VECTOR AUTOREGRESIVO

1. Importar las librerias

```
import numpy as np
import pandas as pd
import statsmodels.api as sm
from statsmodels.tsa.api import VAR
```

2. Cargar las bases de datos

```
import pandas as pd
import yfinance as yf
```

```
acciones = ['TM', 'NSANY',"MBG.DE" ,'VOW3.DE', "HYMTF"]
base = yf.download(acciones,start='2019-1-1',end='2022-1-1')['Close']
base
```

```
[*********************100%%**********************]  5 of 5 completed
```

Date	HYMTF	MBG.DE	NSANY	TM	VOW3.DE
2019-01-02	25.250000	45.250000	16.080000	116.279999	136.259995
2019-01-03	25.250000	44.775002	16.059999	114.650002	134.759995
2019-01-04	25.250000	47.070000	16.360001	119.730003	140.479996
2019-01-07	25.250000	47.160000	16.530001	121.279999	140.639999
2019-01-08	25.250000	47.500000	16.510000	122.309998	143.000000
...	...	...	...	...	...
2021-12-27	42.000000	69.889999	9.720000	185.899994	178.419998
2021-12-28	42.000000	69.599998	9.620000	184.750000	179.339996
2021-12-29	41.549999	68.230003	9.690000	183.679993	177.199997
2021-12-30	40.500000	67.589996	9.640000	184.080002	177.479996
2021-12-31	40.869999	NaN	9.610000	185.300003	NaN

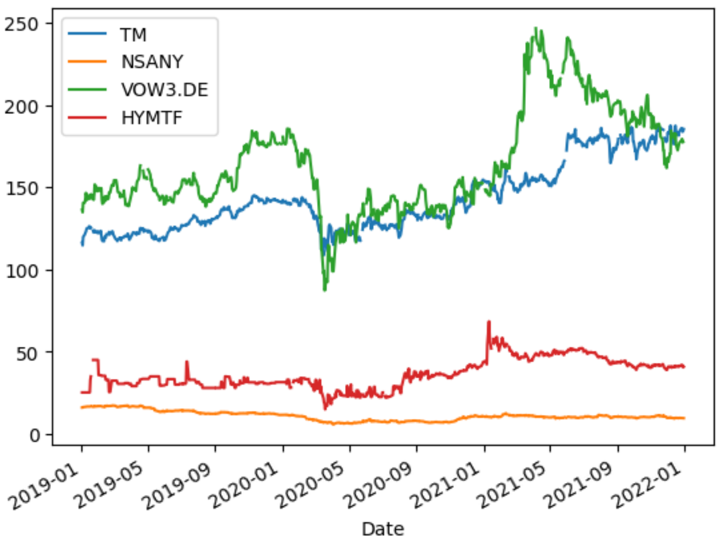
775 rows × 5 columns

3. Seleccionar las variables que vamos a pronosticar

```
mata1 = base[['TM', 'NSANY','VOW3.DE', "HYMTF"]]
```

```
mata1.plot()
```

<Axes: xlabel='Date'>



El observar esta grafica, nos permite visualizar el comportamiento de nuestras tres acciones elegidas, Toyota, Nissan y Volkswaggen a traves del tiempo. A continuación se tomara a cabo una prueba de causalidad.

4. Aplicar la prueba de ***causalidad*** de Clive Granger

```
from statsmodels.tsa.stattools import grangercausalitytests

data = base[["VOW3.DE", "TM"]].dropna()
gc_res = grangercausalitytests(data, 10)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.2516  , p=0.6161  , df_denom=738, df_num=1
ssr based chi2 test:   chi2=0.2526  , p=0.6153  , df=1
likelihood ratio test: chi2=0.2525  , p=0.6153  , df=1
parameter F test:         F=0.2516  , p=0.6161  , df_denom=738, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.2545  , p=0.7753  , df_denom=735, df_num=2
ssr based chi2 test:   chi2=0.5125  , p=0.7739  , df=2
likelihood ratio test: chi2=0.5124  , p=0.7740  , df=2
parameter F test:         F=0.2545  , p=0.7753  , df_denom=735, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.4283  , p=0.7328  , df_denom=732, df_num=3
ssr based chi2 test:   chi2=1.2971  , p=0.7298  , df=3
likelihood ratio test: chi2=1.2960  , p=0.7301  , df=3
parameter F test:         F=0.4283  , p=0.7328  , df_denom=732, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.8439  , p=0.4976  , df_denom=729, df_num=4
ssr based chi2 test:   chi2=3.4171  , p=0.4906  , df=4
likelihood ratio test: chi2=3.4092  , p=0.4918  , df=4
parameter F test:         F=0.8439  , p=0.4976  , df_denom=729, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=0.7208  , p=0.6080  , df_denom=726, df_num=5
ssr based chi2 test:   chi2=3.6585  , p=0.5996  , df=5
likelihood ratio test: chi2=3.6494  , p=0.6009  , df=5
parameter F test:         F=0.7208  , p=0.6080  , df_denom=726, df_num=5

Granger Causality
number of lags (no zero) 6
ssr based F test:         F=1.6937  , p=0.1197  , df_denom=723, df_num=6
ssr based chi2 test:   chi2=10.3452 , p=0.1108  , df=6
likelihood ratio test: chi2=10.2732 , p=0.1136  , df=6
parameter F test:         F=1.6937  , p=0.1197  , df_denom=723, df_num=6
```

```
Granger Causality
number of lags (no zero) 7
ssr based F test:         F=1.4941  , p=0.1660  , df_denom=720, df_num=7
ssr based chi2 test:   chi2=10.6768 , p=0.1533  , df=7
likelihood ratio test: chi2=10.6000 , p=0.1570  , df=7
parameter F test:         F=1.4941  , p=0.1660  , df_denom=720, df_num=7

Granger Causality
number of lags (no zero) 8
ssr based F test:         F=1.3837  , p=0.2000  , df_denom=717, df_num=8
ssr based chi2 test:   chi2=11.3320 , p=0.1836  , df=8
likelihood ratio test: chi2=11.2454 , p=0.1882  , df=8
parameter F test:         F=1.3837  , p=0.2000  , df_denom=717, df_num=8

Granger Causality
```

La primera variable que se quiere explicar es el "close" de la acción de volskwaggen, y la segunda variable la cual es Toyota, se quiere saber si tiene un impacto o si influye.

En este caso, nos damos cuenta que en ningun punto, se puede explicar con un buen nivel de relevancia si la variable tiene algun tipo de impacto. Ya que en ningun caso tenemos un P-value menor a 0.05

```
from statsmodels.tsa.stattools import grangercausalitytests

data = base[["VOW3.DE", "NSANY"]].dropna()
gc_res = grangercausalitytests(data, 10)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.1645  , p=0.6852  , df_denom=738, df_num=1
ssr based chi2 test:   chi2=0.1651  , p=0.6845  , df=1
likelihood ratio test: chi2=0.1651  , p=0.6845  , df=1
parameter F test:         F=0.1645  , p=0.6852  , df_denom=738, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.1262  , p=0.8815  , df_denom=735, df_num=2
ssr based chi2 test:   chi2=0.2541  , p=0.8807  , df=2
likelihood ratio test: chi2=0.2541  , p=0.8807  , df=2
parameter F test:         F=0.1262  , p=0.8815  , df_denom=735, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.1372  , p=0.9378  , df_denom=732, df_num=3
ssr based chi2 test:   chi2=0.4154  , p=0.9370  , df=3
likelihood ratio test: chi2=0.4153  , p=0.9371  , df=3
parameter F test:         F=0.1372  , p=0.9378  , df_denom=732, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.4400  , p=0.7798  , df_denom=729, df_num=4
ssr based chi2 test:   chi2=1.7816  , p=0.7758  , df=4
likelihood ratio test: chi2=1.7795  , p=0.7762  , df=4
parameter F test:         F=0.4400  , p=0.7798  , df_denom=729, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=0.4865  , p=0.7864  , df_denom=726, df_num=5
ssr based chi2 test:   chi2=2.4696  , p=0.7811  , df=5
likelihood ratio test: chi2=2.4655  , p=0.7817  , df=5
parameter F test:         F=0.4865  , p=0.7864  , df_denom=726, df_num=5

Granger Causality
number of lags (no zero) 6
ssr based F test:         F=1.2624  , p=0.2725  , df_denom=723, df_num=6
ssr based chi2 test:   chi2=7.7103  , p=0.2601  , df=6
likelihood ratio test: chi2=7.6702  , p=0.2633  , df=6
parameter F test:         F=1.2624  , p=0.2725  , df_denom=723, df_num=6

Granger Causality
number of lags (no zero) 7
ssr based F test:         F=1.2970  , p=0.2488  , df_denom=720, df_num=7
ssr based chi2 test:   chi2=9.2681  , p=0.2340  , df=7
likelihood ratio test: chi2=9.2101  , p=0.2379  , df=7
parameter F test:         F=1.2970  , p=0.2488  , df_denom=720, df_num=7

Granger Causality
number of lags (no zero) 8
ssr based F test:         F=1.3286  , p=0.2257  , df_denom=717, df_num=8
```

```
ssr based chi2 test:   chi2=10.8809 , p=0.2085  , df=8
likelihood ratio test: chi2=10.8011 , p=0.2132  , df=8
parameter F test:         F=1.3286  , p=0.2257  , df_denom=717, df_num=8

Granger Causality
```

La primera variable que se quiere explicar es volkswaggen, y la segunda variable es Nissan, y se quiere saber si tiene un impacto o si influye.

En este caso, de manera similar al caso anterior, no podemos observar de manera singificativa que la variable se vea afectada en ningun periodo. Es decir, en nigun caso podemos ver un P-value menor a 0.05

5. Estabilicemos las series (sacando las primeras diferencias)

```
mata_difference1 = mata1.diff()
mata_difference1
```

Date	TM	NSANY	VOW3.DE	HYMTF
2019-01-02	NaN	NaN	NaN	NaN
2019-01-03	-1.629997	-0.020000	-1.500000	0.000000
2019-01-04	5.080002	0.300001	5.720001	0.000000
2019-01-07	1.549995	0.170000	0.160004	0.000000
2019-01-08	1.029999	-0.020000	2.360001	0.000000
...	...	...	...	...
2021-12-27	2.119995	-0.080000	1.520004	1.000000
2021-12-28	-1.149994	-0.100000	0.919998	0.000000
2021-12-29	-1.070007	0.070000	-2.139999	-0.450001
2021-12-30	0.400009	-0.049999	0.279999	-1.049999
2021-12-31	1.220001	-0.030001	NaN	0.369999

775 rows × 4 columns

```
from statsmodels.tsa.stattools import adfuller
prueba_estabilidad=adfuller(mata1["TM"].dropna(),autolag="AIC")
print("P-Value: ",prueba_estabilidad[1])
```

```
P-Value:  0.8998778627162349
```

```
from statsmodels.tsa.stattools import adfuller
prueba_estabilidad=adfuller(mata1["NSANY"].dropna(),autolag="AIC")
print("P-Value: ",prueba_estabilidad[1])
```

```
P-Value:  0.41992404322937127
```

```
from statsmodels.tsa.stattools import adfuller
prueba_estabilidad=adfuller(mata1["VOW3.DE"].dropna(),autolag="AIC")
print("P-Value: ",prueba_estabilidad[1])
```

```
P-Value:  0.4013073262966832
```

Aquí podemos ver el primer P-value de las diferentes variables, como podemos ver, este no nos funciona al ser considerablemente mayor a 0.05, por lo que ahora haremos lo mismo con las diferencias.

ESTABILIDAD CON DIFERENCIAS

```
from statsmodels.tsa.stattools import adfuller
prueba_estabilidad=adfuller(mata_difference1["TM"].dropna(),autolag="AIC")
print("P-Value: ",prueba_estabilidad[1])
```

```
P-Value:  2.0004615461447365e-28
```

```
from statsmodels.tsa.stattools import adfuller
prueba_estabilidad=adfuller(mata_difference1["NSANY"].dropna(),autolag="AIC")
print("P-Value: ",prueba_estabilidad[1])
```

```
P-Value:  2.0662337244407428e-08
```

```
from statsmodels.tsa.stattools import adfuller
prueba_estabilidad=adfuller(mata_difference1["VOW3.DE"].dropna(),autolag="AIC")
print("P-Value: ",prueba_estabilidad[1])
```

```
P-Value:  0.0
```

Los P-values ya son menores a 0.05, por lo que podemos seguir adelante.

6. Aplicamos el test de Granger a la base con diferencias

```
data = mata_difference1[["VOW3.DE", "NSANY","TM", "HYMTF"]].dropna()
```

```
from statsmodels.tsa.stattools import grangercausalitytests

data = mata_difference1[["VOW3.DE", "TM"]].dropna()
gc_res = grangercausalitytests(data, 12)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.0023  , p=0.9617  , df_denom=706, df_num=1
ssr based chi2 test:   chi2=0.0023  , p=0.9616  , df=1
likelihood ratio test: chi2=0.0023  , p=0.9616  , df=1
parameter F test:         F=0.0023  , p=0.9617  , df_denom=706, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.7247  , p=0.4848  , df_denom=703, df_num=2
ssr based chi2 test:   chi2=1.4597  , p=0.4820  , df=2
likelihood ratio test: chi2=1.4582  , p=0.4823  , df=2
parameter F test:         F=0.7247  , p=0.4848  , df_denom=703, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=1.2687  , p=0.2840  , df_denom=700, df_num=3
ssr based chi2 test:   chi2=3.8443  , p=0.2788  , df=3
likelihood ratio test: chi2=3.8339  , p=0.2800  , df=3
parameter F test:         F=1.2687  , p=0.2840  , df_denom=700, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=1.0809  , p=0.3649  , df_denom=697, df_num=4
ssr based chi2 test:   chi2=4.3793  , p=0.3571  , df=4
likelihood ratio test: chi2=4.3658  , p=0.3588  , df=4
parameter F test:         F=1.0809  , p=0.3649  , df_denom=697, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=1.5444  , p=0.1738  , df_denom=694, df_num=5
ssr based chi2 test:   chi2=7.8442  , p=0.1650  , df=5
likelihood ratio test: chi2=7.8009  , p=0.1676  , df=5
parameter F test:         F=1.5444  , p=0.1738  , df_denom=694, df_num=5

Granger Causality
number of lags (no zero) 6
ssr based F test:         F=1.2953  , p=0.2570  , df_denom=691, df_num=6
ssr based chi2 test:   chi2=7.9178  , p=0.2442  , df=6
likelihood ratio test: chi2=7.8736  , p=0.2475  , df=6
parameter F test:         F=1.2953  , p=0.2570  , df_denom=691, df_num=6

Granger Causality
number of lags (no zero) 7
ssr based F test:         F=1.1077  , p=0.3562  , df_denom=688, df_num=7
ssr based chi2 test:   chi2=7.9226  , p=0.3395  , df=7
likelihood ratio test: chi2=7.8783  , p=0.3434  , df=7
parameter F test:         F=1.1077  , p=0.3562  , df_denom=688, df_num=7

Granger Causality
number of lags (no zero) 8
ssr based F test:         F=0.9382  , p=0.4841  , df_denom=685, df_num=8
ssr based chi2 test:   chi2=7.6916  , p=0.4642  , df=8
```

```
likelihood ratio test: chi2=7.6497  , p=0.4684  , df=8
parameter F test:         F=0.9382  , p=0.4841  , df_denom=685, df_num=8

Granger Causality
```

Al analizar los diferentes P-values, nos damos cuenta de que en ningun caso se puede rechazar la hipotesis Nula, pues siempre vemos un P-value MAYOR a 0.05, y interpretandolo, Toyota no afecta de manera significativa a Volkswagen.

```
from statsmodels.tsa.stattools import grangercausalitytests

data = mata_difference1[["VOW3.DE", "NSANY"]].dropna()
gc_res = grangercausalitytests(data, 12)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.2477  , p=0.6189  , df_denom=706, df_num=1
ssr based chi2 test:   chi2=0.2487  , p=0.6180  , df=1
likelihood ratio test: chi2=0.2487  , p=0.6180  , df=1
parameter F test:         F=0.2477  , p=0.6189  , df_denom=706, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.2122  , p=0.8088  , df_denom=703, df_num=2
ssr based chi2 test:   chi2=0.4275  , p=0.8076  , df=2
likelihood ratio test: chi2=0.4274  , p=0.8076  , df=2
parameter F test:         F=0.2122  , p=0.8088  , df_denom=703, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.8647  , p=0.4590  , df_denom=700, df_num=3
ssr based chi2 test:   chi2=2.6201  , p=0.4540  , df=3
likelihood ratio test: chi2=2.6153  , p=0.4548  , df=3
parameter F test:         F=0.8647  , p=0.4590  , df_denom=700, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=0.6907  , p=0.5985  , df_denom=697, df_num=4
ssr based chi2 test:   chi2=2.7986  , p=0.5921  , df=4
likelihood ratio test: chi2=2.7930  , p=0.5930  , df=4
parameter F test:         F=0.6907  , p=0.5985  , df_denom=697, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=2.3904  , p=0.0365  , df_denom=694, df_num=5
ssr based chi2 test:   chi2=12.1416 , p=0.0329  , df=5
likelihood ratio test: chi2=12.0382 , p=0.0343  , df=5
parameter F test:         F=2.3904  , p=0.0365  , df_denom=694, df_num=5

Granger Causality
number of lags (no zero) 6
ssr based F test:         F=2.4533  , p=0.0235  , df_denom=691, df_num=6
ssr based chi2 test:   chi2=14.9969 , p=0.0203  , df=6
likelihood ratio test: chi2=14.8394 , p=0.0215  , df=6
parameter F test:         F=2.4533  , p=0.0235  , df_denom=691, df_num=6

Granger Causality
number of lags (no zero) 7
ssr based F test:         F=2.3400  , p=0.0230  , df_denom=688, df_num=7
ssr based chi2 test:   chi2=16.7374 , p=0.0192  , df=7
likelihood ratio test: chi2=16.5413 , p=0.0206  , df=7
parameter F test:         F=2.3400  , p=0.0230  , df_denom=688, df_num=7

Granger Causality
number of lags (no zero) 8
ssr based F test:         F=2.0417  , p=0.0394  , df_denom=685, df_num=8
ssr based chi2 test:   chi2=16.7387 , p=0.0329  , df=8
likelihood ratio test: chi2=16.5422 , p=0.0352  , df=8
parameter F test:         F=2.0417  , p=0.0394  , df_denom=685, df_num=8

Granger Causality
```

En este caso, de manera diferente al caso anterior, si podemos rechazar la hipotesis nula en los periodos 5 6 7 y 8, pues tenemos un P-value MENOR a 0.05, dandonos a entender que en estos periodos, Nissan si afecta de manera significativa a Volkswaggen, en los demas casos NO.

7. IMPLEMENTAMOS EL VAR

```
data1 = mata_difference1[["VOW3.DE","NSANY","TM", "HYMTF"]].dropna()
```

```
data1
```

	VOW3.DE	NSANY	TM	HYMTF
Date				
2019-01-03	-1.500000	-0.020000	-1.629997	0.000000
2019-01-04	5.720001	0.300001	5.080002	0.000000
2019-01-07	0.160004	0.170000	1.549995	0.000000
2019-01-08	2.360001	-0.020000	1.029999	0.000000
2019-01-09	3.479996	0.030001	0.610001	0.000000
...	...	...	...	...
2021-12-23	1.519989	0.170000	2.419998	-0.450001
2021-12-27	1.520004	-0.080000	2.119995	1.000000
2021-12-28	0.919998	-0.100000	-1.149994	0.000000
2021-12-29	-2.139999	0.070000	-1.070007	-0.450001
2021-12-30	0.279999	-0.049999	0.400009	-1.049999

710 rows × 4 columns

```
var = VAR(data1)
x= var.select_order()
x.summary()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: V
  self._init_dates(dates, freq)
```

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	1.810	1.836*	6.111	1.820*
1	1.789	1.921	5.985	1.840
2	1.778	2.015	5.919	1.870
3	1.786	2.128	5.967	1.919
4	1.774	2.221	5.895	1.947
5	1.763*	2.315	5.830*	1.976
6	1.766	2.423	5.846	2.020
7	1.786	2.548	5.964	2.081
8	1.795	2.663	6.022	2.131
9	1.817	2.790	6.154	2.193
10	1.835	2.914	6.271	2.253
11	1.860	3.044	6.430	2.318
12	1.881	3.170	6.569	2.380
13	1.904	3.298	6.720	2.443
14	1.920	3.419	6.829	2.500
15	1.913	3.517	6.785	2.533
16	1.920	3.629	6.833	2.581
17	1.931	3.746	6.914	2.633
18	1.957	3.877	7.104	2.700
19	1.974	3.999	7.229	2.758
20	1.973	4.103	7.224	2.797

El * dice el orden del VAR, por lo que observamos que esto sucede en el periodo 5.

```
results = var.fit(6)
results.summary()
```

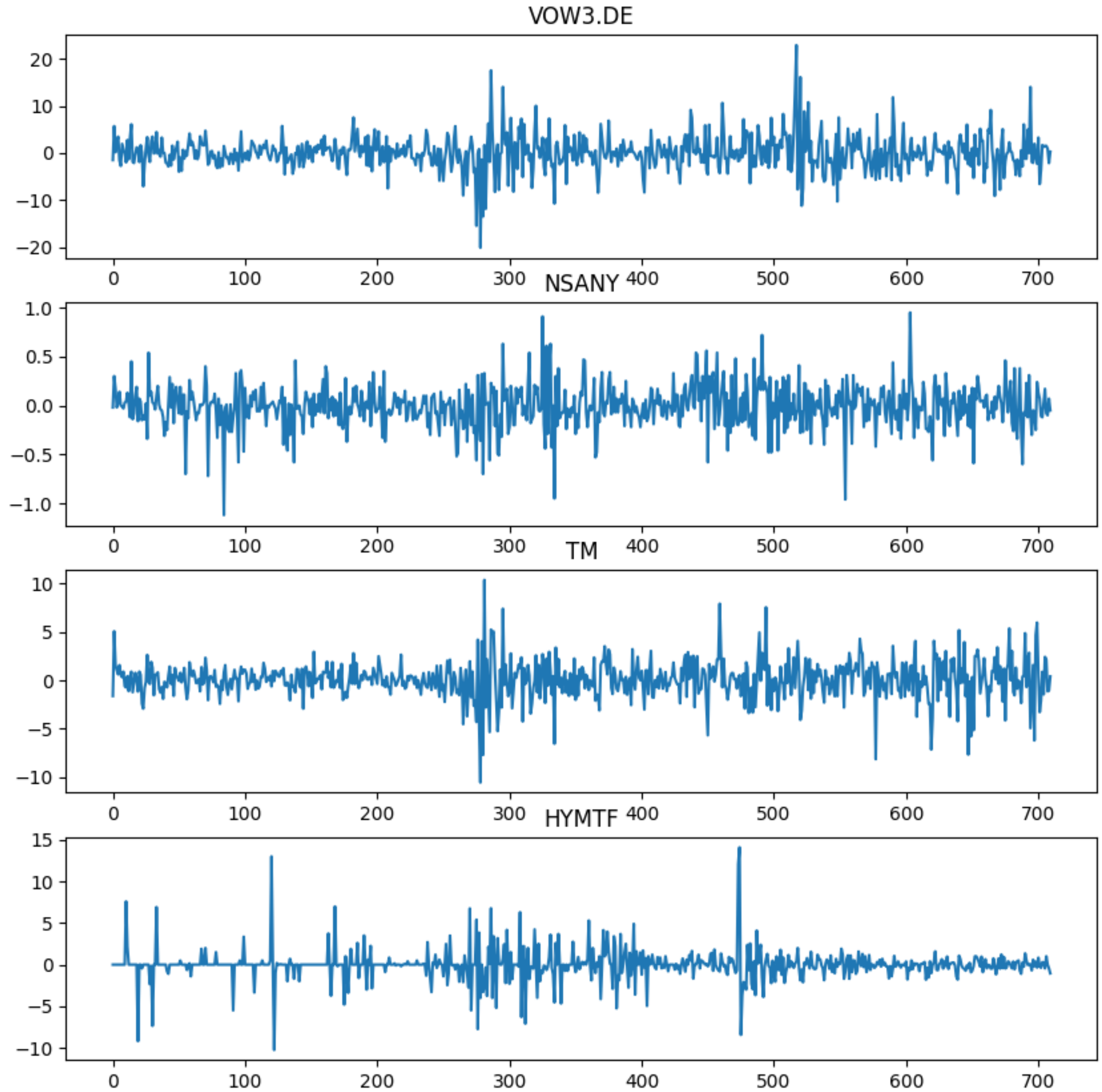
```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Tue, 12, Sep, 2023
Time:                     02:55:48
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                    2.42438
```

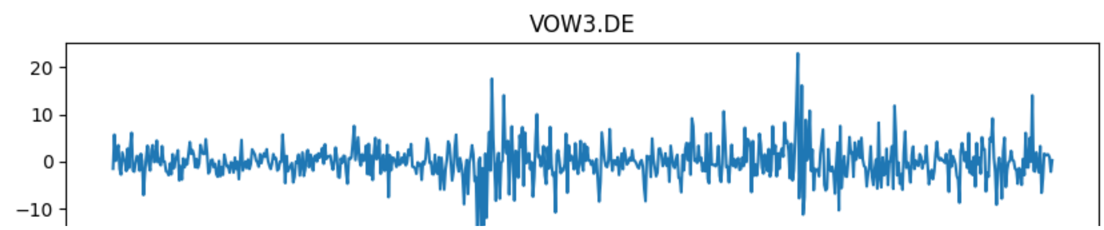
```
Nobs:                    704.000    HQIC:                   2.02725
Log likelihood:         -4521.27    FPE:                    5.91346
AIC:                     1.77711    Det(Omega_mle):         5.14306
--------------------------------------------------------------------
Results for equation VOW3.DE
==============================================================================
                 coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const               0.027745         0.142359            0.195           0.845
L1.VOW3.DE          0.048465         0.041504            1.168           0.243
L1.NSANY            0.666718         0.741259            0.899           0.368
L1.TM               0.002863         0.086964            0.033           0.974
L1.HYMTF            0.018192         0.078148            0.233           0.816
L2.VOW3.DE         -0.032501         0.041321           -0.787           0.432
L2.NSANY           -0.250325         0.750528           -0.334           0.739
L2.TM               0.074486         0.087237            0.854           0.393
L2.HYMTF            0.093250         0.078729            1.184           0.236
L3.VOW3.DE          0.076596         0.041563            1.843           0.065
L3.NSANY           -0.448428         0.746466           -0.601           0.548
L3.TM              -0.097154         0.086995           -1.117           0.264
L3.HYMTF           -0.115078         0.079488           -1.448           0.148
L4.VOW3.DE         -0.076868         0.041507           -1.852           0.064
L4.NSANY            0.252997         0.748263            0.338           0.735
L4.TM               0.031370         0.087120            0.360           0.719
L4.HYMTF            0.131299         0.079561            1.650           0.099
L5.VOW3.DE         -0.026846         0.041521           -0.647           0.518
L5.NSANY            1.684692         0.748051            2.252           0.024
L5.TM               0.047017         0.087099            0.540           0.589
L5.HYMTF           -0.151150         0.079183           -1.909           0.056
L6.VOW3.DE         -0.022252         0.041413           -0.537           0.591
L6.NSANY           -1.217998         0.743997           -1.637           0.102
L6.TM               0.037175         0.087342            0.426           0.670
L6.HYMTF            0.091932         0.078856            1.166           0.244
==============================================================================

Results for equation NSANY
==============================================================================
                 coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const              -0.006553         0.008432           -0.777           0.437
L1.VOW3.DE          0.001450         0.002458            0.590           0.555
L1.NSANY           -0.168918         0.043903           -3.848           0.000
L1.TM               0.014659         0.005151            2.846           0.004
L1.HYMTF           -0.001076         0.004629           -0.232           0.816
L2.VOW3.DE          0.000339         0.002447            0.139           0.890
L2.NSANY           -0.028350         0.044452           -0.638           0.524
L2.TM               0.007807         0.005167            1.511           0.131
L2.HYMTF            0.004431         0.004663            0.950           0.342
L3.VOW3.DE         -0.000158         0.002462           -0.064           0.949
L3.NSANY            0.034205         0.044211            0.774           0.439
```

```
results.irf(6)
```

```
<statsmodels.tsa.vector_ar.irf.IRAnalysis at 0x79dd84d299f0>
```

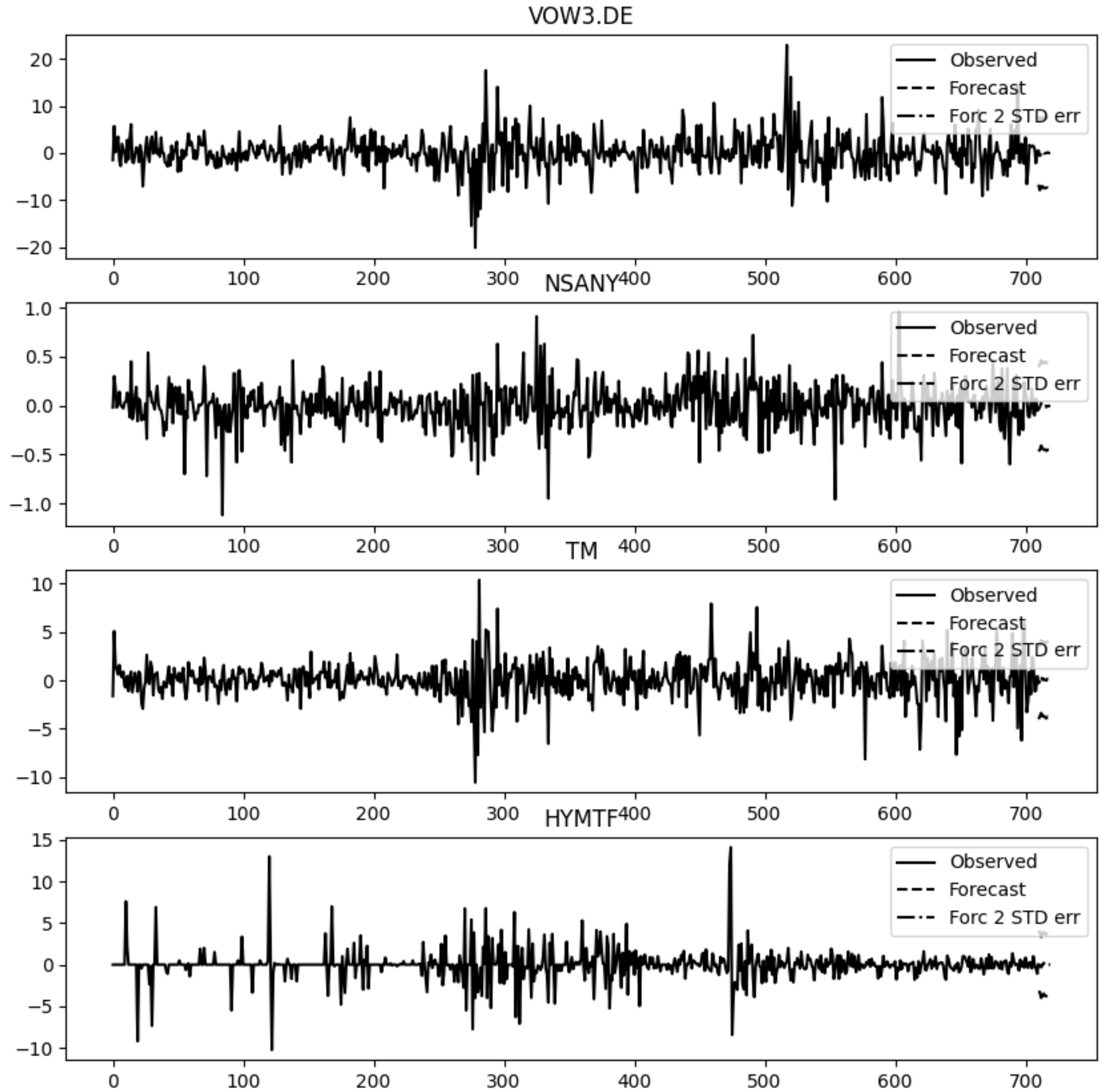
```
results.plot()
```





En este conjunto de gráficas, primero tenemos el comportamiento real de estas variables, y posteriormente tenemos el comportamiento pronesticado sobre los periodos que ya pasaron.

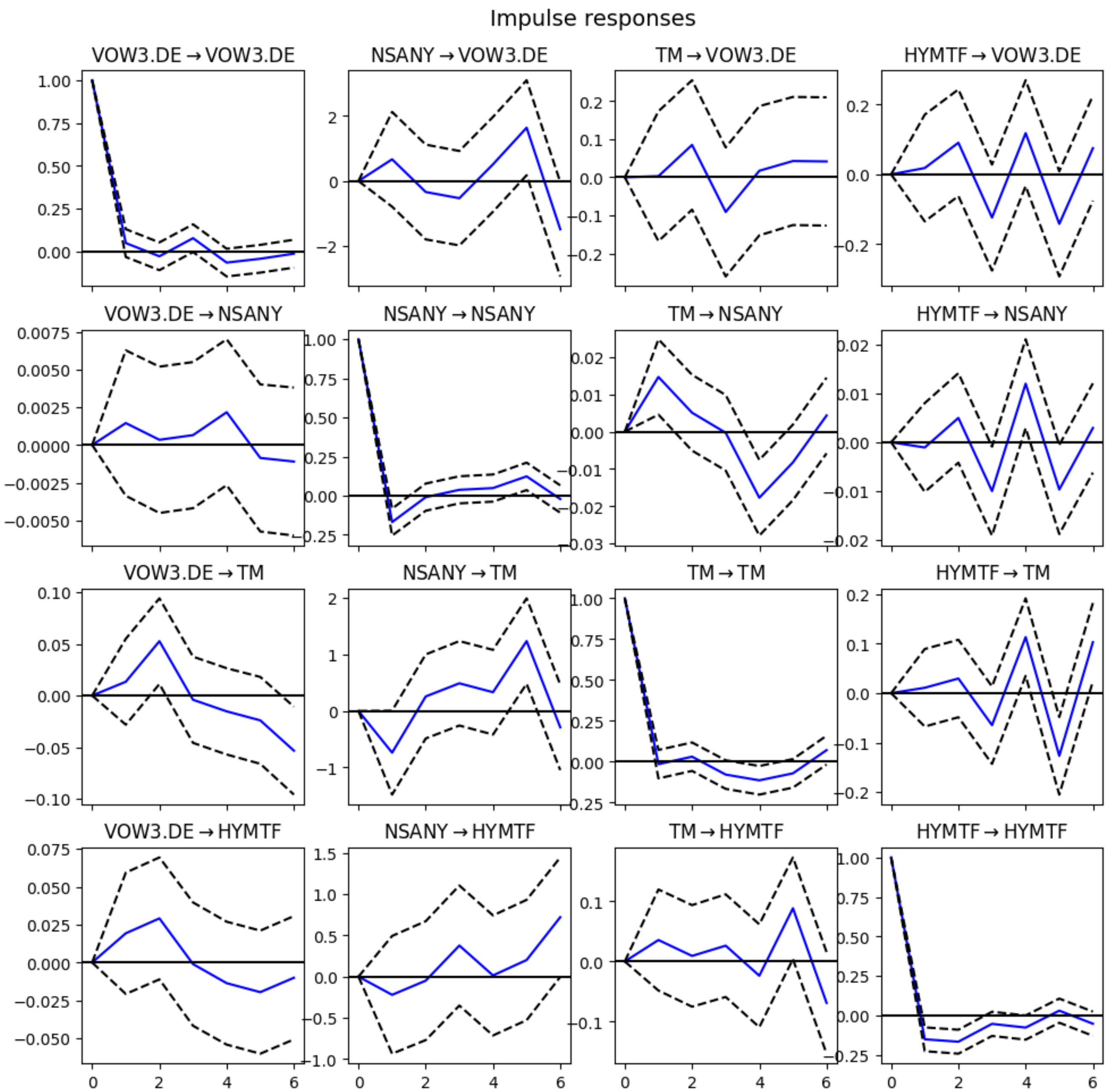

```
results.plot_forecast(10);
```



Aquí podemos ver el comportamiento observado, y de igual manera el comportamiento pronosticado de 8 periodos, de igual manera, tenemos la linea con 2 desviaciones estandares sobre el pronostico. (para arriba y para abajo)

```
irf = results.irf(6)
```

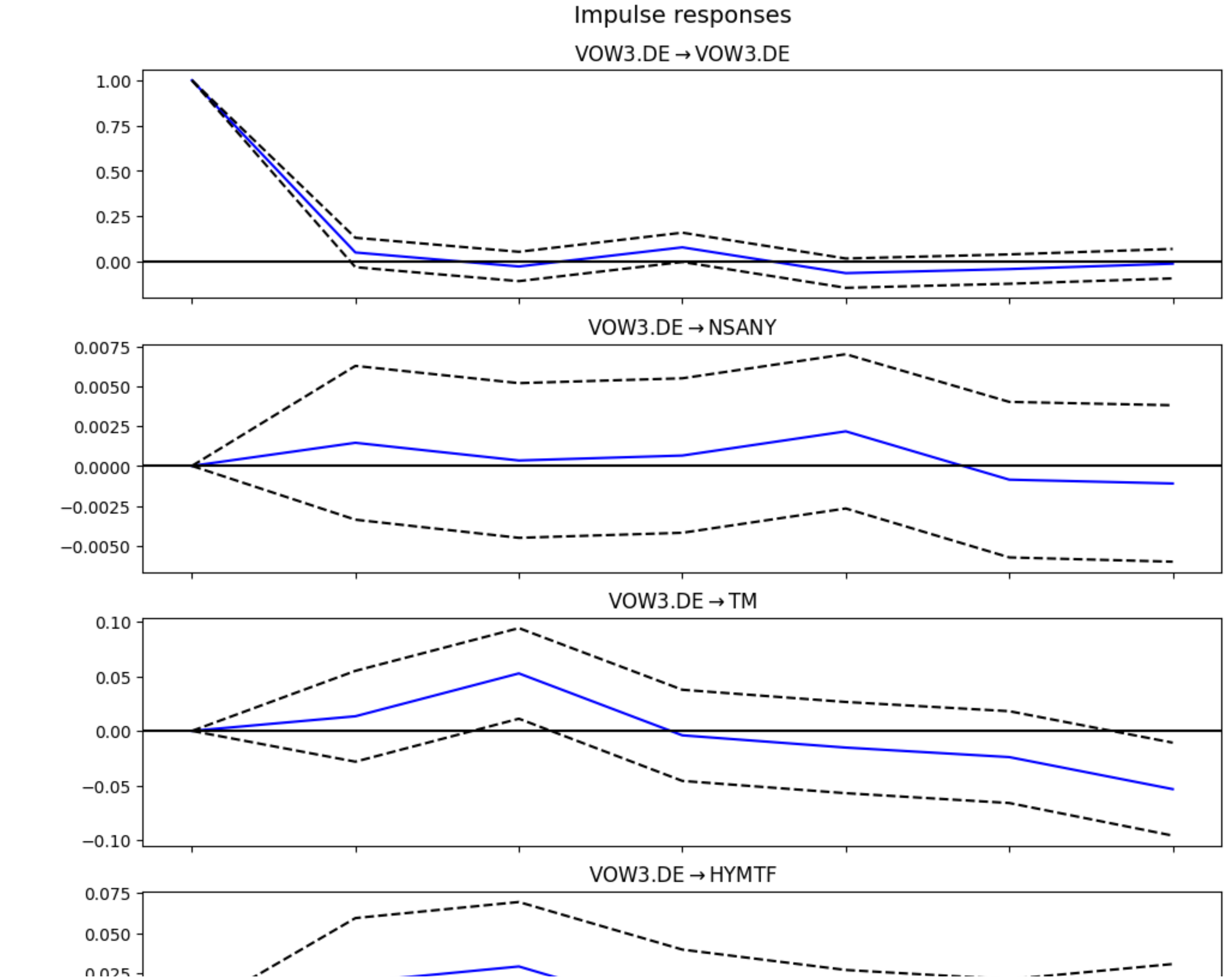
```
irf.plot(orth=False)
```



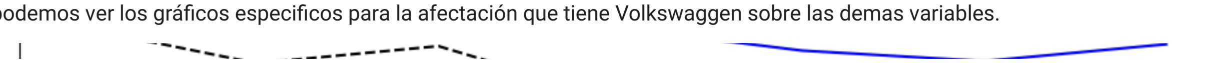
Impulse responses

Al analizar este conjunto de graficas, podemos ver como un "shock" dentro de las diferentes variables que tenemos afecta a las demas, con "shock" nos referimos a una desviación estanda. Y por decir un ejemplo, al analizar la grafica que tenemos en la parte superior al centro, Nissan>Volkswaggen, podemos darnos cuenta de que al tener un shock en la variable de Nissan, Volkswaggen aumenta por aproximadamente 0.5 desviaciones estandar, se normaliza, llega a decrecer debajo de 0, para despues aumentar hasta casi 2 desviaciones estandar. Este mismo analizis se puede realizar a todas las posibles combinaciones de variables que tenemos. De manera un poco menos "tecnica", una posible interpretación es que cuando Nissan recibe un "shock", aproximadamente tres series despues, Volkswaggen aumentara considerablemente. Otro ejemplo podemos verlo en Volskwagen > toyota, donde en un principio se tiene un aumento considerable en toyota, para despues bajar en los siguientes periodos.

```
irf.plot(impulse='VOW3.DE')
```



En este caso podemos ver los gráficos especificos para la afectación que tiene Volkswaggen sobre las demas variables.



```
irf.plot_cum_effects(orth=False)
```