

Unlocking India's Natural Gas Potential: Challenges and Opportunities in a Price-Sensitive Market

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Abstract: The Indian gas market is expected to be one of the fastest growing in the world over the next two decades: the IEA forecasts gas demand to increase at 5.4% per annum over 2007-30 (IEA, 2009) reaching 132 bcm by 2030. Indian primary energy supply is currently dominated by coal (37%), biomass and waste (27%) and oil (26%) while the share of natural gas is only 6%. The potential for growth of the natural gas market in India is tremendous; however, this is a very price sensitive market as the ability of customers to pay differs between sectors. The power generation and fertiliser sectors are the main consumers. Fertiliser producers are subsidised by the government and have limited ability to absorb higher prices. In the power generation sector, gas has to compete against coal for base-load generation. Any change in the power sector or in coal markets will have a huge impact on whether gas is used as a base-load option or for peak purposes, and therefore on future gas demand in the power sector. City gas and industrial users show greater price flexibility, but they are still emerging markets. Historically, gas had been allocated in priority to fertiliser and power plants, while city gas, compressed natural gas (CNG) and industrial had the remainder. The gas price increase will hit the fertiliser sector's profitability by increasing working-capital requirements, which is also facing higher import costs due to rising crude oil prices. Auto gas fuel prices may be increased but should remain competitive against liquid fuels, albeit with a reduced differential as liquid auto fuel prices also rise with increasing crude oil prices. The cost of power generated by gas-based power plants will increase, further affecting their utilisation.

Keywords: Gas Prices, VAR (Vector Auto Regression), ARIMA-GARCH (Auto Regressive Integrated Moving Average-Generalized Autoregressive Conditional Heteroscedasticity), ARCH GARCH Volatility for Gas prices, Forecasting

1. Introduction

The potential for growth of the natural gas market in India is tremendous; however, this is a very price sensitive market as the ability of customers to pay differs between sectors. The power generation and fertiliser sectors are the main consumers. Fertiliser producers are subsidised by the government and have limited ability to absorb higher prices. In the power generation sector, gas has to compete against coal for base-load generation. Any change in the power sector or in coal markets will have a huge impact on whether gas is used as a base-load option or for peak purposes, and therefore on future gas demand in the power sector. City gas and industrial users show greater price flexibility, but they are still emerging markets. Historically, gas had been allocated in priority to fertiliser and power plants, while city gas, compressed natural gas (CNG) and industrial had the remainder. Furthermore, fertiliser producers and power generators were allocated gas at low Administrative Price Mechanism (APM) prices determined by the government. But the recent pricing reforms that took place mid2010 mean the end of low APM prices, and that new gas supplies are likely to be more expensive.

The Indian gas sector, like the whole energy sector, is dominated by state-owned companies. Oil and Natural Gas Corporation (ONGC) and Oil India Ltd (OIL) have dominant upstream positions, while until 2006, GAIL (India) Ltd. alone had been responsible for pipeline gas transport. The state has also a very important role in the regulatory framework and gas policy, in particular the allocation and pricing of gas. Recent reforms have brought more private investors in the upstream and downstream sectors, but a more transparent regulatory framework will be critical to incentivise future private investments.

India has a rather unusual dual gas pricing and supply policy, with APM gas produced by state-owned companies and non-APM gas from private companies and joint ventures (JVs). Until May 2010, prices differed widely from around USD 2/MBtu for APM gas to almost USD 6/MBtu for the most expensive non-APM gas. Such a gap was pushing towards changes. Increasing private supply of gas has been indeed a major policy challenge for the government as the pooling of gas prices was limited by the declining availability of APM gas. Moreover, any effort to keep domestic gas prices low would act as a disincentive for more upstream investment. Two major changes took place in May 2010. APM prices were increased from USD 1.8/MBtu to USD 4.2 MBtu, and ONGC and OIL were allowed to market gas discovered in new fields allocated to them at market prices. This decision will have consequences for producers, and is an important step forward in order to encourage further investments in the upstream sector. Furthermore, if India wants to attract additional LNG in the long term, it would have increasingly to compete on global gas markets at prices potentially higher than the current ones. Meanwhile, the Supreme Court announced its verdict on the five-year battle between Reliance Industry (RIL) and Reliance Natural Resources (RNRL) regarding the price at which RIL was to sell its KG-D6 gas to RNRL: the Court decided that only the government had the right to fix the price in the Production Sharing Contract (PSC) (fixed at USD 4.2/MBtu) when an arm-lengths price is impossible to find. It remains to be seen whether or not such a decision could deter private or foreign upstream investment. Pricing is also key for the demand side due to some sectors' limited ability to absorb high prices: gas-fired plants compete with coal-fired plants while fertiliser producers depend on international urea price and government subsidies. A market approach based on comparison with alternative fuels should be taken.

In the above backdrop and keeping in view the high demand of petroleum products in India with high volatility of prices and India's import bill, this study states about the future trend of international gas prices in preparing India to formulate the best strategy to cope up with any eventuality.

Using ML in Eviews12.0, internationally, the trend of gas prices until 2024M12 has been assessed with the help of two models (1) VAR (Vector Auto Regression) (2) ARIMA-GARCH (Auto Regressive Integrated Moving Average-Generalized Autoregressive Conditional Heteroscedasticity) (3) ARCH GARCH Volatility for Gas prices.

(1) VAR (Vector Auto Regression)

First, what is Vector Autoregression (VAR) and when to use it?

Vector Autoregression (VAR) is a multivariate forecasting algorithm that is used when two or more time series influence each other.

That means, the basic requirements in order to use VAR are:

- 1) We need at least two time series (variables)
- 2) The time series should influence each other

It is called 'Autoregressive' because It is considered as an Autoregressive model as, each variable (Time Series) is modeled as a function of the past values that is the predictors are nothing but the lags (time delayed value) of the series.

Now, how is VAR different from other Autoregressive models like AR, ARMA or ARIMA?

The primary difference is those models are uni-directional, where, the predictors influence the Y and not vice-versa. Whereas, Vector Auto Regression (VAR) is bi-directional. That is, the variables influence each other.

A typical AR (p) model equation looks something like this:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + \epsilon_t$$

Where α is the intercept, a constant and β_1, β_2 till β_p are the coefficients of the lags of Y till order p.

Order 'p' means, up to p-lags of Y is used and they are the predictors in the equation. The ϵ_t is the error, which is considered as white noise.

Alright. So, how does a VAR model's formula look like?

In the VAR model, each variable is modeled as a linear combination of past values of itself and the past values of other variables in the system. Since you have multiple time series that influence each other, it is modeled as a system of equations with one equation per variable (time series).

That is, if you have 5 time series that influence each other, we will have a system of 5 equations.

Therefore, the equation is exactly framed as below:

Let's suppose, you have two variables (Time series) Y1 and Y2, and you need to forecast the values of these variables at time (t).

To calculate Y1 (t), VAR will use the past values of both Y1 as well as Y2. Likewise, to compute Y2 (t), the past values of both Y1 and Y2 be used.

For example, the system of equations for a VAR (1) model with two time series (variables 'Y1' and 'Y2') is as follows:

$$\begin{aligned} Y1, t &= \alpha_1 + \beta_{11} Y1, t-1 + \beta_{12} Y2, t-1 + \epsilon_1, t \\ Y2, t &= \alpha_2 + \beta_{21} Y1, t-1 + \beta_{22} Y2, t-1 + \epsilon_2, t \end{aligned}$$

Where, $Y1, t-1$ and $Y2, t-1$ are the first lag of time series Y1 and Y2 respectively.

The above equation is referred to as a VAR (1) model, because, each equation is of order 1, that is, it contains up to one lag of each of the predictors (Y1 and Y2).

Since the Y terms in the equations are interrelated, the Y's are considered as endogenous variables, rather than as exogenous predictors.

Likewise, the second order VAR (2) model for two variables would include up to two lags for each variable (Y1 and Y2).

$$\begin{aligned} Y_1, t &= \alpha_1 + \beta_{11}, 1Y_1, t-1 + \beta_{12}, 1Y_2, t-1 + \beta_{11}, 2Y_1, t-2 + \beta_{12}, 2Y_2, t-2 + \epsilon_1, t \\ Y_2, t &= \alpha_2 + \beta_{21}, 1Y_1, t-1 + \beta_{22}, 1Y_2, t-1 + \beta_{21}, 2Y_1, t-2 + \beta_{22}, 2Y_2, t-2 + \epsilon_2, t \end{aligned}$$

Can you imagine what a second order VAR (2) model with three variables (Y1, Y2 and Y3) would look like?

$$\begin{aligned} Y_1, t &= \alpha_1 + \beta_{11}, 1Y_1, t-1 + \beta_{12}, 1Y_2, t-1 + \beta_{13}, 1Y_3, t-1 + \beta_{11}, 2Y_1, t-2 + \beta_{12}, 2Y_2, t-2 + \beta_{13}, 2Y_3, t-2 + \epsilon_1, t \\ Y_2, t &= \alpha_2 + \beta_{21}, 1Y_1, t-1 + \beta_{22}, 1Y_2, t-1 + \beta_{23}, 1Y_3, t-1 + \beta_{21}, 2Y_1, t-2 + \beta_{22}, 2Y_2, t-2 + \beta_{23}, 2Y_3, t-2 + \epsilon_2, t \\ Y_3, t &= \alpha_3 + \beta_{31}, 1Y_1, t-1 + \beta_{32}, 1Y_2, t-1 + \beta_{33}, 1Y_3, t-1 + \beta_{31}, 2Y_1, t-2 + \beta_{32}, 2Y_2, t-2 + \beta_{33}, 2Y_3, t-2 + \epsilon_3, t \end{aligned}$$

As we increase the number of time series (variables) in the model the system of equations becomes larger Application:

Exogenous Variable: Gas rice

Endogenous Variable: Crude Oil Prices, Exchange Rates and coal prices

Sample Data Set: 2003M01 2023M04

Source of Data Collection: Federal Reserve Bank of St. Louis and World Bank Open Data

Vector Auto regression Estimates

Date: 08/24/23 Time: 13:38

Sample (adjusted): 2003M04 2021M12

Included observations: 225 after adjustments

Standard errors in () & t-statistics in []

| | GASPRICE | EXR1 | LNCOAL_PRICE | CRUDEOILPRICE |
|-------------------|--------------------------------------|---------------------------------------|--------------------------------------|--------------------------------------|
| GASPRICE(-1) | 0.779046 (0.07013) [11.1079] | -0.001136 (0.00138) [-0.82187] | 0.000105 (0.00013) [0.83158] | 0.001772 (0.00831) [0.21320] |
| GASPRICE(-2) | 0.061829 (0.07016) [0.88124] | 0.000568 (0.00138) [0.41069] | -0.000173 (0.00013) [-1.37548] | -0.001472 (0.00831) [-0.17708] |
| EXR1(-1) | 2.644511 (3.50174) [0.75520] | 0.247249 (0.06901) [3.58301] | -0.001674 (0.00629) [-0.26611] | -0.172996 (0.41489) [-0.41697] |
| EXR1(-2) | -1.647936 (3.42285) [-0.48145] | -0.104156 (0.06745) [-1.54416] | -0.000191 (0.00615) [-0.03105] | -0.090355 (0.40555) [-0.22280] |
| LNCOAL_PRICE(-1) | 8.058531 (38.0679) [0.21169] | 0.026480 (0.75017) [0.03530] | 0.944605 (0.06837) [13.8157] | 1.555764 (4.51036) [0.34493] |
| LNCOAL_PRICE(-2) | -25.43942 (37.6187) [-0.67624] | 0.013017 (0.74132) [0.01756] | -0.000153 (0.06756) [-0.00227] | 0.743693 (4.45714) [0.16685] |
| CRUDEOILPRICE(-1) | 0.439232 (0.54786) [0.80172] | -0.004469 (0.01080) [-0.41397] | 0.000569 (0.00098) [0.57798] | 1.340158 (0.06491) [20.6459] |
| CRUDEOILPRICE(-2) | -0.117122 (0.55354) [-0.21159] | 0.012097 (0.01091) [1.10894] | -7.31E-05 (0.00099) [-0.07353] | -0.413572 (0.06558) [-6.30590] |
| C | 98.18853 (46.2214) [2.12431] | -0.457860 (0.91085) [-0.50267] | 0.254019 (0.08302) [3.05988] | -6.065621 (5.47640) [-1.10759] |
| R-squared | 0.746837 | 0.114713 | 0.957275 | 0.946550 |
| Adj. R-squared | 0.737460 | 0.081924 | 0.955693 | 0.944570 |
| Sum sq. resids | 461535.8 | 179.2304 | 1.488817 | 6479.029 |
| S.E. equation | 46.22488 | 0.910917 | 0.083022 | 5.476815 |
| F-statistic | 79.65058 | 3.498575 | 604.9538 | 478.1410 |
| Log likelihood | -1177.210 | -293.6755 | 245.2772 | -697.2865 |
| Akaike AIC | 10.54409 | 2.690449 | -2.100242 | 6.278103 |
| Schwarz SC | 10.68074 | 2.827093 | -1.963598 | 6.414747 |
| Mean dependent | 229.2108 | 0.123192 | 4.793054 | 66.74631 |

| | | | | |
|---|----------|-----------|----------|----------|
| S.D. dependent | 90.21493 | 0.950692 | 0.394419 | 23.26245 |
| Determinant resid covariance (dof adj.) | | 329.7105 | | |
| Determinant resid covariance | | 280.0385 | | |
| Log likelihood | | -1910.974 | | |
| Akaike information criterion | | 17.30644 | | |
| Schwarz criterion | | 17.85301 | | |
| Number of coefficients | | 36 | | |

VAR Residual Serial Correlation LM Tests

Date: 08/24/23 Time: 13:39

Sample: 2003M01 2024M12

Included observations: 225

Null hypothesis: No serial correlation at lag h

| Lag | LRE* stat | df | Prob. | Rao F-stat | df | Prob. |
|-----|-----------|----|--------|------------|-------------|--------|
| 1 | 10.76648 | 16 | 0.8237 | 0.671191 | (16, 639.1) | 0.8237 |
| 2 | 13.86835 | 16 | 0.6085 | 0.866649 | (16, 639.1) | 0.6086 |
| 3 | 12.56803 | 16 | 0.7040 | 0.784598 | (16, 639.1) | 0.7041 |

Null hypothesis: No serial correlation at lags 1 to h

| Lag | LRE* stat | df | Prob. | Rao F-stat | df | Prob. |
|-----|-----------|----|--------|------------|-------------|--------|
| 1 | 10.76648 | 16 | 0.8237 | 0.671191 | (16, 639.1) | 0.8237 |
| 2 | 25.32152 | 32 | 0.7928 | 0.788790 | (32, 757.6) | 0.7929 |
| 3 | 38.68309 | 48 | 0.8293 | 0.801957 | (48, 776.3) | 0.8296 |

*Edgeworth expansion corrected likelihood ratio statistic.

VAR Residual Heteroscedasticity Tests (Levels and Squares)

Date: 08/24/23 Time: 13:39

Sample: 2003M01 2024M12

Included observations: 225

Joint test:

| Chi-sq | df | Prob. | | | |
|----------|-----|--------|--|--|--|
| 288.8750 | 160 | 0.0000 | | | |

Individual components:

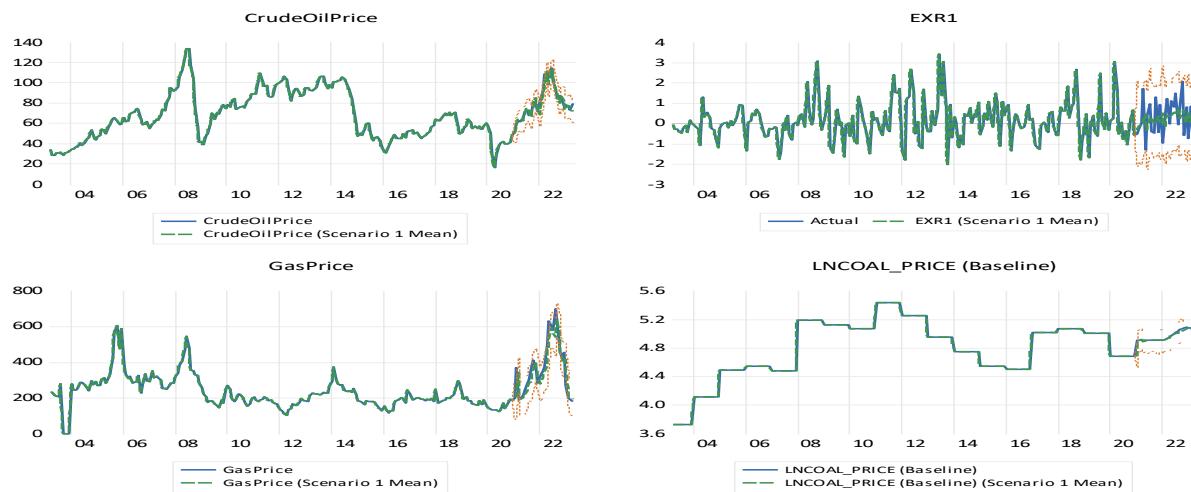
| Dependent | R-squared | F(16,208) | Prob. | Chi-sq(16) | Prob. |
|-----------|-----------|-----------|--------|------------|--------|
| res1*res1 | 0.219520 | 3.656425 | 0.0000 | 49.39209 | 0.0000 |
| res2*res2 | 0.127544 | 1.900470 | 0.0219 | 28.69746 | 0.0261 |
| res3*res3 | 0.048965 | 0.669311 | 0.8223 | 11.01702 | 0.8084 |
| res4*res4 | 0.122677 | 1.817804 | 0.0306 | 27.60233 | 0.0353 |
| res2*res1 | 0.161598 | 2.505686 | 0.0016 | 36.35952 | 0.0026 |
| res3*res1 | 0.198892 | 3.227520 | 0.0001 | 44.75064 | 0.0002 |
| res3*res2 | 0.044145 | 0.600393 | 0.8816 | 9.932689 | 0.8701 |
| res4*res1 | 0.200813 | 3.266530 | 0.0000 | 45.18291 | 0.0001 |
| res4*res2 | 0.097393 | 1.402728 | 0.1426 | 21.91348 | 0.1460 |
| res4*res3 | 0.044839 | 0.610264 | 0.8739 | 10.08867 | 0.8620 |

The above diagnostic tests (LM Test) indicate that model is free from serial correlation as Null Hypothesis is not rejected at 5% confidence level

Similarly, above diagnostic test (Residual Heteroscedasticity Tests) indicates that model is free from Heteroscedasticity as Null Hypothesis is rejected at 5% confidence level.

Testing of Models with Data Set (2003M01 2023M04):

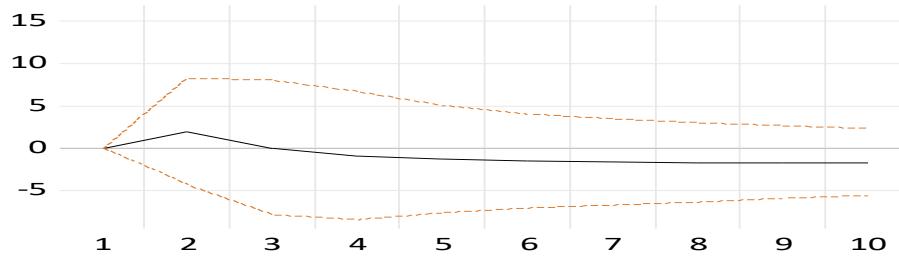
Model testing suggests that all the results lie under 95% confidence band, meaning thereby the adopted model hold good for forecasting purpose.



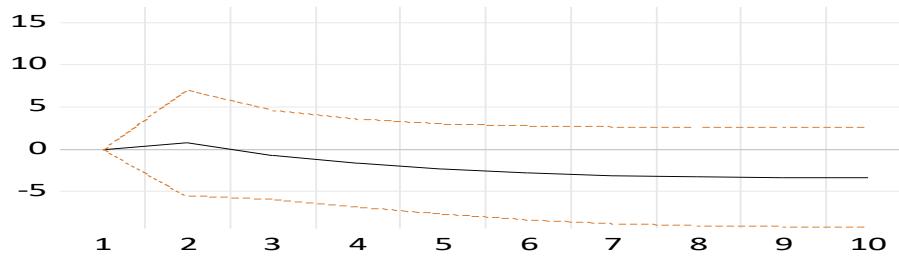
Effects of Crude Oil, Coal Prices and Exchange Rates Innovation:

**Response to Cholesky One S.D. (d.f. adjusted) Innovations
± 2 analytic asymptotic S.E.s**

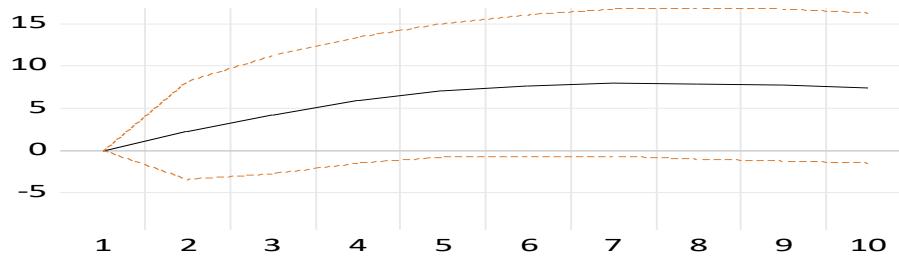
Response of GASPRICE to EXR1 Innovation



Response of GASPRICE to LNCOAL_PRICE Innovation

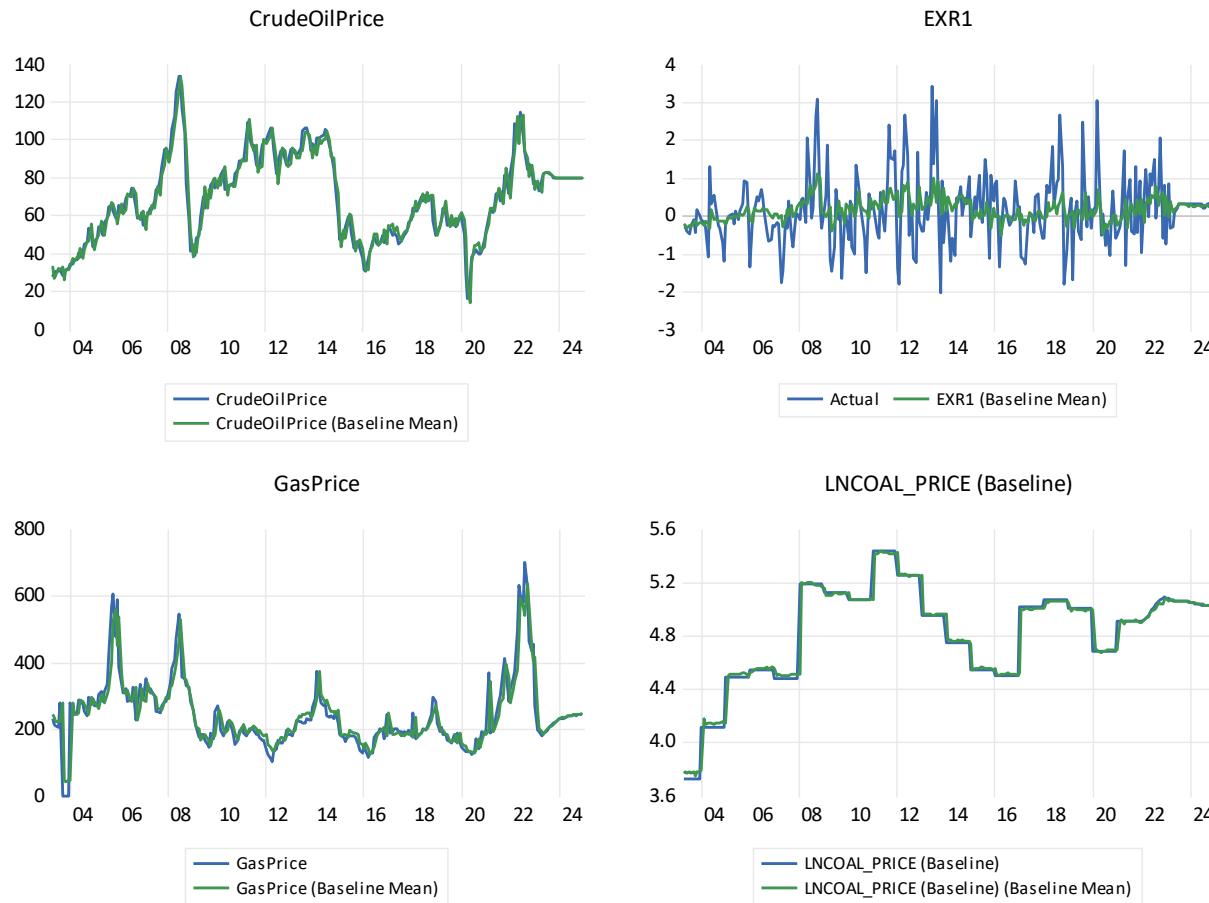


Response of GASPRICE to CRUDEOILPRICE Innovation

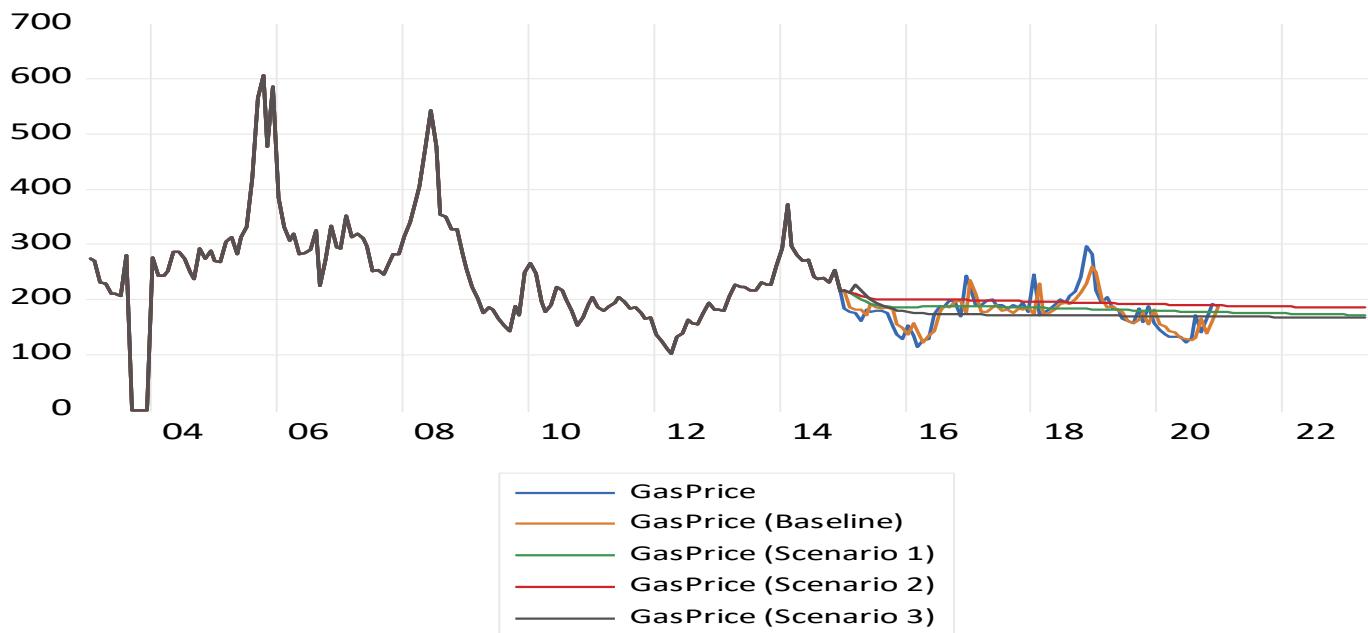


The above graphs indicate that gas prices continuously increase in short run and get stable in long run with the increase in crude oil prices. Similarly with increase in exchange rates and coal prices , the gas prices slightly increase then decrease in short run and get normalised in long run with the trends remaining in negative side only.

Forecasting of International Gas Prices from 2023M05 2024M12:



Effect of Increase in Crude Oil Prices, Coal Prices and Exchange Rates:



A shock of 10% was applied to crude oil prices(scenario1), coal prices(scenario2) and exchange rates (scenario3) during the period 2015M01 2023M04 and results reveal that gas prices get affected more with crude oil prices and less with coal prices and least with the upward variation of exchange rates.

ARIMA-GARCH (Auto Regressive Integrated Moving Average-Generalized Autoregressive Conditional Heteroscedasticity) Model:

The main contributions of this study are as follows : (1) ARIMA model and ARIMA-GARCH combined model have been constructed (2) The future trend of international gas price is predicted, which has certain theoretical value and significance for economic development (3) Comparing with other traditional models, we obtain that the proposed model has higher prediction accuracy.

2. Brief Introduction of ARIMA and GARCH Models

General Form of the ARMA Model

In the ARIMA(p, d, q), AR represents autoregressive, p represents the number of autoregressive terms, MA represents average move, q represents the average number of terms of moving, and d represents the difference number. If

$$Y_t = (1 - B)^d X_t, \quad (2)$$

is a sequence of ARMA(p, q), it indicates that $\{X_t\}$ is a sequence of ARMA(p, q) and the model is shown as follows:

$$\phi(B)(1 - B)^d X_t = \theta(B) \varepsilon_t, \quad t \in Z, \quad (3)$$

where B represents the operator, $(1 - B)$ represents finite difference operator, $\{\varepsilon_t\}$ represents a flanoise in zero-mean, and real polynomial $\phi(z) = 1 - \phi_1 z - \dots - \phi_p z^p$ and $\theta(z) = \theta_0 + \theta_1 z + \dots + \theta_q z^q$ meet the requirements of stationarity and reversibility, respectively.

The modeling steps of ARIMA(p, d, q) model are as follows:

- ① The stationarity test is carried out on the original time series. If the series does not meet the stationarity condition, the difference transformation is needed to make the series meet the stationarity condition, so as to obtain the value of d in the model.
- ② The values of p and q in the model are determined by using ACF and PACF.
- ③ The unknown parameters of the model were estimated and the significance of the parameters and the applicability of the diagnostic model were tested.
- ④ Predict the future value of time series.

The structure of the ARMA model is as follows:

$$X_t = \sum_{j=1}^p \phi_j X_{t-j} + \sum_{j=0}^q \theta_j \varepsilon_{t-j}, \quad t \in Z, \quad (1)$$

$$\left\{ \begin{array}{l} \theta_0 = 1, \\ \phi_p \theta_q \neq 0, \end{array} \right.$$

where $\{\varepsilon_t\}$ represents a flat noise in zero-mean, real polynomial.

$\phi(z) = 1 - \phi_1 z - \dots - \phi_p z^p$ and $\theta(z) = \theta_0 + \theta_1 z + \dots + \theta_q z^q$ meet the requirements of stationarity and reversibility, respectively.

$$\left\{ \begin{array}{l} x_t = f(t, x_{t-1}, x_{t-2}, \dots) + \varepsilon_t, \\ \varepsilon_t = \sqrt{h_t} e_t, \\ h_t = w + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2, \\ e_t \sim IID(0, 1), \end{array} \right. \quad (4)$$

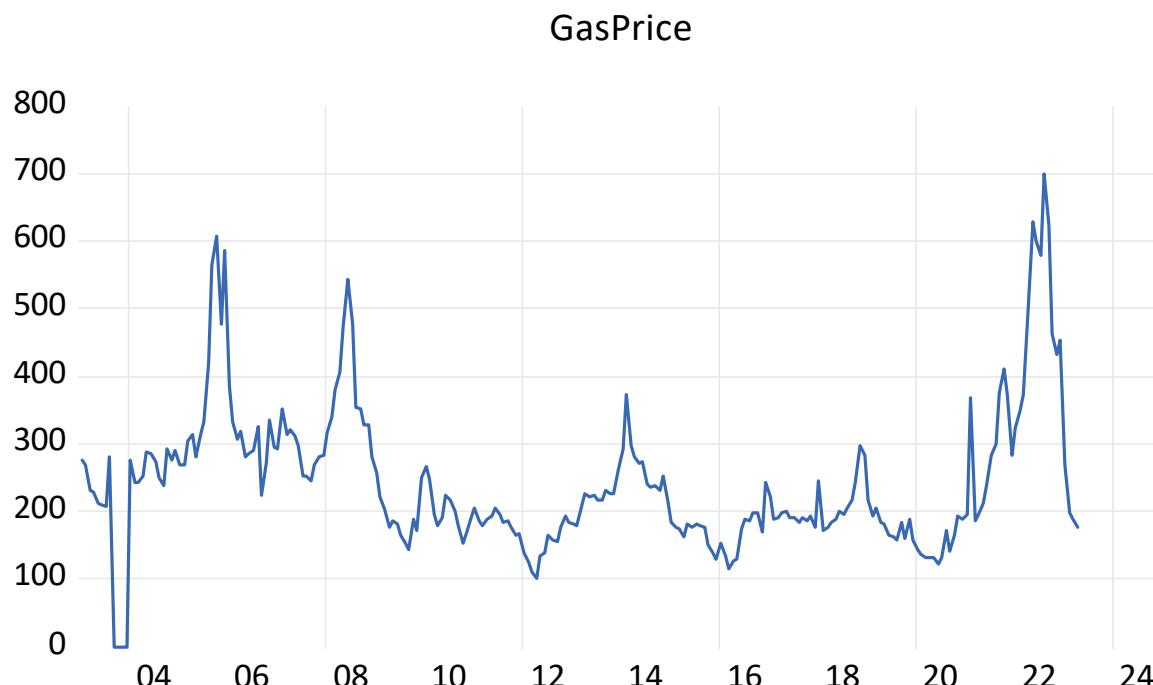
where α_i is nonnegative and $f(t, x_{t-1}, x_{t-2}, \dots)$ is the deterministic information fitting model of $\{x_t\}$.

GARCH Model

$$\left\{ \begin{array}{l} x_t = f(t, x_{t-1}, x_{t-2}, \dots) + \varepsilon_t, \\ \varepsilon_t = \sqrt{h_t} e_t, \\ h_t = w + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \gamma_j h_{t-j}, \\ e_t \sim IID(0, 1), \end{array} \right. \quad (5)$$

where α_i and γ_j are nonnegative and $f(t, x_{t-1}, x_{t-2}, \dots)$ is the deterministic information fitting model of $\{x_t\}$. It is an extension of the ARCH model and claims that h_t has AR $\sum_{j=1}^p \gamma_j h_{t-j}$ and ARCH term is $\sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2$. In general, the GARCH model is easier to identify and estimate, and the GARCH model can capture the flat period and fluctuation period of time series.

3. Results and Discussions



| | | | | |
|---|-----------|--|-------------|--------|
| Null Hypothesis: GASPRICE has a unit root | | | | |
| Exogenous: Constant | | | | |
| Lag Length: 0 (Automatic - based on SIC, maxlag=14) | | | | |
| | | | t-Statistic | Prob.* |
| Augmented Dickey-Fuller test statistic | | | -3.754253 | 0.0039 |
| Test critical values: | 1% level | | -3.457173 | |
| | 5% level | | -2.873240 | |
| | 10% level | | -2.573080 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(GASPRICE)

Method: Least Squares

Date: 08/30/23 Time: 12:03

Sample (adjusted): 2003M02 2023M04

Included observations: 243 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|--------------------|-------------|-----------------------|-------------|--------|
| GASPRICE(-1) | -0.111073 | 0.029586 | -3.754253 | 0.0002 |
| C | 26.57476 | 7.865715 | 3.378556 | 0.0008 |
| R-squared | 0.055252 | Mean dependent var | | |
| Adjusted R-squared | 0.051332 | S.D. dependent var | | |
| S.E. of regression | 49.86821 | Akaike info criterion | | |
| Sum squared resid | 599328.0 | Schwarz criterion | | |
| Log likelihood | -1293.778 | Hannan-Quinn criter. | | |
| F-statistic | 14.09442 | Durbin-Watson stat | | |
| Prob(F-statistic) | 0.000218 | | | |

The above graph shows constant mean and variance over time, it suggests a stationary series, ADF test also indicates stationary at level with 5% as p-value is 0.0039 which is less than 0.05.

Correlogram for ARIMA Model:

| Date: 08/28/23 Time: 09:48 | | | | | | |
|----------------------------|---------------------|----|--------|--------|--------|-------|
| Sample: 2003M01 2023M04 | | | | | | |
| Included observations: 244 | | | | | | |
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
| . ***** | . ***** | 1 | 0.907 | 0.907 | 203.21 | 0.000 |
| . **** | . . | 2 | 0.817 | -0.034 | 368.66 | 0.000 |
| . *** | . . | 3 | 0.734 | -0.010 | 502.66 | 0.000 |
| . ** | * . | 4 | 0.632 | -0.148 | 602.70 | 0.000 |
| . ** | * . | 5 | 0.529 | -0.077 | 672.99 | 0.000 |
| . ** | . * | 6 | 0.466 | 0.160 | 727.79 | 0.000 |
| . ** | . . | 7 | 0.406 | -0.014 | 769.62 | 0.000 |
| . ** | . . | 8 | 0.352 | 0.002 | 801.12 | 0.000 |
| . ** | . . | 9 | 0.305 | -0.041 | 824.84 | 0.000 |
| . ** | . . | 10 | 0.276 | 0.054 | 844.32 | 0.000 |
| . ** | . . | 11 | 0.252 | 0.042 | 860.65 | 0.000 |
| . ** | * . | 12 | 0.218 | -0.076 | 873.00 | 0.000 |
| . * | . . | 13 | 0.200 | 0.049 | 883.36 | 0.000 |
| . * | . . | 14 | 0.190 | 0.023 | 892.75 | 0.000 |
| . * | . . | 15 | 0.170 | -0.023 | 900.35 | 0.000 |
| . * | . . | 16 | 0.145 | -0.047 | 905.86 | 0.000 |
| . * | . . | 17 | 0.124 | -0.026 | 909.95 | 0.000 |
| . * | . * | 18 | 0.114 | 0.078 | 913.40 | 0.000 |
| . * | . . | 19 | 0.095 | -0.035 | 915.78 | 0.000 |
| . . | * . | 20 | 0.062 | -0.106 | 916.79 | 0.000 |
| . . | . . | 21 | 0.036 | -0.014 | 917.15 | 0.000 |
| . . | . * | 22 | 0.028 | 0.096 | 917.37 | 0.000 |
| . . | . . | 23 | 0.012 | -0.000 | 917.41 | 0.000 |
| . . | . . | 24 | 0.001 | -0.019 | 917.41 | 0.000 |
| . . | . . | 25 | -0.003 | -0.033 | 917.41 | 0.000 |
| . . | . . | 26 | -0.005 | 0.027 | 917.42 | 0.000 |
| . . | . * | 27 | 0.002 | 0.091 | 917.42 | 0.000 |
| . . | . . | 28 | 0.016 | 0.012 | 917.48 | 0.000 |
| . . | . * | 29 | 0.034 | 0.013 | 917.81 | 0.000 |
| . . | . * | 30 | 0.066 | 0.099 | 919.04 | 0.000 |
| . * | . . | 31 | 0.091 | 0.006 | 921.36 | 0.000 |

| | | | | | | | | |
|-----|--|-----|--|----|-------|--------|--------|-------|
| . * | | . . | | 32 | 0.104 | -0.057 | 924.45 | 0.000 |
| . * | | * . | | 33 | 0.109 | -0.075 | 927.85 | 0.000 |
| . * | | . . | | 34 | 0.104 | -0.002 | 930.92 | 0.000 |
| . * | | . . | | 35 | 0.088 | 0.016 | 933.15 | 0.000 |
| . . | | * . | | 36 | 0.065 | -0.068 | 934.36 | 0.000 |

Based on above correlogram it is observed that ACF remains large for a long time and PAC cuts off at lag 1, therefore we start with the simplest model: AR(1), MA(1) and ARIMA(1,1,1) until we get a model with significant coefficients.

Summary of the Derived Models:

| Model | Coefficient(s) | White Noise | AIC | SIC |
|-----------|--------------------------------------|-------------|----------|----------|
| AR(1,1,0) | Significant | - | 10.40731 | 10.45030 |
| MA(0,1,1) | Significant | - | 11.30198 | 11.34498 |
| AR(1,1,1) | AR Significant MA Not Significant | - | 10.41432 | 10.47165 |
| AR(2,1,0) | Significant | - | 11.04199 | 11.04899 |
| MA(0,1,2) | Significant | - | 11.47465 | 11.51764 |
| AR(2,1,2) | AR Significant MA Not Significant | - | 11.04024 | 11.09757 |

NOTE:-AR(1,1,0) is based suited depending upon AIC and SC values

ARIMA (1,1,0)

| | | | | |
|--|-------------|-----------------------|-------------|----------|
| Dependent Variable: GASPRICE | | | | |
| Method: ARMA Maximum Likelihood (OPG - BHHH) | | | | |
| Date: 08/30/23 Time: 12:26 | | | | |
| Sample: 2003M01 2023M04 | | | | |
| Included observations: 244 | | | | |
| Convergence achieved after 31 iterations | | | | |
| Coefficient covariance computed using outer product of gradients | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | 241.6224 | 31.29046 | 7.721918 | 0.0000 |
| AR(1) | 0.885692 | 0.019368 | 45.73049 | 0.0000 |
| SIGMASQ | 2457.433 | 102.7659 | 23.91292 | 0.0000 |
| R-squared | 0.789267 | Mean dependent var | | 242.6104 |
| Adjusted R-squared | 0.787518 | S.D. dependent var | | 108.2096 |
| S.E. of regression | 49.88009 | Akaike info criterion | | 10.67563 |
| Sum squared resid | 599613.7 | Schwarz criterion | | 10.71863 |
| Log likelihood | -1299.427 | Hannan-Quinn criter. | | 10.69295 |
| F-statistic | 451.3125 | Durbin-Watson stat | | 1.993777 |
| Prob(F-statistic) | 0.000000 | | | |
| Inverted AR Roots | .89 | | | |

| | | | | | | |
|--|---------------------|----|--------|--------|--------|-------|
| Date: 08/28/23 Time: 14:21 | | | | | | |
| Sample: 2003M01 2023M04 | | | | | | |
| Q-statistic probabilities adjusted for 1 ARMA term | | | | | | |
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
| . . | . . | 1 | 0.035 | 0.035 | 0.2989 | |
| . . | . . | 2 | 0.008 | 0.007 | 0.3152 | 0.574 |
| . * | . * | 3 | 0.139 | 0.139 | 5.1340 | 0.077 |
| . . | . . | 4 | 0.068 | 0.060 | 6.3020 | 0.098 |
| * . | * . | 5 | -0.187 | -0.197 | 15.124 | 0.004 |
| . . | . . | 6 | 0.010 | 0.002 | 15.148 | 0.010 |
| . . | . . | 7 | 0.009 | -0.003 | 15.167 | 0.019 |
| . . | . . | 8 | -0.015 | 0.035 | 15.225 | 0.033 |
| * . | * . | 9 | -0.098 | -0.080 | 17.690 | 0.024 |
| . . | . . | 10 | -0.015 | -0.051 | 17.751 | 0.038 |
| . . | . . | 11 | 0.061 | 0.073 | 18.711 | 0.044 |
| * . | * . | 12 | -0.085 | -0.068 | 20.568 | 0.038 |
| . . | . . | 13 | -0.054 | -0.032 | 21.335 | 0.046 |
| . . | . . | 14 | 0.055 | 0.015 | 22.121 | 0.054 |
| . . | . . | 15 | 0.034 | 0.041 | 22.427 | 0.070 |
| . . | . . | 16 | -0.026 | 0.018 | 22.611 | 0.093 |
| . . | * . | 17 | -0.033 | -0.078 | 22.905 | 0.116 |
| . . | . . | 18 | 0.054 | 0.027 | 23.687 | 0.128 |

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| | | | | | | | | |
|-----|--|-----|--|----|--------|--------|--------|-------|
| . . | | . * | | 19 | 0.069 | 0.085 | 24.964 | 0.126 |
| . . | | . . | | 20 | -0.048 | -0.021 | 25.593 | 0.142 |
| * . | | * . | | 21 | -0.091 | -0.123 | 27.809 | 0.114 |
| . . | | . . | | 22 | 0.039 | -0.012 | 28.219 | 0.134 |
| . . | | . . | | 23 | -0.031 | 0.015 | 28.487 | 0.160 |
| . . | | . . | | 24 | -0.040 | 0.029 | 28.921 | 0.183 |
| . . | | . . | | 25 | -0.010 | -0.040 | 28.949 | 0.222 |
| . . | | * . | | 26 | -0.021 | -0.073 | 29.070 | 0.261 |
| . . | | . . | | 27 | -0.062 | -0.026 | 30.133 | 0.262 |
| . . | | . . | | 28 | -0.025 | 0.007 | 30.305 | 0.301 |
| . . | | * . | | 29 | -0.065 | -0.080 | 31.467 | 0.297 |
| . . | | . . | | 30 | 0.036 | 0.024 | 31.834 | 0.327 |
| . . | | * . | | 31 | 0.055 | 0.090 | 32.676 | 0.337 |
| . . | | . . | | 32 | 0.050 | 0.074 | 33.397 | 0.352 |
| . . | | . . | | 33 | 0.054 | -0.004 | 34.213 | 0.362 |
| . . | | . . | | 34 | 0.059 | -0.018 | 35.194 | 0.365 |
| . . | | . . | | 35 | 0.043 | 0.061 | 35.719 | 0.388 |
| . . | | . . | | 36 | -0.053 | -0.043 | 36.527 | 0.398 |

The above correlogram of residuals are mostly small in magnitude, falling inside the 95% confidence interval, suggesting that residuals are independently distributed (no autocorrelation in the residuals), implying the fitted (1, 1, 0) model is adequate. Moreover, the Q-statistics are greater than alpha=0.05, therefore we are certain that the error terms of the selected model are white noise.

We have also tried for over fitting as per above table which that only AR (1, 1, 0) has been found to be the best depending upon coefficients significance and AIC, SIC values. Which should be minimum for best fitted model.

| Date: 08/28/23 Time: 11:29 | | | | | | | | |
|--|--|---------------------|--|----|--------|--------|--------|-------|
| Sample (adjusted): 2003M02 2023M04 | | | | | | | | |
| Included observations: 243 after adjustments | | | | | | | | |
| Autocorrelation | | Partial Correlation | | AC | PAC | Q-Stat | Prob* | |
| . . | | . . | | 1 | 0.040 | 0.040 | 0.3982 | 0.528 |
| . . | | . . | | 2 | -0.038 | -0.040 | 0.7630 | 0.683 |
| . . | | . . | | 3 | -0.022 | -0.019 | 0.8820 | 0.830 |
| . . | | . . | | 4 | -0.020 | -0.020 | 0.9790 | 0.913 |
| . . | | . . | | 5 | 0.022 | 0.022 | 1.1026 | 0.954 |
| . . | | . . | | 6 | -0.012 | -0.015 | 1.1359 | 0.980 |
| . . | | . . | | 7 | 0.009 | 0.011 | 1.1579 | 0.992 |
| . . | | . . | | 8 | -0.016 | -0.017 | 1.2210 | 0.996 |
| . . | | . . | | 9 | -0.009 | -0.006 | 1.2414 | 0.999 |
| . . | | . . | | 10 | 0.029 | 0.028 | 1.4577 | 0.999 |
| . . | | . . | | 11 | -0.013 | -0.015 | 1.4979 | 1.000 |
| . . | | . . | | 12 | -0.025 | -0.024 | 1.6619 | 1.000 |
| . . | | . . | | 13 | 0.016 | 0.019 | 1.7293 | 1.000 |
| * . | | * . | | 14 | 0.193 | 0.191 | 11.373 | 0.657 |
| . . | | . . | | 15 | 0.030 | 0.014 | 11.612 | 0.708 |
| . . | | . . | | 16 | -0.022 | -0.009 | 11.737 | 0.762 |
| . . | | . . | | 17 | -0.035 | -0.026 | 12.061 | 0.796 |
| . . | | * . | | 18 | 0.063 | 0.077 | 13.100 | 0.786 |
| . . | | . . | | 19 | -0.020 | -0.036 | 13.205 | 0.828 |
| . . | | . . | | 20 | 0.002 | 0.009 | 13.207 | 0.868 |
| . . | | . . | | 21 | -0.042 | -0.048 | 13.676 | 0.883 |
| . . | | . . | | 22 | -0.012 | 0.004 | 13.716 | 0.911 |
| * . | | * . | | 23 | 0.110 | 0.111 | 16.969 | 0.811 |
| . . | | . . | | 24 | -0.007 | -0.027 | 16.984 | 0.849 |
| . . | | . . | | 25 | 0.028 | 0.034 | 17.193 | 0.875 |
| . . | | . . | | 26 | -0.047 | -0.038 | 17.810 | 0.883 |
| . . | | . . | | 27 | 0.041 | 0.056 | 18.267 | 0.895 |
| . . | | . . | | 28 | 0.022 | -0.036 | 18.400 | 0.916 |
| . . | | . . | | 29 | 0.001 | 0.002 | 18.400 | 0.936 |
| . . | | . . | | 30 | -0.024 | -0.028 | 18.558 | 0.949 |
| . . | | . . | | 31 | -0.020 | 0.006 | 18.669 | 0.960 |
| . . | | . . | | 32 | -0.013 | -0.042 | 18.718 | 0.970 |
| . . | | . . | | 33 | -0.007 | -0.006 | 18.731 | 0.978 |
| . . | | . . | | 34 | 0.002 | 0.002 | 18.733 | 0.984 |
| . . | | . . | | 35 | -0.021 | -0.001 | 18.859 | 0.988 |

| | | | | | | | | |
|--|--|---|--|----|-------|-------|--------|-------|
| . | | . | | 36 | 0.035 | 0.039 | 19.209 | 0.990 |
| *Probabilities may not be valid for this equation specification. | | | | | | | | |

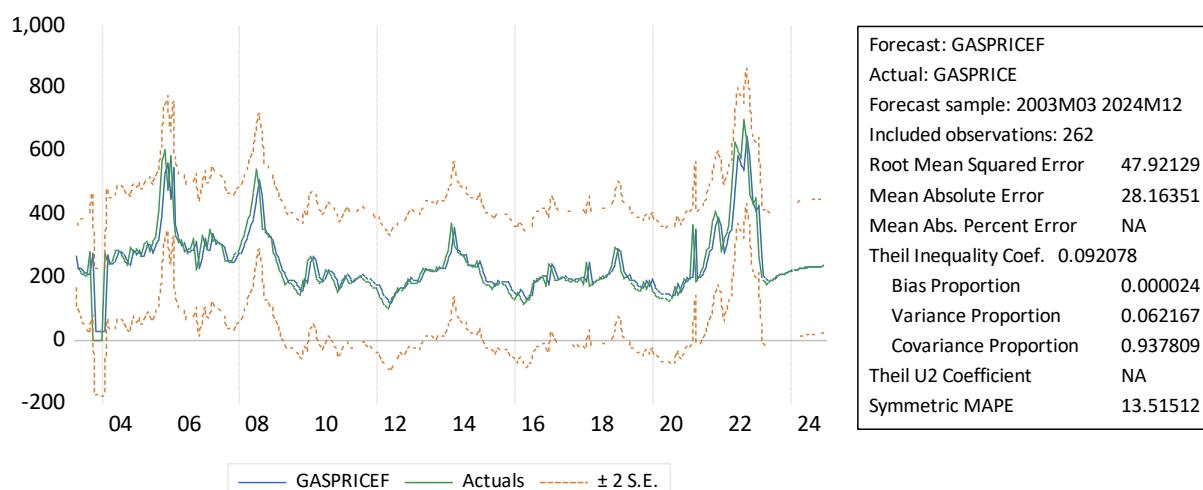
| | | | | |
|---|----------------|----------|---------------------|--------|
| Before fitting GARCH(1,1) into ARIMA(1,0,0) | F-Statistic | 30.84307 | Prob.F(2,34) | 0.0000 |
| | Obs* R-Squared | 27.49670 | Prob. Chi-square(1) | 0.0000 |
| After fitting GARCH(1,1) into ARIMA(1,0,0) | F-Statistic | 0.389439 | Prob.F(2,34) | 0.5332 |
| | Obs* R-Squared | 0.392049 | Prob. Chi-square(1) | 0.5312 |

The ARCH-LM test is conducted to see whether there is a presence of heteroscedasticity in variance. As can be seen that before fitting GARCH (1, 1) into ARIMA (1, 1, 0) model. The p-values are less than 0.05 (Significance level), therefore we reject null hypothesis indicating that heteroscedasticity is present in residual. Which shows the presence of ARCH effect. After fitting GARCH (1, 1) into ARIMA (1, 1, 0) model, again ARCH-LM test is conducted. This time, the values of p are greater than 0.05 and we failed to reject null hypothesis and conclude that there is no more ARCH effect, implying that the residuals are now homoscedastic.

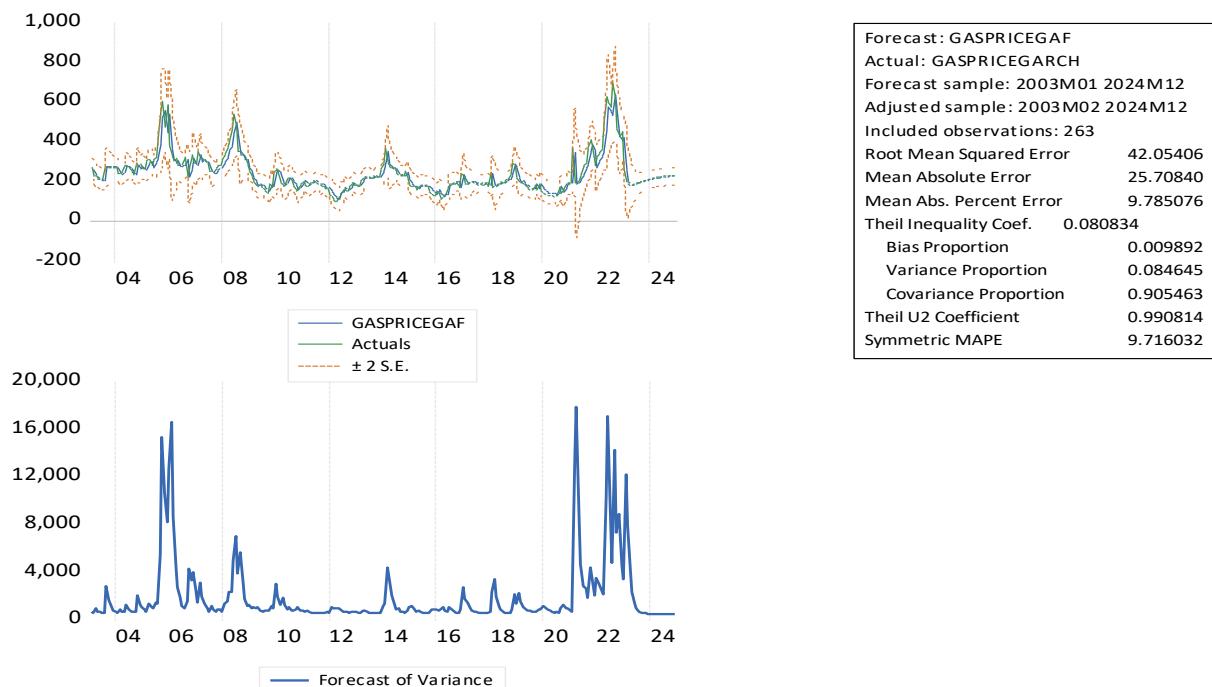
| | | | | |
|--|-------------|-----------------------|-------------|--------|
| Dependent Variable: GASPRICEF | | | | |
| Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) | | | | |
| Date: 08/27/23 Time: 11:22 | | | | |
| Sample (adjusted): 2003M02 2023M04 | | | | |
| Included observations: 243 after adjustments | | | | |
| Convergence achieved after 22 iterations | | | | |
| Coefficient covariance computed using outer product of gradients | | | | |
| Presample variance: backcast (parameter = 0.7) | | | | |
| GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) | | | | |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 22.75606 | 7.453498 | 3.053071 | 0.0023 |
| GASPRICEF(-1) | 0.889300 | 0.032593 | 27.28497 | 0.0000 |
| Variance Equation | | | | |
| C | 246.6076 | 67.24706 | 3.667187 | 0.0002 |
| RESID(-1)^2 | 0.332773 | 0.085672 | 3.884258 | 0.0001 |
| GARCH(-1) | 0.559690 | 0.085989 | 6.508844 | 0.0000 |
| R-squared | 0.822427 | Mean dependent var | | |
| Adjusted R-squared | 0.821690 | S.D. dependent var | | |
| S.E. of regression | 43.84572 | Akaike info criterion | | |
| Sum squared resid | 463309.7 | Schwarz criterion | | |
| Log likelihood | -1215.730 | Hannan-Quinn criter. | | |
| Durbin-Watson stat | 1.877211 | | | |

The above model ARCH (1, 1, 0)-GARCH (1, 1) is better model with statistically significant coefficients, fulfilled the assumption of NID residuals and AIC, SIC are smaller than that ARIMA (1, 1, 0) model. Therefore, we ensure that the ARIMA (1, 1, 0)-GARCH (1, 1) model is our best model for gas prices.

ARIMA (1, 1, 0) model Forecasting



ARCH (1, 1, 0)-GARCH (1, 1) Forecasting



| | Actual Gas Prices(INR) | | ARIMA(1,1,0) forecasted prices(INR) | | ARIMA(1,1,0)-GARCH(1,1) forecasted prices(INR) | VAR forecasted prices(INR) |
|---------|------------------------|---------|-------------------------------------|---------|--|----------------------------|
| 2003M01 | 274.97 | 2003M01 | 274.97 | 2003M01 | 274.97 | 274.97 |
| 2003M02 | 269.58 | 2003M02 | 269.58 | 2003M02 | 269.58 | 269.58 |
| 2003M03 | 266.3861285 | 2003M03 | 266.3861285 | 2003M03 | 231.64 | 231.64 |
| 2003M04 | 232.7828323 | 2003M04 | 232.7828323 | 2003M04 | 228.3 | 228.3 |
| 2003M05 | 229.8246085 | 2003M05 | 229.8246085 | 2003M05 | 211.37 | 211.37 |
| 2003M06 | 214.8297798 | 2003M06 | 214.8297798 | 2003M06 | 210.61 | 210.61 |
| 2003M07 | 214.156651 | 2003M07 | 214.156651 | 2003M07 | 206.21 | 206.21 |
| 2003M08 | 210.2595898 | 2003M08 | 210.2595898 | 2003M08 | 279.47 | 279.47 |
| 2003M09 | 275.1456593 | 2003M09 | 275.1456593 | 2003M09 | 278.932 | 0 |
| 2003M10 | 27.62027243 | 2003M10 | 27.62027243 | 2003M10 | 278.394 | 0 |
| 2003M11 | 27.62027243 | 2003M11 | 27.62027243 | 2003M11 | 277.856 | 0 |
| 2003M12 | 27.62027243 | 2003M12 | 27.62027243 | 2003M12 | 277.318 | 0 |
| 2004M01 | 27.62027243 | 2004M01 | 27.62027243 | 2004M01 | 276.78 | 276.78 |
| 2004M02 | 272.7631377 | 2004M02 | 272.7631377 | 2004M02 | 243.56 | 243.56 |
| 2004M03 | 243.3403255 | 2004M03 | 243.3403255 | 2004M03 | 243.08 | 243.08 |
| 2004M04 | 242.9151915 | 2004M04 | 242.9151915 | 2004M04 | 251.3 | 251.3 |
| 2004M05 | 250.1956104 | 2004M05 | 250.1956104 | 2004M05 | 286.83 | 286.83 |
| 2004M06 | 281.6643799 | 2004M06 | 281.6643799 | 2004M06 | 285.38 | 285.38 |
| 2004M07 | 280.3801211 | 2004M07 | 280.3801211 | 2004M07 | 273.04 | 273.04 |
| 2004M08 | 269.4506357 | 2004M08 | 269.4506357 | 2004M08 | 250.25 | 250.25 |
| 2004M09 | 249.2656299 | 2004M09 | 249.2656299 | 2004M09 | 236.94 | 236.94 |
| 2004M10 | 237.4770197 | 2004M10 | 237.4770197 | 2004M10 | 293.47 | 293.47 |
| 2004M11 | 287.5453995 | 2004M11 | 287.5453995 | 2004M11 | 274.73 | 274.73 |
| 2004M12 | 270.9474615 | 2004M12 | 270.9474615 | 2004M12 | 289.39 | 289.39 |
| 2005M01 | 283.931761 | 2005M01 | 283.931761 | 2005M01 | 269.1 | 269.1 |
| 2005M02 | 265.9609945 | 2005M02 | 265.9609945 | 2005M02 | 268.18 | 268.18 |
| 2005M03 | 265.1461544 | 2005M03 | 265.1461544 | 2005M03 | 304.52 | 304.52 |
| 2005M04 | 297.3323374 | 2005M04 | 297.3323374 | 2005M04 | 312.75 | 312.75 |
| 2005M05 | 304.6216133 | 2005M05 | 304.6216133 | 2005M05 | 281.39 | 281.39 |
| 2005M06 | 276.8461951 | 2005M06 | 276.8461951 | 2005M06 | 313.38 | 313.38 |
| 2005M07 | 305.1796016 | 2005M07 | 305.1796016 | 2005M07 | 332.19 | 332.19 |
| 2005M08 | 321.8395384 | 2005M08 | 321.8395384 | 2005M08 | 420.12 | 420.12 |
| 2005M09 | 399.7187643 | 2005M09 | 399.7187643 | 2005M09 | 565.64 | 565.64 |
| 2005M10 | 528.6052075 | 2005M10 | 528.6052075 | 2005M10 | 606 | 606 |
| 2005M11 | 564.3518874 | 2005M11 | 564.3518874 | 2005M11 | 476.92 | 476.92 |
| 2005M12 | 450.026282 | 2005M12 | 450.026282 | 2005M12 | 585.79 | 585.79 |
| 2006M01 | 546.4519766 | 2006M01 | 546.4519766 | 2006M01 | 384.49 | 384.49 |
| 2006M02 | 368.1614253 | 2006M02 | 368.1614253 | 2006M02 | 332.04 | 332.04 |
| 2006M03 | 321.706684 | 2006M03 | 321.706684 | 2006M03 | 306.88 | 306.88 |
| 2006M04 | 299.4225793 | 2006M04 | 299.4225793 | 2006M04 | 318.69 | 318.69 |
| 2006M05 | 309.882646 | 2006M05 | 309.882646 | 2006M05 | 281.54 | 281.54 |
| 2006M06 | 276.9790494 | 2006M06 | 276.9790494 | 2006M06 | 285.08 | 285.08 |

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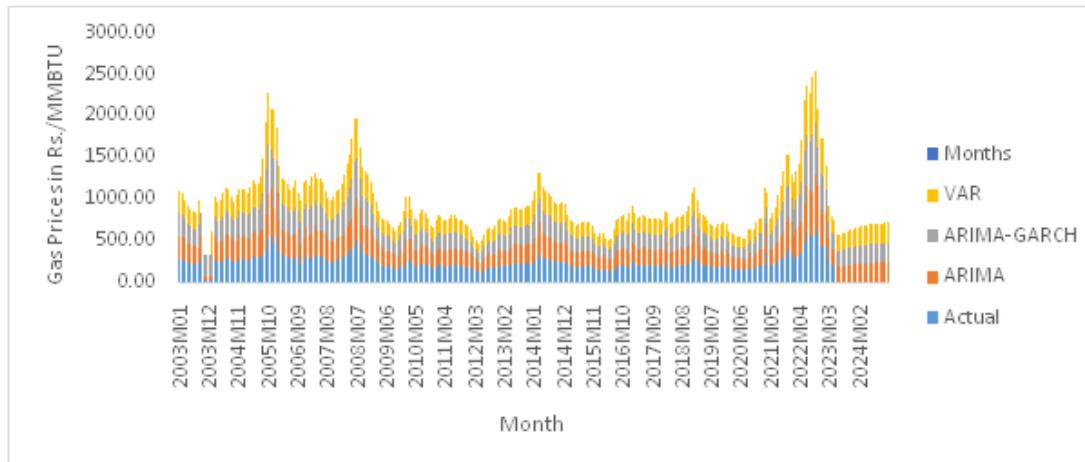
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| | | | | | | |
|---------|-------------|---------|-------------|---------|--------|--------|
| 2006M07 | 280.1144123 | 2006M07 | 280.1144123 | 2006M07 | 290.35 | 290.35 |
| 2006M08 | 284.7820289 | 2006M08 | 284.7820289 | 2006M08 | 325.77 | 325.77 |
| 2006M09 | 316.1533718 | 2006M09 | 316.1533718 | 2006M09 | 224.15 | 224.15 |
| 2006M10 | 226.1489713 | 2006M10 | 226.1489713 | 2006M10 | 270.99 | 270.99 |
| 2006M11 | 267.6349594 | 2006M11 | 267.6349594 | 2006M11 | 334.18 | 334.18 |
| 2006M12 | 323.6020729 | 2006M12 | 323.6020729 | 2006M12 | 293.7 | 293.7 |
| 2007M01 | 287.7491096 | 2007M01 | 287.7491096 | 2007M01 | 291.75 | 291.75 |
| 2007M02 | 286.0220029 | 2007M02 | 286.0220029 | 2007M02 | 351.97 | 351.97 |
| 2007M03 | 339.3586 | 2007M03 | 339.3586 | 2007M03 | 313.46 | 313.46 |
| 2007M04 | 305.2504573 | 2007M04 | 305.2504573 | 2007M04 | 319.93 | 319.93 |
| 2007M05 | 310.9809087 | 2007M05 | 310.9809087 | 2007M05 | 310.43 | 310.43 |
| 2007M06 | 302.5667992 | 2007M06 | 302.5667992 | 2007M06 | 297.56 | 297.56 |
| 2007M07 | 291.1678951 | 2007M07 | 291.1678951 | 2007M07 | 251.39 | 251.39 |
| 2007M08 | 250.2753231 | 2007M08 | 250.2753231 | 2007M08 | 253.07 | 253.07 |
| 2007M09 | 251.7632919 | 2007M09 | 251.7632919 | 2007M09 | 246.07 | 246.07 |
| 2007M10 | 245.5634217 | 2007M10 | 245.5634217 | 2007M10 | 268.69 | 268.69 |
| 2007M11 | 265.5978593 | 2007M11 | 265.5978593 | 2007M11 | 281.6 | 281.6 |
| 2007M12 | 277.0321912 | 2007M12 | 277.0321912 | 2007M12 | 282 | 282 |
| 2008M01 | 277.3864695 | 2008M01 | 277.3864695 | 2008M01 | 314.98 | 314.98 |
| 2008M02 | 306.5967148 | 2008M02 | 306.5967148 | 2008M02 | 339.69 | 339.69 |
| 2008M03 | 328.4822564 | 2008M03 | 328.4822564 | 2008M03 | 379.35 | 379.35 |
| 2008M04 | 363.6089492 | 2008M04 | 363.6089492 | 2008M04 | 405.51 | 405.51 |
| 2008M05 | 386.7787496 | 2008M05 | 386.7787496 | 2008M05 | 473.07 | 473.07 |
| 2008M06 | 446.6163534 | 2008M06 | 446.6163534 | 2008M06 | 542.96 | 542.96 |
| 2008M07 | 508.5176283 | 2008M07 | 508.5176283 | 2008M07 | 477.63 | 477.63 |
| 2008M08 | 450.655126 | 2008M08 | 450.655126 | 2008M08 | 354.25 | 354.25 |
| 2008M09 | 341.3779863 | 2008M09 | 341.3779863 | 2008M09 | 350.39 | 350.39 |
| 2008M10 | 337.9592007 | 2008M10 | 337.9592007 | 2008M10 | 327.36 | 327.36 |
| 2008M11 | 317.561628 | 2008M11 | 317.561628 | 2008M11 | 326.85 | 326.85 |
| 2008M12 | 317.1099232 | 2008M12 | 317.1099232 | 2008M12 | 281.64 | 281.64 |
| 2009M01 | 277.067619 | 2009M01 | 277.067619 | 2009M01 | 255.92 | 255.92 |
| 2009M02 | 254.2875247 | 2009M02 | 254.2875247 | 2009M02 | 222.48 | 222.48 |
| 2009M03 | 224.6698594 | 2009M03 | 224.6698594 | 2009M03 | 202.52 | 202.52 |
| 2009M04 | 206.9913725 | 2009M04 | 206.9913725 | 2009M04 | 175.25 | 175.25 |
| 2009M05 | 182.8384499 | 2009M05 | 182.8384499 | 2009M05 | 184.91 | 184.91 |
| 2009M06 | 191.3942706 | 2009M06 | 191.3942706 | 2009M06 | 181.54 | 181.54 |
| 2009M07 | 188.409476 | 2009M07 | 188.409476 | 2009M07 | 164.44 | 164.44 |
| 2009M08 | 173.264079 | 2009M08 | 173.264079 | 2009M08 | 152.2 | 152.2 |
| 2009M09 | 162.4231632 | 2009M09 | 162.4231632 | 2009M09 | 143.38 | 143.38 |
| 2009M10 | 154.6113268 | 2009M10 | 154.6113268 | 2009M10 | 187.82 | 187.82 |
| 2009M11 | 193.9716452 | 2009M11 | 193.9716452 | 2009M11 | 171.84 | 171.84 |
| 2009M12 | 179.8182274 | 2009M12 | 179.8182274 | 2009M12 | 250.4 | 250.4 |
| 2010M01 | 249.3984843 | 2010M01 | 249.3984843 | 2010M01 | 266.84 | 266.84 |
| 2010M02 | 263.9593221 | 2010M02 | 263.9593221 | 2010M02 | 247.38 | 247.38 |
| 2010M03 | 246.7236832 | 2010M03 | 246.7236832 | 2010M03 | 195.19 | 195.19 |
| 2010M04 | 200.4992228 | 2010M04 | 200.4992228 | 2010M04 | 178.44 | 178.44 |
| 2010M05 | 185.6638192 | 2010M05 | 185.6638192 | 2010M05 | 190.41 | 190.41 |
| 2010M06 | 196.2655972 | 2010M06 | 196.2655972 | 2010M06 | 223.04 | 223.04 |
| 2010M07 | 225.165849 | 2010M07 | 225.165849 | 2010M07 | 217.02 | 217.02 |
| 2010M08 | 219.8339607 | 2010M08 | 219.8339607 | 2010M08 | 200.7 | 200.7 |
| 2010M09 | 205.3794063 | 2010M09 | 205.3794063 | 2010M09 | 179.54 | 179.54 |
| 2010M10 | 186.6380845 | 2010M10 | 186.6380845 | 2010M10 | 152.35 | 152.35 |
| 2010M11 | 162.5560175 | 2010M11 | 162.5560175 | 2010M11 | 167.39 | 167.39 |
| 2010M12 | 175.8768814 | 2010M12 | 175.8768814 | 2010M12 | 191.52 | 191.52 |
| 2011M01 | 197.2487194 | 2011M01 | 197.2487194 | 2011M01 | 203.78 | 203.78 |
| 2011M02 | 208.1073491 | 2011M02 | 208.1073491 | 2011M02 | 185 | 185 |
| 2011M03 | 191.4739833 | 2011M03 | 191.4739833 | 2011M03 | 178.61 | 178.61 |
| 2011M04 | 185.8143875 | 2011M04 | 185.8143875 | 2011M04 | 188.2 | 188.2 |
| 2011M05 | 194.3082096 | 2011M05 | 194.3082096 | 2011M05 | 193.5 | 193.5 |
| 2011M06 | 199.002397 | 2011M06 | 199.002397 | 2011M06 | 204.08 | 204.08 |
| 2011M07 | 208.3730579 | 2011M07 | 208.3730579 | 2011M07 | 195.87 | 195.87 |
| 2011M08 | 201.1014959 | 2011M08 | 201.1014959 | 2011M08 | 183.38 | 183.38 |
| 2011M09 | 190.0391562 | 2011M09 | 190.0391562 | 2011M09 | 186.14 | 186.14 |
| 2011M10 | 192.4836764 | 2011M10 | 192.4836764 | 2011M10 | 175.79 | 175.79 |
| 2011M11 | 183.3167255 | 2011M11 | 183.3167255 | 2011M11 | 164.24 | 164.24 |
| 2011M12 | 173.0869398 | 2011M12 | 173.0869398 | 2011M12 | 166.34 | 166.34 |
| 2012M01 | 174.9469009 | 2012M01 | 174.9469009 | 2012M01 | 137.29 | 137.29 |
| 2012M02 | 149.2174398 | 2012M02 | 149.2174398 | 2012M02 | 123.89 | 123.89 |
| 2012M03 | 137.3491169 | 2012M03 | 137.3491169 | 2012M03 | 109.2 | 109.2 |
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| 2012M05 | 117.0932555 | 2012M05 | 117.0932555 | 2012M05 | 132.58 | 132.58 |
| 2012M06 | 145.0458129 | 2012M06 | 145.0458129 | 2012M06 | 137.83 | 137.83 |
| 2012M07 | 149.6957155 | 2012M07 | 149.6957155 | 2012M07 | 163.8 | 163.8 |
| 2012M08 | 172.6972337 | 2012M08 | 172.6972337 | 2012M08 | 157.79 | 157.79 |
| 2012M09 | 167.3742023 | 2012M09 | 167.3742023 | 2012M09 | 154.95 | 154.95 |

| | | | | | | |
|---------|-------------|---------|-------------|---------|--------|--------|
| 2012M10 | 164.8588264 | 2012M10 | 164.8588264 | 2012M10 | 175.82 | 175.82 |
| 2012M11 | 183.3432964 | 2012M11 | 183.3432964 | 2012M11 | 193.71 | 193.71 |
| 2012M12 | 199.1883931 | 2012M12 | 199.1883931 | 2012M12 | 182.42 | 182.42 |
| 2013M01 | 189.1888883 | 2013M01 | 189.1888883 | 2013M01 | 180.86 | 180.86 |
| 2013M02 | 187.8072029 | 2013M02 | 187.8072029 | 2013M02 | 178.97 | 178.97 |
| 2013M03 | 186.133238 | 2013M03 | 186.133238 | 2013M03 | 207.22 | 207.22 |
| 2013M04 | 211.1541425 | 2013M04 | 211.1541425 | 2013M04 | 226.75 | 226.75 |
| 2013M05 | 228.4517802 | 2013M05 | 228.4517802 | 2013M05 | 222.33 | 222.33 |
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| 2013M09 | 219.6479646 | 2013M09 | 219.6479646 | 2013M09 | 230.55 | 230.55 |
| 2013M10 | 231.817424 | 2013M10 | 231.817424 | 2013M10 | 226.19 | 226.19 |
| 2013M11 | 227.9557906 | 2013M11 | 227.9557906 | 2013M11 | 227.01 | 227.01 |
| 2013M12 | 228.6820611 | 2013M12 | 228.6820611 | 2013M12 | 262.66 | 262.66 |
| 2014M01 | 260.257114 | 2014M01 | 260.257114 | 2014M01 | 292.04 | 292.04 |
| 2014M02 | 286.2788546 | 2014M02 | 286.2788546 | 2014M02 | 371.84 | 371.84 |
| 2014M03 | 356.9573742 | 2014M03 | 356.9573742 | 2014M03 | 297.52 | 297.52 |
| 2014M04 | 291.1324673 | 2014M04 | 291.1324673 | 2014M04 | 279.45 | 279.45 |
| 2014M05 | 275.1279454 | 2014M05 | 275.1279454 | 2014M05 | 270.6 | 270.6 |
| 2014M06 | 267.2895381 | 2014M06 | 267.2895381 | 2014M06 | 272.89 | 272.89 |
| 2014M07 | 269.3177813 | 2014M07 | 269.3177813 | 2014M07 | 240.86 | 240.86 |
| 2014M08 | 240.948947 | 2014M08 | 240.948947 | 2014M08 | 236.27 | 236.27 |
| 2014M09 | 236.8836036 | 2014M09 | 236.8836036 | 2014M09 | 238.66 | 238.66 |
| 2014M10 | 239.0004164 | 2014M10 | 239.0004164 | 2014M10 | 231.28 | 231.28 |
| 2014M11 | 232.4639818 | 2014M11 | 232.4639818 | 2014M11 | 252.88 | 252.88 |
| 2014M12 | 251.5950097 | 2014M12 | 251.5950097 | 2014M12 | 215.1 | 215.1 |
| 2015M01 | 218.1334249 | 2015M01 | 218.1334249 | 2015M01 | 184.54 | 184.54 |
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| 2015M03 | 184.1935643 | 2015M03 | 184.1935643 | 2015M03 | 174.86 | 174.86 |
| 2015M04 | 182.4930285 | 2015M04 | 182.4930285 | 2015M04 | 161.88 | 161.88 |
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| 2015M06 | 188.1260534 | 2015M06 | 188.1260534 | 2015M06 | 176.89 | 176.89 |
| 2015M07 | 184.2909909 | 2015M07 | 184.2909909 | 2015M07 | 180.12 | 180.12 |
| 2015M08 | 187.1517881 | 2015M08 | 187.1517881 | 2015M08 | 179.6 | 179.6 |
| 2015M09 | 186.6912263 | 2015M09 | 186.6912263 | 2015M09 | 175.47 | 175.47 |
| 2015M10 | 183.0333029 | 2015M10 | 183.0333029 | 2015M10 | 150.98 | 150.98 |
| 2015M11 | 161.3426144 | 2015M11 | 161.3426144 | 2015M11 | 137.38 | 137.38 |
| 2015M12 | 149.2971524 | 2015M12 | 149.2971524 | 2015M12 | 127.86 | 127.86 |
| 2016M01 | 140.865329 | 2016M01 | 140.865329 | 2016M01 | 152.76 | 152.76 |
| 2016M02 | 162.9191528 | 2016M02 | 162.9191528 | 2016M02 | 133.76 | 133.76 |
| 2016M03 | 146.0909338 | 2016M03 | 146.0909338 | 2016M03 | 114 | 114 |
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| 2016M05 | 139.4747867 | 2016M05 | 139.4747867 | 2016M05 | 128.42 | 128.42 |
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| 2016M07 | 180.7659218 | 2016M07 | 180.7659218 | 2016M07 | 187.53 | 187.53 |
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| 2016M09 | 193.0328078 | 2016M09 | 193.0328078 | 2016M09 | 198.22 | 198.22 |
| 2016M10 | 203.1828809 | 2016M10 | 203.1828809 | 2016M10 | 196.93 | 196.93 |
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| 2017M09 | 190.7831406 | 2017M09 | 190.7831406 | 2017M09 | 190.8 | 190.8 |
| 2017M10 | 196.6110185 | 2017M10 | 196.6110185 | 2017M10 | 186.15 | 186.15 |
| 2017M11 | 192.4925334 | 2017M11 | 192.4925334 | 2017M11 | 193.97 | 193.97 |
| 2017M12 | 199.418674 | 2017M12 | 199.418674 | 2017M12 | 177.31 | 177.31 |
| 2018M01 | 184.6629831 | 2018M01 | 184.6629831 | 2018M01 | 245.67 | 245.67 |
| 2018M02 | 245.2091435 | 2018M02 | 245.2091435 | 2018M02 | 171.88 | 171.88 |
| 2018M03 | 179.8536552 | 2018M03 | 179.8536552 | 2018M03 | 175.53 | 175.53 |
| 2018M04 | 183.0864447 | 2018M04 | 183.0864447 | 2018M04 | 182.54 | 182.54 |
| 2018M05 | 189.2951718 | 2018M05 | 189.2951718 | 2018M05 | 189.12 | 189.12 |
| 2018M06 | 195.1230497 | 2018M06 | 195.1230497 | 2018M06 | 199.99 | 199.99 |
| 2018M07 | 204.7505623 | 2018M07 | 204.7505623 | 2018M07 | 194.42 | 194.42 |
| 2018M08 | 199.8172371 | 2018M08 | 199.8172371 | 2018M08 | 205.82 | 205.82 |
| 2018M09 | 209.9141684 | 2018M09 | 209.9141684 | 2018M09 | 215.46 | 215.46 |
| 2018M10 | 218.4522753 | 2018M10 | 218.4522753 | 2018M10 | 241.47 | 241.47 |
| 2018M11 | 241.4892214 | 2018M11 | 241.4892214 | 2018M11 | 296.63 | 296.63 |
| 2018M12 | 290.3441981 | 2018M12 | 290.3441981 | 2018M12 | 281.91 | 281.91 |

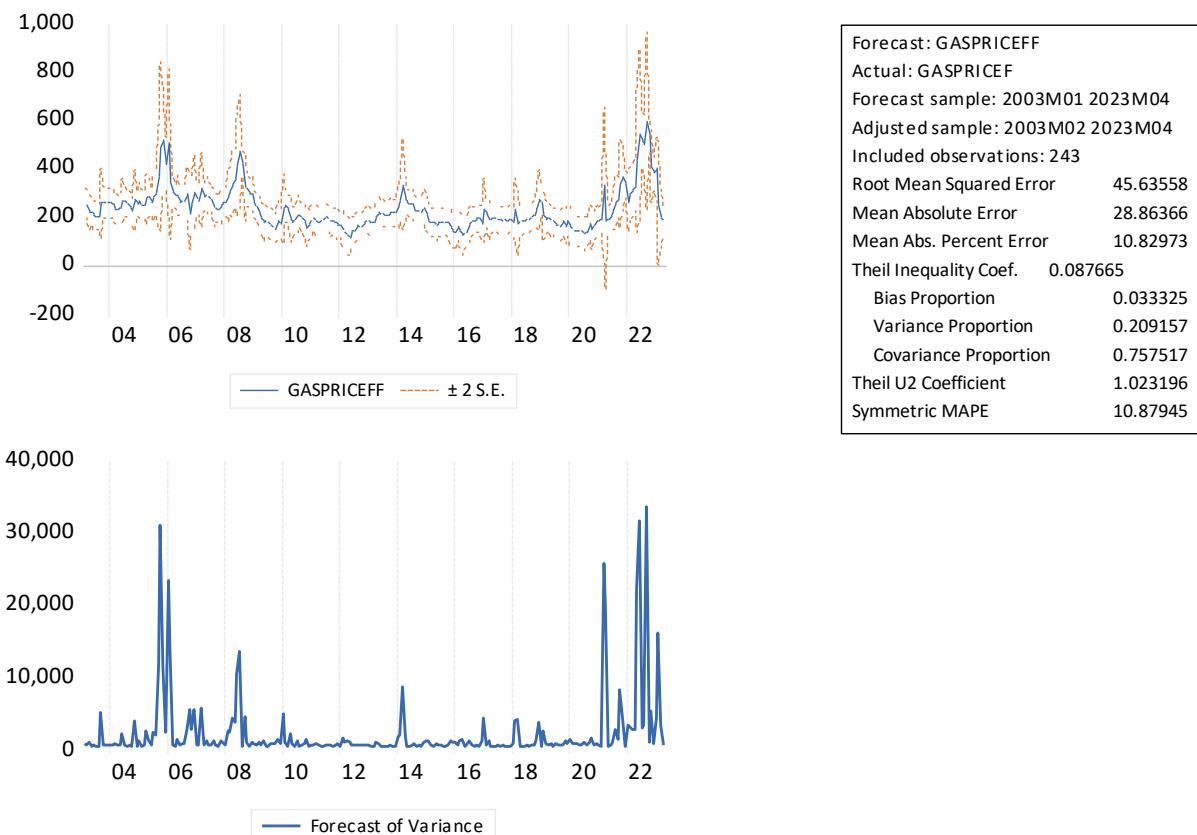
| | | | | | | |
|---------|-------------|---------|-------------|---------|--------|--------|
| 2019M01 | 277.3067569 | 2019M01 | 277.3067569 | 2019M01 | 217.2 | 217.2 |
| 2019M02 | 219.9933859 | 2019M02 | 219.9933859 | 2019M02 | 192.97 | 192.97 |
| 2019M03 | 198.5329783 | 2019M03 | 198.5329783 | 2019M03 | 203.57 | 203.57 |
| 2019M04 | 207.921353 | 2019M04 | 207.921353 | 2019M04 | 183.29 | 183.29 |
| 2019M05 | 189.9594436 | 2019M05 | 189.9594436 | 2019M05 | 182.15 | 182.15 |
| 2019M06 | 188.9497504 | 2019M06 | 188.9497504 | 2019M06 | 165.26 | 165.26 |
| 2019M07 | 173.9903495 | 2019M07 | 173.9903495 | 2019M07 | 161.01 | 161.01 |
| 2019M08 | 170.2261426 | 2019M08 | 170.2261426 | 2019M08 | 157.94 | 157.94 |
| 2019M09 | 167.5070567 | 2019M09 | 167.5070567 | 2019M09 | 183.33 | 183.33 |
| 2019M10 | 189.9948714 | 2019M10 | 189.9948714 | 2019M10 | 159.87 | 159.87 |
| 2019M11 | 169.2164495 | 2019M11 | 169.2164495 | 2019M11 | 187.86 | 187.86 |
| 2019M12 | 194.0070731 | 2019M12 | 194.0070731 | 2019M12 | 156.61 | 156.61 |
| 2020M01 | 166.3290814 | 2020M01 | 166.3290814 | 2020M01 | 144.08 | 144.08 |
| 2020M02 | 155.2313138 | 2020M02 | 155.2313138 | 2020M02 | 135.75 | 135.75 |
| 2020M03 | 147.8534683 | 2020M03 | 147.8534683 | 2020M03 | 132.28 | 132.28 |
| 2020M04 | 144.7801042 | 2020M04 | 144.7801042 | 2020M04 | 131.81 | 131.81 |
| 2020M05 | 144.3638272 | 2020M05 | 144.3638272 | 2020M05 | 132.4 | 132.4 |
| 2020M06 | 144.8863876 | 2020M06 | 144.8863876 | 2020M06 | 122.65 | 122.65 |
| 2020M07 | 136.2508542 | 2020M07 | 136.2508542 | 2020M07 | 130.53 | 130.53 |
| 2020M08 | 143.2301366 | 2020M08 | 143.2301366 | 2020M08 | 171.75 | 171.75 |
| 2020M09 | 179.7385148 | 2020M09 | 179.7385148 | 2020M09 | 141.12 | 141.12 |
| 2020M10 | 152.6096544 | 2020M10 | 152.6096544 | 2020M10 | 165.32 | 165.32 |
| 2020M11 | 174.0434912 | 2020M11 | 174.0434912 | 2020M11 | 192.35 | 192.35 |
| 2020M12 | 197.9838469 | 2020M12 | 197.9838469 | 2020M12 | 187.09 | 187.09 |
| 2021M01 | 193.3250873 | 2021M01 | 193.3250873 | 2021M01 | 195.2 | 195.2 |
| 2021M02 | 200.5080797 | 2021M02 | 200.5080797 | 2021M02 | 368.92 | 368.92 |
| 2021M03 | 354.3711427 | 2021M03 | 354.3711427 | 2021M03 | 186.35 | 186.35 |
| 2021M04 | 192.6696725 | 2021M04 | 192.6696725 | 2021M04 | 194.23 | 194.23 |
| 2021M05 | 199.6489549 | 2021M05 | 199.6489549 | 2021M05 | 212.01 | 212.01 |
| 2021M06 | 215.396625 | 2021M06 | 215.396625 | 2021M06 | 237.59 | 237.59 |
| 2021M07 | 238.0527219 | 2021M07 | 238.0527219 | 2021M07 | 283.18 | 283.18 |
| 2021M08 | 278.4315904 | 2021M08 | 278.4315904 | 2021M08 | 300.43 | 300.43 |
| 2021M09 | 293.7098419 | 2021M09 | 293.7098419 | 2021M09 | 376.17 | 376.17 |
| 2021M10 | 360.7924368 | 2021M10 | 360.7924368 | 2021M10 | 410.47 | 410.47 |
| 2021M11 | 391.1718005 | 2021M11 | 391.1718005 | 2021M11 | 373.91 | 373.91 |
| 2021M12 | 358.7907644 | 2021M12 | 358.7907644 | 2021M12 | 281.76 | 281.76 |
| 2022M01 | 277.1739025 | 2022M01 | 277.1739025 | 2022M01 | 322.36 | 322.36 |
| 2022M02 | 313.1331493 | 2022M02 | 313.1331493 | 2022M02 | 349.65 | 349.65 |
| 2022M03 | 337.3037859 | 2022M03 | 337.3037859 | 2022M03 | 372.07 | 372.07 |
| 2022M04 | 357.1610843 | 2022M04 | 357.1610843 | 2022M04 | 497.47 | 497.47 |
| 2022M05 | 468.2273293 | 2022M05 | 468.2273293 | 2022M05 | 629.3 | 629.3 |
| 2022M06 | 584.988598 | 2022M06 | 584.988598 | 2022M06 | 598.86 | 598.86 |
| 2022M07 | 558.0280198 | 2022M07 | 558.0280198 | 2022M07 | 578.04 | 578.04 |
| 2022M08 | 539.5878346 | 2022M08 | 539.5878346 | 2022M08 | 699.29 | 699.29 |
| 2022M09 | 646.9784424 | 2022M09 | 646.9784424 | 2022M09 | 622.72 | 622.72 |
| 2022M10 | 579.16072 | 2022M10 | 579.16072 | 2022M10 | 462.71 | 462.71 |
| 2022M11 | 437.4405456 | 2022M11 | 437.4405456 | 2022M11 | 432.05 | 432.05 |
| 2022M12 | 410.2851144 | 2022M12 | 410.2851144 | 2022M12 | 452.99 | 452.99 |
| 2023M01 | 428.8315831 | 2023M01 | 428.8315831 | 2023M01 | 267.78 | 267.78 |
| 2023M02 | 264.7918761 | 2023M02 | 264.7918761 | 2023M02 | 196.6 | 196.6 |
| 2023M03 | 201.7480538 | 2023M03 | 201.7480538 | 2023M03 | 189.27 | 189.27 |
| 2023M04 | 195.255904 | 2023M04 | 203.3258165 | 2023M04 | 177.16 | 177.16 |
| 2023M05 | | 2023M05 | 196.969479 | 2023M05 | 183 | 185 |
| 2023M06 | | 2023M06 | 186.468081 | 2023M06 | 188 | 192 |
| 2023M07 | | 2023M07 | 193.2666739 | 2023M07 | 193 | 195 |
| 2023M08 | | 2023M08 | 198.4696787 | 2023M08 | 198 | 203 |
| 2023M09 | | 2023M09 | 203.6726835 | 2023M09 | 202 | 211 |
| 2023M10 | | 2023M10 | 208.0085208 | 2023M10 | 206 | 217 |
| 2023M11 | | 2023M11 | 212.3443581 | 2023M11 | 209 | 222 |
| 2023M12 | | 2023M12 | 215.8130279 | 2023M12 | 212 | 225 |
| 2024M01 | | 2024M01 | 219.2816978 | 2024M01 | 215 | 231 |
| 2024M02 | | 2024M02 | 221.8832002 | 2024M02 | 218 | 231 |
| 2024M03 | | 2024M03 | 224.4847026 | 2024M03 | 220 | 232 |
| 2024M04 | | 2024M04 | 226.2190375 | 2024M04 | 222 | 234 |
| 2024M05 | | 2024M05 | 227.9533724 | 2024M05 | 224 | 238 |
| 2024M06 | | 2024M06 | 229.6877073 | 2024M06 | 226 | 239 |
| 2024M07 | | 2024M07 | 231.4220423 | 2024M07 | 228 | 240 |
| 2024M08 | | 2024M08 | 232.2892097 | 2024M08 | 229 | 242 |
| 2024M09 | | 2024M09 | 233.1563772 | 2024M09 | 230 | 240 |
| 2024M10 | | 2024M10 | 234.0235447 | 2024M10 | 231 | 241 |
| 2024M11 | | 2024M11 | 234.8907121 | 2024M11 | 232 | 245 |
| 2024M12 | | 2024M12 | 235.7578796 | 2024M12 | 233 | 248 |

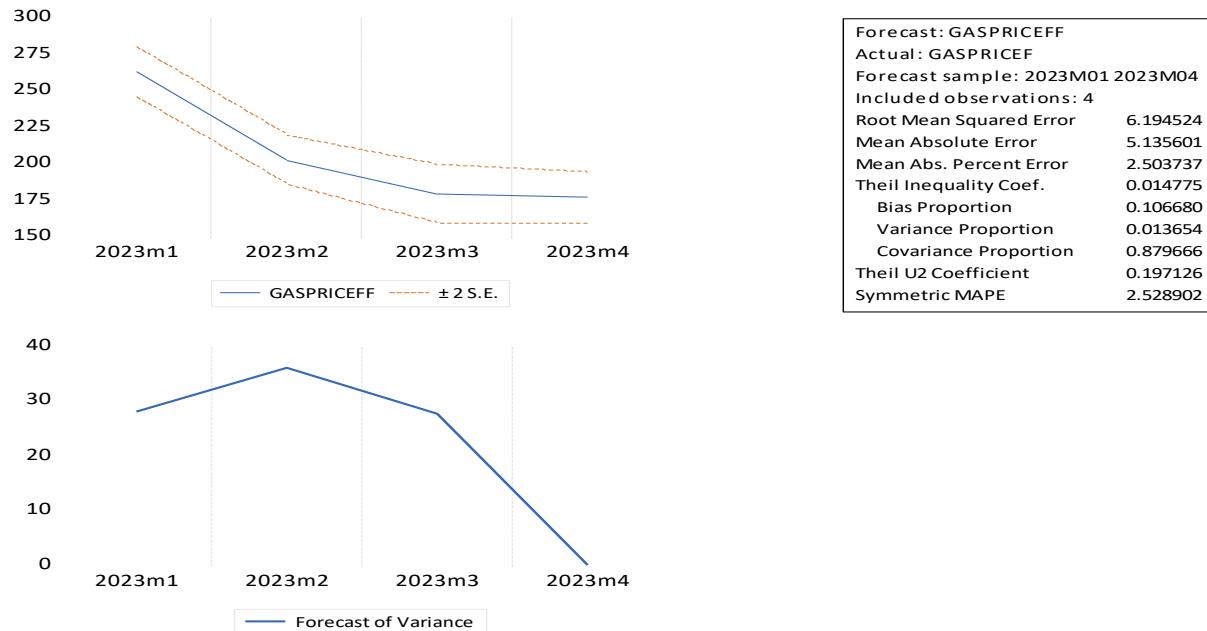
The Graphical Representation of Forecasted Gas Prices through Various Models is depicted below:



Further, we have also forecasted the ARCH and GARCH volatility.

ARCH Volatility





The above graphs show that there is a stability in return of gas prices, however there is intense volatility, before 2023m1 there was increased volatility which gradually decreased by 2023m4.

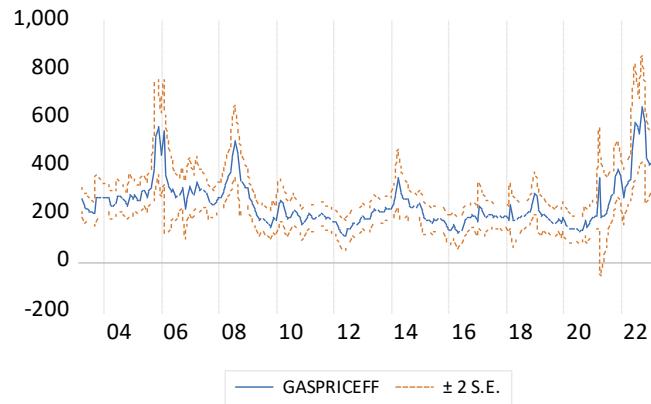
GARCH Volatility:

| | | | | |
|--|-------------------|-----------------------|-------------|----------|
| Dependent Variable: GASPRICEF | | | | |
| Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) | | | | |
| Date: 08/27/23 Time: 11:22 | | | | |
| Sample (adjusted): 2003M02 2023M04 | | | | |
| Included observations: 243 after adjustments | | | | |
| Convergence achieved after 22 iterations | | | | |
| Coefficient covariance computed using outer product of gradients | | | | |
| Presample variance: backcast (parameter = 0.7) | | | | |
| GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) | | | | |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 22.75606 | 7.453498 | 3.053071 | 0.0023 |
| GASPRICEF(-1) | 0.889300 | 0.032593 | 27.28497 | 0.0000 |
| | Variance Equation | | | |
| C | 246.6076 | 67.24706 | 3.667187 | 0.0002 |
| RESID(-1)^2 | 0.332773 | 0.085672 | 3.884258 | 0.0001 |
| GARCH(-1) | 0.559690 | 0.085989 | 6.508844 | 0.0000 |
| R-squared | 0.822427 | Mean dependent var | | 247.0554 |
| Adjusted R-squared | 0.821690 | S.D. dependent var | | 103.8340 |
| S.E. of regression | 43.84572 | Akaike info criterion | | 10.04716 |
| Sum squared resid | 463309.7 | Schwarz criterion | | 10.11904 |
| Log likelihood | -1215.730 | Hannan-Quinn criter. | | 10.07611 |
| Durbin-Watson stat | 1.877211 | | | |

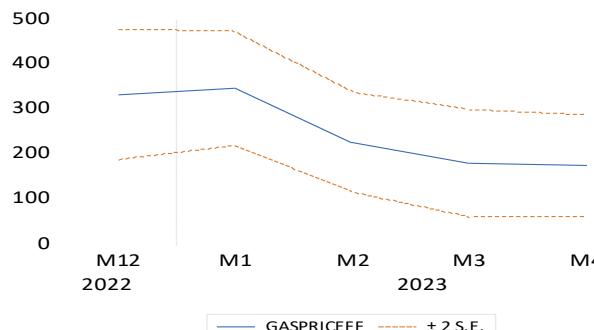
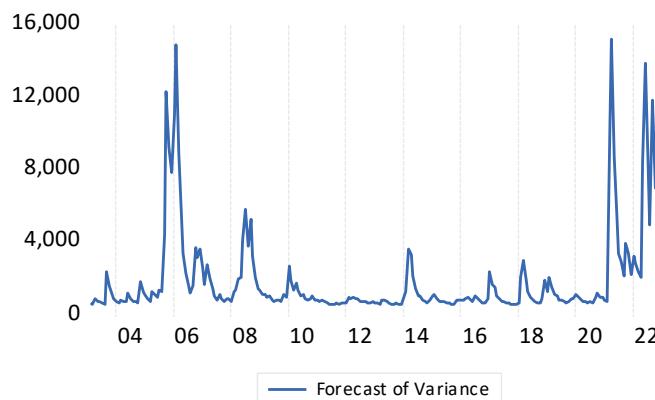
Here, we can write

$$\text{Volatility} \sigma_t^2 = 246.6067 + 0.332773 \varepsilon_{t-1}^2 + 0.559690 \sigma_{t-1}^2$$

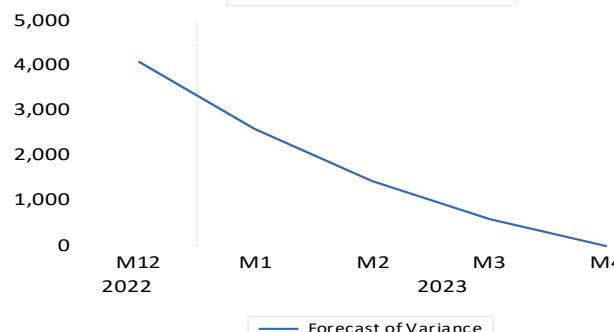
$\beta_1 = 0.332773$ and $\beta_2 = 0.559690$, Here $\beta_1 + \beta_2 = 0.892463 < 1$ and $\beta_2 > \beta_1$, meaning thereby there is a persistence volatility in gas prices irrespective of reason and since $\beta_1 + \beta_2 = 0.892463 < 1$ means there is a decaying volatility and the decaying volatility rate would be 0.107537.



| | |
|-------------------------|-----------------|
| Forecast: GASPRICEFF | |
| Actual: GASPRICEFF | |
| Forecast sample: | 2003M01 2023M04 |
| Adjusted sample: | 2003M02 2023M04 |
| Included observations: | 243 |
| Root Mean Squared Error | 43.66485 |
| Mean Absolute Error | 27.46069 |
| Mean Abs. Percent Error | 10.40494 |
| Theil Inequality Coef. | 0.082762 |
| Bias Proportion | 0.009406 |
| Variance Proportion | 0.069887 |
| Covariance Proportion | 0.920708 |
| Theil U2 Coefficient | 0.989582 |
| Symmetric MAPE | 10.33666 |



| | |
|-------------------------|-----------------|
| Forecast: GASPRICEFF | |
| Actual: GASPRICEFF | |
| Forecast sample: | 2022M12 2023M04 |
| Included observations: | 5 |
| Root Mean Squared Error | 65.59373 |
| Mean Absolute Error | 47.55247 |
| Mean Abs. Percent Error | 15.23471 |
| Theil Inequality Coef. | 0.121170 |
| Bias Proportion | 0.001574 |
| Variance Proportion | 0.199413 |
| Covariance Proportion | 0.799013 |
| Theil U2 Coefficient | 0.439840 |
| Symmetric MAPE | 15.00220 |



Forecast of Variance

The above graphs show that there is stability in return of gas prices, however there is intense volatility, before 2022m12 there was increased volatility which gradually decreased and became stable by 2023m4.

4. Conclusion

Concluded that due to intense volatility in international gas prices the gas transmission company in India could see an impact of its earnings due to high gas prices as predicted. The company imports gas from the US market, the prices of which are linked to the US gas prices. Thus, higher gas prices in the US will increase the gas sourcing cost for Transmission Company. Along with this, if gas usage declines in India due to higher prices, the same will lead to a lower amount of gas being transmitted through its pipe line, which will eventually lead to lower earning.

India's largest gas importer earns a majority part of its income from gas regasification. Reducing gas imports to the country could hurt regasification income. In the month of July, 2022, total LNG imports in India declined by 10% YoY and 8% MoM, due to a sharp increase in spot LNG prices and also likely due to shortages driven by lower supply on some of the long-term contracts.

City gas distribution companies also stand to market as the blended gas cost increases. Currently, CGD are sourcing 6% of their gas requirement for CNG and household usage from the spot market, while the gas supplied for industrial use is fully sourced through spot market. Owing to rising gas prices in the Asian market, the blended gas cost will also increase for CGSs.

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