1</sub> | -0.518      | 0.078  | -6.652*      |
| (LPG) <sub>t-1</sub>      | 0.059       | 0.225  | 0.263        |
| Constant                  | 0.001       | 0.692  | 0.002        |
| ECT                       | -0.039      | 0.125  | -0.313       |

For the KEROSENE price, 3.9% of such imbalances are corrected every two weeks



Table: 9 LPG Model

| Parameters                | Coefficient | S.E   | t-statistics |
|---------------------------|-------------|-------|--------------|
| <b>LPG Model</b>          |             |       |              |
| (Gasoline) <sub>t-1</sub> | 0.054       | 0.106 | 0.505        |
| (Gasoil) <sub>t-1</sub>   | -0.080      | 0.216 | -0.370       |
| (Kerosene) <sub>t-1</sub> | 0.010       | 0.051 | -0.197       |
| (LPG) <sub>t-1</sub>      | -0.450      | 0.147 | -3.058*      |
| Constant                  | 0.020       | 0.452 | 0.044        |
| ECT                       | -0.036      | 0.081 | -0.437       |

In the case of LPG price, only 3.6% of such imbalances are corrected.





# Short Run Relationship

The short run relationships of the models are explained by the VEC model coefficients as presented in Table 6, 7, 8, 9

## Gasoline

Looking at the coefficients, it is observed (Table 6) that in the short-run, GASOLINE price [3.65\*] is significant. This is an indication that GASOLINE price exhibits an increment of 69.1% by itself and 2.21% reduction by GASOIL price whiles the others are not significant.



# Short Run Relationship

## Gasoil

Also, it is observed that GASOIL price [4.17\*] is significant by Gasoline. This is an indication that GASOIL price exhibits an increment of 52.4% by GASOLINE price with a 78.3% reduction by itself.

The other products also exhibit both increment and reduction by themselves and/or other products. This is because the coefficients of these products are significant. The short-run results also indicate that the variables influence each other.

Considering GASOLINE price as the dependent variable, it appears the ex-pump prices of the other products influence it. The consequence of this result is that increase ex-pump prices of one or more products are likely to influence others



# Long And Short Run Relationship

Now, having analyzed both the short and long-run relationships existing among the variables, the VEC models are estimated, diagnosed, and validated, and finally, forecasts are generated.



# Estimation of VEC Model

The VEC models are estimated using these equations,

$$w_t = c + \phi_{11}w_{t-1} + \phi_{12}x_{t-1} + \phi_{13}y_{t-1} + \phi_{14}z_{t-1} + \epsilon_t \quad (1)$$

$$x_t = c + \phi_{21}w_{t-1} + \phi_{22}x_{t-1} + \phi_{23}y_{t-1} + \phi_{24}z_{t-1} + \epsilon_t \quad (2)$$

$$y_t = c + \phi_{31}w_{t-1} + \phi_{32}x_{t-1} + \phi_{33}y_{t-1} + \phi_{34}z_{t-1} + \epsilon_t \quad (3)$$

$$z_t = c + \phi_{41}w_{t-1} + \phi_{42}x_{t-1} + \phi_{43}y_{t-1} + \phi_{44}z_{t-1} + \epsilon_t \quad (4)$$



The results of VAR are reported by the 4 equations below. The VEC models are computed with one lag. The models relating the products to their lags and that of others may best be described as;

$$\begin{bmatrix} w_t \\ x_t \\ y_t \\ z_t \end{bmatrix} = \begin{bmatrix} 0.006 \\ 0.017 \\ 0.001 \\ 0.020 \end{bmatrix} + \begin{bmatrix} 0.691 & 0.0221 & 0.027 & -0.580 \\ 0.524 & -0.783 & -0.002 & -0.214 \\ 0.058 & -0.002 & -0.518 & 0.059 \\ 0.054 & -0.080 & 0.010 & -0.450 \end{bmatrix} \begin{bmatrix} w_{t-1} \\ x_{t-1} \\ y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} ECT_{pg} & 0 & 0 & 0 \\ 0 & ECT_g & 0 & 0 \\ 0 & 0 & ECT_k & 0 \\ 0 & 0 & 0 & ECT_l \end{bmatrix} \begin{bmatrix} -1.613 \\ -0.695 \\ -0.039 \\ -0.036 \end{bmatrix}$$



where,  $\begin{bmatrix} w_t \\ x_t \\ y_t \\ z_t \end{bmatrix}$ , represents the projects GASOLINE, GASOIL, KEROSENE,

LPG prices at the time t,  $\begin{bmatrix} ECT_{pg} & 0 & 0 & 0 \\ 0 & ECT_g & 0 & 0 \\ 0 & 0 & ECT_k & 0 \\ 0 & 0 & 0 & ECT_l \end{bmatrix}$

refers to the error corrected terms (ECT) for each model, (pg, g, k, and L respectively representing GASOLINE, GASOIL, KEROSENE, and LPG

prices), and  $\begin{bmatrix} w_{t-1} \\ x_{t-1} \\ y_{t-1} \\ z_{t-1} \end{bmatrix}$  referring to the lags of the products (i.e. lag 1).

The summary of the results of the VEC models is presented in Table 10



Table: 10 Summary Results of the Models

| Statistics/Products | GASOLINE | GASOIL | KEROSENE | LPG   |
|---------------------|----------|--------|----------|-------|
| F-statistic         | 31.515   | 18.810 | 9.884    | 8.133 |
| Prob (F-statistic)  | 0.000    | 0.000  | 0.000    | 0.000 |
| S.E.                | 9.562    | 6.351  | 8.218    | 5.367 |
| R-squared           | 53.9%    | 41.1%  | 26.8%    | 23.1% |

Table 10 is a summary of the statistics of the VEC models. The results indicate that the models perform creditably well. GASOIL appears to be the best in terms of the variability accounted for.



# Model Diagnostics

After modeling, some forecasts are normally estimated. But before the estimated model can be used to generate any forecast, it is imperative to undertake residual analysis or model diagnostics.

The diagnostic test results include Q- statistics, residual portmanteau test, residual serial correlations, and white heteroscedasticity test. Tables 11 to 13 provide information on the analysis of the residuals of the models.





Table: 11 VEC Residual Portmanteau Tests for Autocorrelations

| Lags | Q-Stat  | Prob. | Adj Q-Stat | P-Value | df  |
|------|---------|-------|------------|---------|-----|
| 1    | 7.6189  | NA*   | 7.677      | NA*     | NA* |
| 2    | 21.603  | 0.157 | 21.879     | 0.147   | 16  |
| 3    | 29.843  | 0.576 | 30.312     | 0.552   | 32  |
| 4    | 44.304  | 0.625 | 45.228     | 0.587   | 48  |
| 5    | 50.472  | 0.891 | 51.641     | 0.867   | 64  |
| 6    | 111.265 | 0.012 | 115.351    | 0.006   | 80  |
| 7    | 131.458 | 0.010 | 136.684    | 0.004   | 96  |
| 8    | 188.126 | 0.000 | 197.038    | 0.000   | 112 |
| 9    | 197.007 | 0.000 | 206.575    | 0.000   | 128 |
| 10   | 202.285 | 0.001 | 212.289    | 0.000   | 144 |
| 11   | 216.121 | 0.002 | 227.393    | 0.000   | 160 |
| 12   | 230.102 | 0.004 | 242.784    | 0.001   | 176 |



# VEC Residual Portmanteau Tests for Autocorrelations

The null hypothesis is that there are no residual autocorrelations up to lag  $h$ . The test is valid only for lags larger than the selected lag order. We observe that the residual passes the white noise test since no autocorrelation is left in the VEC model after lag 1.

## Lagrange Multiplier Test

The LM (Lagrange Multiplier) test is a statistical test used to assess the goodness of fit of a model. It is also known as the Lagrange Multiplier (LM) test for model specification.



Table: 12 VECM Residual Serial Correlation LM Tests

| Lags | LM-Stat | P-values |
|------|---------|----------|
| 1    | 18.022  | 0.323    |
| 2    | 18.924  | 0.273    |
| 3    | 8.073   | 0.947    |
| 4    | 14.278  | 0.578    |
| 5    | 6.001   | 0.988    |
| 6    | 66.795  | 0.000    |
| 7    | 20.731  | 0.189    |
| 8    | 69.676  | 0.000    |
| 9    | 8.623   | 0.928    |
| 10   | 5.030   | 0.996    |
| 11   | 14.290  | 0.577    |
| 12   | 14.019  | 0.597    |



Table: 13 VEC Residual Heteroskedasticity

| Dependent | R-squared | F (34,163) | P-value | Chi-square (34) | P-Value |
|-----------|-----------|------------|---------|-----------------|---------|
| res1*res1 | 0.292     | 3.415      | 0.001   | 38.236          | 0.290   |
| res2*res2 | 0.093     | 0.850      | 0.615   | 12.184          | 0.093   |
| res3*res3 | 0.216     | 2.280      | 0.009   | 28.266          | 0.216   |
| res4*res4 | 0.065     | 0.573      | 0.881   | 8.474           | 0.065   |
| res2*res1 | 0.215     | 2.273      | 0.009   | 28.198          | 0.215   |
| res3*res1 | 0.155     | 1.516      | 0.116   | 20.262          | 0.155   |
| res3*res2 | 0.181     | 1.835      | 0.041   | 23.753          | 0.181   |
| res4*res1 | 0.064     | 0.569      | 0.884   | 8.414           | 0.064   |
| res4*res2 | 0.049     | 0.425      | 0.964   | 6.387           | 0.049   |
| res4*res3 | 0.265     | 2.980      | 0.001   | 34.654          | 0.264   |



# VEC Residual Heteroskedasticity

Table 13 presents the results of a Heteroscedasticity test, which assesses whether the variances of the error terms in a linear regression model are consistent. The test assumes normal distribution of error terms and aims to verify if variances across the series remain constant.

The findings indicate that the variances are indeed constant, as evidenced by the Chi-Square test's p-value exceeding 0.05. This conclusion is further supported by the p-values from both the F and Chi-square tests.



# Model Validation

Model validation and certification are crucial in the modeling process, aiding stakeholders in reducing costs, time, and risks associated with extensive product testing. These procedures are essential for establishing trust in statistical models.

Data was divided into training and validation sets, with 70% of data points used for modeling (2007 to 2012) and the remaining for validation (2013 to 2015). Out-of-sample forecasts for 2013 to 2015 were employed for model validation, comparing predicted product prices to actual prices.

The forecasts closely resembled the original prices, demonstrating the models' effectiveness and accuracy.



# Model Validation

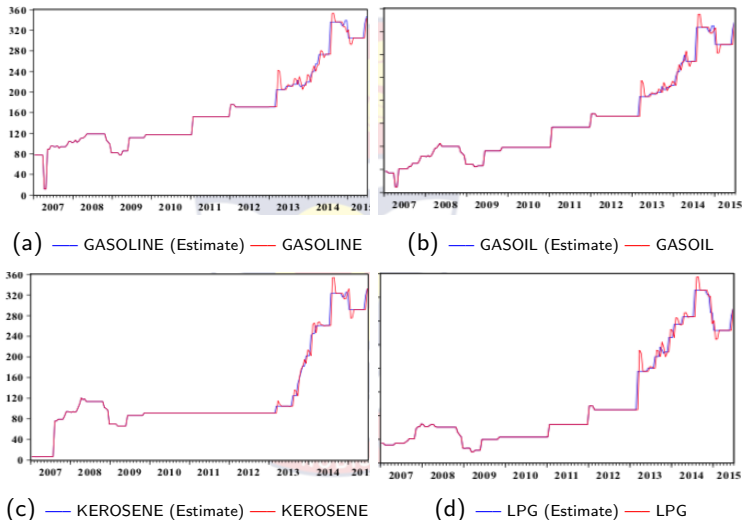


Figure: 5 Model Validation



# Forecast of Ex-Pump Prices of Products

After model diagnostics and validation, we, therefore, forecast the prices of the products for the next 12 period as shown in Table 14 on page 47





Table: 14 Forecasts of Ex-pump Prices for the four Products

| Period | Premium Gasoline | Gas Oil | Kerosene | LPG     |
|--------|------------------|---------|----------|---------|
| 1      | 172.037          | 172.360 | 91.401   | 130.290 |
| 2      | 173.121          | 172.360 | 91.887   | 130.693 |
| 3      | 173.962          | 172.360 | 92.475   | 131.114 |
| 4      | 174.684          | 172.360 | 93.115   | 131.548 |
| 5      | 175.392          | 206.830 | 93.765   | 131.985 |
| 6      | 176.123          | 206.830 | 94.406   | 132.420 |
| 7      | 176.874          | 206.830 | 95.038   | 132.854 |
| 8      | 177.631          | 206.830 | 95.667   | 133.287 |
| 9      | 178.389          | 206.830 | 96.296   | 133.720 |
| 10     | 179.144          | 206.830 | 96.926   | 134.153 |
| 11     | 179.897          | 211.110 | 97.557   | 134.586 |
| 12     | 180.650          | 211.110 | 98.188   | 135.019 |



## Do forecasted petroleum prices follow the same trend as historical data?

It was noticed that the forecasts for the series consistently rise as time progresses.

This aligns with the trend seen in the original products (Figure 1). Therefore, the prices of petroleum products have consistently increased over the years, as expected.

Next, we look at causality among the products, hereafter referred to as Granger causality.



# Granger Causality Test

Table 15 and 16 on page 50 presents the results of the Granger causality test conducted for various variables.

This test evaluates whether one variable has a causal influence on another.

## Granger Causality

$H_0$  : The potential causal variable(s) do not Granger cause the dependent variable

$H_1$  : The potential causal variable(s) do Granger cause the dependent variable



Table: 15 Granger Causality

**Dependent variable: GASOLINE**

| Excluded | $\chi^2$ | df | p-value |
|----------|----------|----|---------|
| GASOIL   | 4.889    | 1  | 0.027   |
| KEROSENE | 0.086    | 1  | 0.769   |
| LPG      | 2.436    | 1  | 0.119   |
| All      | 32.268   | 3  | 0.000   |

**Dependent variable: GASOIL**

| Excluded | $\chi^2$ | df | p-value |
|----------|----------|----|---------|
| GASOLINE | 17.345   | 1  | 0.000   |
| KEROSENE | 0.001    | 1  | 0.976   |
| LPG      | 1.506    | 1  | 0.220   |
| All      | 33.009   | 3  | 0.000   |



Table: 16 Granger Causality

**Dependent variable: KEROSENE**

| Excluded | $\chi^2$ | df | p-value |
|----------|----------|----|---------|
| GASOLINE | 0.129    | 1  | 0.720   |
| GASOIL   | 0.065    | 1  | 0.798   |
| LPG      | 0.069    | 1  | 0.793   |
| All      | 0.241    | 3  | 0.973   |

**Dependent variable: LPG**

| Excluded | $\chi^2$ | df | p-value |
|----------|----------|----|---------|
| GASOLINE | 0.255    | 1  | 0.614   |
| GASOIL   | 0.137    | 1  | 0.711   |
| KEROSENE | 0.039    | 1  | 0.844   |
| All      | 0.349    | 3  | 0.951   |



# Granger Causality

The findings reveal that GASOLINE price is Granger caused by at least one of the other products. Specifically, GASOIL price Granger causes GASOLINE price, indicating a causal relationship between them. However, KEROSENE and LPG do not exhibit a Granger causality with GASOLINE price.

Similarly, GASOLINE price Granger causes GASOIL price, suggesting a bidirectional relationship between them. However, none of the other product prices significantly Granger cause KEROSENE or LPG prices.

Although GASOLINE and GASOIL prices contribute to explaining the variability in KEROSENE and LPG prices to some extent, their contributions are not statistically significant. In summary, a bidirectional relationship is observed between GASOLINE and GASOIL prices, highlighting their mutual influence on each other's prices.

# Summary of Results

In the previous section, we obtained a VEC model with a lag of 1. The model's performance indicates a close fit to the data, as confirmed by model validation.

However, the model statistics reveal lower percentage variations in GASOLINE, GASOIL, KEROSENE, and LPG prices compared to expectations, with figures notably lower than depicted in the model fit graph.



# Summary of Results

Surprisingly, the performance statistics are higher for a VAR model, as shown in Table 17 on Page 55. Particularly, the lowest R-square (90.3%) is observed for GASOLINE prices in the VAR model.

Despite better fits obtained in the VEC graphs compared to those in the appendices, it's expected that the performance statistics for the VEC model should at least match those in Table 15, given that the VEC model is intended to improve upon VAR.





Table: 17 Summary Results of VAR Models

| Statistics/Products | GASOLINE | GASOIL  | KEROSENE | LPG     |
|---------------------|----------|---------|----------|---------|
| <b>F-statistic</b>  | 294.988  | 763.646 | 379.972  | 497.413 |
| <b>p-value</b>      | 0.000    | 0.000   | 0.000    | 0.000   |
| <b>S.E.</b>         | 9.468    | 5.928   | 0.366    | 4.573   |
| <b>R-square</b>     | 0.903    | 0.960   | 0.923    | 0.940   |



# Discussions and Findings

The study findings reveal dynamic relationships among ex-pump prices of petroleum products in the long run, indicating dynamically stable models. Short-term results suggest mutual influence of prices, particularly GASOLINE and GASOIL.

Analysis including granger causality supports these relationships, showing direct effects on prices. Forecasts demonstrate increasing trends over time, reflecting historical patterns. Petroleum product prices have consistently risen over years, impacting economic policies due to their significance in energy supply.



# Discussions and Findings

Literature highlights various effects of oil price shocks on economic variables, though some studies present conflicting views. The model's fitness, as depicted in model fit graphs, differs from model statistics, which were anticipated to explain over 90% variation, a result observed in corresponding VAR models.



# Chapter Summary

In this chapter, it is evident that ex-pump prices of petroleum products exhibit a consistent upward trend over the observed period. Short-term fluctuations indicate interdependence among product prices, while stability prevails in the medium to long term, with Premium Gasoline and Gas Oil prices playing pivotal roles.

Analysis through Granger causality confirms these findings. A VEC model of order 1 emerges as suitable, outperforming the VAR model with varying R-square values. Notably, Premium Gasoline and Gas Oil prices demonstrate competitive dynamics, reflecting their interchangeable usage patterns.

