Welcome to Stock Market Analysis project!

In this portfolio project I have done an analysis on stocks from five different companies in healthcare industry over the stock data for one year time period. I have used pandas to get stock information from yahoo Finance, visualize different aspects of it, and finally I have analyzed the risk of a stock, based on its previous performance history. I have also used Monte Carlo method to predict future stock price.

In the projects the following questions will be answerd through analysis and visualization.

1.) What was the change in price of the stock over time?

2.) What was the daily return of the stock on average?

3.) What was the correlation between different stocks' closing prices?

4.) What was the correlation between different stocks' daily returns?

5.) How much value do we put at risk by investing in a particular stock?

6.) How can we attempt to predict future stock behavior?

In [5]:
```python
#Importing Libraries for the Analysis

import pandas as pd
from pandas import Series,DataFrame
import numpy as np

# For Visualization
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
%matplotlib inline


# For time stamps
from datetime import datetime

# For division
from __future__ import division
```

In [6]:
```python
# For reading data for Yahoo Finance

import pandas_datareader as dr
```

Creating dataframe for each companies in Health Care industry with the data taken from Yahoo finance within the period '2021-07-10'-'2022-07-10' Healthcare Industry companies: United Health Group Incorporated(UNH), Eli & Lily (LLY), Johnson & Johnson (J&J), Pfizer(PFE), Novo Nordisk(NVO)

In [7]:
```python
UNH=dr.get_data_yahoo('UNH',start='2021-07-10',end='2022-07-10')
LLY=dr.get_data_yahoo('LLY',start='2021-07-10',end='2022-07-10')
JNJ=dr.get_data_yahoo('JNJ',start='2021-07-10',end='2022-07-10')
PFE=dr.get_data_yahoo('PFE',start='2021-07-10',end='2022-07-10')
NVO=dr.get_data_yahoo('NVO',start='2021-07-10',end='2022-07-10')
```

In [8]:
```python
# Different way : Getting data for all companies with For Loops
health_list=['UNH','LLY','JNJ','PFE','NVO']
for stock in health_list:
    globals()[stock]=dr.get_data_yahoo(stock,start='2021-07-10',end='2022-07-10')
```

In [10]:
```python
PFE.head()
```

Out[10]:

Date	High	Low	Open	Close	Volume	Adj Close
2021-07-12	40.250000	39.599998	39.660000	39.759998	24513000.0	38.451939
2021-07-13	39.799999	39.529999	39.770000	39.650002	12222000.0	38.345566
2021-07-14	40.029999	39.660000	39.720001	39.950001	15888600.0	38.635696
2021-07-15	40.189999	39.860001	39.950001	40.090000	20250800.0	38.771080
2021-07-16	40.349998	39.930000	40.139999	40.349998	24270400.0	39.022530

In [11]:
```python
#summary stats
UNH.describe()
```

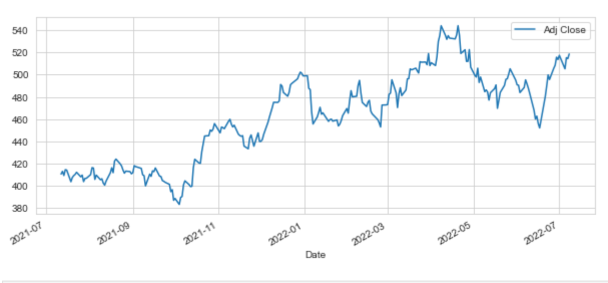
Out[11]:

	High	Low	Open	Close	Volume	Adj Close
count	251.000000	251.000000	251.000000	251.000000	2.510000e+02	251.000000
mean	469.266694	459.537051	464.126215	464.661076	3.076912e+06	461.428653
std	39.791978	38.122297	38.861917	39.129624	1.261639e+06	40.336668
min	393.690002	383.119995	389.339996	387.010010	1.284200e+06	383.246979
25%	425.169998	419.580002	422.049988	423.134995	2.409400e+06	417.555054
50%	473.179993	462.000000	467.190002	468.410004	2.977400e+06	465.368378
75%	499.970001	488.504990	494.005005	495.050003	3.535400e+06	492.562622
max	553.289978	539.000000	545.500000	546.010010	1.586110e+07	544.069763

In stock we see two columns, closing price and adjusted closing price. The closing price refers to the price the stock was traded at last whereas Adjusted closing price is the closing price adjusted for corporate actions such as dividend payouts, stock splits, or the issuance of more shares.

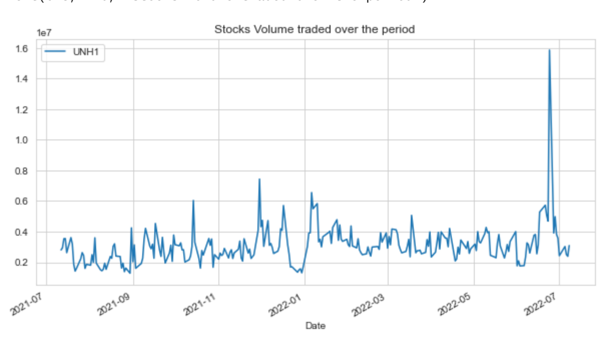
In [12]:
```python
#Having a look thorugh plot of the Adj closing price of United Health Group
UNH['Adj Close'].plot(legend=True,figsize=(10,4))
```

Out[12]: <AxesSubplot:xlabel='Date'>



In [13]:
```python
#Volume of stocks traded over the 1 year period

UNH['Volume'].plot(legend=True,figsize=(10,5))
plt.legend(['UNH1'])
plt.title('Stocks Volume traded over the period')
# visibly in July 2022 there is a huge peak in the stock volume being traded for UNH
```

Out[13]: Text(0.5, 1.0, 'Stocks Volume traded over the period')

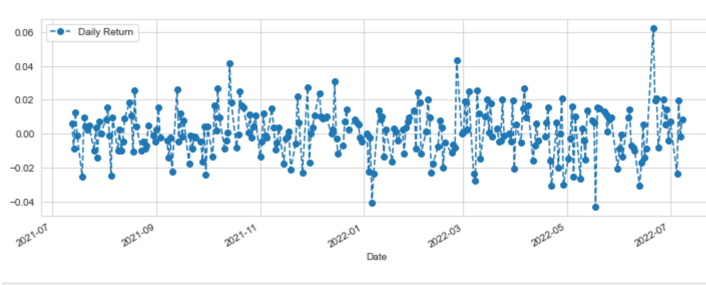


Daily Return analysis: To do the analysis we will use the percentage change in Adj closing price in each day.

In [14]:
```python
# We'll use pct_change to find the percent change of stock for each day

UNH['Daily Return'] = UNH['Adj Close'].pct_change()
```

In [15]:
```python
# Then we'll plot the daily return percentage

UNH['Daily Return'].plot(figsize=(12,4),legend=True,linestyle='--',marker='o')
```

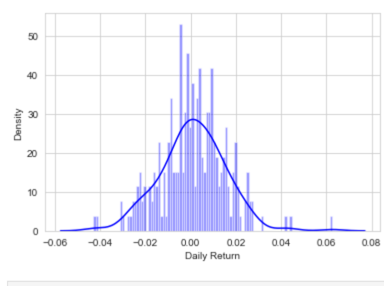
Out[15]: <AxesSubplot:xlabel='Date'>



In [16]:
```python
# We use the dropna() here, otherwise the NaN values can't be read by seaborn
sns.distplot(UNH['Daily Return'].dropna(),bins=100,color='blue')

# Could have also done:
#AAPL['Daily Return'].hist()
```

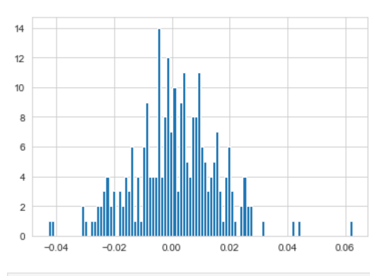
```
C:\Users\T470\AppData\Roaming\Python\Python310\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[16]: <AxesSubplot:xlabel='Daily Return', ylabel='Density'>



In [17]:
```python
UNH['Daily Return'].hist(bins=100)
```

Out[17]: <AxesSubplot:>



In [18]:
```python
#Grab all the closing prices for the tech stock list into one DataFrame
closing_df=dr.get_data_yahoo(health_list,start='2021-07-10',end='2022-07-10')['Adj Close']
```

In [19]:
```python
closing_df.head()
```

Out[19]:

Symbols / Date	UNH	LLY	JNJ	PFE	NVO
2021-07-12	410.553650	232.729950	165.252945	38.451939	85.311806
2021-07-13	413.020660	232.029831	165.048203	38.345562	85.370918
2021-07-14	409.270752	233.065247	166.169525	38.635693	85.646751
2021-07-15	414.510742	228.253067	164.170654	38.771084	86.306786
2021-07-16	414.165375	229.229309	163.907394	39.022533	87.341164

In [20]:
```python
#make a new health_returns dataframe with percentage chagnge data
health_returns=closing_df.pct_change()
```

In [21]:
```python
health_returns.head()
```

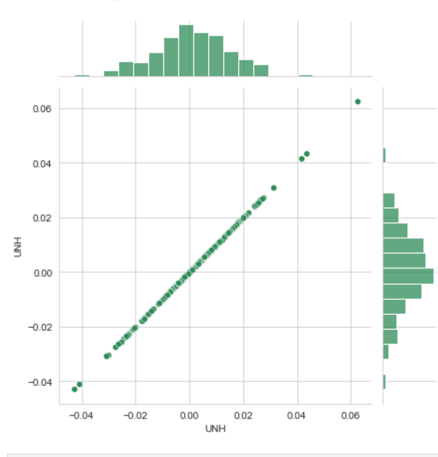
Out[21]:

Symbols / Date	UNH	LLY	JNJ	PFE	NVO
2021-07-12	NaN	NaN	NaN	NaN	NaN
2021-07-13	0.006009	-0.003008	-0.001239	-0.002766	0.000693
2021-07-14	-0.009079	0.004462	0.006794	0.007566	0.003231
2021-07-15	0.012803	-0.020647	-0.012029	0.003504	0.007706
2021-07-16	-0.000833	0.004277	-0.001604	0.006485	0.011985

In [22]:
```python
# Comparing UnitedHealth Group Incorporated to itself should show a perfectly linear relationship
sns.jointplot('UNH','UNH',health_returns,kind='scatter',color='seagreen')
```

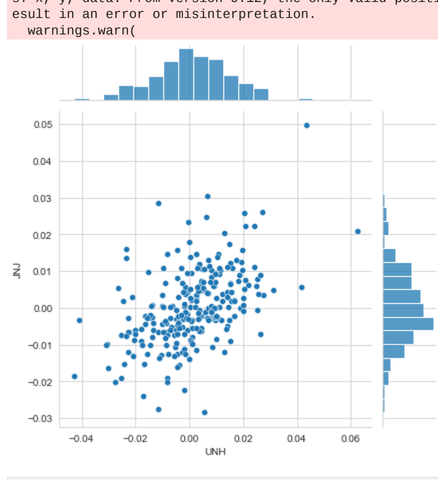
```
C:\Users\T470\AppData\Roaming\Python\Python310\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y, data. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[22]: <seaborn.axisgrid.JointGrid at 0x1e792c67070>



In [23]:
```python
# We'll use joinplot to compare the daily returns of United Health group and Johnson & Johnson
j=sns.jointplot('UNH','JNJ',health_returns,kind='scatter')
```

```
C:\Users\T470\AppData\Roaming\Python\Python310\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y, data. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [24]:
```python
import scipy.stats as stats
sns.set(font_scale=1.5)
```

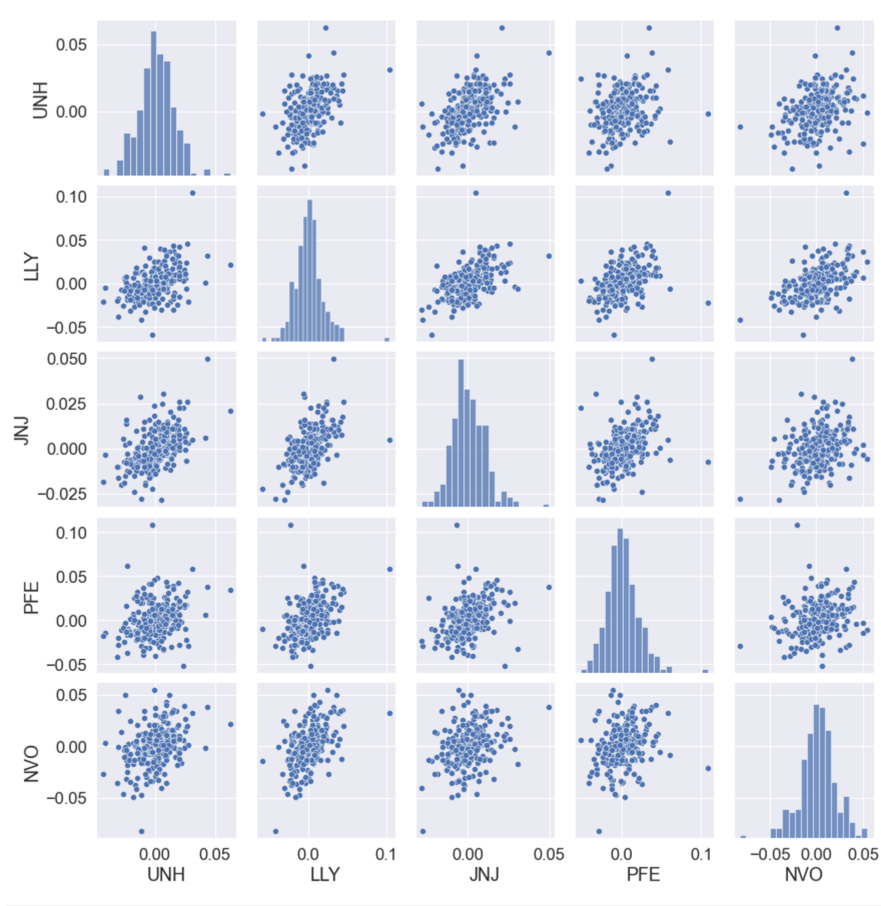
In [25]:
```python
health_returns[['UNH','JNJ']].corr(method='pearson')
```

Out[25]:

Symbols / Symbols	UNH	JNJ
UNH	1.000000	0.500324
JNJ	0.500324	1.000000

In [26]:
```python
# We can simply call pairplot on our DataFrame for an automatic visual analysis of all the comparisons
sns.set(font_scale=1.5)
sns.pairplot(health_returns.dropna())
```

Out[26]: <seaborn.axisgrid.PairGrid at 0x1e792d7bd00>



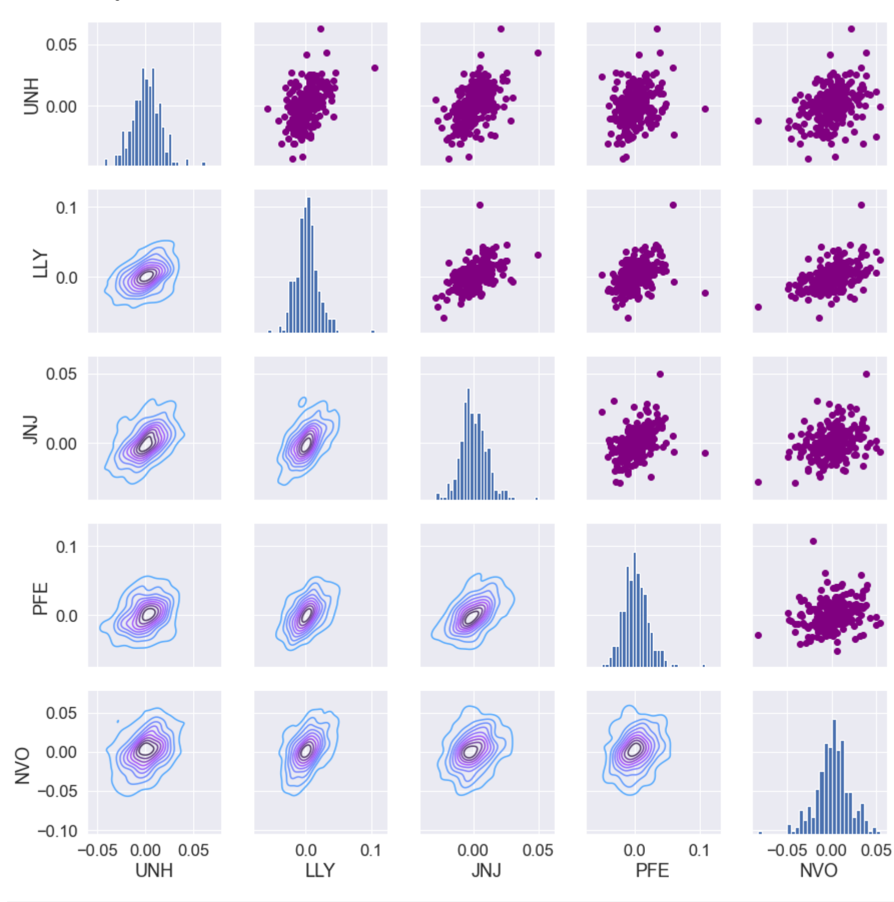
In [27]:
```python
health_returns[['LLY','NVO']].corr(method='pearson')
```

Out[27]:

Symbols / Symbols	LLY	NVO
LLY	1.000000	0.485204
NVO	0.485204	1.000000

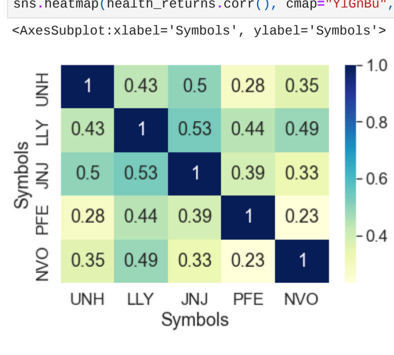
In [28]:
```python
# Set up our figure by naming it returns_fig, call PairPLot on the DataFrame
returns_fig = sns.PairGrid(health_returns.dropna())

# Using map_upper we can specify what the upper triangle will look like.
returns_fig.map_upper(plt.scatter,color='purple')

# We can also define the lower triangle in the figure, inclufing the plot type (kde) or the color map (BluePurple)
returns_fig.map_lower(sns.kdeplot,cmap='cool_d')

# Finally we'll define the diagonal as a series of histogram plots of the daily return
returns_fig.map_diag(plt.hist,bins=30)
```

Out[28]: <seaborn.axisgrid.PairGrid at 0x1e78e377c70>



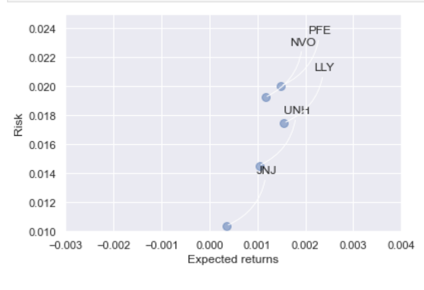
In [29]:
```python
# Let's go ahead and use sebron for a quick correlation plot for the daily returns
#sns.corrplot(health_returns.dropna(),annot=True)

sns.heatmap(health_returns.corr(), cmap="YlGnBu", annot=True)
```

Out[29]: <AxesSubplot:xlabel='Symbols', ylabel='Symbols'>



Just as from the PairPlot we see here numerically and visually that Johnson & Johnson and Eli lily & Company had the strongest correlation of daily stock return. It's also interesting to see that all the companies from the industry are positively correlated with JNJ and LLY being the highest correlation and Novo nordisk and Pfizer lowest pearson correlation value. Now that we've done some daily return analysis, let's go ahead and start looking deeper into actual risk analysis.

In [30]:
```python
sns.set_style('whitegrid')
sns.set(font_scale=1)
# Let's start by defining a new DataFrame as a clenaed version of the oriignal tech_rets DataFrame
rets = health_returns.dropna()

area = np.pi*20

plt.scatter(rets.mean(), rets.std(),alpha = 0.5,s =area)

# Set the x and y limits of the plot.
plt.ylim([0.01,0.025])
plt.xlim([-0.003,0.004])

#Set the plot axis titles
plt.xlabel('Expected returns')
plt.ylabel('Risk')

for label, x, y in zip(rets.columns, rets.mean(), rets.std()):
    plt.annotate(
        label,
        xy = (x, y), xytext = (50, 50),
        textcoords = 'offset points', ha = 'right', va = 'bottom',
        arrowprops = dict(arrowstyle = '-', connectionstyle = 'arc3,rad=-0.3'))
```



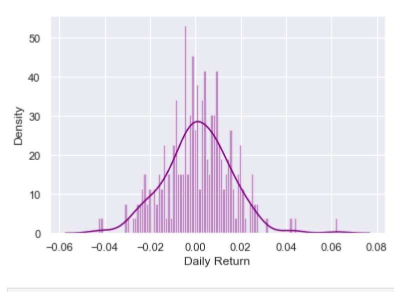
From the risk aalysis we prefer to invest in stocks that has higher expected returns and less Risk. From the analysis, Johnson & Johnson seems to have a very low risk but with lowest expecte returns among all the other companies. Eli Lily seems to have the highest expected returns among all the companies. United health group altghou had a little less return but poses lower risk than Eli Lily. Novo nordisk and pfizer both has higher returns but with high risk. Ideal investment would be to invest in United health group.

Value at Risk: Let's define a value at risk parameter for our stocks. We can treat value at risk as the amount of money we could expect to lose (aka putting at risk) for a given confidence interval. Here Value at risk is analyzed using the "bootstrap" method.For this method we will calculate the empirical quantiles from a histogram of daily returns

In [31]:
```python
# Lets pick United health group stocks to get Daily Returns histogram.
# We use of dropna() here, otherwise the NaN values can't be read by seaborn
sns.distplot(UNH['Daily Return'].dropna(),bins=100,color='purple')
```

```
C:\Users\T470\AppData\Roaming\Python\Python310\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[31]: <AxesSubplot:xlabel='Daily Return', ylabel='Density'>



In [32]:
```python
# To ger the risk value of stock we use quantile.
# The 0.05 empirical quantile of daily returns
rets['UNH'].quantile(0.05)
```

Out[32]: -0.023516431110474197

The 0.05 empirical quantile of daily returns is at -0.023. That means that with 95% confidence, our worst daily loss will not exceed 2.3%. If we have a $10000 dollar investment, our one-day$5230. so we with 95% confidence we can say we only going to lose $230 out of$10000 investment.

In [33]:
```python
rets['LLY'].quantile(0.05)
```

Out[33]: -0.023589604810083202

In [34]:
```python
# Set up our time horizon
days = 365

# Now our delta
dt = 1/days

# Now let's grab our mu (drift) from the expected return data we got for AAPL
mu = rets.mean()['UNH']

# Now let's grab the volatility of the stock from the std() of the average return
sigma = rets.std()['UNH']
```

In [35]:
```python
def stock_monte_carlo(start_price,days,mu,sigma):
    ''' This function takes in starting stock price, days of simulation,mu,sigma, and returns simulated price array'''

    # Define a price array
    price = np.zeros(days)
    price[0] = start_price
    # Schok and Drift
    shock = np.zeros(days)
    drift = np.zeros(days)

    # Run price array for number of days
    for x in range(1,days):

        # Calculate Schock
        shock[x] = np.random.normal(loc=mu * dt, scale=sigma * np.sqrt(dt))
        # Calculate Drift
        drift[x] = mu * dt
        # Calculate Price
        price[x] = price[x-1] + (price[x-1] * (drift[x] + shock[x]))

    return price
```

In [36]:
```python
UNH1=np.round(UNH.loc[:,:],decimals=2)
UNH
```

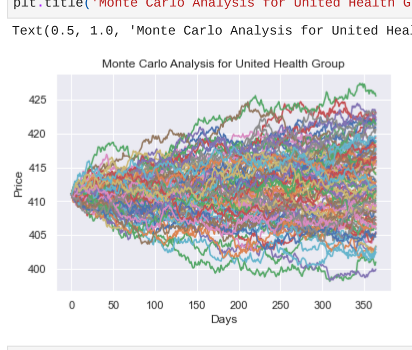
Out[36]:

Date	High	Low	Open	Close	Volume	Adj Close	Daily Return
2021-07-12	416.399994	410.309998	411.019989	416.040009	2802600.0	410.553619	NaN
2021-07-13	419.690002	415.709991	416.380005	418.540009	2948900.0	413.020660	0.006009
2021-07-14	422.529999	413.350006	420.769989	414.739990	3538700.0	409.270721	-0.009079
2021-07-15	421.730011	407.200012	411.910004	420.049988	3546500.0	414.510742	0.012803
2021-07-16	422.290009	417.640015	421.359985	419.700012	2625400.0	414.165375	-0.000833
...	...	...	...	...	...	...	...
2022-07-01	517.530029	502.309998	512.320007	517.400024	2426000.0	517.400024	0.007340
2022-07-05	511.000000	492.250000	507.640015	505.239990	3029600.0	505.239990	-0.023502
2022-07-06	517.409973	504.299988	505.640015	515.289978	2506700.0	515.289978	0.019892
2022-07-07	517.299988	512.229980	515.250000	514.380005	2385400.0	514.380005	-0.001766
2022-07-08	528.369995	511.010010	512.309998	518.630005	3092100.0	518.630005	0.008262

251 rows × 7 columns

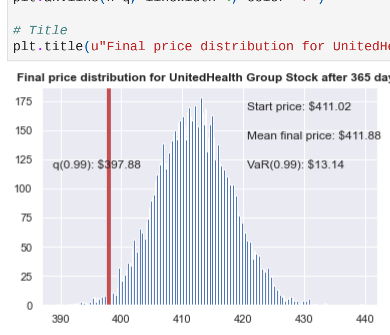
In [37]:
```python
# Get start price from UNH.head()
start_price = 411.02

for run in range(100):
    plt.plot(stock_monte_carlo(start_price,days,mu,sigma))
plt.xlabel("Days")
plt.ylabel("Price")
plt.title('Monte Carlo Analysis for United Health Group')
```

Out[37]: Text(0.5, 1.0, 'Monte Carlo Analysis for United Health Group')



In [38]:
```python
# Set a large numebr of runs
runs = 10000

# Create an empty matrix to hold the end price data
simulations = np.zeros(runs)

# Set the print options of numpy to only display 0-5 points from an array to suppress output
np.set_printoptions(threshold=5)

for run in range(runs):
    # Set the simulation data point as the last stock price for that run
    simulations[run] = stock_monte_carlo(start_price,days,mu,sigma)[days-1];
```

In [39]:
```python
# Now we'lll define q as the 1% empirical qunatile, this basically means that 99% of the values should fall between here
q = np.percentile(simulations, 1)

# Now let's plot the distribution of the end prices
plt.hist(simulations,bins=200)

# Using plt.figtext to fill in some additional information onto the plot

# Starting Price
plt.figtext(0.6, 0.8, s="Start price: $%.2f" %start_price)
# Mean ending price
plt.figtext(0.6, 0.7, "Mean final price: $%.2f" % simulations.mean())

# Variance of the price (within 99% confidence interval)
plt.figtext(0.6, 0.6, "VaR(0.99): $%.2f" % (start_price - q,))

# Display 1% quantile
plt.figtext(0.15, 0.6, "q(0.99): $%.2f" % q)

# Plot a line at the 1% quantile result
plt.axvline(x=q, linewidth=4, color='r')

# Title
plt.title(u"Final price distribution for UnitedHealth Group Stock after %s days" % days, weight='bold');
```



Now we have looked at the 1% empirical quantile of the final price distribution to estimate the Value at Risk for the UnitedHealth Group, which looks to be $13.14 for every investment of$411.02 (the price of one inital United Heath Group stock).The value at risk is $397.88

This basically means for every initial stock you purchase your putting about $13.14 at risk 99% of the time from our Monte Carlo Simulation.