NetFlix Market Cap Time Series Analysis

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Abstract

Netflix is one of the most successful video websites in the United States. Futher, it is also the most profitable video website in the world. It is interesting to explore its future development. In this experiment, we apply Prophet procedure to build a time series model and make preditions about its future market cap. Additionally, we also use GARCH model to fit data which is popular in the finance field. Further, we make preditions based on the best model.

Introduction

Netflix is already one of the biggest media companyies in the world. Depsite this, there are some fast-growing media companies like Hulu, Youtube is running after it. We are interested to explore its future development. We plan to apply Prophet procedure to build a time series model to predict its future market cap. Its future development is impossible to be determined only by market cap. However, it is expected to find out some clues about future car development trend.

The Data and Data Generating Process

In [61]:
```
import warnings
warnings.filterwarnings('ignore')
```

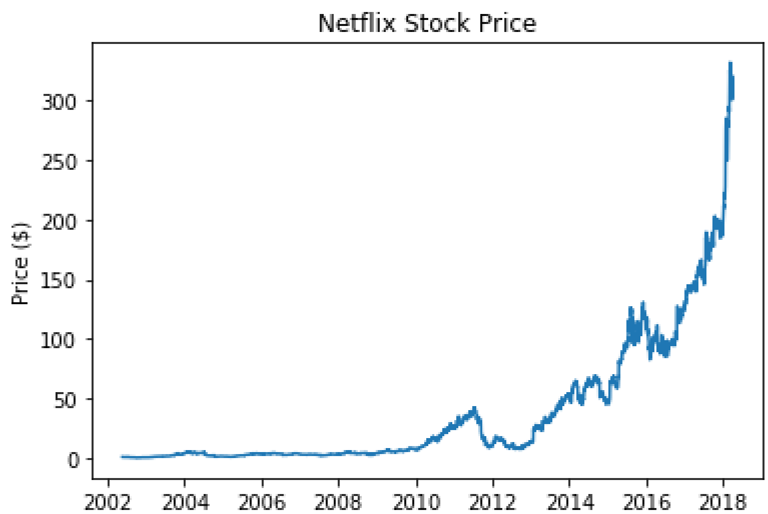
In [62]:
```
import quandl as ql
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import fbprophet as fb
```

In [5]:
```
ql.ApiConfig.api_key = 'L1SeDskg7iEAdJ62rRTv'
```

It is a pretty complicated and time-consuming process to retrive and well-structured data from Internet manully. In this case, I use a convenient python financial data package -- Quandl. It contains almost unlimited financial data. Further, it can provide us with well-formated data.

In [6]:
```
data = ql.get('WIKI/NFLX')
```

In [7]:
```
plt.plot(data.index, data['Adj. Close'])
plt.title('Netflix Stock Price')
plt.ylabel('Price ($)');
plt.show()
```



The market cap of a company can be affected by lots of variables. It is reason take variables like daily stock prices and stock vlomue into account. However, some social and political event can also have crucial effecs on market cap. We are not able to add these things into model so we have to skip these unpredictable factors.

In this case, it is clear that variables like open price, daily highest price, daily lowest price and close price have directive influence on its market cap. Further, stock volume is also important because it is not fair to determine market cap by its stock price. For example, some companies have very high stock prices but its stock volume is small. In this case, its market cap is limited by volume. Addtionally, we conisder some adjusted factors like Adj. High since adjusted variables sometimes can demonstrate information clearly.

$$Cap\ value\ =\ Adj.Close\ Price\ *\ Stock\ volume$$

In [8]:
```
nflx_shares = {2005: 459e6, 2006:484e6, 2007:482e6, 2008:440e6, 2009:409e6, 20
10:380e6, 2011:381e6, 2012:412e6, 2013:425e6, 2014:432e6, 2015:436e6, 2016: 43
9e6, 2017:447e6, 2018:451e6}
```

In [9]:
```
data['Year'] = data.index.year
```

In [10]:
```python
data = data[data['Year'] >= 2005]
```

In [11]:
```python
data.reset_index(level=0, inplace = True)
data['cap'] = 0
```

In [12]:
```python
data.head(5)
```

Out[12]:

	Date	Open	High	Low	Close	Volume	Ex-Dividend	Split Ratio	Adj. Open	Adj. High	Adj. Low
0	2005-01-03	12.48	12.60	11.52	11.92	1619200.0	0.0	1.0	1.782857	1.800000	1.645714
1	2005-01-04	11.92	11.95	11.25	11.66	2478900.0	0.0	1.0	1.702857	1.707143	1.607143
2	2005-01-05	11.74	11.74	11.09	11.20	1818900.0	0.0	1.0	1.677143	1.677143	1.584286
3	2005-01-06	11.20	11.37	11.01	11.05	1181900.0	0.0	1.0	1.600000	1.624286	1.572857
4	2005-01-07	11.11	11.55	11.00	11.12	1070100.0	0.0	1.0	1.587143	1.650000	1.571429

In [13]:
```python
for i, year in enumerate(data['Year']):

    shares = nflx_shares.get(year)
    data['cap'][i] = shares * data['Adj. Close'][i]
```

Exploratory Data Analysis

Data Format

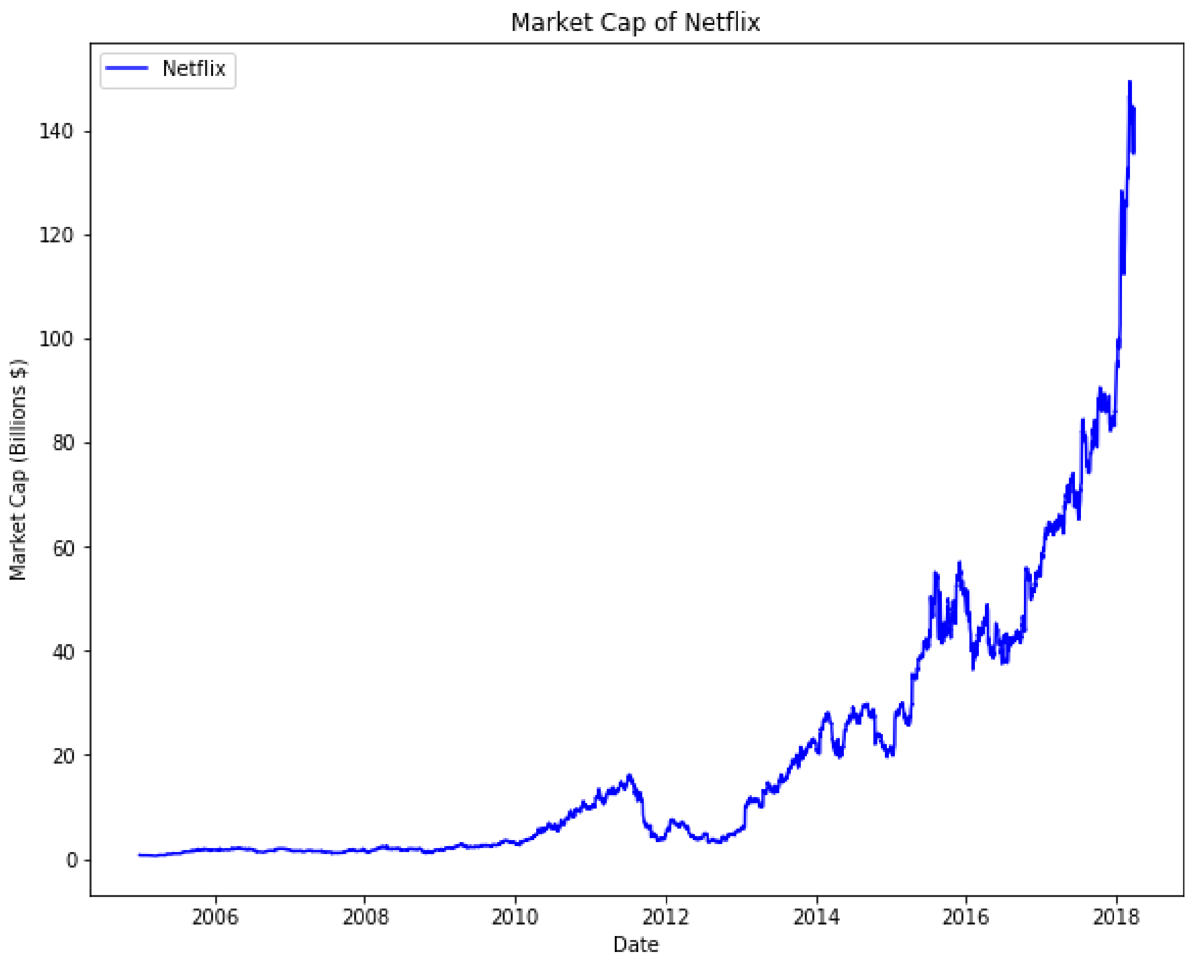
In [14]:
```python
nflx = data[['Date', 'cap']].copy()

nflx['cap'] = nflx['cap'] / 1e9

nflx.head()
```

Out[14]:

	Date	cap
0	2005-01-03	0.781611
1	2005-01-04	0.764563
2	2005-01-05	0.734400
3	2005-01-06	0.724564
4	2005-01-07	0.729154

Visualization of Cap Value

In [15]:
```
plt.figure(figsize=(10, 8))
plt.plot(nflx['Date'], nflx['cap'], 'b-', label = 'Netflix')
plt.xlabel('Date'); plt.ylabel('Market Cap (Billions $)'); plt.title('Market C
ap of Netflix')
plt.legend();
```



In [16]:
```
nflx = nflx.rename(columns={'Date': 'ds', 'cap': 'y'})
```

Data Analysis

Statistical Model

FB Prophet

Formal Model

Prophet Model can be roughly represented by these formulas below.

$y(t) = g(t) + h(t) + s(t) + \epsilon(t)$

$g(t) = (k + \alpha(t)\delta) \cdot t + (m + \alpha(t)^T \gamma)$ (1)

$s(t) = \sum_{n=1}^{N} (a_n cos(\frac{2\pi nt}{p}) + b_n sin(\frac{2\pi nt}{p}))$ (2)

$h(t) = Z(t)\mathbf{k}$ (3)

$Z(t) = [1(t \in D_1), \ldots, 1(t \in D_L)], \mathbf{k} = (k_1, \ldots, k_L)^T$

Model Discussion

I decide to apply Prophet Model which is explored by Facebook. Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. The financial data usually have seasonal variations and it also related with holidays. Therefore, I think this model might fit the data well.

Model Fitting Process

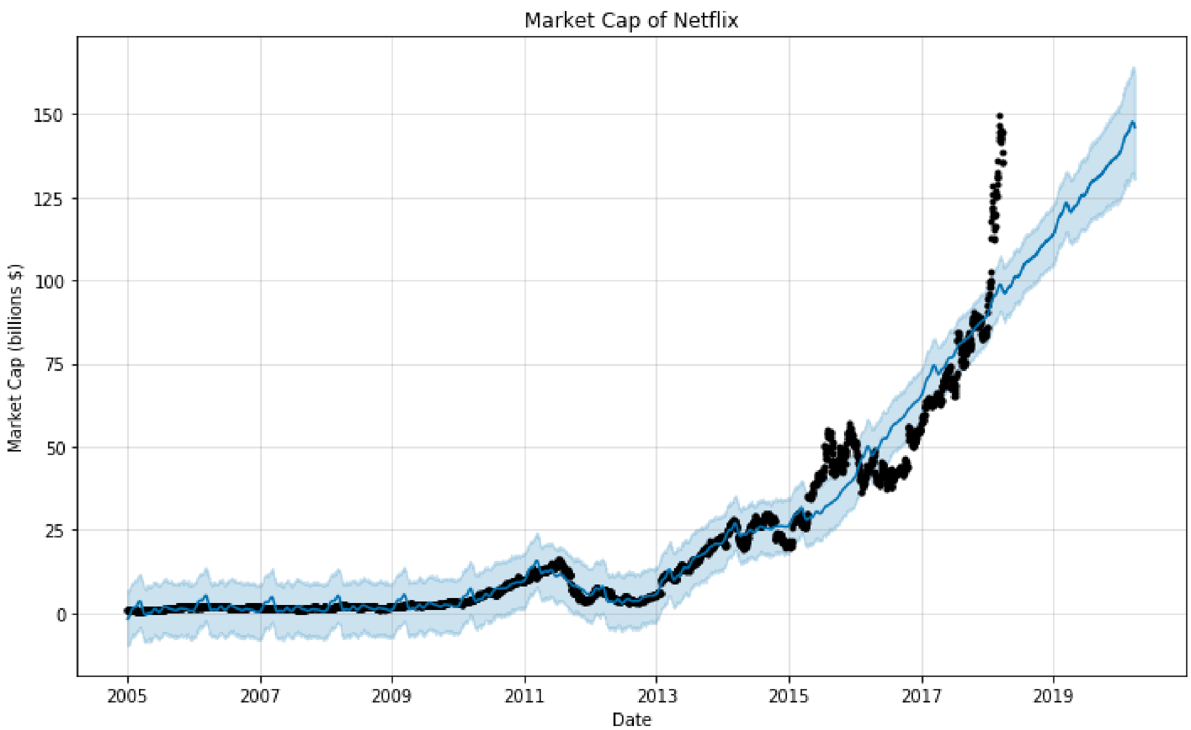
In [17]:
```
nf_prophet = fb.Prophet(changepoint_prior_scale=0.85, daily_seasonality=True)
nf_prophet.fit(nflx)
```

Out[17]:
```
<fbprophet.forecaster.Prophet at 0x1c2ff3915c0>
```

In [18]:
```
nf_forecast = nf_prophet.make_future_dataframe(periods=365 * 2, freq='D')


nf_forecast = nf_prophet.predict(nf_forecast)
```

Prediction Visualization

In [19]:
```
nf_prophet.plot(nf_forecast, xlabel = 'Date', ylabel = 'Market Cap (billions
 $)')
plt.title('Market Cap of Netflix');
```



Data Transformation

Log Transformation

In [20]:
```
nf_log = nflx.copy()
```

In [21]:
```
nf_log.head(5)
```

Out[21]:

	ds	y
0	2005-01-03	0.781611
1	2005-01-04	0.764563
2	2005-01-05	0.734400
3	2005-01-06	0.724564
4	2005-01-07	0.729154

In [22]:
```
nf_log['y'] = nf_log['y'].map(lambda x: np.log(x))
```

In [23]:
```
nf_log.head(5)
```

Out[23]:

	ds	y
0	2005-01-03	-0.246398
1	2005-01-04	-0.268451
2	2005-01-05	-0.308701
3	2005-01-06	-0.322185
4	2005-01-07	-0.315870

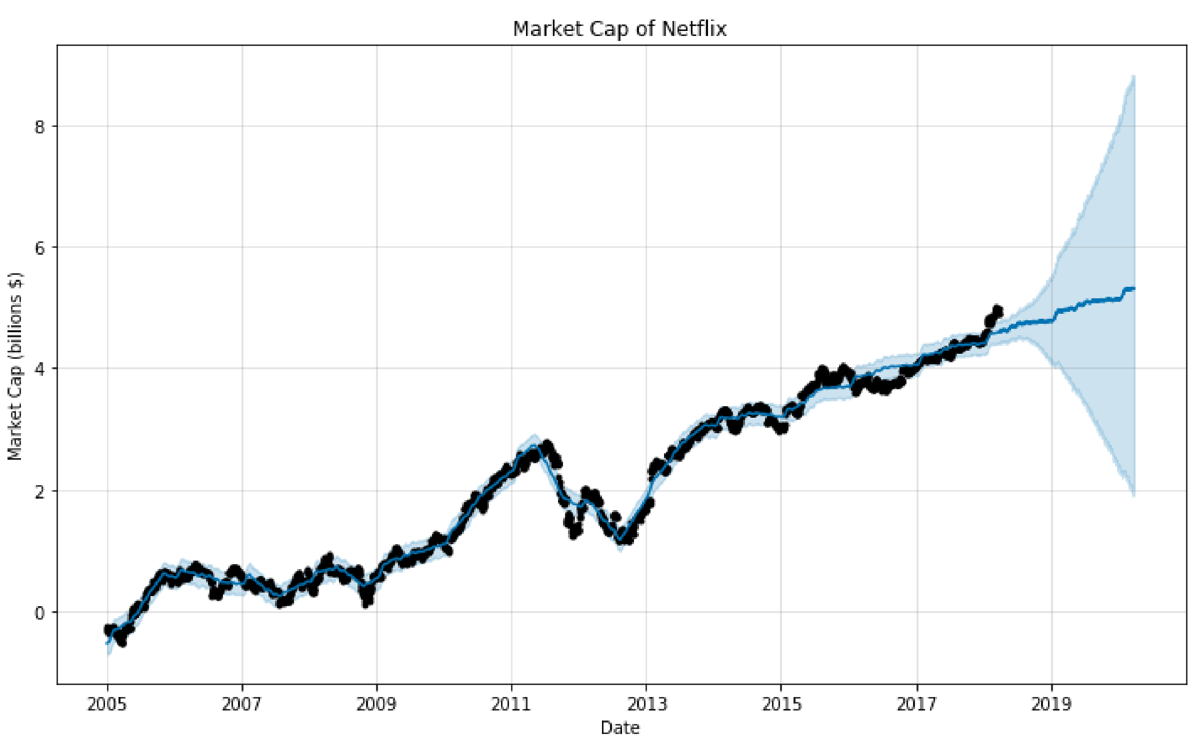
In [24]:
```
nf_log_prophet = fb.Prophet(changepoint_prior_scale=0.85, daily_seasonality=True)
nf_log_prophet.fit(nf_log)
```

Out[24]:
```
<fbprophet.forecaster.Prophet at 0x1c2a0009550>
```

In [25]:
```
nf_log_forecast = nf_log_prophet.make_future_dataframe(periods=365 * 2, freq='D')


nf_log_forecast = nf_log_prophet.predict(nf_forecast)
```

Prediction Visualization

In [26]:
```
nf_log_prophet.plot(nf_log_forecast, xlabel = 'Date', ylabel = 'Market Cap (billions $)')
plt.title('Market Cap of Netflix');
```



Stationary Test Functions

In [27]:

```
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

def draw_trend(timeSeries, size):
    f = plt.figure(facecolor='white')

    rol_mean = timeSeries.rolling(window=size).mean()

    rol_weighted_mean = pd.DataFrame.ewm(timeSeries, span=size).mean()

    timeSeries.plot(color='blue', label='Original')
    rol_mean.plot(color='red', label='Rolling Mean')
    rol_weighted_mean.plot(color='black', label='Weighted Rolling Mean')
    plt.legend(loc='best')
    plt.title('Rolling Mean')
    plt.show()

def draw_ts(timeSeries):
    f = plt.figure(facecolor='white')
    timeSeries.plot(color='blue')
    plt.show()

'''
    Unit Root Test
   The null hypothesis of the Augmented Dickey-Fuller is that there is a unit
   root, with the alternative that there is no unit root. That is to say the
   bigger the p-value the more reason we assert that there is a unit root
'''
def testStationarity(ts):
    dftest = adfuller(ts)
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags
Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    return dfoutput


def draw_acf_pacf(ts, lags=31):
    ##plt.figure(figsize=(12, 8))

    f = plt.figure(facecolor='white')
    ax1 = f.add_subplot(211)
    plot_acf(ts, lags=31, ax=ax1)
    ax2 = f.add_subplot(212)
    plot_pacf(ts, lags=31, ax=ax2)
    plt.tight_layout()
    plt.show()
```

ARIMA Model

In [28]:
```
nflx.head(6)
```

Out[28]:

	ds	y
0	2005-01-03	0.781611
1	2005-01-04	0.764563
2	2005-01-05	0.734400
3	2005-01-06	0.724564
4	2005-01-07	0.729154
5	2005-01-10	0.738990

In [29]:
```
arima_data = nflx.copy()
arima_data.set_index('ds', inplace = True)
```

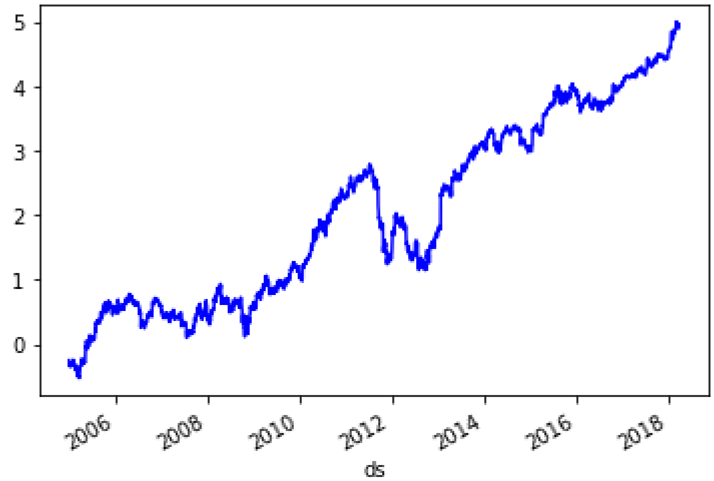
In [30]:
```
ts = arima_data['y'].copy()
testStationarity(ts)
```

Out[30]:
```
Test Statistic                    3.982803
p-value                           1.000000
#Lags Used                       29.000000
Number of Observations Used    3300.000000
Critical Value (1%)              -3.432333
Critical Value (5%)              -2.862416
Critical Value (10%)             -2.567236
dtype: float64
```

In [31]:
```
ts_log = np.log(ts).copy()
testStationarity(ts_log)
```

Out[31]:
```
Test Statistic                   -0.198435
p-value                           0.938708
#Lags Used                        1.000000
Number of Observations Used    3328.000000
Critical Value (1%)              -3.432316
Critical Value (5%)              -2.862409
Critical Value (10%)             -2.567233
dtype: float64
```

In [32]:
```
draw_ts(ts_log)
```

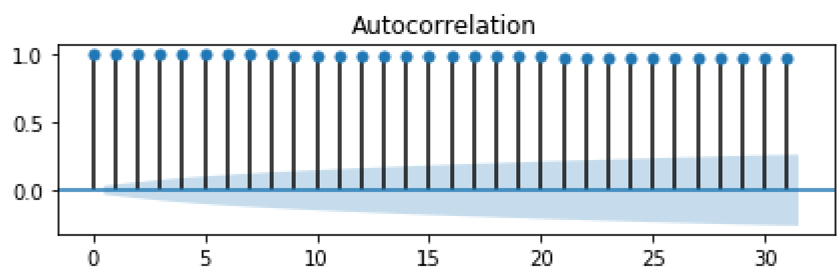


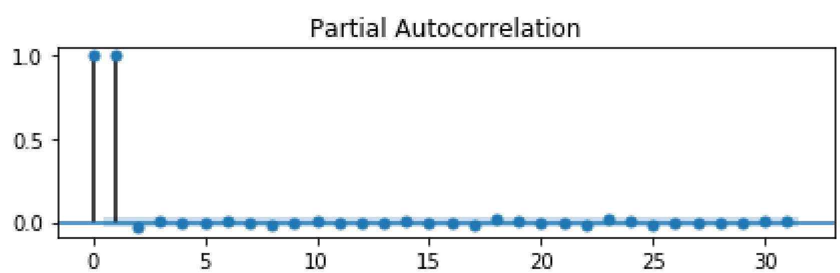
PCF and ACF Test

In [34]:
```
arima_log = arima_data.copy()
```

In [35]:
```
arima_log['y'] = arima_log['y'].map(lambda x: np.log(x))
```

In [36]:
```
draw_acf_pacf(ts_log)
```





Stepwise ARIMA

In [37]:
```
from pmdarima.arima import auto_arima
```

In [38]:
```
stepwise_model = auto_arima(ts_log, start_p=1, start_q=1,
                            max_p=3, max_q=3, m=12,
                            start_P=0, seasonal=False,
                            d=1, D=1, trace=True,
                            error_action='ignore',
                            suppress_warnings=True,
                            stepwise=True)
print(stepwise_model.aic())
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-13128.434, Time=0.43 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-13125.762, Time=0.31 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-13129.650, Time=0.21 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-13129.888, Time=0.63 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-13120.728, Time=0.04 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=-13128.933, Time=0.36 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=-13127.072, Time=0.37 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=-13125.435, Time=0.18 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0] intercept
Total fit time: 2.530 seconds
-13129.887914062423
```

GARCH Model

In [39]:
```
from arch import arch_model
```

Formal Model

The autoregressive conditional heteroscedasticity (ARCH) model is a statistical model for time series data that describes the variance of the current error term or innovation as a function of the actual sizes of the previous time periods' error terms[1]; often the variance is related to the squares of the previous innovations. The ARCH model is appropriate when the error variance in a time series follows an autoregressive (AR) model; if an autoregressive moving average (ARMA) model is assumed for the error variance, the model is a generalized autoregressive conditional heteroskedasticity (GARCH) model[2].

$r_t = c_1 + \sum_{i=1}^{R} \phi_i r_{t-i} + \sum_{j=1}^{M} \phi_j \epsilon_{t-j} + \epsilon_t$

$\epsilon_t = u_t \sqrt{h_t}$

$h_t = k + \sum_{i=1}^{q} G_i h_{t-i} + \sum_{j=1}^{p} A_i \epsilon_{t-i}^2$

Model Discussion

ARCH models are commonly employed in modeling financial time series that exhibit time-varying volatility and volatility clustering, i.e. periods of swings interspersed with periods of relative calm. ARCH-type models are sometimes considered to be in the family of stochastic volatility models, although this is strictly incorrect since at time t the volatility is completely pre-determined (deterministic) given previous values[3]. In this case, the variance of stock prices is not constant so the traditional regression model is not feasible here. The variance of stock price is likely to vary with time. Therefore, GARCH model maybe be suitable in this case.

Model Fitting Process

In [40]:
```
nf_arch = arch_model(ts)
```

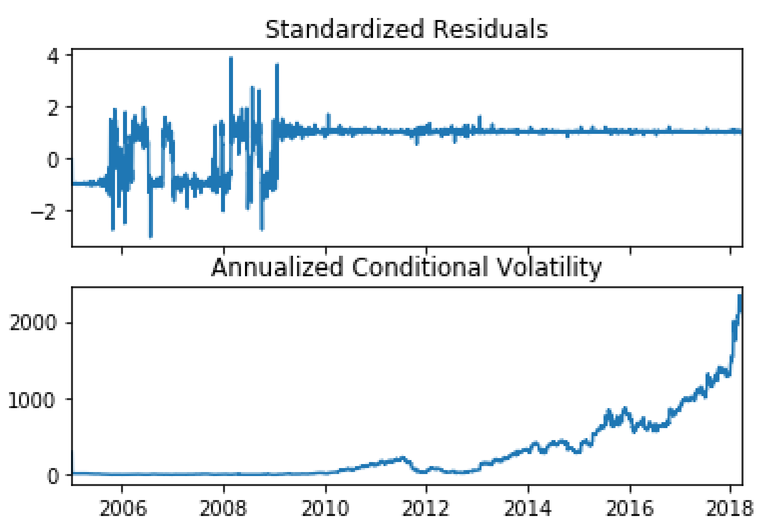
In [41]:
```
res = nf_arch.fit(update_freq=0)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 8919.93199267234
            Iterations: 24
            Function evaluations: 150
            Gradient evaluations: 24
```

In [42]:
```
print(res.summary())
```

```
                     Constant Mean - GARCH Model Results                      
==============================================================================
=
Dep. Variable:                      y   R-squared:                      -0.46
4
Mean Model:             Constant Mean   Adj. R-squared:                 -0.46
4
Vol Model:                      GARCH   Log-Likelihood:               -8919.9
3
Distribution:                  Normal   AIC:                           17847.
9
Method:            Maximum Likelihood   BIC:                           17872.
3
                                        No. Observations:                 333
0
Date:                Tue, Nov 24 2020   Df Residuals:                     332
6
Time:                        18:14:26   Df Model:                            
4
                                 Mean Model                                 
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
mu             1.7959  2.807e-02     63.985      0.000 [  1.741,  1.851]
                              Volatility Model                              
==============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
------------------------------------------------------------------------------
omega      3.2474e-03  7.138e-04      4.550  5.376e-06  [1.848e-03,4.646e-03]
alpha[1]       0.9965  8.078e-03    123.364      0.000      [  0.981,  1.012]
beta[1]    6.0694e-04  1.345e-03      0.451      0.652 [-2.029e-03,3.242e-03]
==============================================================================

Covariance estimator: robust
```

In [43]:
```
fig1 = res.plot(annualize='D')
```

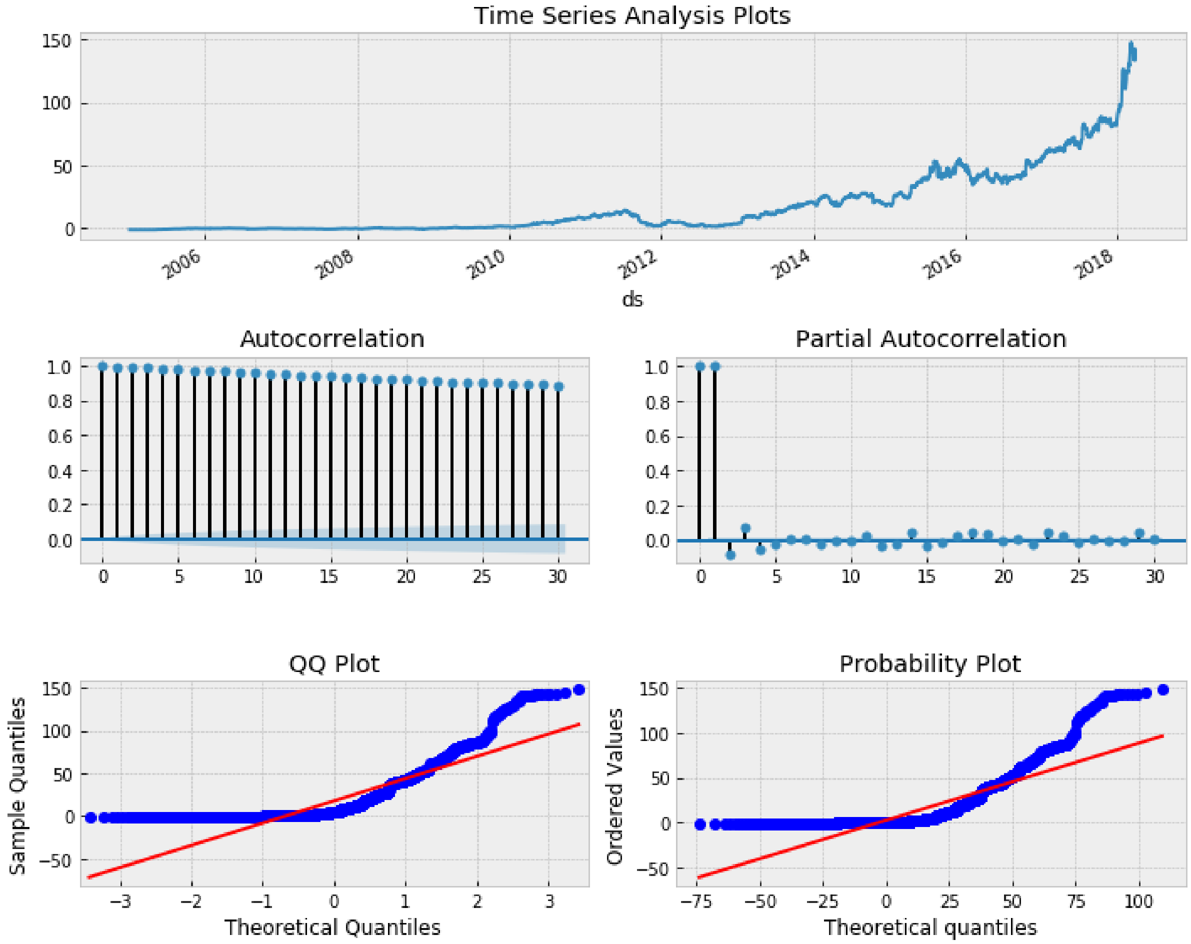


Plot Function

In [44]:
```python
import statsmodels.formula.api as smf
import statsmodels.tsa.api as smt
import statsmodels.api as sm
import scipy.stats as scs
```

In [45]:
```python
def tsplot(y, lags=None, figsize=(10, 8), style='bmh'):
    if not isinstance(y, pd.Series):
        y = pd.Series(y)
    with plt.style.context(style):
        fig = plt.figure(figsize=figsize)
        #mpl.rcParams['font.family'] = 'Ubuntu Mono'
        layout = (3, 2)
        ts_ax = plt.subplot2grid(layout, (0, 0), colspan=2)
        acf_ax = plt.subplot2grid(layout, (1, 0))
        pacf_ax = plt.subplot2grid(layout, (1, 1))
        qq_ax = plt.subplot2grid(layout, (2, 0))
        pp_ax = plt.subplot2grid(layout, (2, 1))

        y.plot(ax=ts_ax)
        ts_ax.set_title('Time Series Analysis Plots')
        smt.graphics.plot_acf(y, lags=lags, ax=acf_ax, alpha=0.5)
        smt.graphics.plot_pacf(y, lags=lags, ax=pacf_ax, alpha=0.5)
        sm.qqplot(y, line='s', ax=qq_ax)
        qq_ax.set_title('QQ Plot')
        scs.probplot(y, sparams=(y.mean(), y.std()), plot=pp_ax)

        plt.tight_layout()
    return
```

In [46]:
```
tsplot(res.resid, lags=30)
```



The plots indicates that the current model didn't fit the data well. Moreover, the autocorrelations are pretty high and went down slowly. Based on that, we can conclude that we need do some data transformations. Firstly, we tried the log transformation.

Log Transformation

In [47]:
```
nf_log_arch = arch_model(ts_log)
```

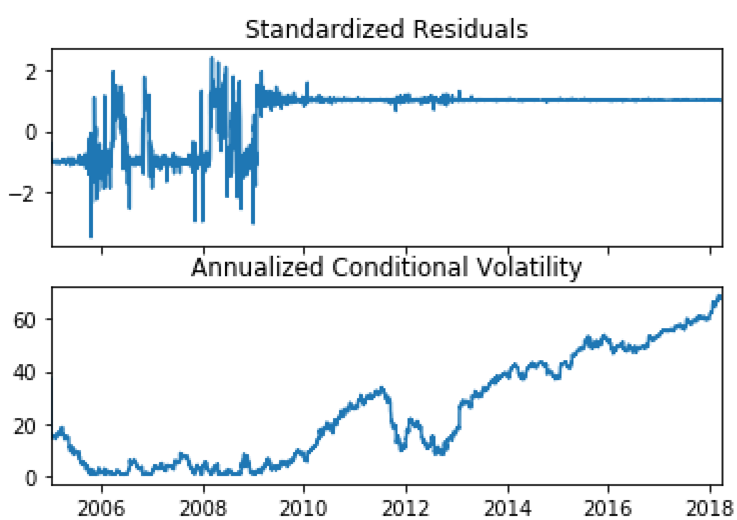
In [48]:
```
res_log = nf_log_arch.fit(update_freq=0)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 3968.960141154397
            Iterations: 26
            Function evaluations: 165
            Gradient evaluations: 25
```

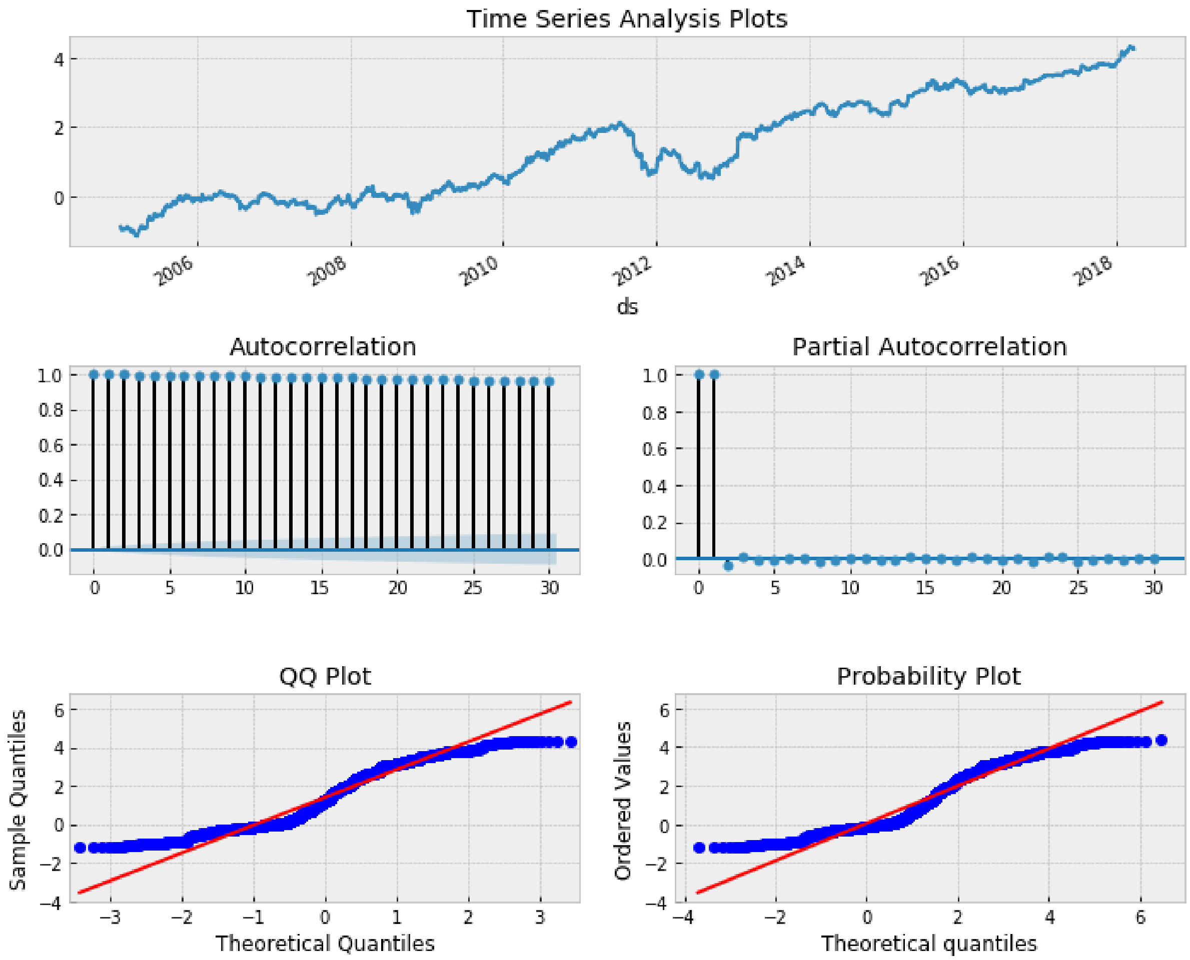
In [49]:
```
print(res_log.summary())
```

```
                     Constant Mean - GARCH Model Results
=============================================================================
=
Dep. Variable:                      y   R-squared:                     -0.92
5
Mean Model:             Constant Mean   Adj. R-squared:                -0.92
5
Vol Model:                      GARCH   Log-Likelihood:               -3968.9
6
Distribution:                  Normal   AIC:                           7945.9
2
Method:            Maximum Likelihood   BIC:                           7970.3
6
                                        No. Observations:                 333
0
Date:                Tue, Nov 24 2020   Df Residuals:                     332
6
Time:                        18:14:47   Df Model:
4
                                 Mean Model
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
mu             0.6481  6.483e-03     99.964      0.000 [  0.635,  0.661]
                              Volatility Model
=============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
-----------------------------------------------------------------------------
omega      6.1575e-04  1.188e-04      5.184  2.174e-07  [3.829e-04,8.486e-04]
alpha[1]       1.0000  2.174e-02     45.992      0.000      [  0.957,  1.043]
beta[1]        0.0000  1.812e-02      0.000      1.000 [-3.551e-02,3.551e-02]
=============================================================================

Covariance estimator: robust
```

In [50]:
```
fig = res_log.plot(annualize='D')
```



In [51]:
```
tsplot(res_log.resid, lags=30)
```



According to the QQ plot, the model fitted transformed data much better. However, the autocorrelation problems still exist. Therefore, we have to try the other transformation. In this case, we applied difference transformation here.

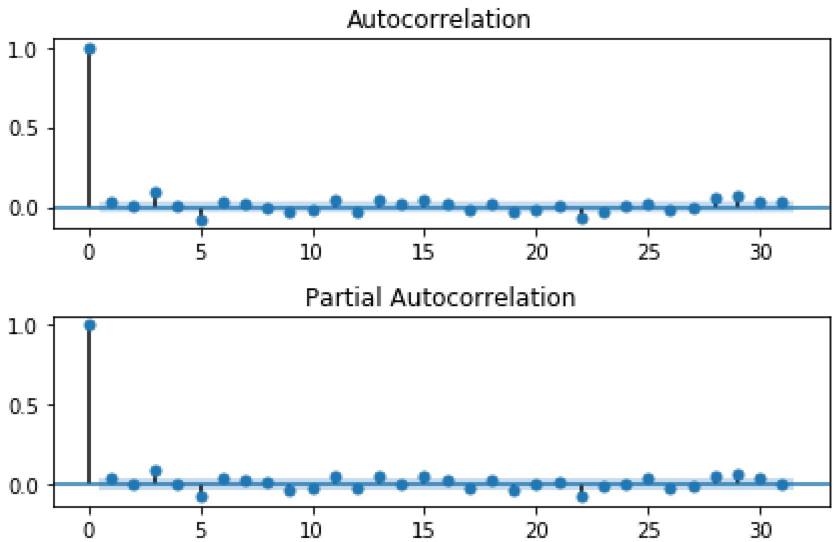
Difference Function

In [52]:
```
## diff func
def diff(y):
    base = y[0]
    tmp = y[0]
    n = len(y)
    ret = [];
    ret.append(0);
    for i in range(1, n):
        ret.append(y[i] - tmp)
        tmp = y[i]
    return base, ret
```

Difference Transformation

In [53]:
```
base, ts_diff = diff(ts)
```

In [54]:
```
draw_acf_pacf(ts_diff)
```



In [55]:
```
nf_diff_arch = arch_model(ts_diff)
```

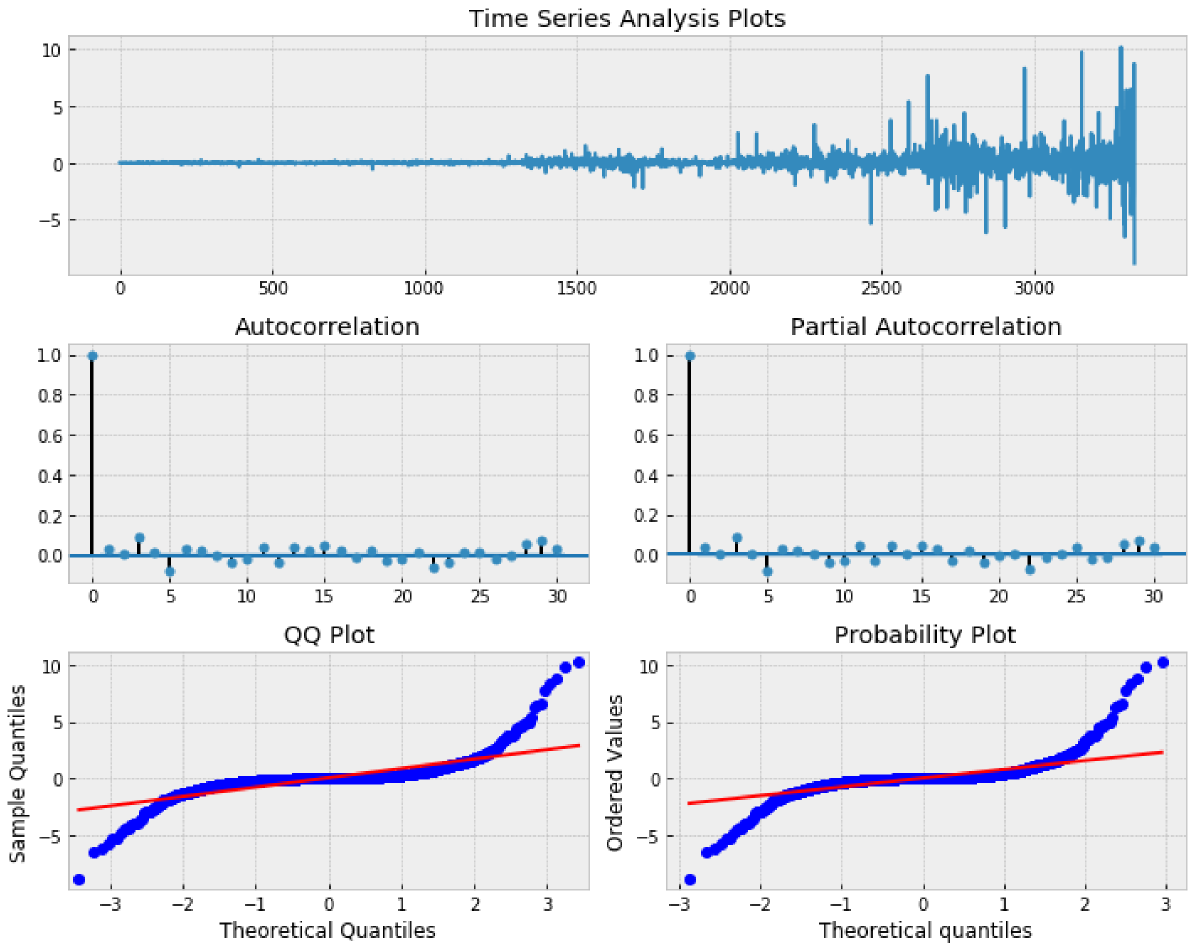
In [56]:
```
res_diff = nf_diff_arch.fit(update_freq=0)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 1082.0226568370804
            Iterations: 15
            Function evaluations: 86
            Gradient evaluations: 11
```

In [57]:
```python
print(res_diff.summary())
```

```
                     Constant Mean - GARCH Model Results                      
==============================================================================
=
Dep. Variable:                      y   R-squared:                       -0.00
2
Mean Model:             Constant Mean   Adj. R-squared:                  -0.00
2
Vol Model:                      GARCH   Log-Likelihood:                -1082.0
2
Distribution:                  Normal   AIC:                            2172.0
5
Method:            Maximum Likelihood   BIC:                            2196.4
9
                                        No. Observations:                  333
0
Date:                Tue, Nov 24 2020   Df Residuals:                      332
6
Time:                        18:15:11   Df Model:                             
4
                                 Mean Model                                   
==============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
------------------------------------------------------------------------------
mu         2.8502e-03  2.282e-03      1.249      0.212 [-1.622e-03,7.322e-03]
                              Volatility Model                              
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
omega      4.3160e-03  4.985e-04      8.658  4.806e-18 [3.339e-03,5.293e-03]
alpha[1]       0.2476  2.272e-02     10.900  1.147e-27     [  0.203,  0.292]
beta[1]        0.7523  2.454e-02     30.656 2.229e-206     [  0.704,  0.800]
============================================================================

Covariance estimator: robust
```

In [58]:
```
tsplot(res_diff.resid, lags=30)
```



Based on the results, the autocorrelation plot and the partial autocorrelation plots seem much better. Further, the QQ plot noted that the current model fitted data well.

Prediction

GARCH Simulation Forecasts

Simulation-based forecasts use the model random number generator to simulate draws of the standardized residuals, e_{t+h}. These are used to generate a pre-specified number of paths of the variances which are then averaged to produce the forecasts. In models like GARCH which evolve in the squares of the residuals, there are few advantages to simulation-based forecasting.

Assume there are B simulated paths. A single simulated path is generated using

$$\sigma^2_{t+h,b} = \omega + \alpha\epsilon^2_{t+h-1,b} + \beta\sigma^2_{t+h-1,b}$$

$$\epsilon_{t+h,b} = e_{t+h,b}\sqrt{\sigma^2_{t+h,b}}$$

where the simulated shocks are $e_{t+1,b}, e_{t+2,b}, \ldots, e_{t+h,b}$ where b is included to indicate that the simulations are independent across paths. Note that the first residual, ϵ_t, is in-sample and so is not simulated.

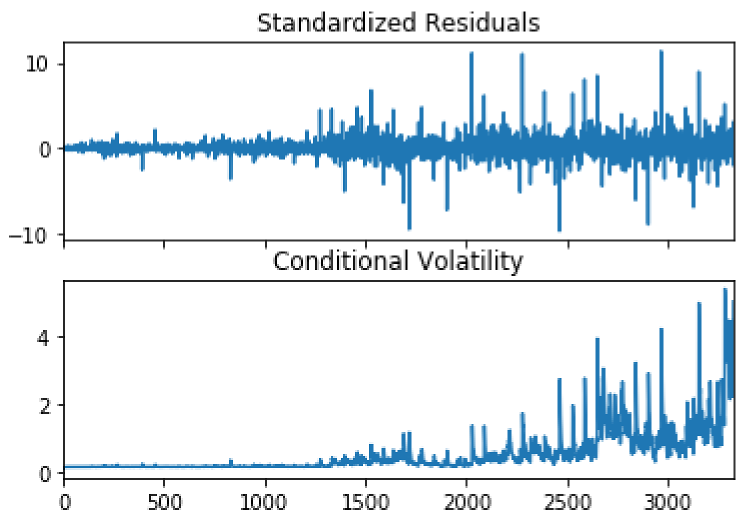
The final variance forecasts are then computed using the B simulations

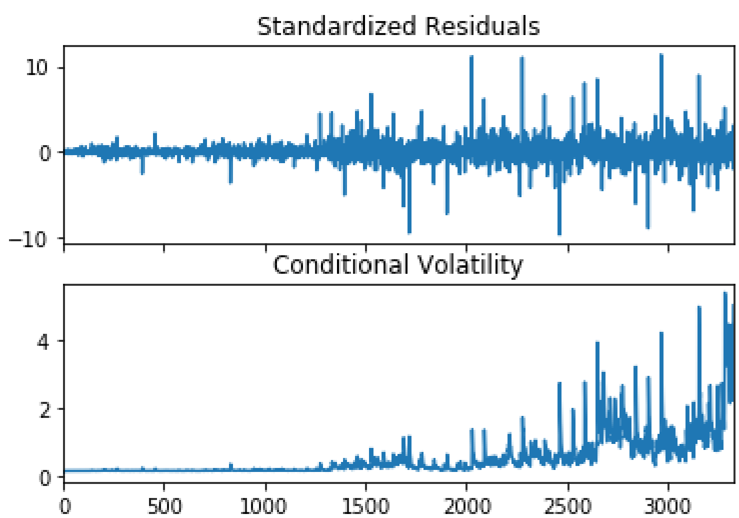
$$E_t[\epsilon^2_{t+h}] = \sigma^2_{t+h} = B^{-1}\sum_{b=1}^{B}\sigma^2_{t+h,b}$$

In [59]:
```
forecasts = res_diff.forecast(horizon=10)
```

In [60]:
```
res_diff.plot()
```

Out[60]:





In [66]:
```
forecasts = res_diff.forecast(horizon=10, method='simulation')
```

Reference

[1] Engle, Robert F. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". Econometrica. 50 (4): 987–1007. doi:10.2307/1912773. JSTOR 1912773.

[2] Bollerslev, Tim (1986). "Generalized Autoregressive Conditional Heteroskedasticity". Journal of Econometrics. 31 (3): 307–327. CiteSeerX 10.1.1.468.2892. doi:10.1016/0304-4076(86)90063-1.

[3] Brooks, Chris (2014). Introductory Econometrics for Finance (3rd ed.). Cambridge: Cambridge University Press. p. 461. ISBN 9781107661455.

[4] https://facebook.github.io/prophet/ (https://facebook.github.io/prophet/)