In [1]:

```
%matplotlib inline
import pandas as pd
import numpy as np
import statsmodels.graphics.tsaplots as sgt
import statsmodels.tsa.stattools as sts
from arch import arch_model
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from arch.univariate import StudentsT
from arch.univariate import GARCH, ConstantMean, SkewStudent
from statsmodels.graphics.tsaplots import plot_acf
```

In [2]:

```
def LLR_test(mod_1, mod_2, DF = 1):
    L1 = mod_1.fit(start_ar_lags = 11).llf
    L2 = mod_2.fit(start_ar_lags = 11).llf
    LR = (2*(L2-L1))
    p = chi2.sf(LR, DF).round(3)
    return p
```

In [3]:

```
df = pd.read_csv("C://Users//Aymen//Downloads//historical_data_chia.csv")
#dataset imported from https://messari.io/asset/chia/historical
df=df.rename(columns={'Price (Open)': 'Prices'})
df.index=df["Date"]
df=df.drop(columns="Date")
df
```

Out[3]:

	Price (High)	Prices	Price (Low)	Volatility
Date				
2021-08-20	258.826068	247.454476	245.701714	1.656711
2021-08-19	249.667440	242.820771	236.016771	1.667944
2021-08-18	253.846502	249.405928	232.402111	1.725865
2021-08-17	268.101467	263.224945	247.005490	1.714825
2021-08-16	273.497740	266.930991	259.877601	1.714198
...	...	...	...	...
2021-05-10	1221.454135	1162.225042	871.012842	5.732244
2021-05-09	1350.784291	1347.946790	1027.619106	6.013396
2021-05-08	1466.512928	963.816191	963.816191	5.049672
2021-05-07	1214.174020	582.058558	579.210130	6.163453
2021-05-06	585.253430	570.261510	561.585500	0.000000

107 rows × 4 columns

In [4]:

```
#checking for missing values
print(df.isna().sum())
df
```

```
Price (High)     0
Prices           0
Price (Low)      0
```

```
Volatility      2
dtype: int64
```

Out[4]:

	Price (High)	Prices	Price (Low)	Volatility
Date				
2021-08-20	258.826068	247.454476	245.701714	1.656711
2021-08-19	249.667440	242.820771	236.016771	1.667944
2021-08-18	253.846502	249.405928	232.402111	1.725865
2021-08-17	268.101467	263.224945	247.005490	1.714825
2021-08-16	273.497740	266.930991	259.877601	1.714198
...	...	...	...	...
2021-05-10	1221.454135	1162.225042	871.012842	5.732244
2021-05-09	1350.784291	1347.946790	1027.619106	6.013396
2021-05-08	1466.512928	963.816191	963.816191	5.049672
2021-05-07	1214.174020	582.058558	579.210130	6.163453
2021-05-06	585.253430	570.261510	561.585500	0.000000

107 rows × 4 columns

In [5]:

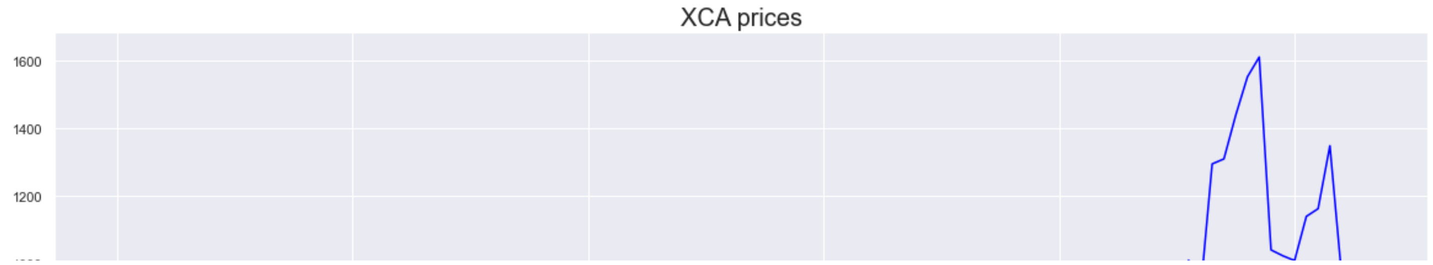
```
df["returns"]=list(df['Prices'].pct_change(2).mul(100))
df["sq_returns"]=list(df['returns'].pct_change(3).mul(100))
df[:10]
```

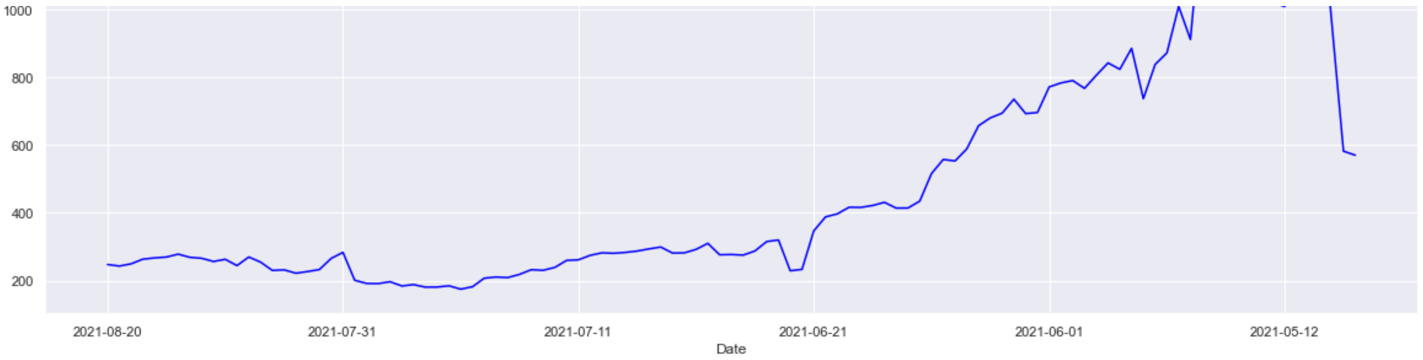
Out[5]:

	Price (High)	Prices	Price (Low)	Volatility	returns	sq_returns
Date						
2021-08-20	258.826068	247.454476	245.701714	1.656711	NaN	NaN
2021-08-19	249.667440	242.820771	236.016771	1.667944	NaN	NaN
2021-08-18	253.846502	249.405928	232.402111	1.725865	0.788610	NaN
2021-08-17	268.101467	263.224945	247.005490	1.714825	8.402977	NaN
2021-08-16	273.497740	266.930991	259.877601	1.714198	7.026723	NaN
2021-08-15	271.767540	269.451716	254.599199	NaN	2.365570	199.966880
2021-08-14	280.337955	278.007512	260.341612	NaN	4.149582	-50.617715
2021-08-13	281.529700	268.611587	264.068405	1.731453	-0.311792	-104.437232
2021-08-12	296.123322	265.826716	252.730803	1.736405	-4.381463	-285.218055
2021-08-11	280.886342	256.343979	255.021631	1.758674	-4.567043	-210.060323

In [6]:

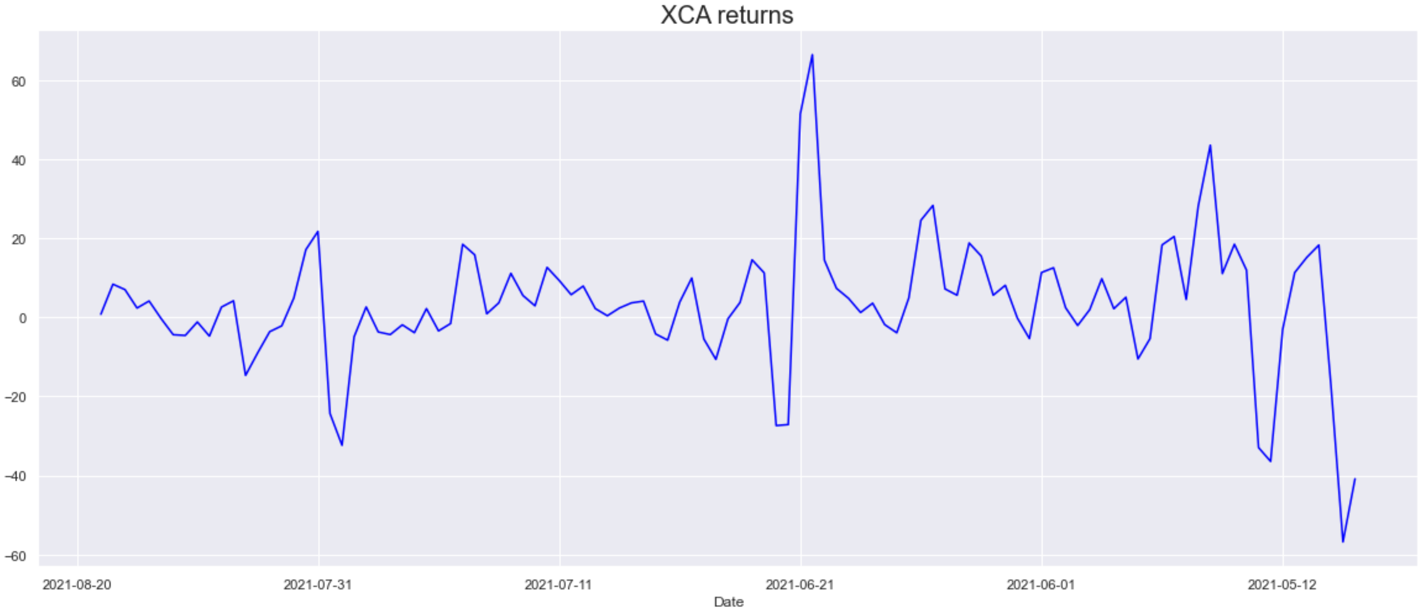
```
df["Prices"].plot(figsize= (20,8), color = "blue")
plt.title("XCA prices" , size=20 )
plt.show()
```





In [7]:

```
df["returns"].plot(figsize= (20,8), color = "blue")
plt.title("XCA returns" , size=20 )
plt.show()
```



splitting the data

In [8]:

```
# split into train/test
n_test =20
train, test = df[:-n_test], df[-n_test:]
len(train)
```

Out[8]:

```
87
```

creating models simple Arch(1) vs GARCH(1,1) comparaison

In [17]:

```
mod_garch = arch_model(df.returns[2:], vol = "GARCH", p = 1, q = 1, mean = "constant", d
ist = "Normal")
mod_garch.distribution = StudentsT()
res_garch = mod_garch.fit( update_freq = 10) #last_obs = start_date,

mod_arch = arch_model(df.returns[2:], vol = "GARCH", p = 1, q = 0, mean = "constant", di
st = "Normal")
mod_arch.distribution = StudentsT()
res_arch = mod_arch.fit( update_freq = 10) #last_obs = start_date,
```

```
Iteration:      10,   Func. Count:     63,   Neg. LLF: 409.0381323264093
Iteration:      20,   Func. Count:    123,   Neg. LLF: 408.7213188592233
Optimization terminated successfully    (Exit mode 0)
Optimization terminated successfully    (Exit mode 0)
            Current function value: 408.7213188592233
            Iterations: 21
            Function evaluations: 128
            Gradient evaluations: 21
Iteration:     10,   Func. Count:     58,   Neg. LLF: 478.50434425120187
Iteration:     20,   Func. Count:    112,   Neg. LLF: 410.69347722500714
Iteration:     30,   Func. Count:    166,   Neg. LLF: 408.7258628072066
Optimization terminated successfully    (Exit mode 0)
            Current function value: 408.72580614757504
            Iterations: 32
            Function evaluations: 175
            Gradient evaluations: 32
```

In [18]:

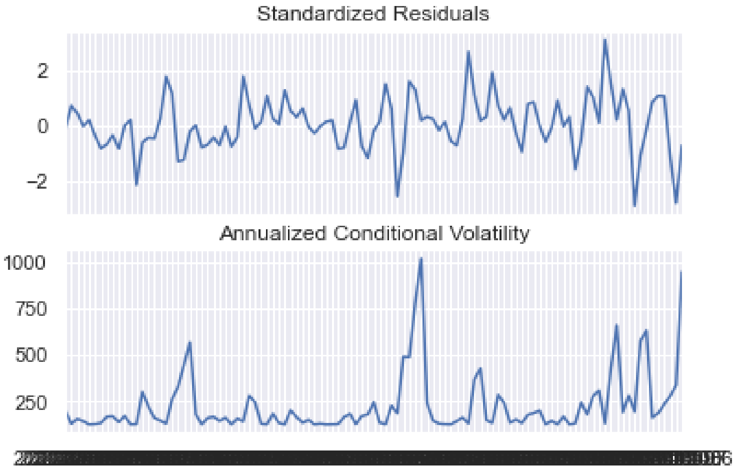
```
print(res_garch.summary(),res_arch.summary())
```

```
                        Constant Mean - GARCH Model Results                         
====================================================================================
Dep. Variable:                      returns   R-squared:                       0.000
Mean Model:                   Constant Mean   Adj. R-squared:                  0.000
Vol Model:                            GARCH   Log-Likelihood:               -408.721
Distribution:      Standardized Student's t   AIC:                           827.443
Method:                  Maximum Likelihood   BIC:                           840.712
                                              No. Observations:                  105
Date:                      Fri, Aug 20 2021   Df Residuals:                      104
Time:                              18:22:57   Df Model:                            1
                               Mean Model                               
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
mu             2.6278      1.577      1.667  9.560e-02 [ -0.463,  5.718]
                             Volatility Model                             
==========================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
--------------------------------------------------------------------------
omega         61.6418     26.487      2.327  1.995e-02 [  9.728,1.136e+02]
alpha[1]       0.9926      0.291      3.412  6.449e-04   [  0.422,  1.563]
beta[1]    7.4349e-03  9.663e-02  7.694e-02      0.939   [ -0.182,  0.197]
                              Distribution                              
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu             5.2522      2.091      2.512  1.200e-02 [  1.154,  9.350]
========================================================================

Covariance estimator: robust                          Constant Mean - ARCH Model Results

====================================================================================
Dep. Variable:                      returns   R-squared:                       0.000
Mean Model:                   Constant Mean   Adj. R-squared:                  0.000
Vol Model:                             ARCH   Log-Likelihood:               -408.726
Distribution:      Standardized Student's t   AIC:                           825.452
Method:                  Maximum Likelihood   BIC:                           836.067
                                              No. Observations:                  105
Date:                      Fri, Aug 20 2021   Df Residuals:                      104
Time:                              18:22:57   Df Model:                            1
                                 Mean Model                                 
===========================================================================
                 coef    std err          t      P>|t|     95.0% Conf. Int.
---------------------------------------------------------------------------
mu             2.6594      1.362      1.953  5.087e-02 [-1.004e-02,  5.329]
                             Volatility Model                             
==========================================================================
                 coef    std err          t      P>|t|    95.0% Conf. Int.
--------------------------------------------------------------------------
omega         62.9162     19.577      3.214  1.310e-03 [ 24.547,1.013e+02]
alpha[1]       1.0000      0.307      3.258  1.122e-03   [  0.398,  1.602]
                              Distribution                              
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
```

```
nu              5.2223      2.078      2.513  1.197e-02 [  1.149,   9.295]
===========================================================================

Covariance estimator: robust
```

In [19]:

```
fig = res_garch.plot(annualize="D" )
fig.size=(20,8)
```



In [20]:

```
print(res_garch.params)
```

```
mu             2.627843
omega         61.641787
alpha[1]       0.992565
beta[1]        0.007435
nu             5.252184
Name: params, dtype: float64
```

example of a simulation

In [21]:

```
sim_data = mod_garch.simulate(res_garch.params, 1000)
sim_data.head()
```

```
C:\Users\Aymen\.conda\envs\p36workshop\lib\site-packages\arch\univariate\volatility.py:10
76: InitialValueWarning: Parameters are not consistent with a stationary model. Using the
intercept
to initialize the model.

  warn(initial_value_warning, InitialValueWarning)
```

Out[21]:

	data	volatility	errors
0	9.280345	8.693726	6.652502
1	4.818300	10.301964	2.190457
2	1.834243	8.197151	-0.793600
3	10.151724	7.922530	7.523881
4	-12.921453	10.876413	-15.549296

In [22]:

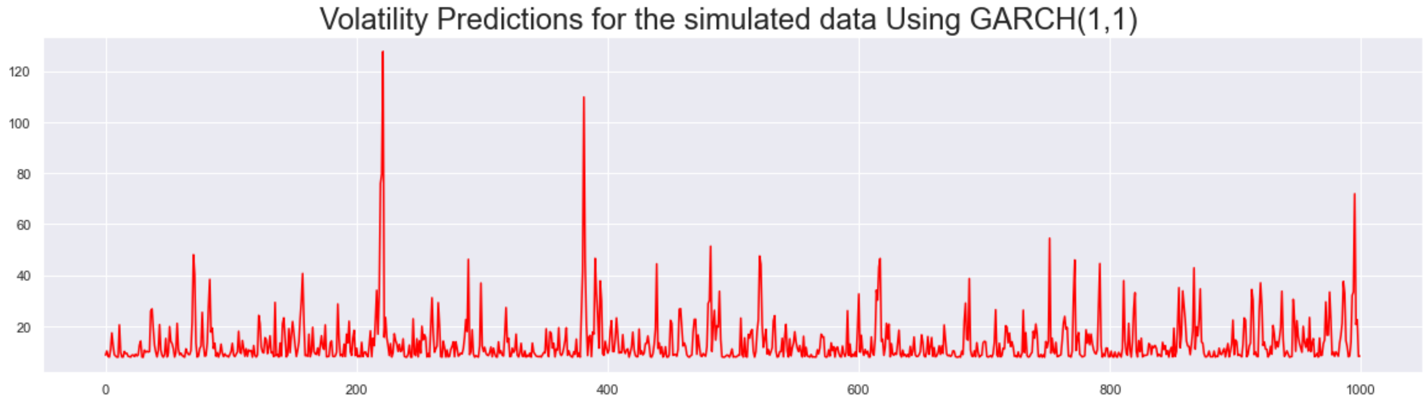
```
#pred_garch = res_garch.forecast(horizon = 100, align = 'target' , reindex=False)
#pred_garch.variance
#pred_garch.residual_variance
```

In [23]:

```
pred_garch = res_garch.forecast(horizon = 100, align = 'target' , reindex=False)
```

In [25]:

```
sim_data.volatility.plot(figsize = (20,5), color = "red", zorder = 2)
plt.title("Volatility Predictions for the simulated data Using GARCH(1,1) ", size = 24)
#1 normal arch apramater and 1 corrective past error term
#this is proven to be the best model as higher order ones will recursively include the ot
her correctif terms that are are encapsulated in 'yesterday' 's error term (n-1)th
plt.show()
```



In [ ]: