lab-2-series-de-tiempo

August 10, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.tsa as tsa
import statsmodels as sm
from datetime import datetime
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX

from sklearn.preprocessing import PowerTransformer, StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from keras.models import Sequential
from keras.layers import LSTM, Dense
```

[2]:
```
df_imp = pd.read_excel('IMPORTACION-VOLUMEN-2023-05.xlsx',␣
 ↪sheet_name='IMPORTACION',skiprows = 6,
                            nrows=270, header=0,usecols= 'A, G, I, K, L, U',␣
 ↪engine='openpyxl').dropna()

df_imp.head()
```

[2]:
```
        Fecha  Diesel bajo azufre  Gas licuado de petróleo  Gasolina regular  \
0 2001-01-01                 0.0            194065.738095         177776.50
1 2001-02-01                 0.0            170703.380952         123115.99
2 2001-03-01                 0.0            161837.371429         161726.42
3 2001-04-01                 0.0            163048.642857         127338.74
4 2001-05-01                 0.0            171518.861905         168730.19

   Gasolina superior  Diesel alto azufre
0          373963.96           566101.99
1          243091.07           489525.80
2          312084.38           575559.68
```

```
3          285054.89          437745.42
4          300913.67          552609.13
```

[3]:
```
df_imp.tail()
```

[3]:
```
          Fecha  Diesel bajo azufre  Gas licuado de petróleo  Gasolina regular  \
264 2023-01-01          1442099.08                497780.69         909391.13
265 2023-02-01          1267967.39                652984.71         725101.20
266 2023-03-01          1317519.91                711978.35         803262.67
267 2023-04-01          1417182.73                647666.30         922032.39
268 2023-05-01          1428099.62                713348.99         947633.29

     Gasolina superior  Diesel alto azufre
264          578792.14                 0.0
265          685183.06                 0.0
266          633849.05                 0.0
267          572201.36                 0.0
268          668478.73                 0.0
```

[4]:
```
(df_imp.iloc[:,1] != 0).idxmax(), (df_imp.iloc[:,5] == 0).idxmax() # las␣
 ↪volumnas se pueden sumar en una sola
```

[4]:
```
(204, 204)
```

[5]:
```
df_imp['Diesel'] = df_imp['Diesel bajo azufre'] + df_imp['Diesel alto azufre']
df_imp.drop(['Diesel bajo azufre', 'Diesel alto azufre'], axis=1, inplace=True)
```

[6]:
```
df_imp.info(), df_imp.shape
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 269 entries, 0 to 268
Data columns (total 5 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Fecha                    269 non-null    datetime64[ns]
 1   Gas licuado de petróleo  269 non-null    float64
 2   Gasolina regular         269 non-null    float64
 3   Gasolina superior        269 non-null    float64
 4   Diesel                   269 non-null    float64
dtypes: datetime64[ns](1), float64(4)
memory usage: 12.6 KB
```

[6]:
```
(None, (269, 5))
```

[7]:
```
df_imp.describe().applymap(lambda x: f"{int(x):,}")
```

[7]:
```
       Gas licuado de petróleo Gasolina regular Gasolina superior     Diesel
count                      269              269               269        269
mean                   399,026          381,883           478,288    863,979
std                    190,173          219,364           153,277    276,545
min                    100,561           81,015           170,292    229,764
25%                    218,257          201,907           363,352    678,749
50%                    396,363          305,285           456,588    824,047
75%                    540,671          528,347           582,374  1,050,560
max                    960,840          987,872         1,227,173  1,595,698
```

[8]:
```
df_p_nac_1 = pd.read_excel('Precios-Promedio-Nacionales-Diarios-2023.xlsx',␣
 ↪sheet_name='2021',skiprows = 6,
                            nrows=366, header=0,usecols= 'A,C:E, G',␣
 ↪engine='openpyxl')
df_p_nac_1.drop(0, inplace=True)
df_p_nac_2 = pd.read_excel('Precios-Promedio-Nacionales-Diarios-2023.xlsx',␣
 ↪sheet_name='2022',skiprows = 6,
                            nrows=366, header=0,usecols= 'A,C:E, G',␣
 ↪engine='openpyxl')
df_p_nac_2.drop(0, inplace=True)
df_p_nac_3 = pd.read_excel('Precios-Promedio-Nacionales-Diarios-2023.xlsx',␣
 ↪sheet_name='2023',skiprows = 7,
                            nrows=213, header=0,usecols= 'A,C:E, G',␣
 ↪engine='openpyxl')
df_p_nac_3.drop(0, inplace=True)
```

[9]:
```
df_p_nac_1.head()
```

[9]:
```
       FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
1 2021-01-01    21.91   21.11  17.61                  99
2 2021-01-02    21.91   21.11  17.61                  99
3 2021-01-03    21.91   21.11  17.61                  99
4 2021-01-04    21.91   21.11  17.61                  99
5 2021-01-05    21.91   21.11  17.61                  99
```

[10]:
```
df_p_nac_1.tail()
```

[10]:
```
         FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
361 2021-12-27    28.69   27.91  24.51                 122
362 2021-12-28    28.69   27.91  24.51                 122
363 2021-12-29    28.69   27.91  24.51                 122
364 2021-12-30    28.69   27.91  24.51                 122
365 2021-12-31    28.69   27.91  24.51                 122
```

[11]:
```
df_p_nac_2.head()
```

[11]:
```
        FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
1 2022-01-01    28.69   27.91  24.51                 122
2 2022-01-02    28.69   27.91  24.51                 122
3 2022-01-03    28.79   27.99   24.6                 122
4 2022-01-04    28.79   27.99   24.6                 122
5 2022-01-05    28.79   27.99   24.6                 122
```

[12]:
```
df_p_nac_2.tail()
```

[12]:
```
          FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
361 2022-12-27    32.55   30.99  33.75                 122
362 2022-12-28    32.55   30.99  33.75                 122
363 2022-12-29    32.55   30.99  33.75                 122
364 2022-12-30    32.55   30.99  33.75                 122
365 2022-12-31    32.55   30.99  33.75                 122
```

[13]:
```
df_p_nac_3.head()
```

[13]:
```
        FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
1 2023-01-01    32.55   30.99  33.75                 122
2 2023-01-02    32.55   30.99  33.75                 122
3 2023-01-03    32.56   31.42  35.31                 122
4 2023-01-04    32.56   31.42  35.31                 122
5 2023-01-05    32.56   31.42  35.31                 122
```

[14]:
```
df_p_nac_3.tail()
```

[14]:
```
          FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
208 2023-07-27    34.78   33.28  28.47                 135
209 2023-07-28    34.78   33.28  28.47                 135
210 2023-07-29    34.78   33.28  28.47                 135
211 2023-07-30    34.78   33.28  28.47                 135
212 2023-07-31    36.29   34.77  29.68                 135
```

[15]:
```
df_precios = pd.concat([df_p_nac_1, df_p_nac_2, df_p_nac_3], ignore_index=True)
df_precios.head()
```

[15]:
```
        FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
0 2021-01-01    21.91   21.11  17.61                  99
1 2021-01-02    21.91   21.11  17.61                  99
2 2021-01-03    21.91   21.11  17.61                  99
3 2021-01-04    21.91   21.11  17.61                  99
4 2021-01-05    21.91   21.11  17.61                  99
```

[16]:
```
df_precios.tail()
```

[16]:
```
           FECHA Superior Regular Diesel Glp Cilindro 25Lbs.
937 2023-07-27    34.78   33.28  28.47                   135
938 2023-07-28    34.78   33.28  28.47                   135
939 2023-07-29    34.78   33.28  28.47                   135
940 2023-07-30    34.78   33.28  28.47                   135
941 2023-07-31    36.29   34.77  29.68                   135
```

[17]:
```python
df_precios.info(), df_precios.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 942 entries, 0 to 941
Data columns (total 5 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   FECHA                942 non-null    datetime64[ns]
 1   Superior             942 non-null    object
 2   Regular              942 non-null    object
 3   Diesel               942 non-null    object
 4   Glp Cilindro 25Lbs.  942 non-null    object
dtypes: datetime64[ns](1), object(4)
memory usage: 36.9+ KB
```

[17]:
```
(None, (942, 5))
```

[18]:
```python
columnas_precios = list(df_precios.columns[1:])
columnas_precios
```

[18]:
```
['Superior', 'Regular', 'Diesel', 'Glp Cilindro 25Lbs.']
```

[19]:
```python
df_precios[columnas_precios] = df_precios[columnas_precios].astype(float)
df_precios.info(), df_precios.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 942 entries, 0 to 941
Data columns (total 5 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   FECHA                942 non-null    datetime64[ns]
 1   Superior             942 non-null    float64
 2   Regular              942 non-null    float64
 3   Diesel               942 non-null    float64
 4   Glp Cilindro 25Lbs.  942 non-null    float64
dtypes: datetime64[ns](1), float64(4)
memory usage: 36.9 KB
```

[19]:
```
(None, (942, 5))
```

[20]:
```python
df_precios.describe()
```

[20]:

```
         Superior     Regular      Diesel  Glp Cilindro 25Lbs.
count  942.000000  942.000000  942.000000           942.000000
mean    32.339915   31.185817   28.495563           123.651921
std      4.555857    4.225467    6.059121             8.420853
min     21.910000   21.110000   17.610000            99.000000
25%     28.790000   27.990000   23.090000           120.000000
50%     33.100000   31.800000   27.680000           122.000000
75%     35.550000   34.230000   33.847500           122.000000
max     43.240000   40.500000   41.270000           147.000000
```

[21]:

```python
df_precios.iloc[:,1:].describe().applymap(lambda x: f"{int(x):,}")
```

[21]:

```
      Superior Regular Diesel Glp Cilindro 25Lbs.
count      942     942    942                 942
mean        32      31     28                 123
std          4       4      6                   8
min         21      21     17                  99
25%         28      27     23                 120
50%         33      31     27                 122
75%         35      34     33                 122
max         43      40     41                 147
```

[22]:

```python
df_consumo = pd.read_excel('CONSUMO-2023-05.xlsx',␣
↪sheet_name='CONSUMO',skiprows = 5,
                           nrows=282, header=1,usecols= 'A, G, K, L, U',␣
↪engine='openpyxl').dropna()
df_consumo.tail()
```

[22]:

```
         Fecha  Diesel bajo azufre  Gasolina regular  Gasolina superior  \
276 2023-01-01          1285932.51         804524.73          599501.29
277 2023-02-01          1226884.63         737345.64          544144.00
278 2023-03-01          1463008.43         875010.34          656941.64
279 2023-04-01          1248429.37         798128.36          585642.20
280 2023-05-01          1346554.12         866826.79          646221.20

     Diesel alto azufre
276                 0.0
277                 0.0
278                 0.0
279                 0.0
280                 0.0
```

[23]:

```python
(df_consumo.iloc[:,1] != 0).idxmax(), (df_consumo.iloc[:,4] == 0).idxmax()
```

[23]:

```
(216, 216)
```

[24]:
```
df_consumo['Diesel'] = df_consumo['Diesel bajo azufre'] + df_consumo['Diesel␣
↪alto azufre']
df_consumo.drop(['Diesel bajo azufre', 'Diesel alto azufre'], axis=1,␣
↪inplace=True)
```

[25]:
```
df_consumo.head()
```

[25]:

	Fecha	Gasolina regular	Gasolina superior	Diesel
0	2000-01-01	202645.20	308156.82	634667.06
1	2000-02-01	205530.96	307766.31	642380.66
2	2000-03-01	229499.56	331910.29	699807.25
3	2000-04-01	210680.40	315648.08	586803.98
4	2000-05-01	208164.34	319667.97	656948.20

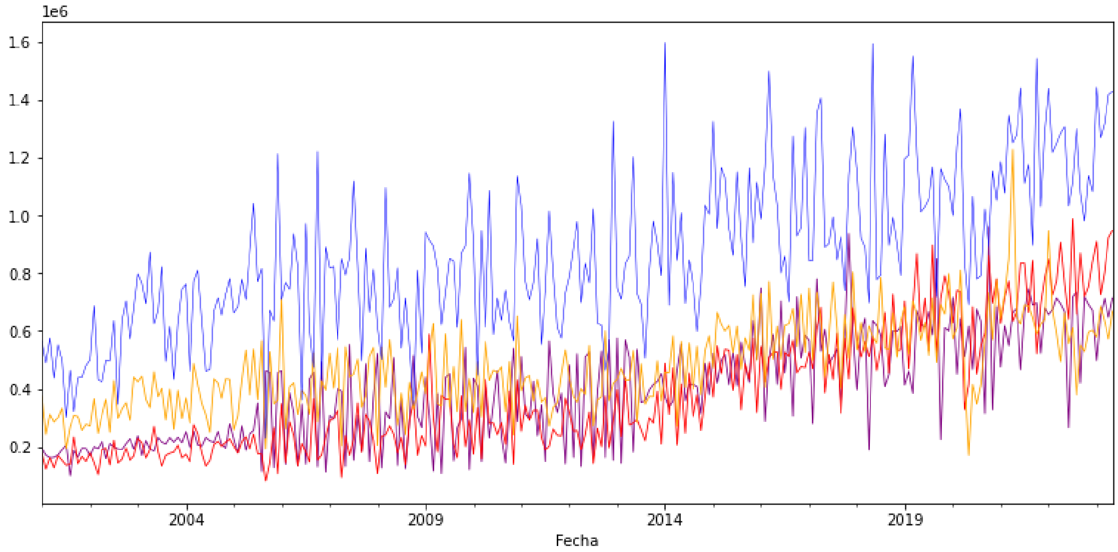
[26]:
```
df_imp.set_index('Fecha', inplace=True)
df_precios.set_index('FECHA', inplace=True)
df_consumo.set_index('Fecha', inplace=True)
```

0.1 Descripción de las series de tiempo

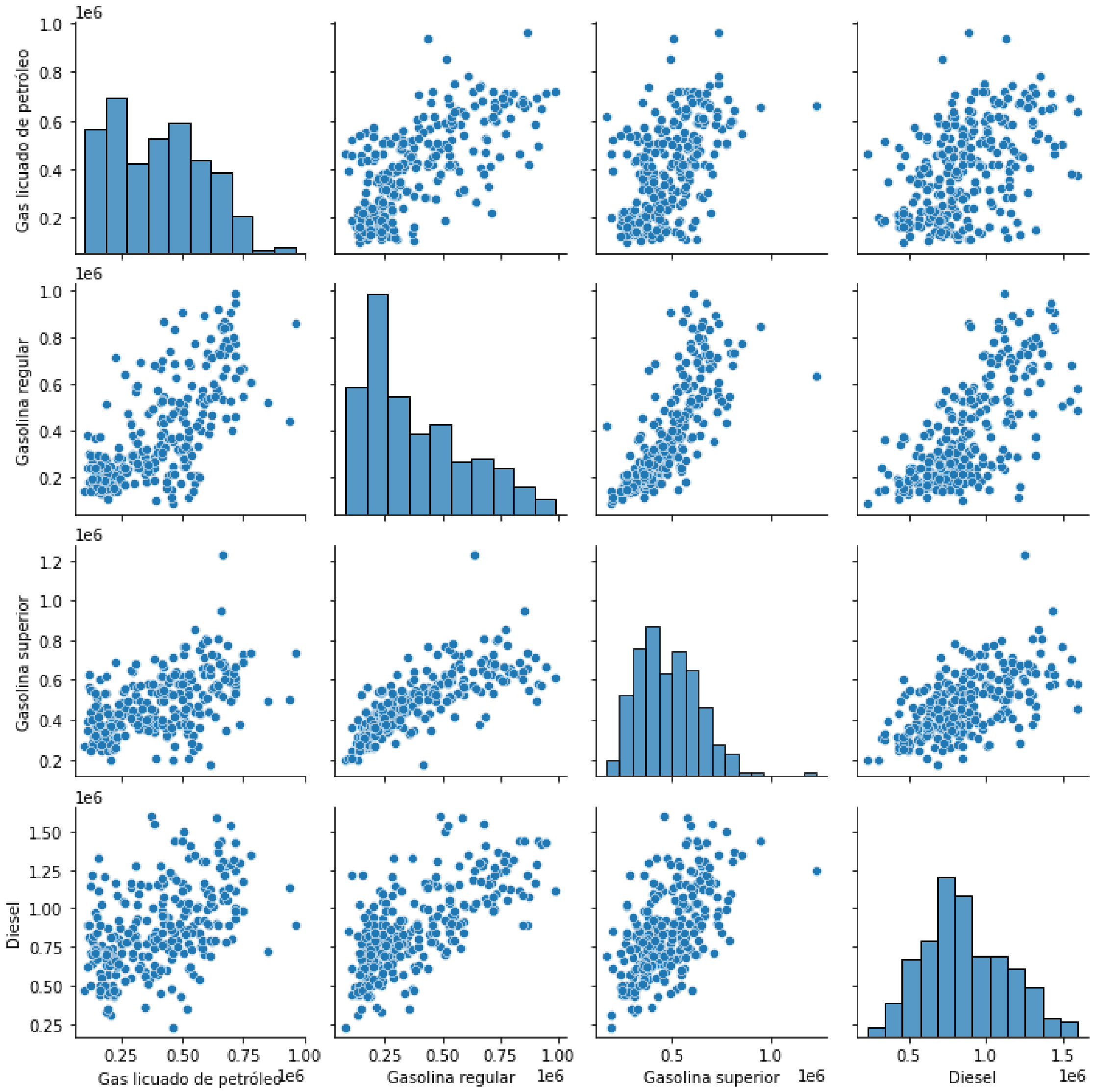
Se importaron tres archivos: 1. De "IMPORTACION-VOLUMEN-2023-05" se importaron los volumenes de importación de combustibles de las columnas Diesel Bajo en Azufre, Gas Licuado de Petróleo, Gasolina Regular, Gsolina Superior y Diesel alto en Azufre calculado de forma mensual de Enero 2020 a Mayo 2023 dando 269 observaciones. 2. De "Precios-Promedio-Nacionales-Diarios-2023" se importaron los precios promedio nacionales de forma diaria de las columnas de Super, Regular, Diesel y Gas Licuado Propano de 25 lbs un total de 942 observaciones. 3. De "CONSUMO-2023-05" se importaron los volúmenes de consumo mensuales de Diesel bajo zufre, Gasolina regulars, Gasolinea superior y Diesel alto azufre un total de 281 observaciones.

0.2 Analisis exploratorio

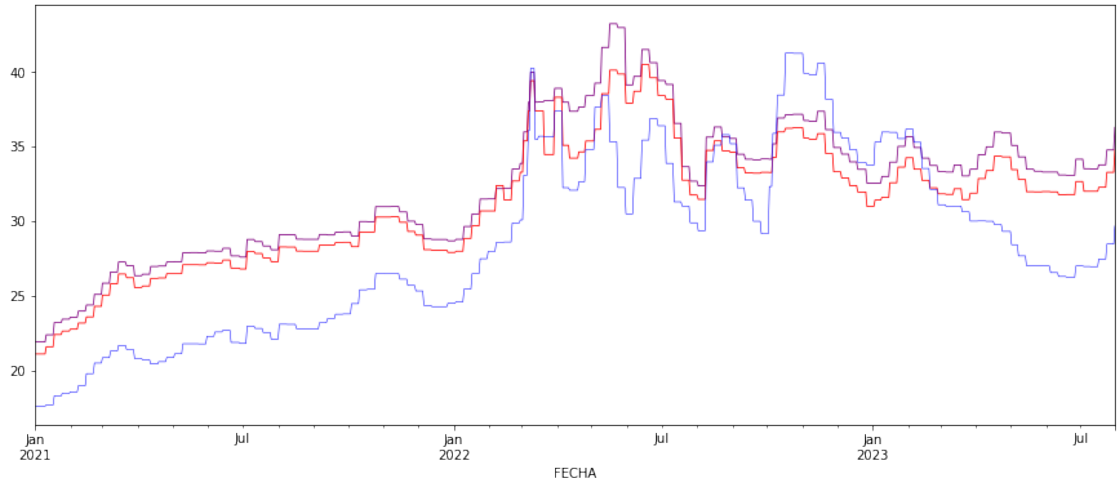
[27]:
```
plt.figure(figsize=(13,6))
df_imp['Gas licuado de petróleo'].plot(color='purple', linewidth=0.8)
df_imp['Gasolina regular'].plot(color='red', linewidth=0.8)
df_imp['Gasolina superior'].plot(color='orange', linewidth=0.8)
df_imp['Diesel'].plot(color='blue', linewidth=0.5)
plt.show()
```

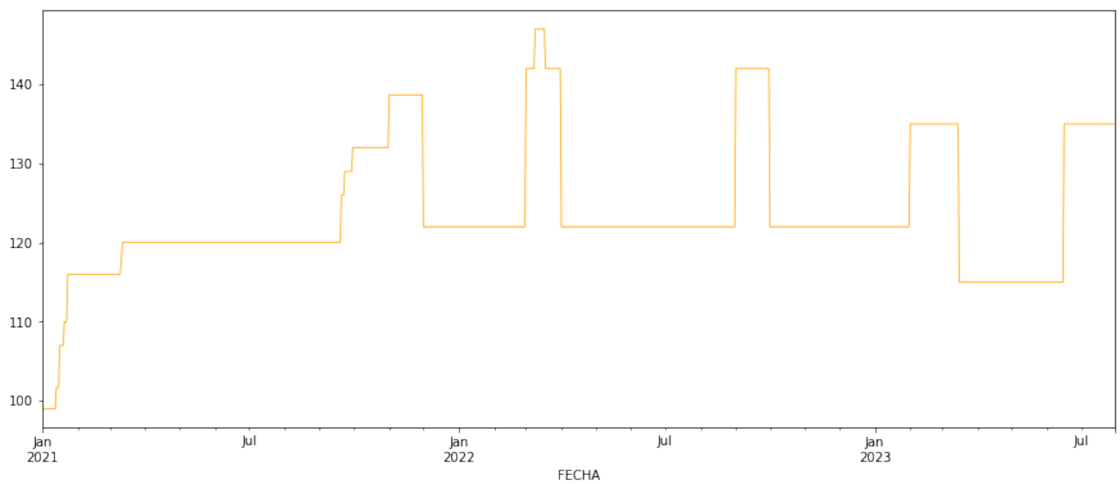


[28]:
```
sns.pairplot(df_imp)
plt.show()
```

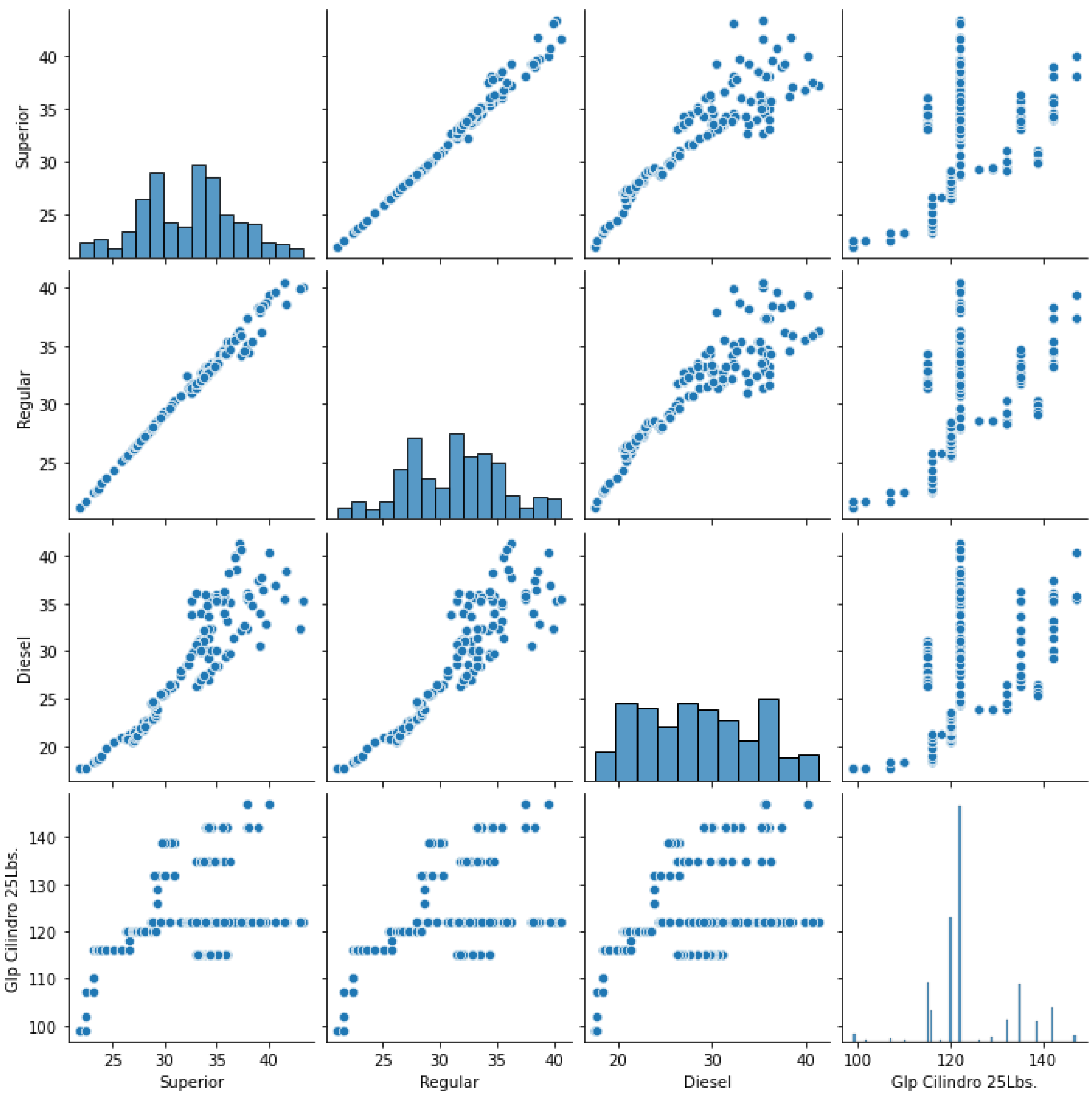


[29]:
```
plt.figure(figsize=(15,6))
df_precios['Superior'].plot(color='purple', linewidth=0.8)
df_precios['Regular'].plot(color='red', linewidth=0.8)
df_precios['Diesel'].plot(color='blue', linewidth=0.5)
plt.show()

plt.figure(figsize=(15,6))
df_precios['Glp Cilindro 25Lbs.'].plot(color='orange', linewidth=0.8)
plt.show()
```

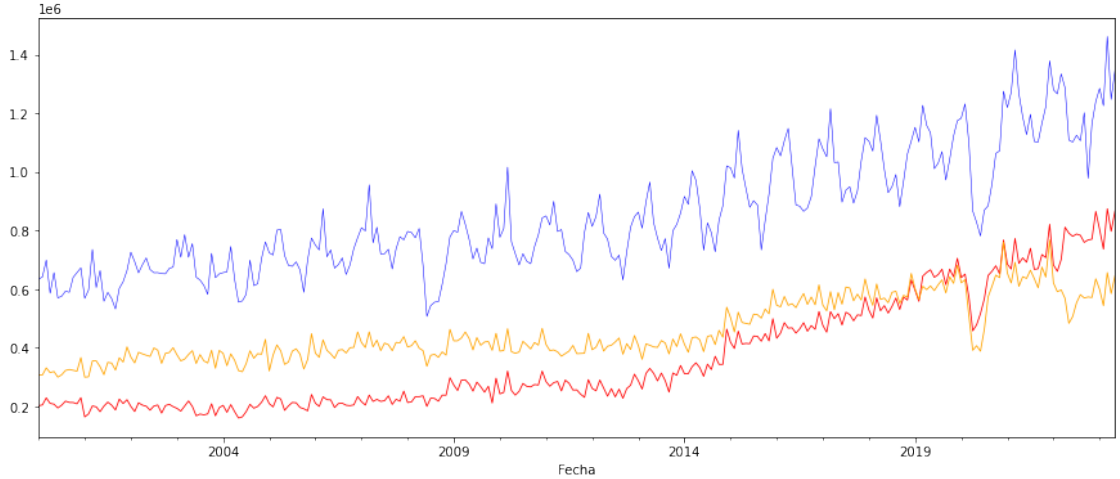




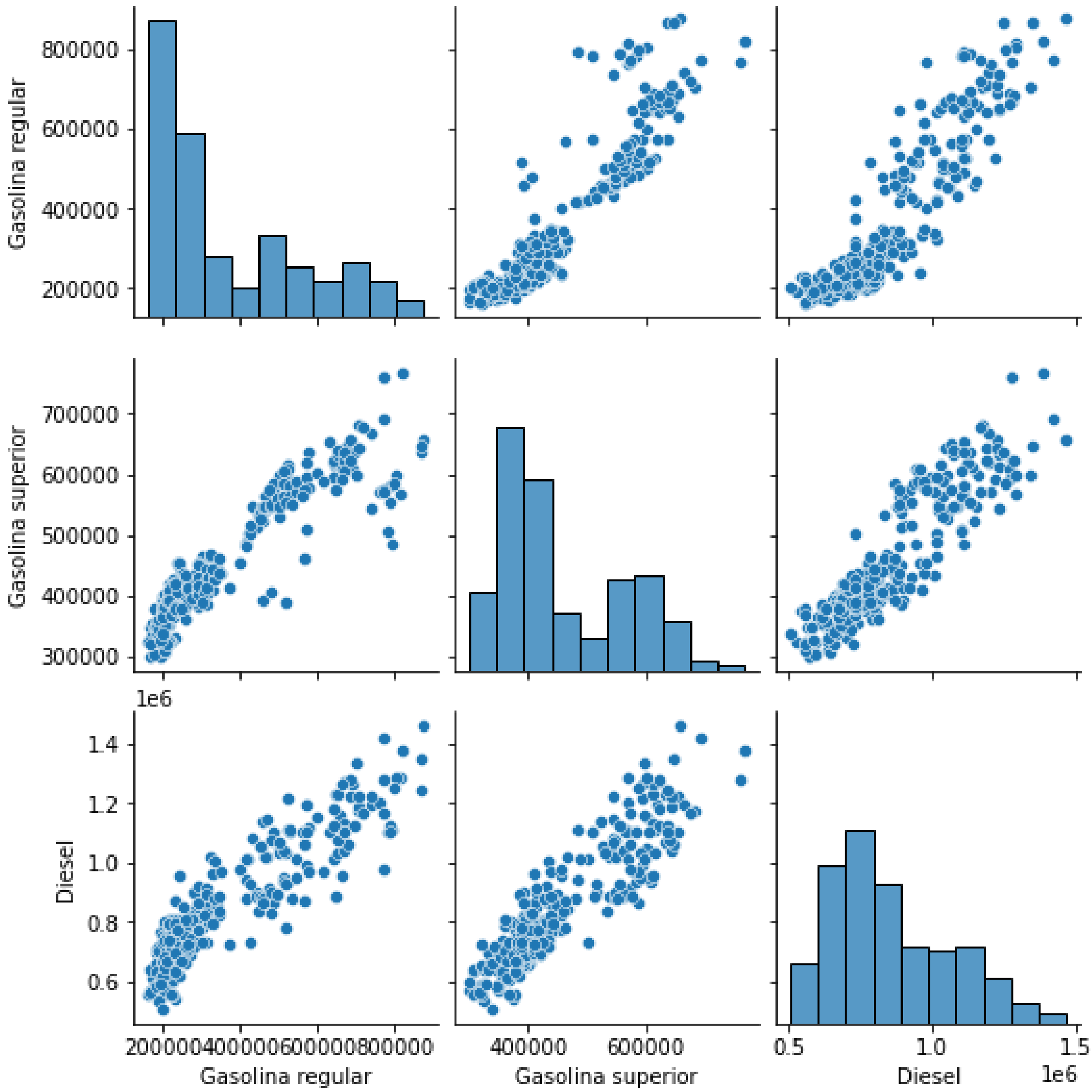
[30]:
```
sns.pairplot(df_precios)
plt.show()
```



[31]:
```
plt.figure(figsize=(15,6))
df_consumo['Gasolina regular'].plot(color='red', linewidth=0.8)
df_consumo['Gasolina superior'].plot(color='orange', linewidth=0.8)
df_consumo['Diesel'].plot(color='blue', linewidth=0.5)
plt.show()
```



[32]:
```
sns.pairplot(df_consumo)
plt.show()
```



1 ARIMA

Hemo decidio utilizar las siguientes columnas para trabajar con arima: - Importacion: Gas licuado de petróleo como df1 - Precios: Gasolina superior como df2 - Consumo: Diesel df3

[33]:
```
df1 = df_imp['Gasolina regular']
df2 = df_precios['Superior']
df3 = df_consumo['Diesel']
```

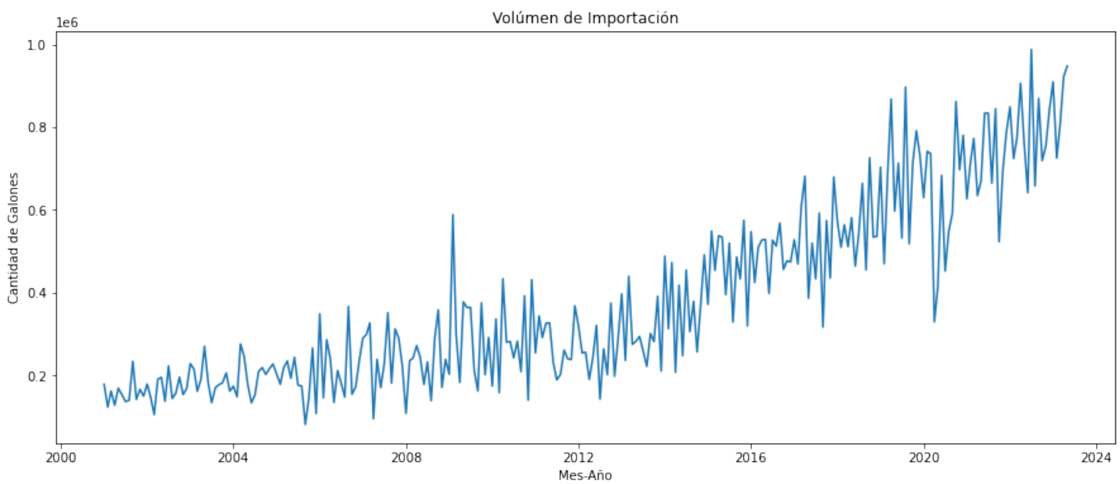
[34]:
```
df1.head(), df2.head(), df3.head()
```

[34]:
```
(Fecha
 2001-01-01    177776.50
 2001-02-01    123115.99
 2001-03-01    161726.42
 2001-04-01    127338.74
 2001-05-01    168730.19
 Name: Gasolina regular, dtype: float64,
 FECHA
 2021-01-01    21.91
 2021-01-02    21.91
 2021-01-03    21.91
 2021-01-04    21.91
 2021-01-05    21.91
 Name: Superior, dtype: float64,
 Fecha
 2000-01-01    634667.06
 2000-02-01    642380.66
 2000-03-01    699807.25
 2000-04-01    586803.98
 2000-05-01    656948.20
 Name: Diesel, dtype: float64)
```

1.0.1 Importacion de Gasolina regular

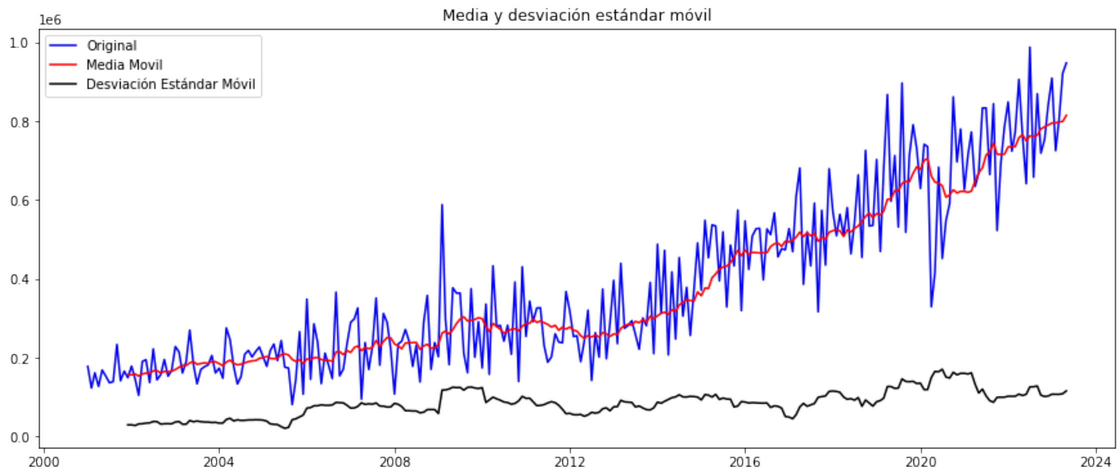
Exploracion

[35]:
```
plt.figure(figsize=(15,6))
plt.plot(df1)
plt.gca().set(title="Volúmen de Importación", xlabel="Mes-Año",␣
 ↪ylabel="Cantidad de Galones")
plt.show()
```



[36]:

```
# Se calcula la media móvil y la desviación estandar móvil de los últimos 12␣
    ↪meses.
mediaMovil = df1.rolling(window=12).mean()
deMovil = df1.rolling(window=12).std()
# Se grafican los resultados.
plt.figure(figsize=(15,6))
original = plt.plot(df1, color="blue", label="Original")
media = plt.plot(mediaMovil, color='red', label = 'Media Movil')
ds = plt.plot(deMovil,color='black', label = 'Desviación Estándar Móvil')
plt.legend(loc = 'best')
plt.title('Media y desviación estándar móvil')
plt.show(block=False)
```

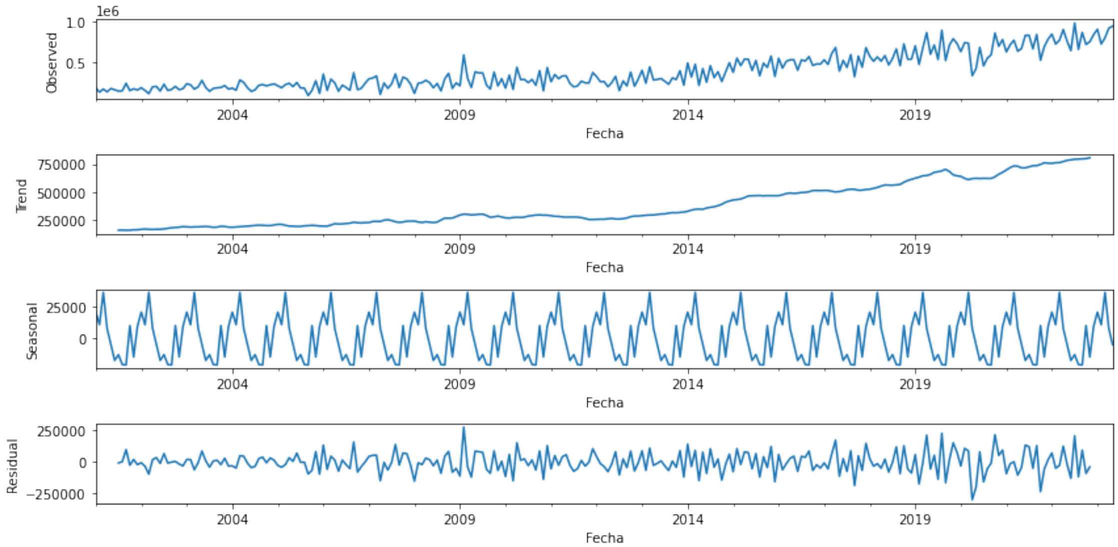


Se observa que ni la media ni la varianza son estacionarias

[37]:

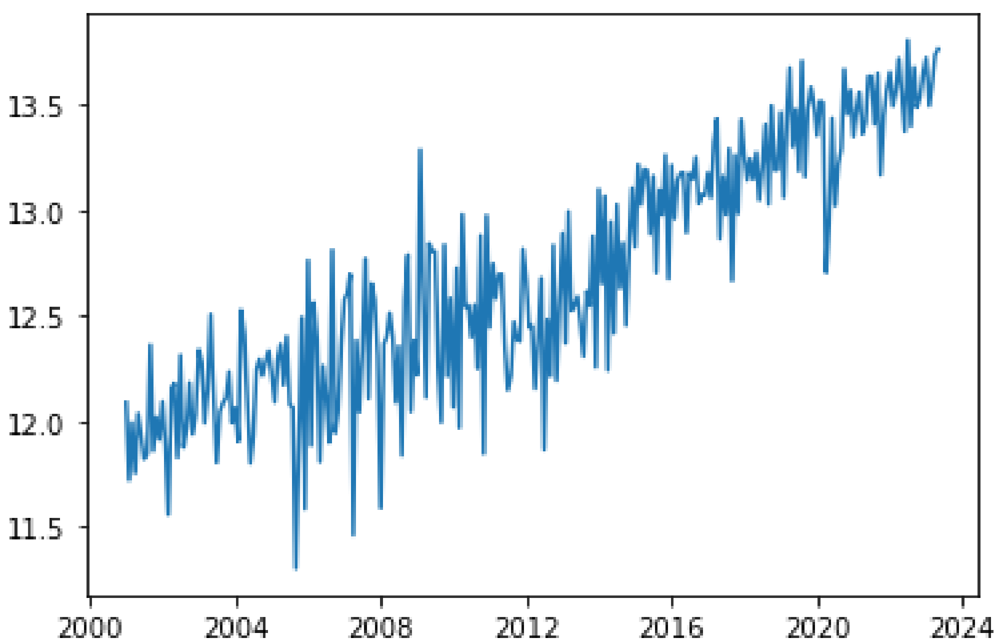
```
result = seasonal_decompose(df1)
# Create a new figure with a specific size
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(12, 6))

# Plot the components on separate subplots
result.observed.plot(ax=ax1)
ax1.set_ylabel('Observed')

result.trend.plot(ax=ax2)
ax2.set_ylabel('Trend')

result.seasonal.plot(ax=ax3)
ax3.set_ylabel('Seasonal')

result.resid.plot(ax=ax4)
ax4.set_ylabel('Residual')
```

```
# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```



[38]:
```
df1_log = np.log(df1)
plt.plot(df1_log)
```

[38]: [<matplotlib.lines.Line2D at 0x228e1540be0>]



[39]:

```
mediaMovil_log = df1_log.rolling(window=12).mean()
deMovil_log = df1_log.rolling(window=12).std()
#Graficando los resultados con logaritmo.
#serie_df1_log = plt.plot(df1_log, color="blue", label="df1_log")
#media_movil_df1_log = plt.plot(mediaMovil_log, color='red', label = 'Media␣
↪Movil_log')
ds_log = plt.plot(deMovil_log,color='black', label = 'Desviación Estándar␣
↪Móvil_log')
plt.legend(loc = 'best')
plt.title('Desviación estándar móvil transformada con LN')
plt.show(block=False)
```

[40]:

```
print('\033[1mResultados del Test de Dickey Fuller de la serie Importación␣
↪Gasolina Regular\033[0m')
df1_test = adfuller(df1, autolag='AIC')
salida_df1 = pd.Series(df1_test[0:4], index=['Estadístico de␣
↪prueba','p-value','# de retardos usados','# de observaciones usadas'])
for key,value in df1_test[4].items():
        salida_df1['Critical Value (%s)'%key] = value
print(salida_df1)
```

Resultados del Test de Dickey Fuller de la serie Importación Gasolina

Regular
```
Estadístico de prueba           1.090748
p-value                         0.995137
# de retardos usados            9.000000
# de observaciones usadas     259.000000
Critical Value (1%)            -3.455853
Critical Value (5%)            -2.872765
Critical Value (10%)           -2.572752
dtype: float64
```

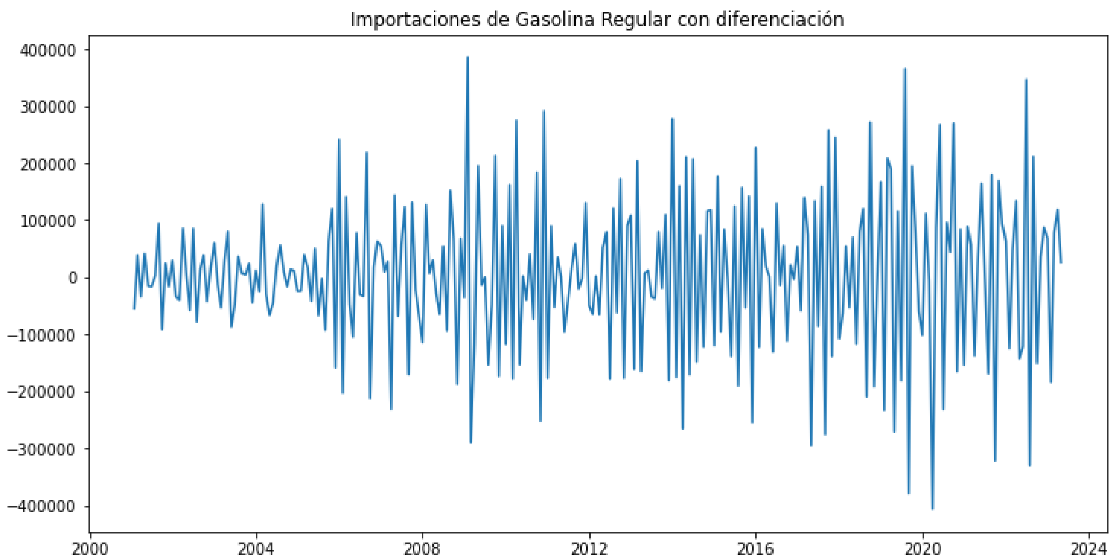
[41]:
```
print('\033[1mResultados del Test de Dickey Fuller para 1 diferenciación de la␣
↪serie Importación Gasolina regular\033[0m')
df1_diff = df1.diff()
df1_diff.dropna(inplace=True)
df1_test = adfuller(df1_diff)
salida_df1 = pd.Series(df1_test[0:4], index=['Estadístico de␣
↪prueba','p-value','# de retardos usados','# de observaciones usadas'])
for key,value in df1_test[4].items():
        salida_df1['Critical Value (%s)'%key] = value
print(salida_df1)
```

Resultados del Test de Dickey Fuller para 1 diferenciación de la serie

Importación Gasolina regular
```
Estadístico de prueba       -9.852868e+00
p-value                      4.437791e-17
# de retardos usados         8.000000e+00
# de observaciones usadas    2.590000e+02
Critical Value (1%)         -3.455853e+00
Critical Value (5%)         -2.872765e+00
Critical Value (10%)        -2.572752e+00
dtype: float64
```

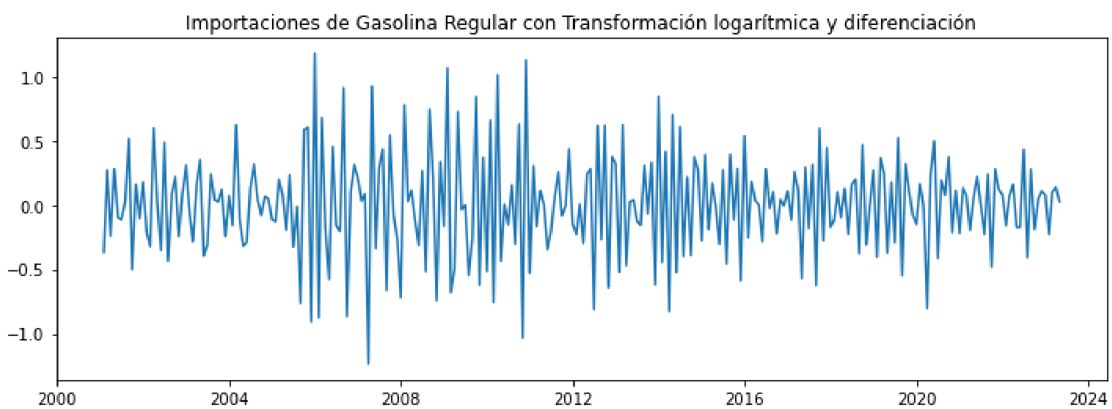
[42]:
```
plt.figure(figsize=(12, 6))
plt.title('Importaciones de Gasolina Regular con diferenciación')
plt.plot(df1_diff)
```

[42]: [<matplotlib.lines.Line2D at 0x228ddaa31f0>]



[43]:
```
plt.figure(figsize=(12, 4))
df1_log_diff = df1_log.diff()
plt.title('Importaciones de Gasolina Regular con Transformación logarítmica y␣
↪diferenciación')
plt.plot(df1_log_diff)
```

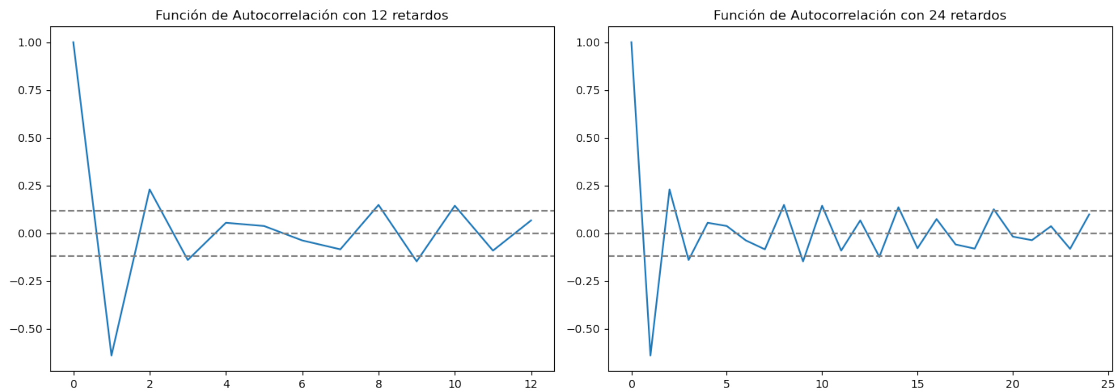
[43]: [<matplotlib.lines.Line2D at 0x228e05ff580>]



[44]:
```
df1_log_diff.dropna(inplace = True)
df1_log_diff_acf = acf(df1_log_diff,nlags=5,fft=False)
df1_log_diff_pacf = pacf(df1_log_diff, nlags=36)
df1_log_diff_acf, df1_log_diff_pacf
```

[44]:
```
(array([ 1.        , -0.63980275,  0.22972522, -0.1397927 ,  0.05508003,
         0.03811285]),
 array([ 1.        , -0.64219901, -0.30798694, -0.27215995, -0.25438727,
        -0.10156584, -0.04916746, -0.2515719 , -0.109741  , -0.19573169,
        -0.12725689, -0.06880904,  0.02507143, -0.17524294, -0.09741736,
        -0.05721368,  0.00913106,  0.10158407, -0.15873323, -0.15162316,
        -0.03222279, -0.0305563 ,  0.00159169, -0.04679743, -0.09825368,
        -0.12212896, -0.01962758,  0.01365864,  0.05888865, -0.03679905,
         0.09447004, -0.06584161,  0.02074825,  0.03536952, -0.24681957,
         0.1588869 ,  0.03900979]))
```

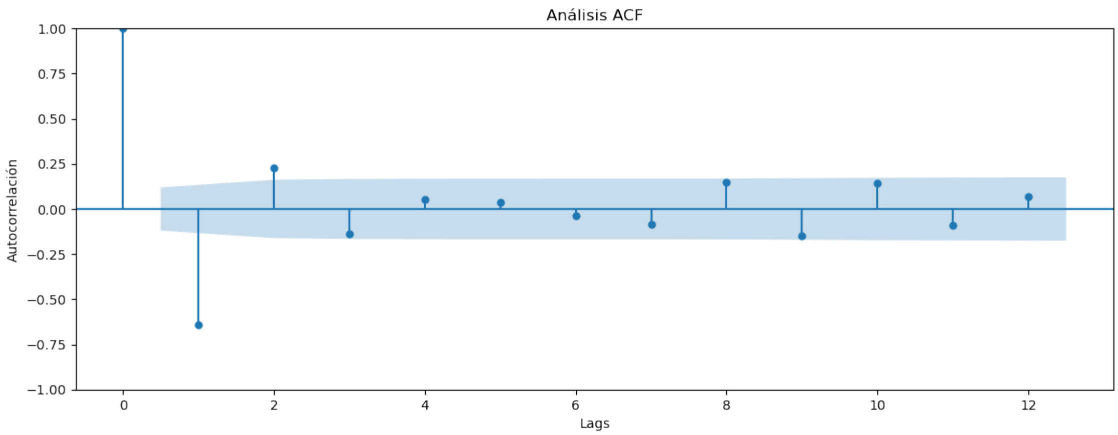
[45]:
```python
plt.rcParams['figure.figsize'] = [14, 5]
plt.rcParams['figure.dpi'] = 100 # 200 e.g. is really fine, but slower

#Plot ACF:
plt.subplot(121)
plt.plot(acf(df1_log_diff,nlags=12,fft=False))
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.title('Función de Autocorrelación con 12 retardos')

plt.subplot(122)
plt.plot(acf(df1_log_diff,nlags=24,fft=False))
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df1_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.title('Función de Autocorrelación con 24 retardos')

plt.tight_layout()
```



[46]:
```python
plt.figure(figsize=(10, 6))
plot_acf(df1_log_diff, lags=12)
```

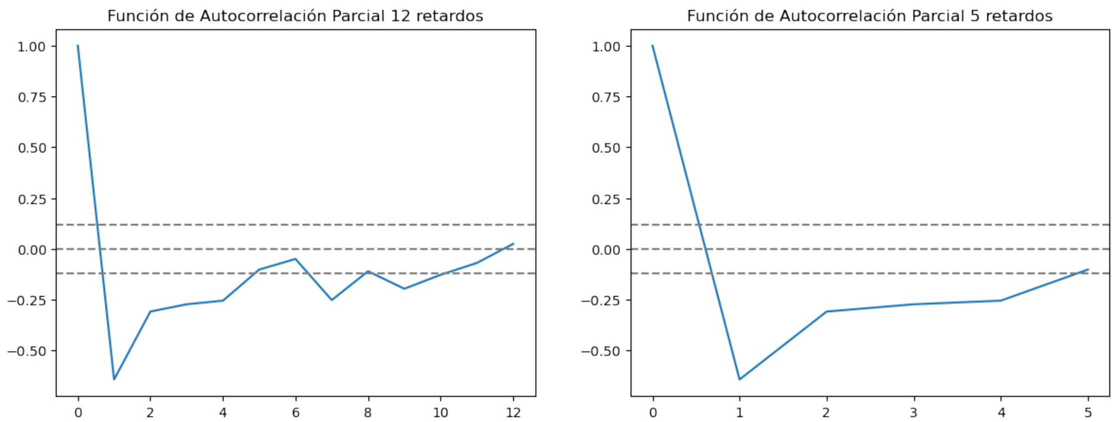
```
plt.xlabel('Lags')
plt.ylabel('Autocorrelación')
plt.title('Análisis ACF')
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



[47]:
```
#plot PACF
plt.subplot(121)
plt.plot(pacf(df1_log_diff, nlags=12))
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.title('Función de Autocorrelación Parcial 12 retardos')

plt.subplot(122)
plt.plot(pacf(df1_log_diff, nlags=5))
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(df1_log_diff)),linestyle='--',color='gray')
plt.title('Función de Autocorrelación Parcial 5 retardos')
```

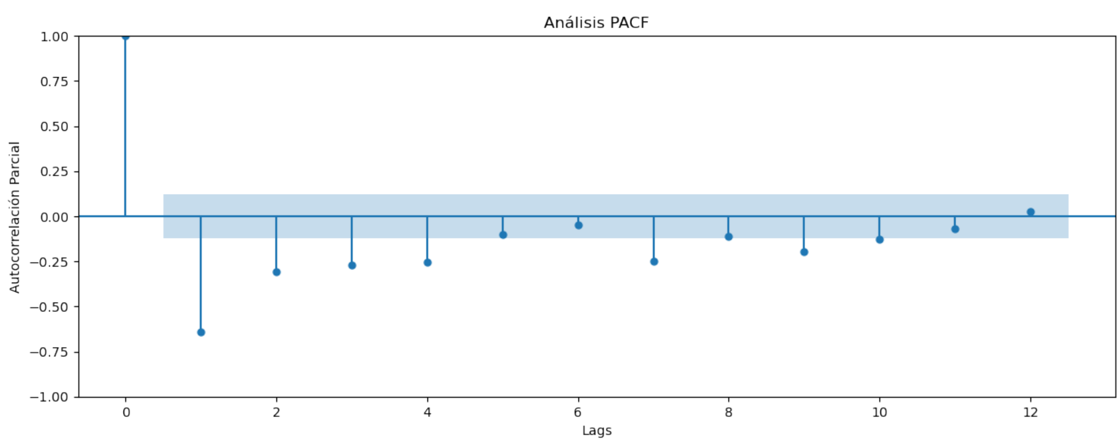
[47]:
```
Text(0.5, 1.0, 'Función de Autocorrelación Parcial 5 retardos')
```



[48]:
```
plt.figure(figsize=(10, 6))
plot_pacf(df1_log_diff, lags=12)
plt.xlabel('Lags')
plt.ylabel('Autocorrelación Parcial')
plt.title('Análisis PACF')
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348:
FutureWarning: The default method 'yw' can produce PACF values outside of the
[-1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker
('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```

```
<Figure size 1000x600 with 0 Axes>
```



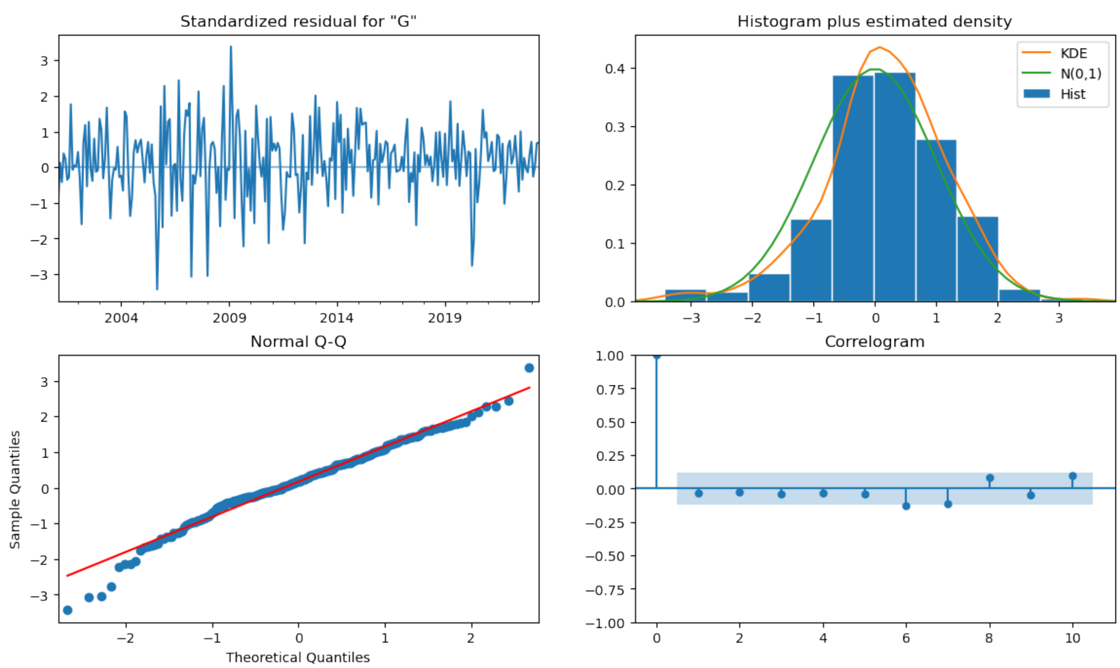
para el P podemos usar 5

No parece haber estacionalidad

[49]:
```
#df1_log = df1_log.resample("M").last()
df1_modelo512 = ARIMA(df1_log, order=(5,1,2), freq ='MS')
resultado_df1_modelo512 = df1_modelo512.fit()
print(resultado_df1_modelo512.summary().tables[1])
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4176      1.127     -0.370      0.711      -2.627       1.792
ar.L2          0.0011      0.336      0.003      0.997      -0.657       0.660
ar.L3         -0.0622      0.111     -0.561      0.575      -0.279       0.155
ar.L4         -0.0107      0.155     -0.069      0.945      -0.314       0.292
ar.L5          0.0508      0.090      0.564      0.573      -0.126       0.228
ma.L1         -0.6447      1.128     -0.572      0.568      -2.855       1.566
ma.L2         -0.1559      0.889     -0.175      0.861      -1.898       1.586
sigma2         0.0711      0.006     12.781      0.000       0.060       0.082
==============================================================================
```

[50]:
```
resultado_df1_modelo512.plot_diagnostics(figsize=(14, 8))
plt.show()
```



Los residuos presentan una distribución normal, y parecen comportarse como un ruido blanco dado que en el correlograma no hay autocorrelaciones significativas

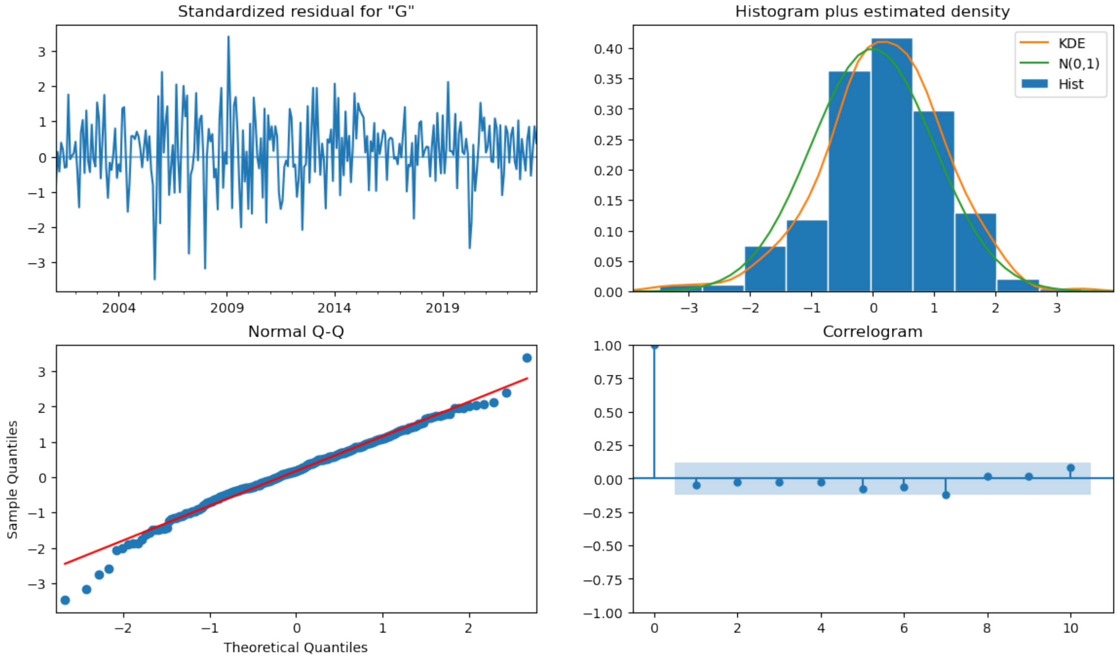
[51]:
```
df1_modelo513 = ARIMA(df1_log, order=(5,1,3), freq ='MS')
resultado_df1_modelo513 = df1_modelo513.fit()
print(resultado_df1_modelo513.summary().tables[1])
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -1.1787      0.098    -12.034      0.000      -1.371      -0.987
ar.L2         -1.0688      0.159     -6.703      0.000      -1.381      -0.756
ar.L3         -0.2446      0.189     -1.295      0.195      -0.615       0.125
ar.L4         -0.0549      0.137     -0.401      0.688      -0.323       0.213
ar.L5         -0.0112      0.078     -0.143      0.886      -0.164       0.142
ma.L1          0.1467      0.084      1.752      0.080      -0.017       0.311
ma.L2          0.1211      0.078      1.549      0.121      -0.032       0.274
ma.L3         -0.7740      0.069    -11.251      0.000      -0.909      -0.639
sigma2         0.0693      0.005     12.638      0.000       0.059       0.080
==============================================================================
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:604:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

[52]:
```
resultado_df1_modelo513.plot_diagnostics(figsize=(14, 8))
plt.show()
```



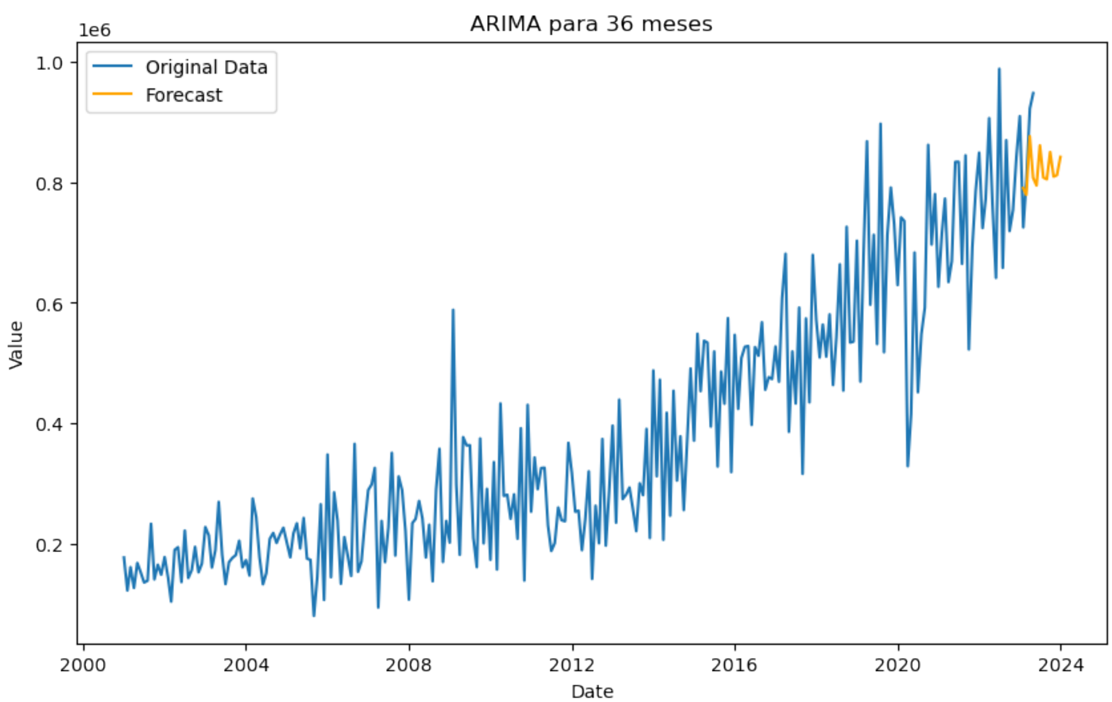
[53]:
```
print("Resultados de AIC (Akaike information criterion)")
print("Modelo 512=",resultado_df1_modelo512.aic)
print("Modelo 513=",resultado_df1_modelo513.aic)
print("Resultados de BIC (Bayesian information criterion)")
print("Modelo 512=",resultado_df1_modelo512.bic)
print("Modelo 513=",resultado_df1_modelo513.bic)
```

```
Resultados de AIC (Akaike information criterion)
Modelo 512= 69.58469079482742
Modelo 513= 63.007380612464054
Resultados de BIC (Bayesian information criterion)
Modelo 512= 98.31258663891427
Modelo 513= 95.32626343706175
```

De acuerdo a ambos indicadores es mejor el modelo p=5, d=1, q=3 por lo que este es el que será usado para predecir pues tinene un valor menor en AIC y en BIC Predicción Importaciones de Gasolina Regular con el mejor modelo

[54]:
```
# Generate forecast for the next 12 months
forecast_steps = 12
forecast = resultado_df1_modelo513.forecast(steps=forecast_steps)
forecast_original_scale = np.exp(forecast)

# Create a date range for the forecasted months
last_date = df1.index[-6]  # Assuming 'df' is your original data DataFrame
```

```
forecast_index = pd.date_range(start=last_date, periods=forecast_steps + 1,
 freq='M')[1:]

# Create a DataFrame to hold the forecasted values
forecast_df = pd.DataFrame({'Forecast': forecast}, index=forecast_index)


# Plot the original data and the forecasted values
plt.figure(figsize=(10, 6))
plt.plot(df1, label='Original Data')
plt.plot(forecast_df.index, forecast_original_scale, label='Forecast',
 color='orange')
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('ARIMA para 36 meses')
plt.legend()
plt.show()
```

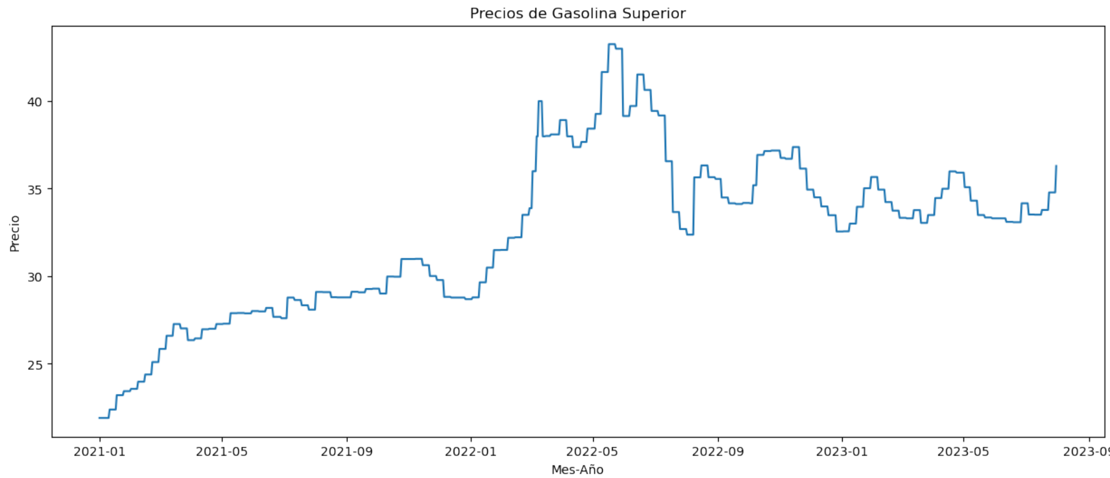


1.0.2 Precios de Gasolina Superior

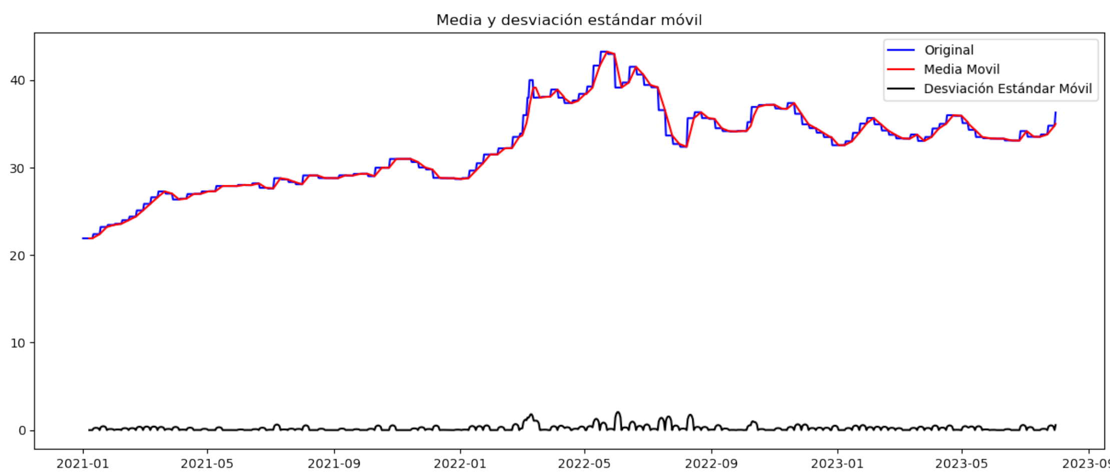
Exploracion

[55]:
```
plt.figure(figsize=(15,6))
plt.plot(df2)
```

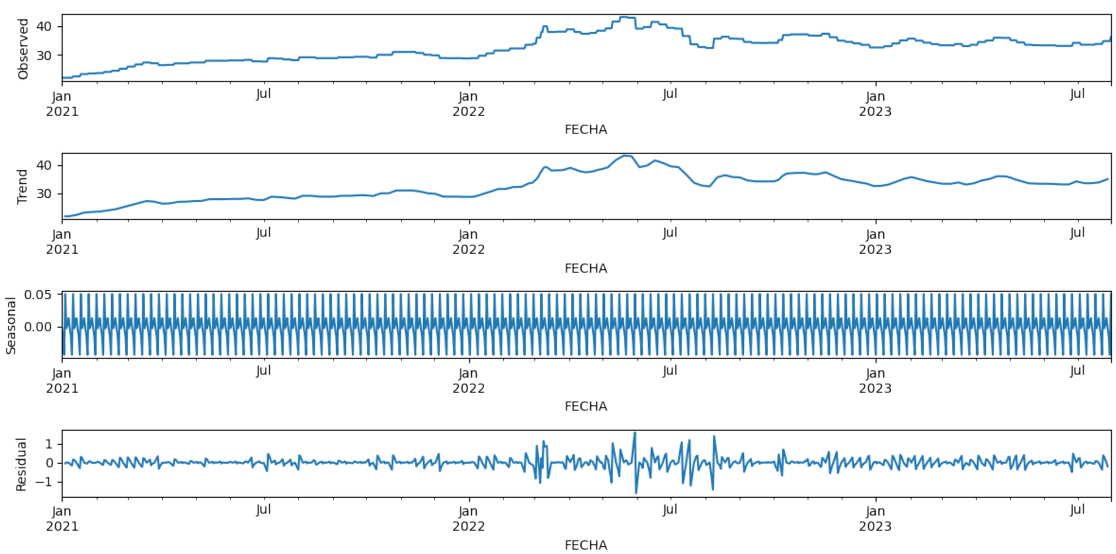
```
plt.gca().set(title="Precios de Gasolina Superior", xlabel="Mes-Año",␣
 ↪ylabel="Precio")
plt.show()
```



[56]:
```
# Se calcula la media móvil y la desviación estandar móvil de los últimos 12␣
 ↪meses.
mediaMovil_df2 = df2.rolling(window=7).mean()
deMovil_df2 = df2.rolling(window=7).std()
# Se grafican los resultados.
plt.figure(figsize=(15,6))
original = plt.plot(df2, color="blue", label="Original")
media = plt.plot(mediaMovil_df2, color='red', label = 'Media Movil')
ds = plt.plot(deMovil_df2,color='black', label = 'Desviación Estándar Móvil')
plt.legend(loc = 'best')
plt.title('Media y desviación estándar móvil')
plt.show(block=False)
```



[57]:
```
result = seasonal_decompose(df2)
# Create a new figure with a specific size
fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(12, 6))

# Plot the components on separate subplots
result.observed.plot(ax=ax1)
ax1.set_ylabel('Observed')

result.trend.plot(ax=ax2)
ax2.set_ylabel('Trend')

result.seasonal.plot(ax=ax3)
ax3.set_ylabel('Seasonal')

result.resid.plot(ax=ax4)
ax4.set_ylabel('Residual')

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```



No parece haber tendencia

[58]:
```
print('\033[1mResultados del Test de Dickey Fuller de la serie Precios Gasolina␣
↪Superior\033[0m')
df2_test = adfuller(df2, autolag='AIC')
```

```
salida_df2 = pd.Series(df2_test[0:4], index=['Estadístico de␣
↪prueba','p-value','# de retardos usados','# de observaciones usadas'])
for key,value in df2_test[4].items():
        salida_df2['Critical Value (%s)'%key] = value
print(salida_df2)
```

```
Resultados del Test de Dickey Fuller de la serie Precios Gasolina
Superior
Estadístico de prueba          -2.345554
p-value                         0.157696
# de retardos usados            7.000000
# de observaciones usadas     934.000000
Critical Value (1%)            -3.437371
Critical Value (5%)            -2.864639
Critical Value (10%)           -2.568420
dtype: float64
```

El valor P aún es mayor de 0.05, no se puede rechazar

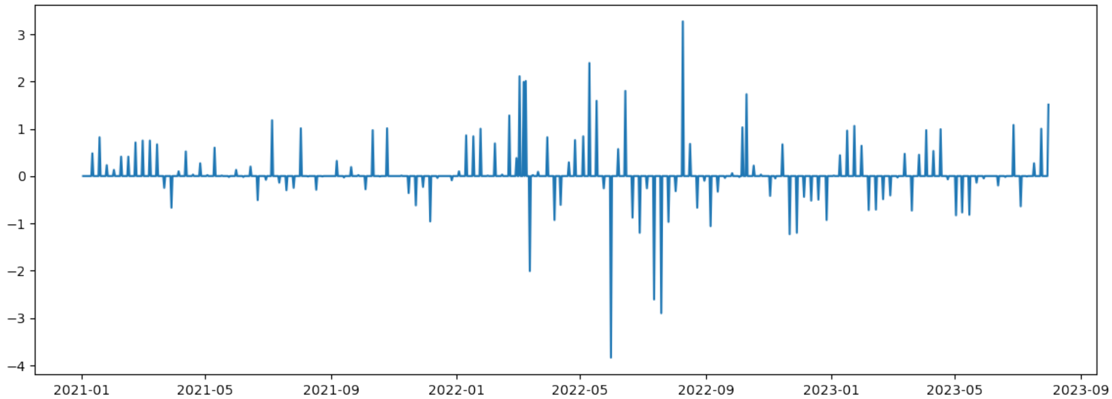
[59]:
```
print('\033[1mResultados del Test de Dickey Fuller para 1 diferenciación de la␣
↪serie Precios Gasolina Superior\033[0m')
df2_diff = df2.diff()
df2_diff.dropna(inplace=True)
df2_test = adfuller(df2_diff)
salida_df2 = pd.Series(df2_test[0:4], index=['Estadístico de␣
↪prueba','p-value','# de retardos usados','# de observaciones usadas'])
for key,value in df2_test[4].items():
        salida_df2['Critical Value (%s)'%key] = value
print(salida_df2)
```

```
Resultados del Test de Dickey Fuller para 1 diferenciación de la serie
Precios Gasolina Superior
Estadístico de prueba       -8.535789e+00
p-value                      1.008898e-13
# de retardos usados         6.000000e+00
# de observaciones usadas    9.340000e+02
Critical Value (1%)         -3.437371e+00
Critical Value (5%)         -2.864639e+00
Critical Value (10%)        -2.568420e+00
dtype: float64
```

Con una diferenciación se anula acepta la Hipótesis alternativa

[60]:
```
plt.plot(df2_diff)
```

[60]:
```
[<matplotlib.lines.Line2D at 0x228e1888040>]
```

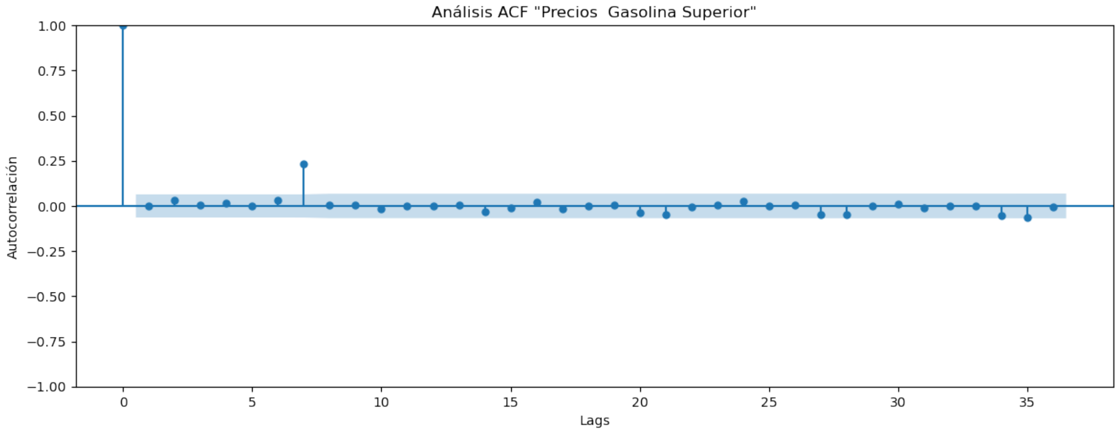


[61]:
```
df2_diff.dropna(inplace = True)
df2_diff_acf = acf(df2_diff,nlags=12,fft=False)
df2_diff_pacf = pacf(df2_diff, nlags=36)
df2_diff_acf, df2_diff_pacf
```

[61]:
```
(array([ 1.00000000e+00, -1.68259614e-03,  3.24949192e-02,  4.64532552e-03,
         1.48948761e-02, -1.49575012e-03,  2.99319549e-02,  2.34814760e-01,
         5.49055449e-03,  5.82181753e-03, -1.41412108e-02,  4.27028945e-04,
        -2.37006595e-03]),
 array([ 1.00000000e+00, -1.68438613e-03,  3.25613862e-02,  4.77316740e-03,
         1.39293581e-02, -1.76074392e-03,  2.91991345e-02,  2.37155701e-01,
         6.29794789e-03, -9.94653598e-03, -1.80803917e-02, -6.17082383e-03,
         1.33502459e-04, -7.28867855e-03, -9.56818921e-02, -1.41073124e-02,
         2.71259281e-02, -6.15290964e-03,  2.25098490e-03,  3.51999768e-03,
        -4.00348411e-02, -2.02119141e-02,  2.26717790e-03, -5.72068553e-04,
         3.16591770e-02, -1.96180529e-03,  1.46151740e-03, -2.85567143e-02,
        -3.92765859e-02,  3.33340379e-03,  9.99064945e-03, -2.78959076e-02,
        -3.60200750e-03,  3.60790103e-03, -4.26500646e-02, -5.52877200e-02,
        -4.98884312e-03]))
```

[62]:
```
plt.figure(figsize=(10, 6))
plot_acf(df2_diff, lags=36)
plt.xlabel('Lags')
plt.ylabel('Autocorrelación')
plt.title('Análisis ACF "Precios  Gasolina Superior"')
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```

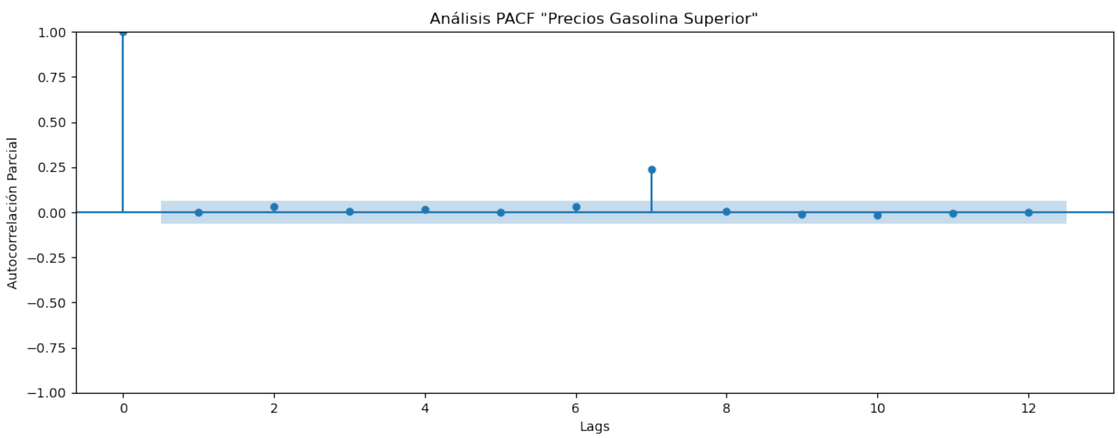


Se sugiere un valor de desde de 7 para el Q No Parece haber un componente de temporadas

[63]:
```
plt.figure(figsize=(8, 6))
plot_pacf(df2_diff, lags=12)
plt.xlabel('Lags')
plt.ylabel('Autocorrelación Parcial')
plt.title('Análisis PACF "Precios Gasolina Superior"')
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348:
FutureWarning: The default method 'yw' can produce PACF values outside of the
[-1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker
('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```

```
<Figure size 800x600 with 0 Axes>
```



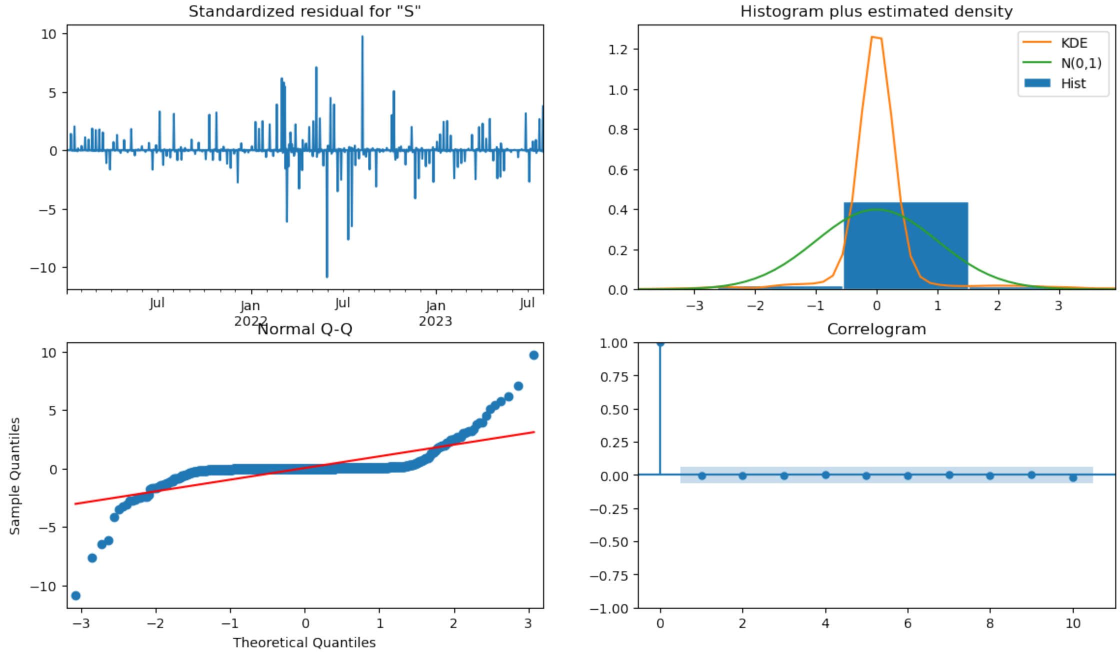
Se sugiere un componente de 7 para el P

[64]:
```
df2_modelo717 = ARIMA(df2, order=(7,1,7), freq ='D')
resultado_df2_modelo717 = df2_modelo717.fit()
print(resultado_df2_modelo717.summary().tables[1])
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0252      0.470      0.054      0.957      -0.896       0.946
ar.L2         -0.0077      0.461     -0.017      0.987      -0.912       0.896
ar.L3          0.0285      0.189      0.151      0.880      -0.342       0.399
ar.L4         -0.0277      0.370     -0.075      0.940      -0.754       0.698
ar.L5         -0.0141      0.616     -0.023      0.982      -1.221       1.193
ar.L6          0.1327      0.231      0.575      0.565      -0.319       0.585
ar.L7         -0.0736      0.098     -0.752      0.452      -0.265       0.118
ma.L1         -0.0350      0.422     -0.083      0.934      -0.863       0.793
ma.L2          0.0456      0.433      0.105      0.916      -0.803       0.895
ma.L3         -0.0240      0.157     -0.153      0.878      -0.331       0.283
ma.L4          0.0422      0.376      0.112      0.911      -0.695       0.779
ma.L5          0.0042      0.556      0.007      0.994      -1.085       1.093
ma.L6         -0.0996      0.218     -0.458      0.647      -0.526       0.327
ma.L7          0.3337      0.102      3.274      0.001       0.134       0.533
sigma2         0.1162      0.001     89.942      0.000       0.114       0.119
==============================================================================
```

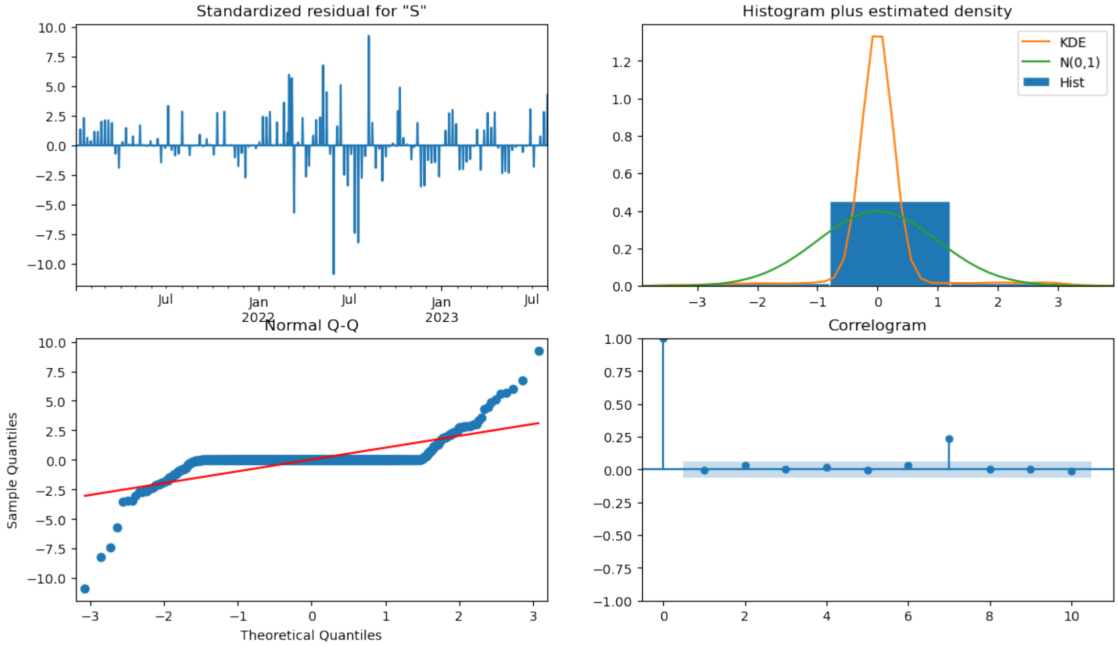
[65]:
```
resultado_df2_modelo717.plot_diagnostics(figsize=(14, 8))
plt.show()
```



[66]:
```
df2_modelo010 = ARIMA(df2, order=(0,1,0), freq ='D')
resultado_df2_modelo010 = df2_modelo010.fit()
print(resultado_df2_modelo010.summary().tables[1])
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2         0.1246      0.001     98.495      0.000       0.122       0.127
==============================================================================

C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

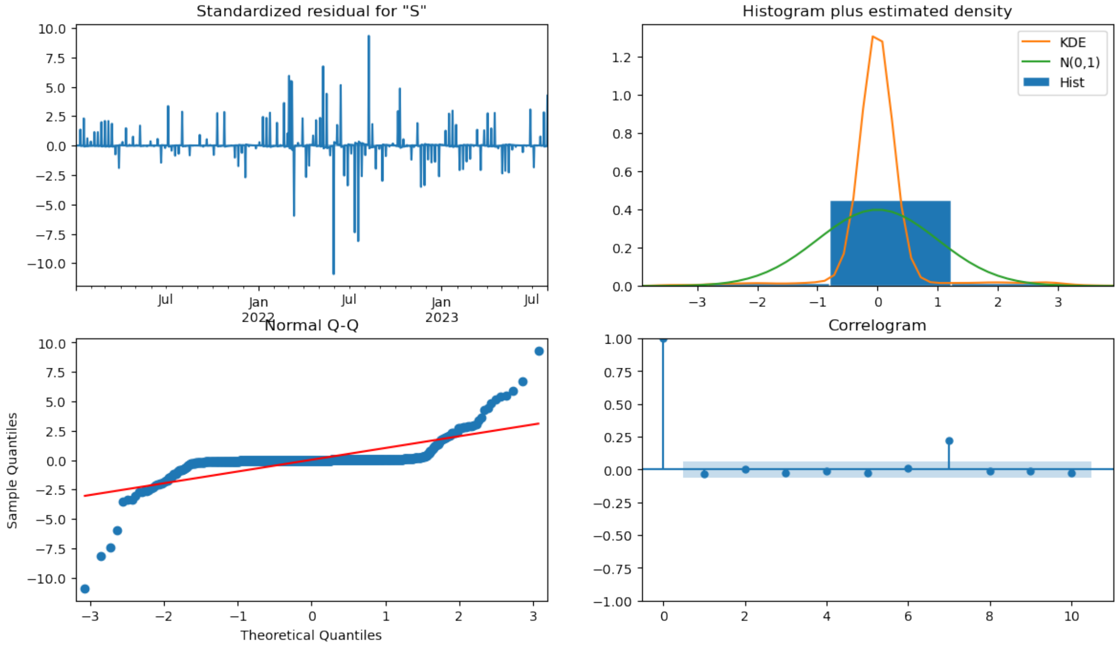
[67]:
```
resultado_df2_modelo010.plot_diagnostics(figsize=(14, 8))
plt.show()
```



[68]:
```
df2_modelo111 = ARIMA(df2, order=(1,1,1), freq ='D')
resultado_df2_modelo111 = df2_modelo111.fit()
print(resultado_df2_modelo111.summary().tables[1])
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9017      0.107      8.460      0.000       0.693       1.111
ma.L1         -0.8717      0.133     -6.552      0.000      -1.132      -0.611
sigma2         0.1240      0.002     80.865      0.000       0.121       0.127
==============================================================================
```

[69]:
```
resultado_df2_modelo111.plot_diagnostics(figsize=(14, 8))
plt.show()
```



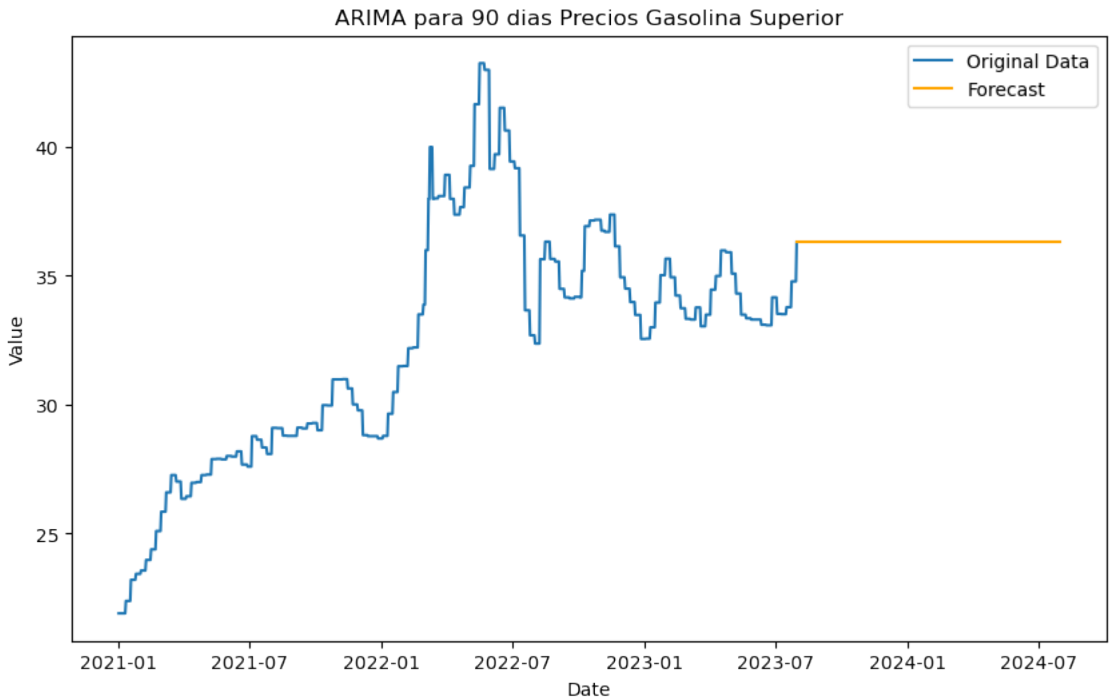
[70]:
```
print("Resultados de AIC (Akaike information criterion)")
print("Modelo 717=",resultado_df2_modelo717.aic)
print("Modelo 010=",resultado_df2_modelo010.aic)
print("Modelo 111=",resultado_df2_modelo111.aic)
print("Resultados de BIC (Bayesian information criterion)")
print("Modelo 717=",resultado_df2_modelo717.bic)
print("Modelo 010=",resultado_df2_modelo010.bic)
print("Modelo 111=",resultado_df2_modelo111.bic)
```

```
Resultados de AIC (Akaike information criterion)
Modelo 717= 675.8725376274368
Modelo 010= 712.6509335511615
Modelo 111= 712.2318202601184
Resultados de BIC (Bayesian information criterion)
Modelo 717= 748.5766847212175
Modelo 010= 717.4978766907469
Modelo 111= 726.7726496788746
```

el mejor modelo para ser el 010 procedemos a pronosticar #### Predicción con el mejor modelo Precios Gasolina Superior

[71]:
```
# Generate forecast for the next 90 dias
forecast_steps = 365
forecast = resultado_df2_modelo010.forecast(steps=forecast_steps)

# Create a date range for the forecasted months
last_date = df2[-1]  # Assuming 'df' is your original data DataFrame
```

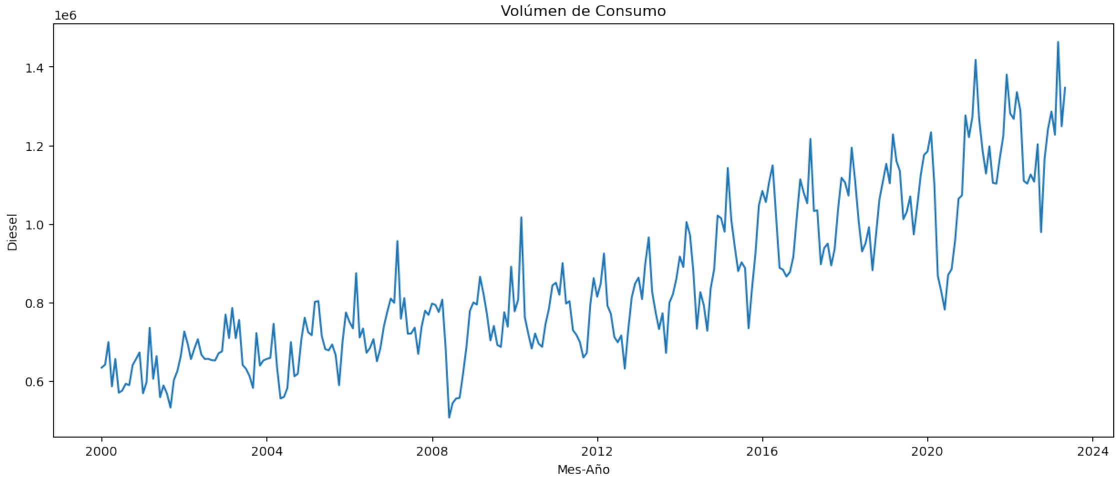
```
forecast_index = pd.date_range(start=last_date, periods=forecast_steps + 1,␣
 ↪freq='D')[1:]

# Plot the original data and the forecasted values
plt.figure(figsize=(10, 6))
plt.plot(df2, label='Original Data')
plt.plot(forecast, label='Forecast', color='orange')
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('ARIMA para 90 dias Precios Gasolina Superior')
plt.legend()
plt.show()
```



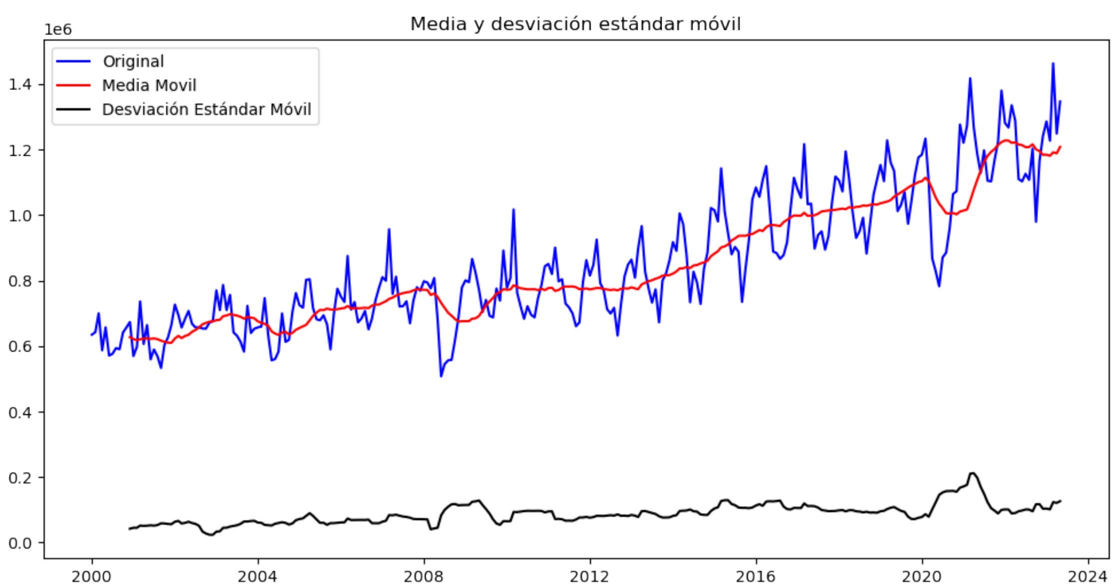
1.0.3 Consumos Gasolina Diesel

Exploración

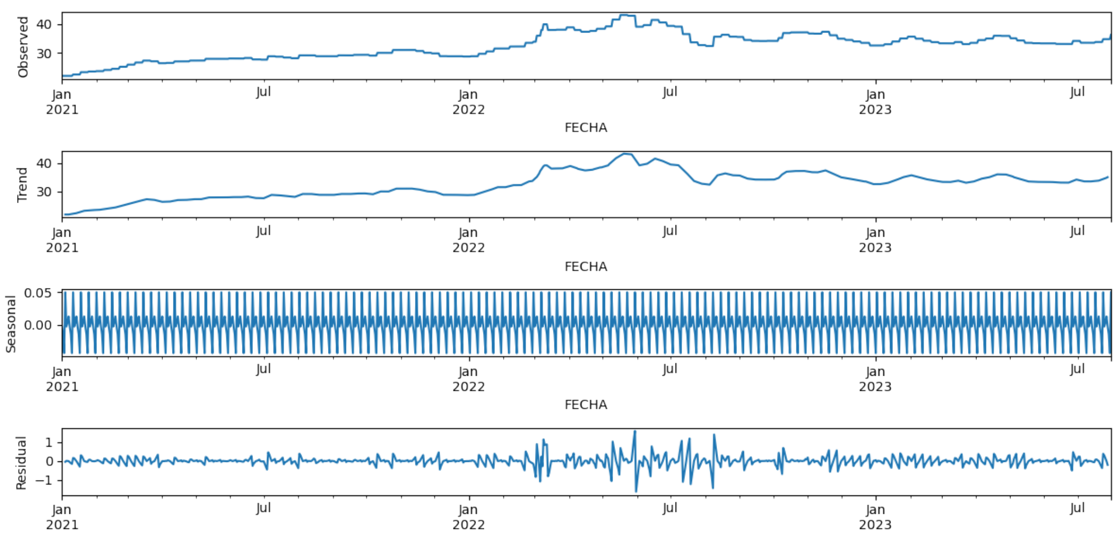
[72]:
```
plt.figure(figsize=(15,6))
plt.plot(df3)
plt.gca().set(title="Volúmen de Consumo", xlabel="Mes-Año", ylabel="Diesel")
plt.show()
```



[73]:
```python
# Se calcula la media móvil y la desviación estandar móvil de los últimos 12␣
↪meses.
mediaMovil_df3 = df3.rolling(window=12).mean()
deMovil_df3 = df3.rolling(window=12).std()
# Se grafican los resultados.
plt.figure(figsize=(12,6))
original_df3 = plt.plot(df3, color="blue", label="Original")
media_df3 = plt.plot(mediaMovil_df3, color='red', label = 'Media Movil')
ds_df3 = plt.plot(deMovil_df3,color='black', label = 'Desviación Estándar␣
↪Móvil')
plt.legend(loc = 'best')
plt.title('Media y desviación estándar móvil')
plt.show(block=False)
```

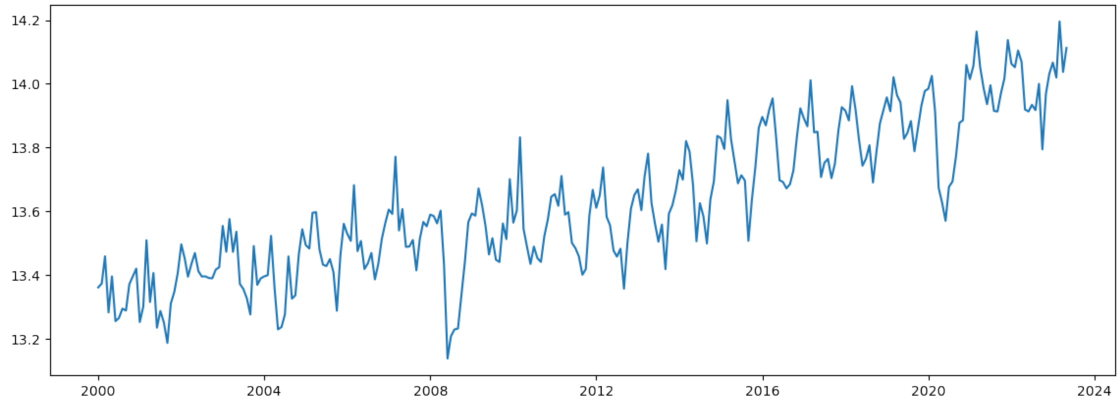


[74]:
```
result_df3 = seasonal_decompose(df3)
# Create a new figure with a specific size
fig_df3, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(12, 6))

# Plot the components on separate subplots
result.observed.plot(ax=ax1)
ax1.set_ylabel('Observed')

result.trend.plot(ax=ax2)
ax2.set_ylabel('Trend')

result.seasonal.plot(ax=ax3)
ax3.set_ylabel('Seasonal')

result.resid.plot(ax=ax4)
ax4.set_ylabel('Residual')

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```

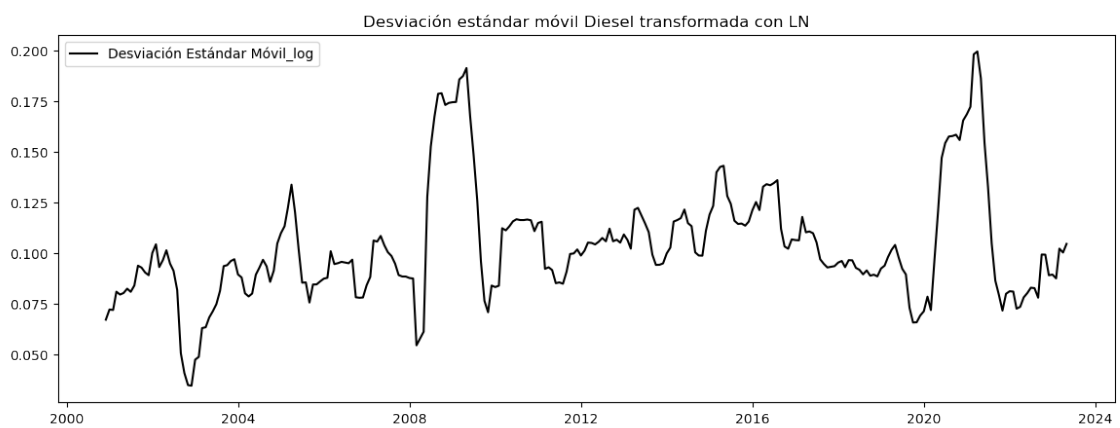


[75]:
```
df3_log = np.log(df3)
plt.plot(df3_log)
```

[75]:
```
[<matplotlib.lines.Line2D at 0x228e02e5700>]
```



[76]:
```
mediaMovil_log_df3 = df3_log.rolling(window=12).mean()
deMovil_log_df3 = df3_log.rolling(window=12).std()
#Graficando los resultados con logaritmo.
#serie_df3_log = plt.plot(df3_log, color="blue", label="df3_log")
#media_movil_df3_log = plt.plot(mediaMovil_log_df3, color='red', label = 'Media␣
↪Movil_log')
ds_log = plt.plot(deMovil_log_df3,color='black', label = 'Desviación Estándar␣
↪Móvil_log')
plt.legend(loc = 'best')
plt.title('Desviación estándar móvil Diesel transformada con LN')
plt.show(block=False)
```



Se tienen dos claros picos de la crisis del 2008 y el Covid pero en general es bastante estable

[77]:
```
print('\033[1mResultados del Test de Dickey Fuller de la serie Consumo␣
↪Diesel\033[0m')
df3_test = adfuller(df3, autolag='AIC')
```

```python
salida_df3 = pd.Series(df3_test[0:4], index=['Estadístico de␣
↪prueba','p-value','# de retardos usados','# de observaciones usadas'])
for key,value in df3_test[4].items():
        salida_df3['Critical Value (%s)'%key] = value
print(salida_df3)
```

```
Resultados del Test de Dickey Fuller de la serie Consumo Diesel
Estadístico de prueba           0.018032
p-value                         0.959998
# de retardos usados           12.000000
# de observaciones usadas     268.000000
Critical Value (1%)            -3.454988
Critical Value (5%)            -2.872386
Critical Value (10%)           -2.572549
dtype: float64
```

El valor p e mayor a 0.05 se procede a diferenciar 1 vez

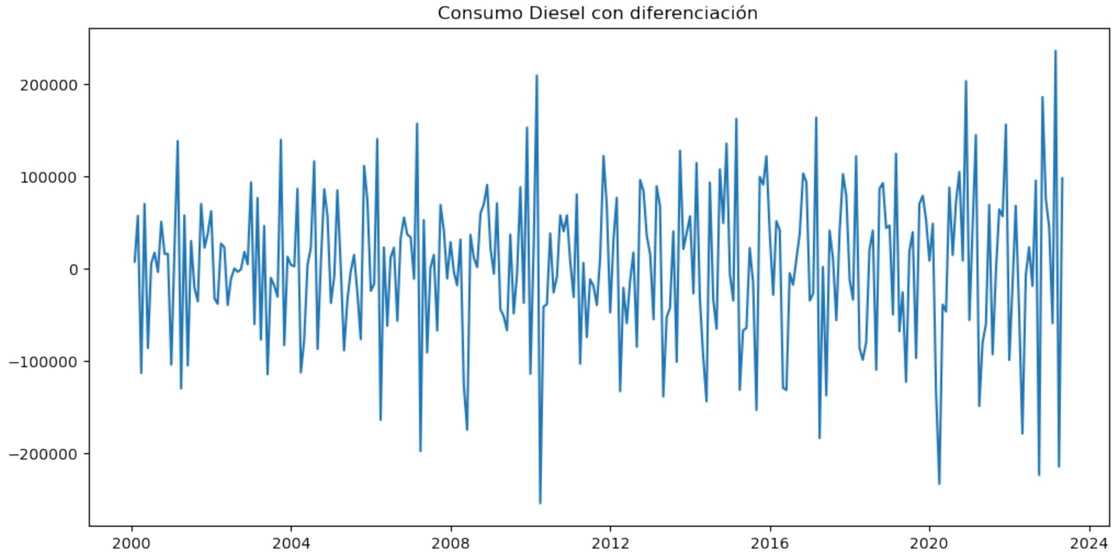
[78]:
```python
print('\033[1mResultados del Test de Dickey Fuller para 1 diferenciación de la␣
↪serie Consumo Diesel\033[0m')
df3_diff = df3.diff()
df3_diff.dropna(inplace=True)
df3_test = adfuller(df3_diff)
salida_df3 = pd.Series(df3_test[0:4], index=['Estadístico de␣
↪prueba','p-value','# de retardos usados','# de observaciones usadas'])
for key,value in df3_test[4].items():
        salida_df3['Critical Value (%s)'%key] = value
print(salida_df3)
```

```
Resultados del Test de Dickey Fuller para 1 diferenciación de la serie

Consumo Diesel
Estadístico de prueba       -6.884266e+00
p-value                      1.407679e-09
# de retardos usados         1.100000e+01
# de observaciones usadas    2.680000e+02
Critical Value (1%)         -3.454988e+00
Critical Value (5%)         -2.872386e+00
Critical Value (10%)        -2.572549e+00
dtype: float64
```

El p-valor es menor a 0.05 se rechaza la hipótesis nula, Ha: No hay raices unitarias se acepta

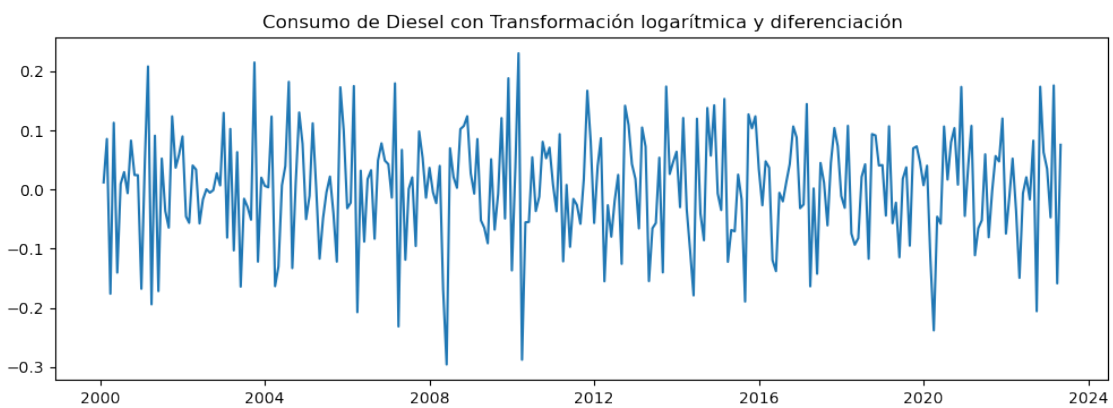
[79]:
```python
plt.figure(figsize=(12, 6))
plt.title('Consumo Diesel con diferenciación')
plt.plot(df3_diff)
```

[79]:
```
[<matplotlib.lines.Line2D at 0x228e04250d0>]
```



[80]:
```
plt.figure(figsize=(12, 4))
df3_log_diff = df3_log.diff()
plt.title('Consumo de Diesel con Transformación logarítmica y diferenciación')
plt.plot(df3_log_diff)
```

[80]: [<matplotlib.lines.Line2D at 0x228e0359460>]

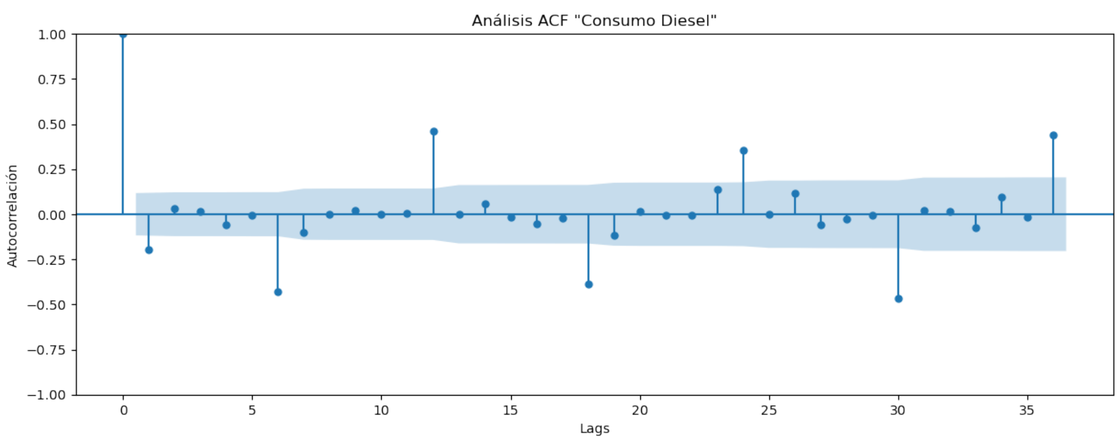


[81]:
```
df3_log_diff.dropna(inplace = True)
df3_log_diff_acf = acf(df3_log_diff,nlags=5,fft=False)
df3_log_diff_pacf = pacf(df3_log_diff, nlags=36)
df3_log_diff_acf, df3_log_diff_pacf
```

[81]: (array([1.   , -0.19722102, 0.02907365, 0.01670783, -0.06106934,
        -0.0078728]),
 array([1.   , -0.19792791, -0.01029599, 0.02155302, -0.05637933,
        -0.03308451, -0.46748652, -0.38169926, -0.21806094, -0.07405124,
        -0.11861396, -0.21578912, 0.23083654, 0.04752106, 0.03563811,
         0.01913844, -0.02180888, -0.02791521, -0.20400601, -0.24574491,
        -0.14732467, -0.13522994, -0.21210924, -0.03270305, 0.15932065,
        -0.06794954, 0.05472767, 0.01121561, -0.06728093, 0.07590124,
        -0.25579207, -0.12546835, 0.06216934, -0.09476825, 0.05986017,
        -0.14906471, 0.13643478]))

[82]:
```
plt.figure(figsize=(10, 6))
plot_acf(df3_log_diff, lags=36)
plt.xlabel('Lags')
plt.ylabel('Autocorrelación')
plt.title('Análisis ACF "Consumo Diesel"')
plt.show()
```

<Figure size 1000x600 with 0 Axes>



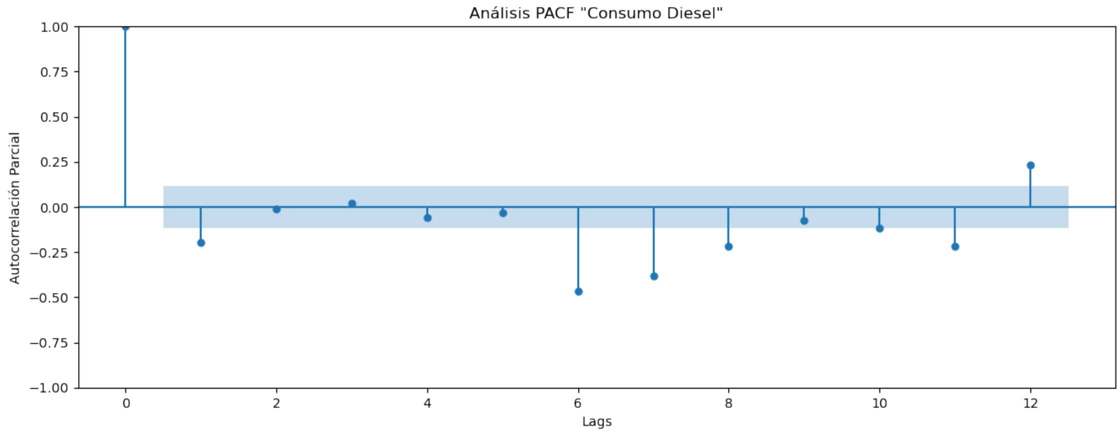
Se sugiere un valor de desde de 2 para el Q Parece haber un componente de temporadas anual por las correlaciones de 12 24 y 36 meses

[83]:
```
plt.figure(figsize=(8, 6))
plot_pacf(df3_log_diff, lags=12)
plt.xlabel('Lags')
plt.ylabel('Autocorrelación Parcial')
plt.title('Análisis PACF "Consumo Diesel"')
plt.show()
```

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348:
FutureWarning: The default method 'yw' can produce PACF values outside of the

```
[-1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker
('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```

```
<Figure size 800x600 with 0 Axes>
```



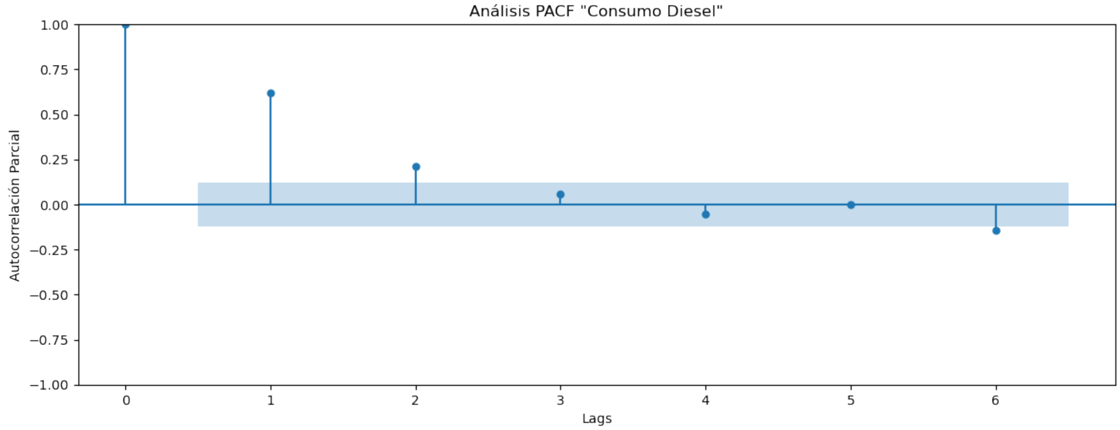
para el P podemos usar 2 también

[84]:
```python
df3_log_D = df3_log.diff(12)
df3_log_D.dropna(inplace=True)
```

[85]:
```python
plt.figure(figsize=(8, 6))
plot_pacf(df3_log_D, lags=6)
plt.xlabel('Lags')
plt.ylabel('Autocorrelación Parcial')
plt.title('Análisis PACF "Consumo Diesel"')
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348:
FutureWarning: The default method 'yw' can produce PACF values outside of the
[-1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker
('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```

```
<Figure size 800x600 with 0 Axes>
```



Luego de hacer una diferenciación estacional, podemos observar que prácticamente se anulan los coeficientes después de p=3. Probemos el siguiente componente estacional: - P = 3 - D = 1 - Q = 0

[86]:
```
df3_modelo212 = SARIMAX(df3_log, order=(2,1,2), seasonal_order=(3,1,2,12),␣
 ↪enforce_stationarity=False, enforce_invertibility=False)
df3_resultado_m212 = df3_modelo212.fit()
print(df3_resultado_m212.summary().tables[1])
```

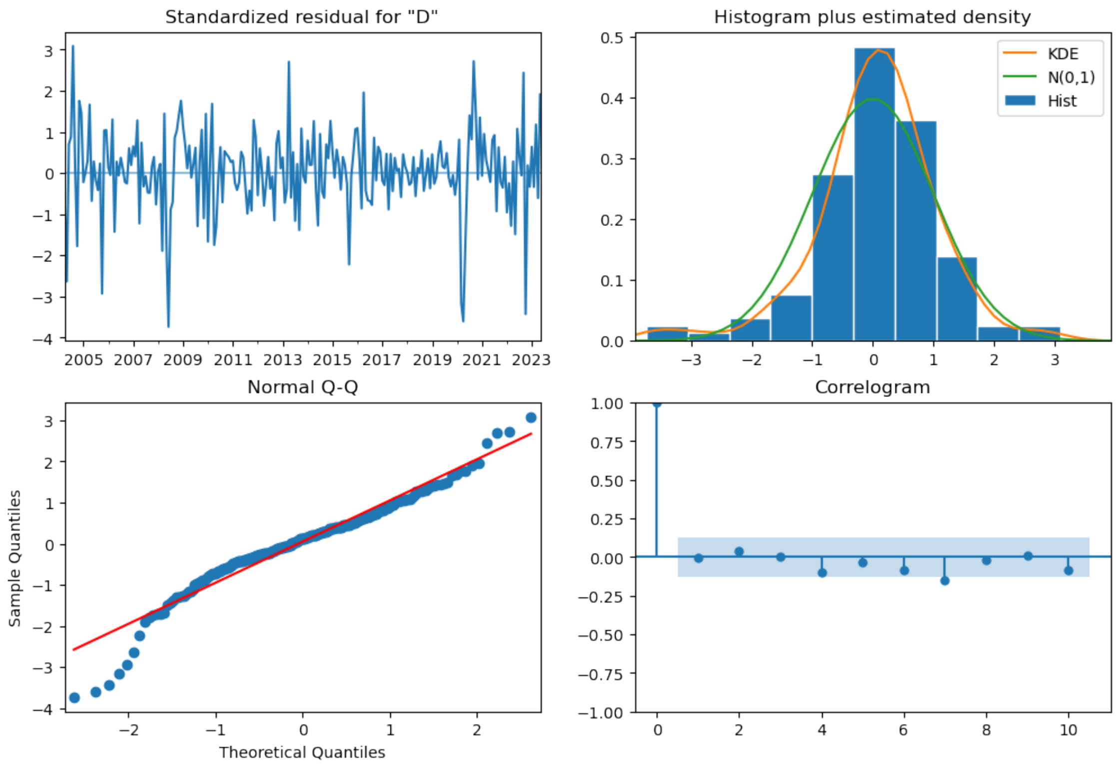
```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:604:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6773      0.263     -2.572      0.010      -1.194      -0.161
ar.L2         -0.0417      0.128     -0.325      0.745      -0.293       0.210
ma.L1          1.0071      0.411      2.451      0.014       0.202       1.812
ma.L2         -0.6462      0.303     -2.131      0.033      -1.241      -0.052
ar.S.L12      -0.2644      0.203     -1.303      0.192      -0.662       0.133
ar.S.L24      -0.1147      0.102     -1.121      0.262      -0.315       0.086
ar.S.L36      -0.0441      0.082     -0.540      0.589      -0.204       0.116
ma.S.L12      -0.7713      2.443     -0.316      0.752      -5.559       4.017
```

```
ma.S.L24      -0.2246      0.625     -0.359      0.719     -1.449      1.000
sigma2         0.0018      0.004      0.436      0.663     -0.006      0.010
==============================================================================
```

Análisis de residuos

[87]:
```
df3_resultado_m212.plot_diagnostics(figsize=(12, 8))
plt.show()
```



Como se puede obserevar los residuos presentan una distribución masomenos normal, y parecen comportarse como un ruido blanco dado que en el correlograma no hay autocorrelaciones significativas

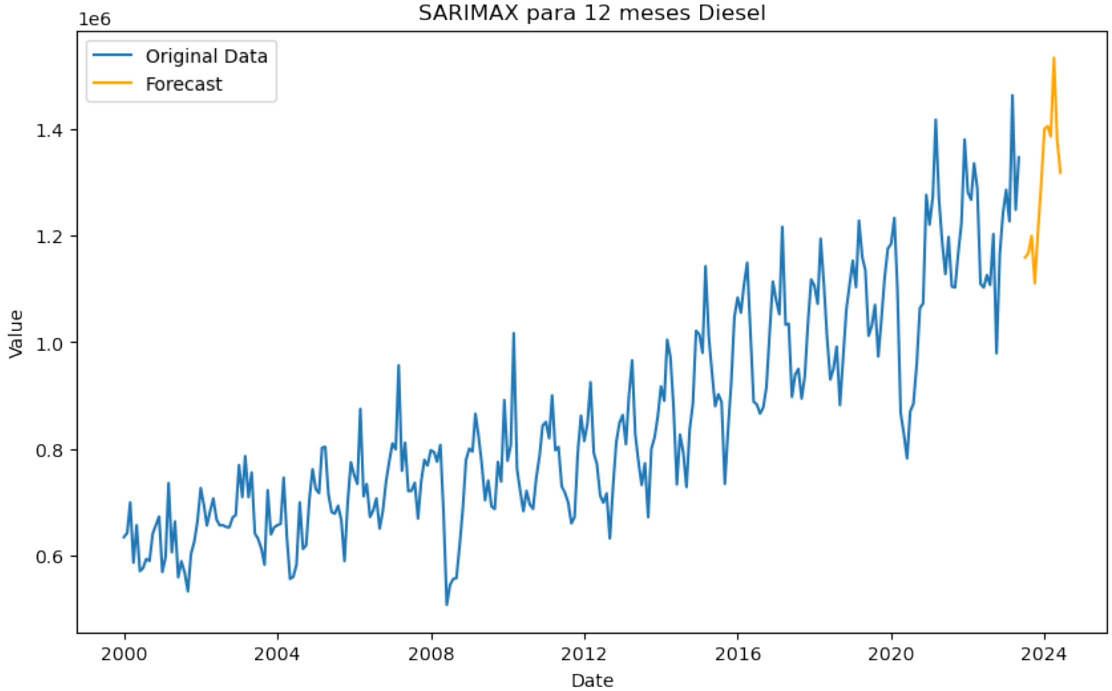
[88]:
```
print("Resultados de AIC (Akaike information criterion)")
print("Modelo 121=",df3_resultado_m212.aic)
print("Modelo 221=",df3_resultado_m212.aic)
```

```
Resultados de AIC (Akaike information criterion)
Modelo 121= -577.3101094727722
Modelo 221= -577.3101094727722
```

Predicción con el mejor modelo

[89]:
```
# Generate forecast for the next 12 months
forecast_steps = 12
```

```
forecast = df3_resultado_m212.forecast(steps=forecast_steps)
forecast_original_scale = np.exp(forecast)

# Create a date range for the forecasted months
last_date = df3.index[-1]  # Assuming 'df' is your original data DataFrame
forecast_index = pd.date_range(start=last_date, periods=forecast_steps + 1,␣
 ↪freq='M')[1:]

# Create a DataFrame to hold the forecasted values
forecast_df = pd.DataFrame({'Forecast': forecast}, index=forecast_index)


# Plot the original data and the forecasted values
plt.figure(figsize=(10, 6))
plt.plot(df3.index, df3.values, label='Original Data')
plt.plot(forecast_df.index, forecast_original_scale, label='Forecast',␣
 ↪color='orange')
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('SARIMAX para 12 meses Diesel')
plt.legend()
plt.show()
```



1.1 Comparacion con LSTM

1.1.1 Importacion de gasolina regular

[90]:
```
# Split data into train and test sets
train_size = int(0.8 * len(df1))
train_df = df1[:train_size]
test_df = df1[train_size:]

# ARIMA model
order = (5, 1, 3)  # Example ARIMA order
arima_model = ARIMA(train_df, order=order)
arima_results = arima_model.fit()

# LSTM model
def create_lstm_model():
    model = Sequential()
    model.add(LSTM(50, input_shape=(1, 1)))
    model.add(Dense(15, activation='relu'))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model

X_train = np.array(train_df).reshape(-1, 1, 1)
y_train = np.array(train_df)

lstm_model = create_lstm_model()
lstm_model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)

# ARIMA
arima_predictions = arima_results.forecast(steps=len(test_df))

# LSTM
lstm_predictions = []
for i in range(len(test_df)):
    lstm_input = np.array([lstm_predictions[-1]] if lstm_predictions else␣
 ↪X_train[-1])
    lstm_pred = lstm_model.predict(lstm_input.reshape(1, 1, 1))
    lstm_predictions.append(lstm_pred[0, 0])

# Calculate RMSE and MAPE for both models
rmse_arima = np.sqrt(mean_squared_error(test_df, arima_predictions))
mape_arima = np.mean(np.abs((test_df - arima_predictions) / test_df)) * 100

rmse_lstm = np.sqrt(mean_squared_error(test_df, lstm_predictions))
mape_lstm = np.mean(np.abs((test_df - lstm_predictions) / test_df)) * 100

# Print the results
```

```python
print("ARIMA - RMSE:", rmse_arima)
print("ARIMA - MAPE:", mape_arima)
print("LSTM - RMSE:", rmse_lstm)
print("LSTM - MAPE:", mape_lstm)
print("STD:", df1.std())
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

```
1/1 [==============================] - 1s 660ms/step
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1/1 [==============================] - 0s 46ms/step
1/1 [==============================] - 0s 45ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 51ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 26ms/step
ARIMA - RMSE: 200348.75221223445
ARIMA - MAPE: 23.55410108988794
LSTM - RMSE: 728430.4762709666
LSTM - MAPE: 99.999183747892
STD: 219364.3548742019
```

Para esta primera serie, vemos que el rmse es significativamente mejor en el arima que el LSTM utilizado. De hecho este arima es aceptable considerando que un MAPE de 23.55% no esta nada mal considerando el valor de la varianza, ademas de que lo hicimos con el test. Por lo que utilizaremos ARIMA para predecir la

1.1.2 Precios de gasolina superior

[91]:
```
# Split data into train and test sets
train_size = int(0.8 * len(df2))
train_df = df2[:train_size]
test_df = df2[train_size:]

# ARIMA model
order = (0, 1, 0)  # Example ARIMA order
arima_model = ARIMA(train_df, order=order)
arima_results = arima_model.fit()

# LSTM model
def create_lstm_model():
    model = Sequential()
    model.add(LSTM(50, input_shape=(1, 1)))
    model.add(Dense(15, activation='relu'))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model

X_train = np.array(train_df).reshape(-1, 1, 1)
y_train = np.array(train_df)

lstm_model = create_lstm_model()
lstm_model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)

# ARIMA
arima_predictions = arima_results.forecast(steps=len(test_df))

# LSTM
lstm_predictions = []
for i in range(len(test_df)):
    lstm_input = np.array([lstm_predictions[-1]] if lstm_predictions else␣
↪X_train[-1])
    lstm_pred = lstm_model.predict(lstm_input.reshape(1, 1, 1))
    lstm_predictions.append(lstm_pred[0, 0])

# Calculate RMSE and MAPE for both models
rmse_arima = np.sqrt(mean_squared_error(test_df, arima_predictions))
mape_arima = np.mean(np.abs((test_df - arima_predictions) / test_df)) * 100

rmse_lstm = np.sqrt(mean_squared_error(test_df, lstm_predictions))
mape_lstm = np.mean(np.abs((test_df - lstm_predictions) / test_df)) * 100

# Print the results
print("ARIMA - RMSE:", rmse_arima)
```

```python
print("ARIMA - MAPE:", mape_arima)
print("LSTM - RMSE:", rmse_lstm)
print("LSTM - MAPE:", mape_lstm)
print("STD", df2.std())
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

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ARIMA - RMSE: 1.2877411419525537
ARIMA - MAPE: 3.340024289795889
LSTM - RMSE: 2.4154358967476734
LSTM - MAPE: 6.602520454230637
STD 4.555857482383936
```

En este caso el ARIMA tiene un muy buen rendimiento en el test ya que el rmse casi 4 veces mejor que la desviacion estandar, mientras que el LSTM es simplemente aceptable. Por lo tanto nos quedaremos con el ARIMA.

1.1.3 Consumos de diesel

[92]:
```python
# Split data into train and test sets
train_size = int(0.8 * len(df3))
train_df = df3[:train_size]
test_df = df3[train_size:]

# ARIMA model
order = (2,1,2)  # Example ARIMA order
arima_model = ARIMA(train_df, order=order)
arima_results = arima_model.fit()

# LSTM model
def create_lstm_model():
    model = Sequential()
    model.add(LSTM(50, input_shape=(1, 1)))
    model.add(Dense(15, activation='relu'))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model

X_train = np.array(train_df).reshape(-1, 1, 1)
y_train = np.array(train_df)
```

```python
lstm_model = create_lstm_model()
lstm_model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)

# ARIMA
arima_predictions = arima_results.forecast(steps=len(test_df))

# LSTM
lstm_predictions = []
for i in range(len(test_df)):
    lstm_input = np.array([lstm_predictions[-1]] if lstm_predictions else X_train[-1])
    lstm_pred = lstm_model.predict(lstm_input.reshape(1, 1, 1))
    lstm_predictions.append(lstm_pred[0, 0])

# Calculate RMSE and MAPE for both models
rmse_arima = np.sqrt(mean_squared_error(test_df, arima_predictions))
mape_arima = np.mean(np.abs((test_df - arima_predictions) / test_df)) * 100

rmse_lstm = np.sqrt(mean_squared_error(test_df, lstm_predictions))
mape_lstm = np.mean(np.abs((test_df - lstm_predictions) / test_df)) * 100

# Print the results
print("ARIMA - RMSE:", rmse_arima)
print("ARIMA - MAPE:", mape_arima)
print("LSTM - RMSE:", rmse_lstm)
print("LSTM - MAPE:", mape_lstm)
print("STD", df3.std())
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\ProgramData\Anaconda3\lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible
```

```
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'

1/1 [==============================] - 1s 836ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 28ms/step
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1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 28ms/step
ARIMA - RMSE: 195045.63885886592
ARIMA - MAPE: 14.201927554073238
LSTM - RMSE: 1146160.8889994498
LSTM - MAPE: 99.99963639993777
STD 205345.61556490546
```

En este caso el ARIMA sigue siendo superior al LSTM. Aún asi no es muy bueno ninguno de ambos modelos. De elegir nos quedaríamos con el ARIMA.

1.2 Discusión inciso 6

Creemos que las predicciones sí son afectas por la pandemia en particular. Esto se puede apreciar con mayor detalle en la predicción del consumo de Diesel ya que la caida pronunciada en este provoca que los cambio en la proyección del arima sean más pronunciados intentando reflejar la tendencia de los datos históricos. De no ser asi la variación se debería observar menos pronunciada segun la epoca del año.