```
\# The effect of first Official Announcement from Volkswagen to own 49.9% (2009-12-09) Porsche, Second Official Announcement to own 51.1% (2012-07-05) of Porsche and finally the Volksagen Diesel Scandal (2015-09-20).
```

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import yfinance as yf
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
#Importing Data from Yahoo Finance
df=yf.download(tickers="VOW3.DE, PAH3.DE, BMW.DE", interval = "1d", group_by = 'ticker',auto_adjust
= True, treads = True)
```

[********** 3 of 3 completed

In [3]:

```
#some important Dates and Announcements from Volkswagen(VW)

#Start Date
start='2009-01-01'

# first official Announcement (VW announced the own 49.9% of Porsche)
f_ann='2009-12-09'

#Second Announcement(VW announced the purchase of the remaining 51.1% of Porsche)
s_ann='2012-07-05'

# End Date
end='2014-01-01'

#Diesel Scandal emission
d_sca='2015-09-20'
```

Pre-processing Data, Closing prices, Returns, Squared Returns and Volume.

In [4]:

```
#Exacting Closing Prices
df['vog'] = df['VOW3.DE'].Close
df['por'] = df['PAH3.DE'].Close
df['bmw'] = df['BMW.DE'].Close
```

In [5]:

```
# Creating Returns
df['ret_vog'] = df['vog'].pct_change(1).mul(100)
df['ret_por'] = df['por'].pct_change(1).mul(100)
df['ret_bmw'] = df['bmw'].pct_change(1).mul(100)
```

In [6]:

```
# Creating Squared Returns(Volatility)
df['sq_vog'] = df.ret_vog.mul(df.ret_vog)
df['sq_por'] = df.ret_por.mul(df.ret_por)
df['sq_bmw'] = df.ret_bmw.mul(df.ret_bmw)
```

In [10]:

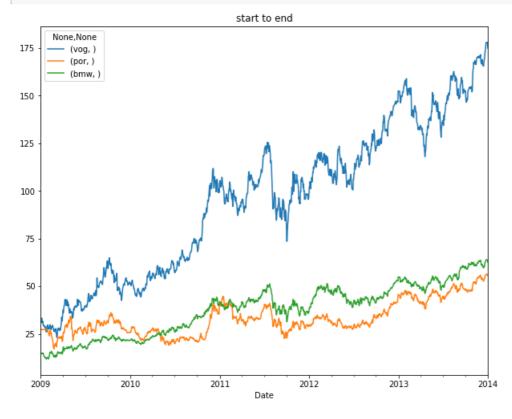
```
#making our frequency Daily for Business working days and filling NA value with bfill or ffill met
hod
df=df.asfreq(freq='b')
df=df.fillna(method='bfill')
```

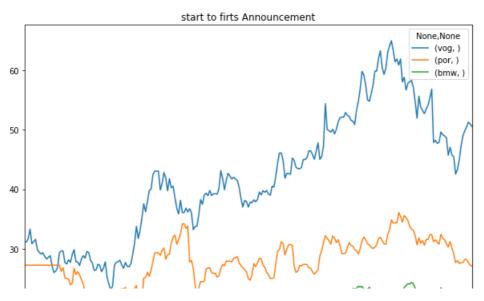
In [12]:

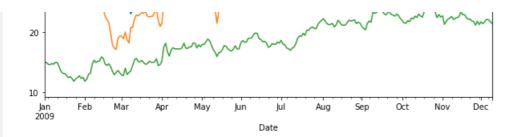
```
# Deleting some surplus data
del df['VOW3.DE'],df['PAH3.DE'],df['BMW.DE']
```

In [39]:

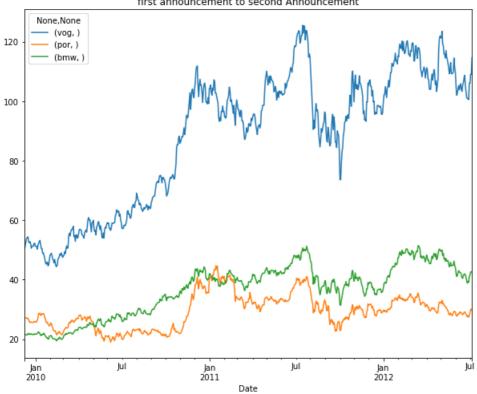
```
#ploting our graphs base on the important annoucements and disiel scandal
df[['vog','por','bmw']][start:end].plot(figsize= (10,8),title='start to end')
df[['vog','por','bmw']][start:f_ann].plot(figsize= (10,8),title='start to firts Announcement')
df[['vog','por','bmw']][f_ann:s_ann].plot(figsize= (10,8),title='first announcement to second
Announcement')
df[['vog','por','bmw']][s_ann:end].plot(figsize= (10,8),title='second announcement to end')
df[['vog','por','bmw']][end:d_sca].plot(figsize= (10,8),title='end to disiel scandal')
df[['vog','por','bmw']][d_sca:].plot(figsize= (10,8),title='start to firts Announcement')
```



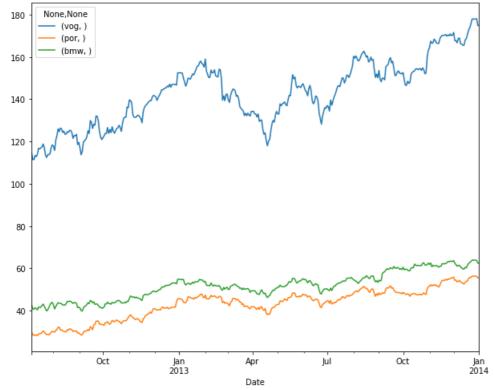








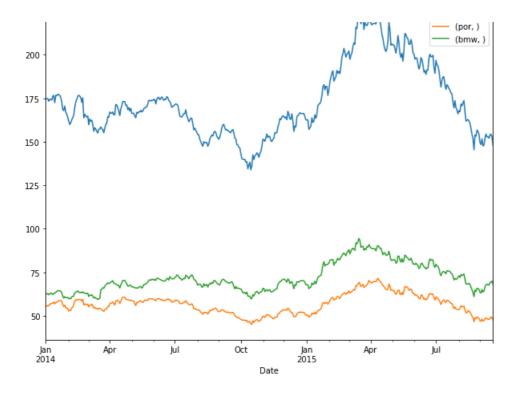


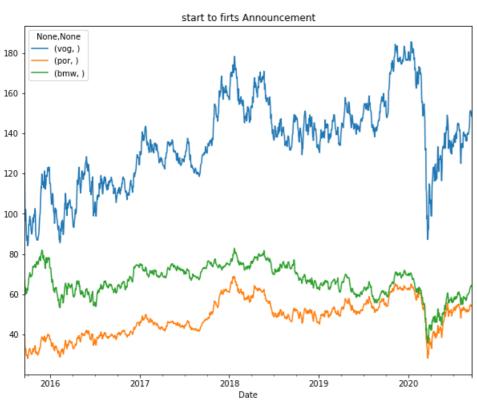


end to disiel scandal

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MAA





In [42]:

```
#correlations for closing prices
import seaborn as sns
df[['vog','por','bmw']].corr()
```

Out[42]:

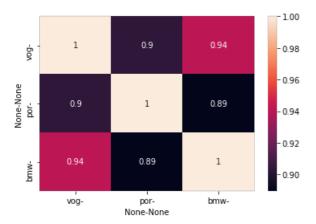
	vog	por	bmw
vog	1.000000	0.902956	0.940954
por	0.902956	1.000000	0.889573
bmw	0.940954	0.889573	1.000000

In [43]:

```
sns.heatmap(df[['vog','por','bmw']].corr(),annot=True)
```

Out[43]:

<matplotlib.axes. subplots.AxesSubplot at 0x16168335d08>



In [32]:

```
print('Correlation among manufacturers from ' + str(start_date) + ' to ' + str(end_date) + '\n')
print('Volkswagen and Porsche correlation: \t'+ str(df['vol'][start_date:end_date].corr(df['por'][s
tart_date:end_date])))
print('Volkswagen and BMW correlation: \t'+ str(df['vol'][start_date:end_date].corr(df['bmw'][start_date:end_date])))
print('Porsche and BMW correlation: \t\t'+ str(df['por'][start_date:end_date].corr(df['bmw'][start_date:end_date])))

4
```

Out[32]:

<matplotlib.axes. subplots.AxesSubplot at 0x1616be7cc48>



In [55]:

```
#Anaylsing correlation from start to end,important announcement dates and diesel scandal annoucement print('Correlation among manufacturers from :\t' + str(start) + ' to ' + str(end) + '\n') print('Volkswagen and Porsche correlation:\t' + str(df['vog'][start:end].corr(df['por'][start:end]))) print('Volkswagen and BMW correlation: \t' + str(df['vog'][start:end].corr(df['bmw'][start:end]))) print('Porsche and BMW correlation: \t\t' + str(df['por'][start:end].corr(df['bmw'][start:end])))
```

Correlation among manufacturers from : 2009-01-01 to 2014-01-01

```
Volkswagen and BMW correlation: 0.9827579671118887
Porsche and BMW correlation: 0.8089641486724635
In [57]:
print('Correlation among manufacturers from :\t' + str(start) + ' to ' + str(f ann) + '\n')
print('Volkswagen and Porsche correlation:\t'+ str(df['vog'][start:f ann].corr(df['por'][start:f an
n1)))
print('Volkswagen and BMW correlation: \t'+ str(df['vog'][start:f ann].corr(df['bmw'][start:f ann])
))
print('Porsche and BMW correlation: \t\t'+ str(df['por'][start:f ann].corr(df['bmw'][start:f ann]))
4
Correlation among manufacturers from : 2009-01-01 to 2009-12-09
Volkswagen and Porsche correlation: 0.7785123807487967
Volkswagen and BMW correlation: 0.9263430965312215
Porsche and BMW correlation: 0.7345779243010784
In [58]:
print('Correlation among manufacturers from :\t' + str(f ann) + ' to ' + str(s ann) + '\n')
print('Volkswagen and Porsche correlation:\t'+ str(df['vog'][f_ann:s_ann].corr(df['por'][f_ann:s_an
n])))
print('Volkswagen and BMW correlation: \t'+ str(df['vog'][f ann:s ann].corr(df['bmw'][f ann:s ann])
))
print('Porsche and BMW correlation: \t\t'+ str(df['por'][f ann:s ann].corr(df['bmw'][f ann:s ann]))
4
Correlation among manufacturers from : 2009-12-09 to 2012-07-05
Volkswagen and Porsche correlation: 0.7422114347356783
Volkswagen and BMW correlation: 0.9795942993967812
Porsche and BMW correlation: 0.7035985449323026
In [59]:
print('Correlation among manufacturers from :\t' + str(s ann) + ' to ' + str(end) + '\n')
print('Volkswagen and Porsche correlation:\t'+ str(df['vog'][s ann:end].corr(df['por'][s ann:end]))
print('Volkswagen and BMW correlation: \t'+ str(df['vog'][s ann:end].corr(df['bmw'][s ann:end])))
print('Porsche and BMW correlation: \t\t'+ str(df['por'][s ann:end].corr(df['bmw'][s ann:end])))
4
Correlation among manufacturers from : 2012-07-05 to 2014-01-01
Volkswagen and Porsche correlation: 0.9405236894284832
Volkswagen and BMW correlation: 0.9284447118744797
Porsche and BMW correlation: 0.9494111752233421
In [60]:
print('Correlation among manufacturers from :\t' + str(end) + ' to ' + str(d sca) + '\n')
print('Volkswagen and Porsche correlation:\t'+ str(df['vog'][end:d_sca].corr(df['por'][end:d_sca]))
print('Volkswagen and BMW correlation: \t'+ str(df['vog'][end:d sca].corr(df['bmw'][end:d sca])))
print('Porsche and BMW correlation: \t\t'+ str(df['por'][end:d sca].corr(df['bmw'][end:d sca])))
4
Correlation among manufacturers from: 2014-01-01 to 2015-09-20
Volkswagen and Porsche correlation: 0.9421376075139968
Volkswagen and BMW correlation: 0.8912208007790657
Porsche and BMW correlation: 0.8045871574266078
In [61]:
print('Correlation among manufacturers from :\t' + str(d sca) + ' to ' + str(df.index[-1]) + '\n')
print('Volkswagen and Porsche correlation:\t'+ str(df['vog'][d sca:].corr(df['por'][d sca:])))
print('Volkswagen and BMW correlation: \t'+ str(df['vog'][d sca:].corr(df['bmw'][d sca:])))
print('Porsche and BMW correlation: \t\t'+ str(df['por'][d sca:].corr(df['bmw'][d sca:])))
```

```
Correlation among manufacturers from: 2015-09-20 to 2020-09-15 00:00:00

Volkswagen and Porsche correlation: 0.9790570450497561

Volkswagen and BMW correlation: 0.32173659309314

Porsche and BMW correlation: 0.3339095623502678
```

Time to fit in the best models for our analysis of the different prices, with Vog and Por and BMW exogenous variables respectively. Our annoucement dates will also be included to draw an explicit conclusion.

```
In [62]:
```

```
from pmdarima.arima import auto_arima,OCSBTest
```

In [65]:

In [66]:

```
# Analysing summary statistics for Vog
mod_start_first_annVog.summary()
```

Out[66]:

Dep. V	ariable:			y No .	Observa	itions:	245
	Model:	SARIMA	AX(1, 0, 0)) L	og Like	lihood	-435.343
	Date:	We	ed, 16 Se 202			AIC	880.686
	Time:		14:56:2	1		ВІС	898.192
\$	Sample:	0	1-01-200	9		HQIC	887.736
		- 1	2-09-200	9			
Covariano	e Type:		ор	g			
	coef	std err	z	P> z	[0.025	0.975]	
intercept	0.3400	0.262	1.296	0.195	-0.174	0.854	
por	0.4034	0.077	5.229	0.000	0.252	0.555	
bmw	0.6617	0.229	2.886	0.004	0.212	1.111	
ar.L1	0.9812	0.013	77.848	0.000	0.956	1.006	
sigma2	2.0188	0.112	18.074	0.000	1.800	2.238	
Lj	ung-Box	(Q): 47	.55	Jarqı	ue-Bera (JB):	263.95	
	Prol	o(Q) : 0	.19	Pr	ob(JB):	0.00	
Heteroske	dasticity	(H): 2	2.44		Skew:	-0.48	
Prob(H) (two-sid	ded): 0	.00	Kı	ırtosis:	7.99	

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [67]:

```
mod_first_second_annVog.summary()
```

Out[67]:

SARIMAX Results

Dep	. Variable:			у N o	o. Observ	ations:	672
	Model:	SARI	MAX(0, 1	, 0)	Log Like	elihood	-1105.059
	Date:	١	Ned, 16 S 20	Sep 020		AIC	2216.118
	Time:		14:57	:01		BIC	2229.644
	Sample:		12-09-20	009		HQIC	2221.357
		-	- 07-05-20	012			
Covaria	nce Type:		(opg			
	coef	std err	z	P> z	[0.025	0.975]	
por	0.8203	0.064	12.833	0.000	0.695	0.946	
bmw	1.5349	0.072	21.267	0.000	1.393	1.676	
sigma2	1.5776	0.064	24.528	0.000	1.452	1.704	
	Ljung-Bo	x (Q):	33.73	Jar	que-Bera (JB):	117.32	
	Pro	b(Q):	0.75	F	Prob(JB):	0.00	
Heteros	kedasticit	y (H):	1.65		Skew:	0.29	
Prob	(H) (two-si	ded):	0.00	ı	Kurtosis:	4.92	

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [68]:

```
mod_second_end_annVog .summary()
```

Out[68]:

Dep.	Variable:			y N	o. Observ	vations:	390
	Model:	SARI	MAX(0, 1	, 0)	Log Lik	elihood	-622.244
	Date	٠ ١	Wed, 16 S	Sep 020		AIC	1250.488
	Time		14:58	:00		BIC	1262.378
	Sample:		07-05-20	012		HQIC	1255.202
- 01-01-2014							
Covariar	nce Type:	1	C	opg			
	coef	std err	z	P> z	[0.025	0.975]	
por	1.7837	0.059	30.369	0.000	1.669	1.899	
bmw	0.8498	0.091	9.381	0.000	0.672	1.027	
sigma2	1.4352	0.070	20.461	0.000	1.298	1.573	
Ljung-Box (Q): 28.08 Jarque-Bera 103.80							

		(JD):	
Prob(Q):	0.92	Prob(JB):	0.00
Heteroskedasticity (H):	0.78	Skew:	-0.39
Prob(H) (two-sided):	0.15	Kurtosis:	5.41

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [69]:

```
mod_end_scandal_annVog.summary()
```

Out[69]:

SARIMAX Results

07 (1 (1171) 0 (rtoodito							
Dep.	Variable:				y N	o. Obse	rvations:	448
	Model:	SARIM	AX(0, 1,	0)x(1, 0,	0, 5)	Log Li	kelihood	-686.483
	Date:		Wed,	16 Sep	2020		AIC	1380.966
	Time:			14:5	58:34		BIC	1397.376
	Sample:			01-01-	2014		HQIC	1387.436
				- 09-18-	2015			
Covaria	nce Type:				opg			
	coef	std err	z	P> z	[0.025	0.975]		
por	2.1800	0.069	31.708	0.000	2.045	2.315		
bmw	0.6491	0.063	10.349	0.000	0.526	0.772		
ar.S.L5	-0.0994	0.046	-2.150	0.032	-0.190	-0.009		
sigma2	1.2630	0.068	18.609	0.000	1.130	1.396		
	Ljung-Bo	x (Q): 3	5.77	Jarq	ue-Bera (JB):	31.21		
	Pro	b(Q):	0.66	P	rob(JB):	0.00		
Heterosl	kedasticit	y (H):	1.30		Skew:	-0.20		
Prob(H) (two-si	ded):	0.11	K	urtosis:	4.23		

Warnings:

 $\begin{tabular}{l} [1] Covariance matrix calculated using the outer product of gradients (complex-step). \end{tabular}$

In [70]:

```
mod_scandal_today_annVog.summary()
```

Out[70]:

Dep. Var	iable:				у	No. Obse	rvations:	1302
M	lodel:	SARIMA	AX(0, 1, 3)x(1, 0,	[1], 5)	Log L	ikelihood	-1935.900
	Date:		Wed	, 16 Sep	2020		AIC	3887.799
	Time:			14:	59:30		BIC	3929.167
Sai	mple:			09-21	-2015		HQIC	3903.320
				- 09-15	-2020			
Covariance 7	Type:				opg			
	coef	std err	z	P> z	[0.025	0.975]		
por 2	.3551	0.028	84.519	0.000	2.300	2.410		

```
bmw 0.4171 0.033 12.678 0.000 0.353 0.482
 ma.L1 -0.0610 0.024 -2.570 0.010 -0.108 -0.014
 ma.L2 -0.0637
               0.023 -2.766 0.006 -0.109 -0.019
 ma.L3 -0.0494
               0.024 -2.047 0.041 -0.097 -0.002
                0.163 -4.767 0.000 -1.096 -0.457
ar.S.L5 -0.7765
ma.S.L5 0.7337
                0.172 4.255 0.000 0.396
                                            1.072
sigma2 1.1481 0.029 38.923 0.000 1.090
                                            1.206
                               Jarque-Bera
      Ljung-Box (Q): 25.55
                                           604.54
                                      (JB):
                                 Prob(JB):
            Prob(Q): 0.96
                                              0.00
Heteroskedasticity (H):
                                             -0.42
  Prob(H) (two-sided):
                     0.27
                                  Kurtosis:
                                              6.23
```

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [72]:

```
# bestfit for por, with vog and bmw exogenous variables
mod start first annPor = auto arima(df.por[start:f ann], exogenous = df[['vog','bmw']][start:f ann
                           m = 5, max p = 5, max q = 5)
mod_first_second_annPor = auto_arima(df.por[f_ann:s_ann], exogenous = df[['vog','bmw']]
[f_ann:s_ann],
                            m = 5, max_p = 5, max_q = 5)
mod_second_end_annPor = auto_arima(df.por[s_ann:end], exogenous = df[['vog','bmw']][s_ann:end],
                            m = 5, max_p = 5, max_q = 5)
mod end scandal annPor= auto_arima(df.por[end:d_sca], exogenous = df[['vog','bmw']][end:d_sca],
                            m = 5, max_p = 5, max_q = 5)
mod_scandal_today_annPor = auto_arima(df.por[d_sca:], exogenous = df[['vog','bmw']][d_sca:],
                            m = 5, max_p = 5, max_q = 5)
```

In [73]:

```
mod start first annPor.summary()
```

Out[73]:

SARIMAX Results

SARIMAX F	Results						
Dep. V	ariable:		У	No. C	Observa	tions:	245
	Model:	SARIMA	X(2, 0, 1)) L	og Likel	ihood	-303.384
	Date:	We	d, 16 Sep 2020			AIC	620.767
	Time:		15:30:31			BIC	645.276
5	Sample:	01	1-01-2009)		HQIC	630.637
		- 12	2-09-2009)			
Covariano	e Type:		opg	l			
	coef	std err	z	P> z	[0.025	0.975]	
intercept	0.2280	0.154	1.480	0.139	-0.074	0.530	
vog	0.1234	0.044	2.798	0.005	0.037	0.210	
bmw	0.7624	0.105	7.244	0.000	0.556	0.969	
ar.L1	1.6732	0.211	7.930	0.000	1.260	2.087	
ar.L2	-0.7001	0.198	-3.533	0.000	-1.088	-0.312	
ma.L1	-0.6167	0.242	-2.552	0.011	-1.090	-0.143	
sigma2	0.6900	0.043	16.182	0.000	0.606	0.774	
Lj	ung-Box	(Q): 34.	57	Jarqu	e-Bera (JB):	660.78	

(JB):

0.00	Prob(JB):	0.71	Prob(Q):
-0.73	Skew:	0.55	Heteroskedasticity (H):
10.91	Kurtosis:	0.01	Prob(H) (two-sided):

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [74]:

```
mod_first_second_annPor.summary()
```

Out[74]:

SARIMAX Results

672	No. Observations:	у	Dep. Variable:
-581.121	Log Likelihood	SARIMAX(1, 1, 1)	Model:
1172.242	AIC	Wed, 16 Sep 2020	Date:
1194.786	BIC	15:31:06	Time:
1180.973	HQIC	12-09-2009	Sample:
		- 07-05-2012	
		opg	Covariance Type:

	coef	std err	z	P> z	[0.025	0.975]
vog	0.1719	0.015	11.127	0.000	0.142	0.202
bmw	0.3170	0.044	7.206	0.000	0.231	0.403
ar.L1	0.6598	0.229	2.882	0.004	0.211	1.109
ma.L1	-0.5909	0.245	-2.412	0.016	-1.071	-0.111
sigma2	0.3309	0.010	32.414	0.000	0.311	0.351

Ljung-Box (Q):	33.39	Jarque-Bera (JB):	1076.70
Prob(Q):	0.76	Prob(JB):	0.00
Heteroskedasticity (H):	1.39	Skew:	0.05
Prob(H) (two-sided):	0.01	Kurtosis:	9.20

Warnings

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [75]:

```
mod_second_end_annPor.summary()
```

Out[75]:

Dep. Variable:		у	No. Observations:	390
Model:	SARIMAX(0, 1, 0)x(0, 0, [1]], 5)	Log Likelihood	-210.347
Date:	Wed, 16 Sep 2	020	AIC	428.694
Time:	15:31	:55	BIC	444.548
Sample:	07-05-20	012	HQIC	434.979
	- 01-01-2	014		
Covariance Type:	(opg		
coef	std err z P> z [0.025	0.975]	

vog	0.2138	0.013	16.876	0.000	0.189	0.239
bmw	0.2392	0.040	6.036	0.000	0.162	0.317
ma.S.L5	-0.1249	0.057	-2.210	0.027	-0.236	-0.014
sigma2	0.1726	0.006	27.851	0.000	0.160	0.185
L	.jung-Box	(Q): 34	1.49	Jarqu	ie-Bera (JB):	613.59
L	.jung-Box Prob	, ,	1.49 0.72	•		613.59 0.00
		(Q): (•	(JB):	

 $\label{eq:complex-step} \mbox{[1] Covariance matrix calculated using the outer product of gradients (complex-step)}.$

In [76]:

```
mod_end_scandal_annPor.summary()
```

Out[76]:

SARIMAX Results

Dep.	Variable:			у N	o. Observ	ations:	448
	Model:	SARI	MAX(0, 1	, 0)	Log Lik	elihood	-197.215
	Date:	\	Ned, 16 S	Sep 020		AIC	400.430
	Time:		15:32	:38		BIC	412.738
	Sample:		01-01-20	014		HQIC	405.283
			- 09-18-20	015			
Covaria	nce Type:		C	ppg			
	coef	std err	z	P> z	[0.025	0.975]	
vog	0.2442	0.008	29.654	0.000	0.228	0.260	
bmw	0.1077	0.018	6.117	0.000	0.073	0.142	
sigma2	0.1415	0.008	18.276	0.000	0.126	0.157	
	Ljung-Bo	x (Q):	33.23	Jar	que-Bera (JB):		
	Pro	b(Q):	0.77	ı	Prob(JB):	0.00	
Heteros	kedasticit	y (H):	0.84		Skew:	0.17	
Prob(H) (two-s	ided):	0.28		Kurtosis:	4.07	

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [78]:

```
mod_scandal_today_annPor.summary()
```

Out[78]:

Dep. Variable:	у	No. Observations:	1302
Model:	SARIMAX(1, 1, 1)x(1, 0, 1, 5)	Log Likelihood	-539.606
Date:	Wed, 16 Sep 2020	AIC	1093.212
Time:	15:33:28	BIC	1129.408
Sample:	09-21-2015	HQIC	1106.792

			-	09-15-2	020	
Covarian	се Туре:				opg	
coef std err z P>izi [0.025 (0.9751		
	coei	std err	Z	P> z	[0.025	0.973]
vog	0.2750	0.004	62.685	0.000	0.266	0.284
bmw	0.1354	0.013	10.582	0.000	0.110	0.160
ar.L1	0.5257	0.236	2.228	0.026	0.063	0.988
ma.L1	-0.5865	0.220	-2.663	0.008	-1.018	-0.155
ar.S.L5	-0.9331	0.050	-18.522	0.000	-1.032	-0.834
ma.S.L5	0.8999	0.060	14.908	0.000	0.782	1.018
sigma2	0.1341	0.003	45.268	0.000	0.128	0.140
Ljung-Bo		x (Q) : 47	.45	Jarqu	e-Bera (JB):	1718.92
	Prol	b(Q): 0	.19	Pro	b(JB):	0.00
Heterosk	edasticity	/ (H) : 1	.85		Skew:	0.72
Prob(H	H) (two-sid	ded): 0	.00	Ku	rtosis:	8.44

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Future prediction of prices for Vog

In [96]:

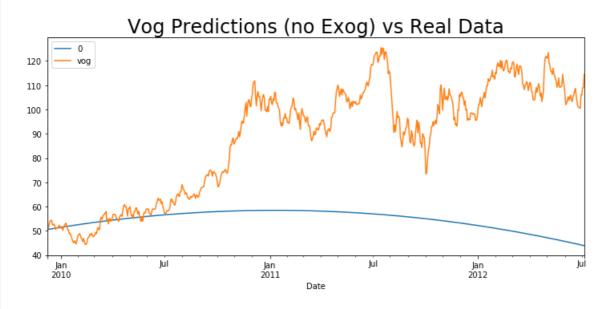
```
#future prediction from start to the first announcement
model_vog_prediction = auto_arima(df.vog[start:f_ann], m = 5, max_p = 5, max_q = 5, max_P = 5,
max_Q = 5, trend = "ct")

prediction_vog = pd.DataFrame(model_vog_prediction.predict(n_periods = len(df[f_ann:s_ann])),
index = df[f_ann:s_ann].index)
prediction_vog[f_ann:s_ann].plot(figsize = (12,5), legend=True)

df.vog[f_ann:s_ann].plot(legend=True)
plt.title("Vog Predictions (no Exog) vs Real Data", size = 24)
```

Out[96]:

Text(0.5, 1.0, 'Vog Predictions (no Exog) vs Real Data')



```
#future prediction from firts to the second announcement
model_vog_prediction = auto_arima(df.vog[f_ann:s_ann], m = 5, max_p = 5, max_q = 5, max_P = 5,
max_Q = 5, trend = "ct")

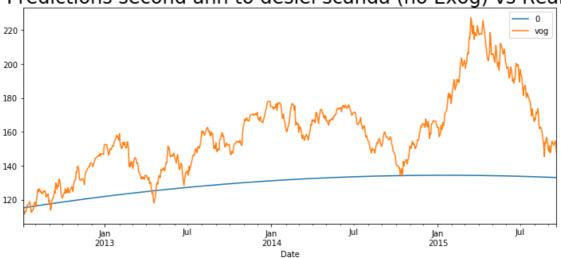
prediction_vog = pd.DataFrame(model_vog_prediction.predict(n_periods = len(df[s_ann:d_sca])),
index = df[s_ann:d_sca].index)
prediction_vog[s_ann:d_sca].plot(figsize = (12,5), legend=True)

df.vog[s_ann:d_sca].plot(legend=True)
plt.title("Vog Predictions second ann to desiel scanda (no Exog) vs Real Data", size = 24)
```

Out[97]:

Text(0.5, 1.0, 'Vog Predictions second ann to desiel scanda (no Exog) vs Real Data')

Vog Predictions second ann to desiel scanda (no Exog) vs Real Data

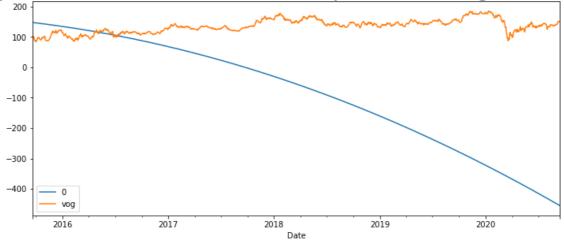


In [99]:

Out[99]:

Text(0.5, 1.0, 'Vog Predictions from desiel scanda to present(no Exog) vs Real Data')

Vog Predictions from desiel scanda to present(no Exog) vs Real Data



In [102]:

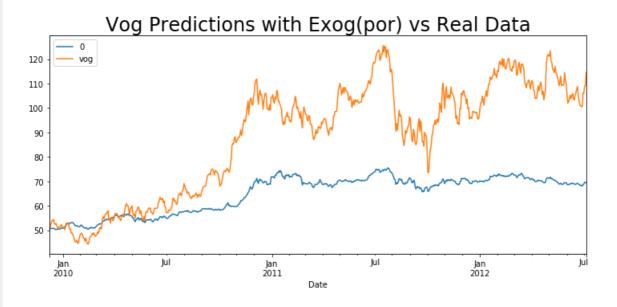
```
#future prediction from start to the first announcement with por as exogenous variable
model_vog_prediction = auto_arima(df.vog[start:f_ann], exogenous = df[['por']][start:f_ann], m = 5,
max_p = 5, max_q = 5, max_P = 5, max_Q = 5, trend = "ct")

prediction_vog_exP = pd.DataFrame(model_vog_prediction.predict(n_periods =
len(df[f_ann:s_ann]), exogenous = df[['por']][f_ann:s_ann]), index = df[f_ann:s_ann].index)
prediction_vog_exP[f_ann:s_ann].plot(figsize = (12,5), legend=True)

df.vog[f_ann:s_ann].plot(legend=True)
plt.title("Vog Predictions with Exog(por) vs Real Data", size = 24)
```

Out[102]:

Text(0.5, 1.0, 'Vog Predictions with Exog(por) vs Real Data')



In [103]:

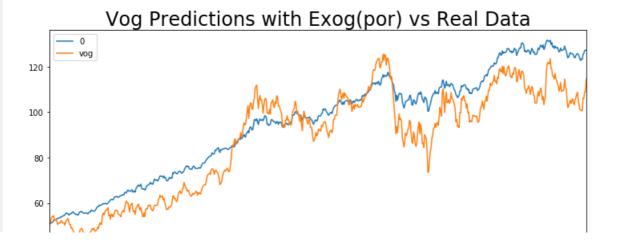
```
#future prediction from start to the first announcement with por as exogenous variable
model_vog_prediction = auto_arima(df.vog[start:f_ann], exogenous = df[['bmw']][start:f_ann], m = 5,
max_p = 5, max_q = 5, max_P = 5, max_Q = 5, trend = "ct")

prediction_vog_exB = pd.DataFrame(model_vog_prediction.predict(n_periods =
len(df[f_ann:s_ann]), exogenous = df[['bmw']][f_ann:s_ann]), index = df[f_ann:s_ann].index)
prediction_vog_exB[f_ann:s_ann].plot(figsize = (12,5), legend=True)

df.vog[f_ann:s_ann].plot(legend=True)
plt.title("Vog_Predictions_with_Exog(bmw) vs_Real_Data", size = 24)
```

Out[103]:

Text(0.5, 1.0, 'Vog Predictions with Exog(por) vs Real Data')





In [104]:

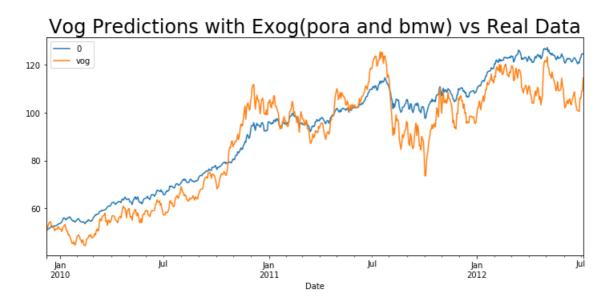
```
#future prediction from start to the first announcement with both por and bmw as exogenous variabl
e
model_vog_prediction = auto_arima(df.vog[start:f_ann], exogenous = df[['por','bmw']][start:f_ann],
m = 5, max_p = 5, max_q = 5, max_P = 5, max_Q = 5, trend = "ct")

prediction_vog_ex = pd.DataFrame(model_vog_prediction.predict(n_periods =
len(df[f_ann:s_ann]), exogenous = df[['por','bmw']][f_ann:s_ann]), index = df[f_ann:s_ann].index)
prediction_vog_ex[f_ann:s_ann].plot(figsize = (12,5), legend=True)

df.vog[f_ann:s_ann].plot(legend=True)
plt.title("Vog_Predictions with Exog(pora and bmw) vs_Real_Data", size = 24)
```

Out[104]:

Text(0.5, 1.0, 'Vog Predictions with Exog(pora and bmw) vs Real Data')



In [108]:

Out[108]:

Text(0.5, 1.0, 'Vog Predictions from desiel scanda to present with exogenous por and bmw vs Real D ata')

Vog Predictions from desiel scanda to present with exogenous por and bmw vs Real Data

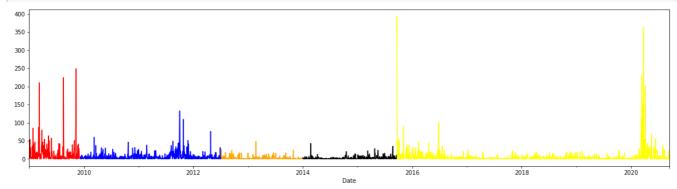




Lets examine the volatility of Vol from start date to desiel scandal

```
In [110]:
```

```
df['sq_vog'][start:f_ann].plot(figsize = (20,5), color = 'red')
df['sq_vog'][f_ann:s_ann].plot(color = 'blue')
df['sq_vog'][s_ann:end].plot(color = 'orange')
df['sq_vog'][end:d_sca].plot(color = 'black')
df['sq_vog'][d_sca:'2020-09-14'].plot(color = 'yellow')
plt.show()
```



In [112]:

```
#Volatility trend for each period
from arch import arch_model
```

In [115]:

```
model_garch_start_f = arch_model(df.ret_vog[start:f_ann], mean = "Constant", vol = "GARCH", p = 1,
q = 1)
results_garch_start_f = model_garch_start_f.fit(update_freq = 5)

model_garch_f_s = arch_model(df.ret_vog[f_ann:s_ann], mean = "Constant", vol = "GARCH", p = 1, q = 1)
results_garch_f_s = model_garch_f_s.fit(update_freq = 5)

model_garch_s_e = arch_model(df.ret_vog[s_ann:end], mean = "Constant", vol = "GARCH", p = 1, q = 1)
results_garch_s_e = model_garch_s_e.fit(update_freq = 5)

model_garch_e_dc = arch_model(df.ret_vog[end:d_sca], mean = "Constant", vol = "GARCH", p = 1, q = 1)
results_garch_e_dc = model_garch_e_dc.fit(update_freq = 5)

model_garch_dc_pre = arch_model(df.ret_vog[d_sca:'2020-09-14'], mean = "Constant", vol = "GARCH", p = 1, q = 1)
results_garch_dc_pre = model_garch_dc_pre.fit(update_freq = 5)
```

```
Iteration:
               5, Func. Count:
                                     35, Neg. LLF: 673.2438089672729
              10,
                   Func. Count:
                                          Neg. LLF: 673.2402452231768
Optimization terminated successfully. (Exit mode 0)
           Current function value: 673.2401928099462
           Iterations: 12
           Function evaluations: 77
           Gradient evaluations: 12
              5,
Iteration:
                   Func. Count:
                                     42,
                                         Neg. LLF: 1526.9228402592855
                                          Neg. LLF: 1526.7316954368935
             10,
                   Func. Count:
                                    72,
Iteration:
Ontimization terminated augeocafully
                                        /E---+ mada 01
```

```
optimization terminated successiumly.
                                           (EXIL MOUE U)
             Current function value: 1526.7316954356486
             Iterations: 10
            Function evaluations: 72
            Gradient evaluations: 10
Iteration: 5, Func. Count: 38, Neg. LLF: 724.5620364427224
Optimization terminated successfully. (Exit mode 0)
             Current function value: 724.5578157320635
             Iterations: 7
             Function evaluations: 51
             Gradient evaluations: 7
Iteration: 5, Func. Count: 40, Neg. LLF: 825.496351472824
Iteration: 10, Func. Count: 73, Neg. LLF: 825.4707320291793
Optimization terminated successfully. (Exit mode 0)
                                              Neg. LLF: 825.4707320291793
            Current function value: 825.4707320282179
             Iterations: 10
             Function evaluations: 73
             Gradient evaluations: 10
                                        38, Neg. LLF: 2713.6026698362484
Iteration:
              5, Func. Count:
Optimization terminated successfully. (Exit mode 0)
             Current function value: 2713.5708492110825
             Iterations: 9
             Function evaluations: 63
             Gradient evaluations: 9
In [116]:
```

```
results_garch_start_f.summary()
```

Out[116]:

Constant Mean - GARCH Model Results

Dep. Variable:	ret_vog	R-squared:	-0.000
Mean Model:	Constant Mean	Adj. R-squared:	-0.000
Vol Model:	GARCH	Log-Likelihood:	-673.240
Distribution:	Normal	AIC:	1354.48
Method:	Maximum Likelihood	BIC:	1368.49
		No. Observations:	245
Date:	Wed, Sep 16 2020	Df Residuals:	241
Time:	20:40:31	Df Model:	4

Mean Model

```
        mu
        0.2661
        0.283
        0.940
        0.347
        [-0.289, 0.821]
```

Volatility Model

		coef	std err	t	P> t	95.0% Conf. Int.
	omega	6.2783	9.790	0.641	0.521	[-12.910, 25.466]
	alpha[1]	0.0372	0.115	0.323	0.747	[-0.189, 0.263]
	beta[1]	0.5200	0.755	0.688	0.491	[-0.961, 2.001]

Covariance estimator: robust

In [117]:

```
{\tt results\_garch\_f\_s.summary()}
```

Out[117]:

Constant Mean - GARCH Model Results

Dep. Variable:	ret_vog	R-squared:	-0.000
Maan Madali	Constant Moon	Adi Doguaradi	0 000

wean woder. Constant iviean Auj. K-squareu: -0.000 Vol Model: GARCH Log-Likelihood: -1526.73 Distribution: AIC: 3061.46 Normal Method: Maximum Likelihood BIC: 3079.50 No. Observations: 672 Wed, Sep 16 2020 Df Residuals: 668 Date: Time: 20:40:31 Df Model: 4

Mean Model

 coef
 std err
 t
 P>|t|
 95.0% Conf. Int.

 mu
 0.1892
 8.634e-02
 2.191
 2.843e-02
 [1.998e-02, 0.358]

Volatility Model

 coef
 std err
 t
 P>|t|
 95.0% Conf. Int.

 omega
 0.1679
 7.914e-02
 2.122
 3.388e-02
 [1.279e-02, 0.323]

 alpha[1]
 0.0688
 1.682e-02
 4.091
 4.301e-05
 [3.585e-02, 0.102]

 beta[1]
 0.9040
 2.108e-02
 42.883
 0.000
 [0.863, 0.945]

Covariance estimator: robust

In [118]:

 ${\tt results_garch_s_e.summary()}$

Out[118]:

Constant Mean - GARCH Model Results

Dep. Variable: -0.001 ret_vog R-squared: Mean Model: Constant Mean Adj. R-squared: -0.001 Vol Model: **GARCH** Log-Likelihood: -724.558 Distribution: Normal AIC: 1457.12 BIC: Method: Maximum Likelihood 1472 98 No. Observations: 390 **Df Residuals:** Date: Wed, Sep 16 2020 386 Time: 20:40:31 Df Model: 4

Mean Model

 mu
 0.2298
 9.845e-02
 2.334
 1.958e-02
 [3.685e-02, 0.423]

Volatility Model

 coef
 std err
 t
 P>|t|
 95.0% Conf. Int.

 omega
 0.7719
 0.677
 1.141
 0.254
 [-0.554, 2.098]

 alpha[1]
 0.1853
 0.145
 1.273
 0.203
 [-9.991e-02, 0.470]

 beta[1]
 0.5136
 0.331
 1.550
 0.121
 [-0.136, 1.163]

Covariance estimator: robust

In [119]:

results_garch_e_dc.summary()

Out[119]:

Constant Mean - GARCH Model Results

Dep. Variable:	ret_vog	R-squared:	-0.000
Mean Model:	Constant Mean	Adj. R-squared:	-0.000
Vol Model:	GARCH	Log-Likelihood:	-825.471
Distribution:	Normal	AIC:	1658.94
Method:	Maximum Likelihood	BIC:	1675.36
		No. Observations:	448
Date:	Wed, Sep 16 2020	Df Residuals:	444
Time:	20:40:31	Df Model:	4

Mean Model

 coef
 std err
 t
 P>|t|
 95.0% Conf. Int.

 mu
 -0.0470
 6.969e-02
 -0.675
 0.500
 [-0.184,8.957e-02]

Volatility Model

	coef	std err	t	P> t	95.0% Conf. Int.
omega	0.0213	2.156e-02	0.987	0.323	[-2.097e-02,6.356e-02]
alpha[1]	0.0479	2.574e-02	1.859	6.305e-02	[-2.603e-03,9.831e-02]
beta[1]	0.9466	2.803e-02	33.776	4.480e-250	[0.892, 1.001]

Covariance estimator: robust

In [120]:

results_garch_dc_pre.summary()

Out[120]:

Constant Mean - GARCH Model Results

Dep. Variable:	ret_vog	R-squared:	-0.001
Mean Model:	Constant Mean	Adj. R-squared:	-0.001
Vol Model:	GARCH	Log-Likelihood:	-2713.57
Distribution:	Normal	AIC:	5435.14
Method:	Maximum Likelihood	BIC:	5455.83
		No. Observations:	1301
Date:	Wed, Sep 16 2020	Df Residuals:	1297
Time:	20:40:31	Df Model:	4

Mean Model

 mu
 coef
 std err
 t
 P>|t|
 95.0% Conf. Int.

 [-2.035e-03, 0.188]

Volatility Model

		coef	std err	t	P> t	95.0% Conf. Int.
	omega	0.0905	3.859e-02	2.346	1.895e-02	[1.491e-02, 0.166]
	alpha[1]	0.0868	2.522e-02	3.441	5.804e-04	[3.734e-02, 0.136]
	beta[1]	0.8907	2.787e-02	31.958	4.165e-224	[0.836, 0.945]

Covariance estimator: robust

```
model garch final = arch model(df.ret vog[start:'2020-09-14'], mean = "Constant", vol = "GARCH", p
= 1, q = 1)
results_garch_final = model_garch_final.fit(last_obs=d_sca,update freq=5)
Iteration:
                                      36,
                                            Neg. LLF: 3772.697091936414
                5,
                     Func. Count:
                                     71,
                                            Neg. LLF: 3769.960813970977
Iteration:
               10,
                    Func. Count:
                                  102,
                                          Neg. LLF: 3769.9520034944235
Iteration:
              15,
                   Func. Count:
Optimization terminated successfully.
                                        (Exit mode 0)
            Current function value: 3769.9520034942498
            Iterations: 15
            Function evaluations: 102
            Gradient evaluations: 15
```

In [158]:

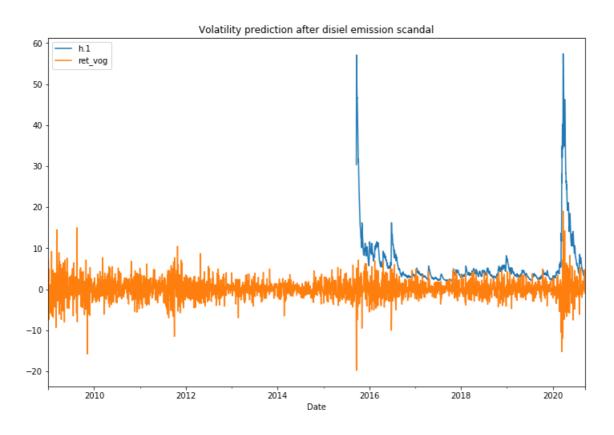
```
forecast_garch=results_garch_final.forecast()
```

In [164]:

```
forecast_garch.residual_variance[d_sca:'2020-09-14'].plot(figsize=(12,8),legend=True)
df.ret_vog[start:'2020-09-14'].plot(legend=True)
plt.title('Volatility prediction after diesel emission scandal')
```

Out[164]:

Text(0.5, 1.0, 'Volatility prediction after disiel emission scandal')



In [160]:

Iterations: 11

Function evaluations: 77 Gradient evaluations: 11

In [161]:

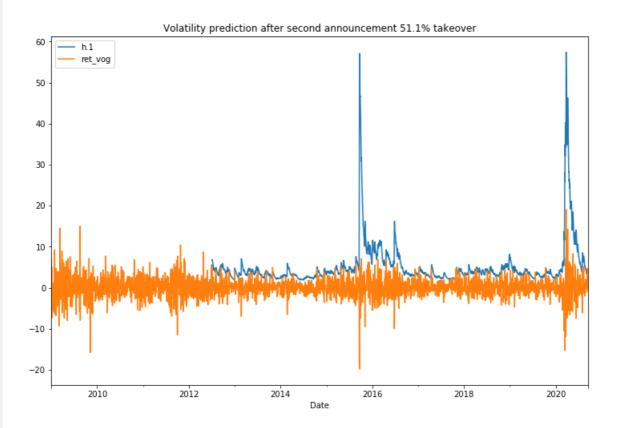
```
forecast_garch=results_garch_final.forecast()
```

In [165]:

```
forecast_garch.residual_variance[s_ann:'2020-09-14'].plot(figsize=(12,8),legend=True)
df.ret_vog[start:'2020-09-14'].plot(legend=True)
plt.title('Volatility prediction after second announcement 51.1% takeover')
```

Out[165]:

Text(0.5, 1.0, 'Volatility prediction after second announcement 51.1% takeover')



In []: