StockReturnsAnalysis

September 29, 2021

1 Stock and Benchmark Returns Analysis

```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import math
     import scipy.stats as scs
     from scipy import stats
     import statsmodels.api as sm
     import warnings
     warnings.filterwarnings("ignore")
     # fix_yahoo_finance is used to fetch data
     import fix_yahoo_finance as yf
     yf.pdr_override()
[2]: # input
    market = "SPY"
     symbol = 'AAPL'
     start = '2016-01-01'
```

```
[2]: # input
market = "SPY"
symbol = 'AAPL'
start = '2016-01-01'
end = '2019-01-01'

# Read data
data = yf.download(symbol,start,end)
stock_market = yf.download(market, start, end)
```

```
[3]: from datetime import datetime

def days_between(start, end):
    start = datetime.strptime(start, "%Y-%m-%d")
    end = datetime.strptime(end, "%Y-%m-%d")
    n = abs((end - start).days)
```

```
return n
     days_between(start, end)
[3]: 1096
[4]: start = datetime.strptime(start, "%Y-%m-%d")
     end = datetime.strptime(end, "%Y-%m-%d")
     n = abs((end - start).days)
[5]:
     data.head()
[5]:
                                                                  Adj Close \
                       Open
                                   High
                                                 Low
                                                           Close
     Date
     2016-01-04
                 102.610001
                             105.370003
                                          102.000000
                                                      105.349998
                                                                  98.446655
                 105.750000
                             105.849998
                                          102.410004
                                                      102.709999
     2016-01-05
                                                                  95.979675
                100.559998
                                                      100.699997
     2016-01-06
                             102.370003
                                           99.870003
                                                                  94.101387
     2016-01-07
                  98.680000
                             100.129997
                                           96.430000
                                                       96.449997
                                                                  90.129868
     2016-01-08
                  98.550003
                              99.110001
                                           96.760002
                                                       96.959999
                                                                  90.606438
                   Volume
     Date
     2016-01-04
                 67649400
     2016-01-05
                 55791000
     2016-01-06
                 68457400
     2016-01-07
                 81094400
     2016-01-08
                 70798000
[6]: stock_market.head()
[6]:
                                                                    Adj Close \
                       Open
                                   High
                                                 Low
                                                           Close
     Date
     2016-01-04
                 200.490005
                             201.029999
                                          198.589996
                                                      201.020004
                                                                  186.836166
     2016-01-05
                 201.399994
                             201.899994
                                          200.050003
                                                      201.360001
                                                                  187.152161
     2016-01-06
                 198.339996
                             200.059998
                                          197.600006
                                                      198.820007
                                                                   184.791367
     2016-01-07
                 195.330002
                             197.440002
                                          193.589996
                                                      194.050003
                                                                  180.357925
     2016-01-08
                 195.190002
                             195.850006
                                          191.580002
                                                      191.919998
                                                                  178.378235
                    Volume
     Date
     2016-01-04
                 222353500
     2016-01-05 110845800
     2016-01-06
                 152112600
     2016-01-07
                 213436100
     2016-01-08
                 209817200
[7]: rf = 0.01
```

```
[8]: close_px = data[ 'Adj Close']
      returns = close_px.pct_change().dropna()
 [9]: p = np.array(data['Adj Close'])
      mp = np.array(stock_market['Adj Close'])
      dollar vol = np.array(data['Volume']*p)
      market_dollar_vol = np.array(stock_market['Volume']*mp)
[10]: benchmark = stock_market['Adj Close'].pct_change().dropna()
      excess_returns = np.array(returns) - np.array(benchmark)
[11]: data['returns'] = data[ 'Adj Close'].pct_change().dropna()
      benchmark['returns'] = stock_market['Adj Close'].pct_change().dropna()
[12]: data['rea_var'] = 252 * np.cumsum(data['returns']**2) / np.arange(len(data))
      data['rea vol'] = np.sqrt(data['rea var'])
```

Alpha is measure of performance on a risk-adjusted basis Alpha also known as "Jensen index".

Beta is a measure of the volatility, or systematic risk or of a secruity or a portfolio. Beta is used in the capital asset pricing model (CAPM), a model that calculates the expected return of an asset based on its beta and expected market returns.

R-Squared is a statistical measure that represents the percentage of a fund or security's movements that can be explained by movements in a benchmark index (S&P 500).

```
[13]: def adj_close_statistics(close_px):
              sta = scs.describe(close_px)
              print("%14s %15s" % ('statistic', 'value'))
              print(30 * "-")
              print("%14s %15.5f" % ('size', sta[0]))
              print("%14s %15.5f" % ('min', sta[1][0]))
              print("%14s %15.5f" % ('max', sta[1][1]))
              print("%14s %15.5f" % ('mean', sta[2]))
              print("%14s %15.5f" % ('std', np.sqrt(sta[3])))
              print("%14s %15.5f" % ('skew', sta[4]))
              print("%14s %15.5f" % ('kurtosis', sta[5]))
      adj_close_statistics(close_px)
```

statistic	value
size	754.00000
min	85.39510
max	227.83980
mean	142.97159
std	38.35211

```
skew 0.22706
kurtosis -0.96764
```

```
[14]: def print stock statistics(data):
       print("RETURN SAMPLE STATISTICS")
       print("----")
       print("Mean of Daily Log Returns %9.6f" % np.mean(returns))
       print("Std of Daily Log Returns %9.6f" % np.std(returns))
       print("Mean of Annua. Log Returns %9.6f" % (np.mean(returns) * 252))
       print("Std of Annua. Log Returns %9.6f" % (np.std(returns) * math.

sqrt(252)))
       print("----")
       print("Skew of Sample Log Returns %9.6f" % scs.skew(returns))
       print("----")
       print("Kurt of Sample Log Returns %9.6f" % scs.kurtosis(returns))
       scs.kurtosistest(returns)[1])
       print("----")
       scs.normaltest(returns)[1])
       print("----")
       print("Realized Volatility %9.6f" % data['rea_vol'].iloc[-1])
print("Realized Variance %9.6f" % data['rea_var'].iloc[-1])
       print("Realized Variance %9.6f" % data['rea_v
print("----")
       print("Anderson Normality Test:
       print(stats.anderson(returns))
       print("----")
                                                                 ")
       print("Shapiro_Wilk Test:
       print(stats.shapiro(returns))
       print("Sharpe Ratio of Daily Returns:
                                                         ")
       print("{0:.8f}".format(np.mean(returns) / np.std(returns)))
       print("Trading Sharpe for Daily:
       print("{0:.8f}".format((n*6.5) * (np.mean(returns)-rf // np.std(returns)*np.
     \rightarrowsqrt(n*6.5))))
       print("Sharpe of Annua. Returns w/ days: ")
       print("{0:.8f}".format((252) * (np.mean(returns)-rf // np.std(returns)*np.

sqrt(252))))
       print("Sharpe of Annua. Returns w/ days & hours:")
       print("{0:.8f}".format((252*6.5) * (np.mean(returns)-rf // np.
     →std(returns)*np.sqrt(252*6.5))))
print("-----")
       print("Amihud Illiquidity
                                         %9.6g" % np.mean(np.
     →divide(abs(returns),dollar_vol[1:])))
       print("----")
       print("Kelly Formula:
       print("{0:.8f}".format(np.mean(returns) - rf // (np.std(returns))**2))
```

```
print("Compounded Levered Return:
                                         ")
   print("{0:.8f}".format(rf + (((252) * (np.mean(returns)-rf / np.

→std(returns)*np.sqrt(252)))**2) // 2))
   print("Compounded Unlevered Return:
                                    ")
   print("{0:.8f}".format(((np.mean(returns))*252)-(((np.std(returns))*np.
 \rightarrowsqrt(252))**2) // 2))
   return
print_stock_statistics(data)
RETURN SAMPLE STATISTICS
Mean of Daily Log Returns 0.000718
Std of Daily Log Returns 0.014907
Mean of Annua. Log Returns 0.180839
Std of Annua. Log Returns 0.236637
_____
Skew of Sample Log Returns -0.057076
Skew Normal Test p-value 0.518853
Kurt of Sample Log Returns 3.603211
Kurt Normal Test p-value    0.000000
_____
Normal Test p-value
                      0.000000
_____
Realized Volatility
                     0.236911
Realized Variance 0.056127
_____
Anderson Normality Test:
AndersonResult(statistic=11.294812364065251, critical_values=array([0.573,
0.653, 0.783, 0.913, 1.086]), significance_level=array([15., 10., 5., 2.5,
1. 1))
Shapiro_Wilk Test:
(0.9423431754112244, 1.6331307413298203e-16)
Sharpe Ratio of Daily Returns:
0.04814037
Trading Sharpe for Daily:
5.11229805
Sharpe of Annua. Returns w/ days:
0.18083929
Sharpe of Annua. Returns w/ days & hours:
1.17545539
 Amihud Illiquidity
                           2.07985e-12
_____
```

Kelly Formula:

```
-44.99928238
Compounded Levered Return:
3600372.01000000
Compounded Unlevered Return:
0.18083929
```

```
[15]: def print_market_information(benchmark):
       print("RETURN BENCHMARK STATISTICS")
       print("----")
       print("Mean of Daily Log Returns %9.6f" % np.mean(benchmark['returns']))
       print("Std of Daily Log Returns %9.6f" % np.std(benchmark['returns']))
       print("Mean of Annua. Log Returns %9.6f" % (np.mean(benchmark['returns']) *__
     →252))
       print("Std of Annua. Log Returns %9.6f" % (np.std(benchmark['returns']) *__
     \rightarrowmath.sqrt(252)))
       print("----")
       print("Skew of Sample Log Returns %9.6f" % scs.skew(benchmark['returns']))
       →skewtest(benchmark['returns'])[1])
       print("----")
       print("Kurt of Sample Log Returns %9.6f" % scs.
     →kurtosis(benchmark['returns']))
       print("----")
       print("Normal Test p-value %9.6f" % scs.
     →normaltest(benchmark['returns'])[1])
       print("----")
       print("Anderson Normality Test:
                                           ")
       print(stats.anderson(benchmark['returns']))
       return
    print_market_information(benchmark)
```

RETURN BENCHMARK STATISTICS

```
Normal Test p-value
     Anderson Normality Test:
     AndersonResult(statistic=18.24201097391233, critical_values=array([0.573, 0.653,
     0.783, 0.913, 1.086]), significance level=array([15., 10., 5., 2.5, 1.]))
[16]: def linreg(returns, benchmark):
         X = benchmark
         y = returns
         beta, intercept, r_squared, p_value, std_err = stats.linregress(X, y)
         alpha = np.mean(y) - beta * np.mean(X)
                           = ", alpha)
         print("alpha
         print("beta
                              = ", beta)
         print("r_squared
                             = ", r_squared)
         return beta, alpha, r_squared
      def print_market_stock(returns, benchmark):
             y = returns
             x = benchmark
             x = sm.add_constant(x)
             model = sm.OLS(y,x)
             results = model.fit()
             print(results.summary())
      # daily quotes and log returns
      def quotes_returns(returns):
          ''' Plots quotes and returns. '''
         plt.figure(figsize=(9, 6))
         data['returns'].plot()
         plt.title('Stock Daily Returns')
         plt.ylabel('Daily log returns')
         plt.grid(True)
         plt.axis('tight')
      # histogram of annualized daily log returns
      def return_histogram(returns):
         ''' Plots a histogram of the returns. '''
         plt.figure(figsize=(9, 5))
         x = np.linspace(min(returns), max(returns), 100)
         plt.hist(np.array(returns), bins=50, normed=True)
         y = dN(x, np.mean(returns), np.std(returns))
         plt.plot(x, y, linewidth=2)
         plt.xlabel('Log Returns')
         plt.ylabel('Frequency/Probability')
         plt.grid(True)
      # Q-Q plot of annualized daily log returns
```

0.000000

```
def return_qqplot(returns):
   ''' Generates a Q-Q plot of the returns.'''
   plt.figure(figsize=(9, 5))
    sm.qqplot(returns, line='s')
   plt.grid(True)
   plt.title('Q-Q of Annualized Daily Log Returns')
   plt.xlabel('Theoretical Quantiles')
   plt.ylabel('Sample Quantiles')
# realized volatility
def realized_volatility(returns):
    ''' Plots the realized volatility. '''
   plt.figure(figsize=(9, 5))
   data['rea_vol'].plot()
   plt.title('Stock Volatility')
   plt.ylabel('Realized Volatility')
   plt.grid(True)
# mean return, volatility and correlation (252 days moving = 1 year)
def rolling_statistics(returns):
    ''' Calculates and plots rolling statistics (mean, std, correlation). '''
   plt.figure(figsize=(11, 8))
   plt.subplot(311)
   mr = returns.rolling(252).mean() * 252
   mr.plot()
   plt.grid(True)
   plt.ylabel('returns (252d)')
   plt.axhline(mr.mean(), color='r', ls='dashed', lw=1.5)
   plt.subplot(312)
   vo = returns.rolling(252).std() * math.sqrt(252)
   vo.plot()
   plt.grid(True)
   plt.ylabel('volatility (252d)')
   plt.axhline(vo.mean(), color='r', ls='dashed', lw=1.5)
   vx = plt.axis()
   plt.subplot(313)
   co = mr.rolling(252).corr(vo, 252)
   co.plot()
   plt.grid(True)
   plt.ylabel('correlation (252d)')
   cx = plt.axis()
   plt.axis([vx[0], vx[1], cx[2], cx[3]])
   plt.axhline(co.mean(), color='r', ls='dashed', lw=1.5)
```

```
if __name__ == '__main__':
    linreg(returns, benchmark['returns'])
    print_market_stock(returns, benchmark['returns'])
    quotes_returns(returns)
    return_qqplot(returns)
    realized_volatility(returns)
    rolling_statistics(returns)
```

alpha = 0.00024005764515231987 beta = 1.1896463453886688

 $r_{squared} = 0.6516289975275974$

OLS Regression Results

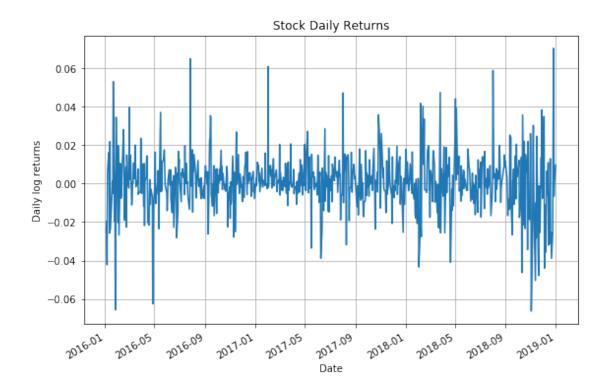
______ Dep. Variable: Adj Close R-squared: 0.425 Model: OLS Adj. R-squared: 0.424 Method: Least Squares F-statistic: 554.2 Least Squares F-statistic: 554.2 Sun, 17 Nov 2019 Prob (F-statistic): 3.25e-92 Date: Time: 17:56:19 Log-Likelihood: 2306.7 No. Observations: 753 AIC: -4609. Df Residuals: 751 BIC: -4600.

Df Model: 1
Covariance Type: nonrobust

=========	=======	========	=======			========		
	coef	std err	t	P> t	[0.025	0.975]		
const	0.0002	0.000	0.581	0.561	-0.001	0.001		
Adj Close	1.1896	0.051	23.542	0.000	1.090	1.289		
=========						========		
Omnibus:		129	.078 Durl	oin-Watson:		1.710		
Prob(Omnibus):	0	.000 Jaro	que-Bera (JB):	1646.468		
Skew:		0	.307 Prol	o(JB):		0.00		
Kurtosis:		10	.218 Cond	d. No.		122.		

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



<Figure size 648x360 with 0 Axes>

