strategy

March 17, 2024

[184]:
```python
import yfinance as yf
spy_data = yf.download('SPY', start='2010-01-01', end='2023-12-31')['Adj Close']
gld_data = yf.download('GLD', start='2010-01-01', end='2023-12-31')['Adj Close']
vix_data = yf.download('GLD', start='2010-01-01', end='2023-12-31')['Adj Close']
spy_returns = spy_data.pct_change().dropna()
gld_returns = gld_data.pct_change().dropna()
vix_returns = gld_data.pct_change().dropna()
# spy_annual_returns = (1 + spy_returns).resample('Y').prod() - 1
# gld_annual_returns = (1 + gld_returns).resample('Y').prod() - 1
correlation_spy_gold = spy_returns.corr(gld_returns)
correlation_matrix = pd.concat([spy_returns, gld_returns, vix_returns], axis=1).
↪corr()
correlation_matrix.columns = ['SPY', 'GLD', 'VIX']
correlation_matrix.index = ['SPY', 'GLD', 'VIX']
print(correlation_matrix)
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed

          SPY       GLD       VIX
SPY  1.000000  0.044096  0.044096
GLD  0.044096  1.000000  1.000000
VIX  0.044096  1.000000  1.000000
```

[164]:
```python
import yfinance as yf
import pandas as pd

start_date = '2017-01-01'
end_date = '2024-01-01'

# Select 6 random stocks
stock_symbols = ['GOOGL', 'CYCC', 'NPV', 'AMZN', 'PTLC', 'NFLX']
# stock_symbols = ['SPY']
#select Gold eth and volatility (VIX)
gold_symbol = 'GLD'
vix_symbol = '^VIX'
```

```python
# Retrieve historical data
stocks_data = yf.download(stock_symbols, start=start_date, end=end_date,␣
 ↪progress=False)['Adj Close']
gold_data = yf.download(gold_symbol, start=start_date, end=end_date,␣
 ↪progress=False)['Adj Close']
vix_data = yf.download(vix_symbol, start=start_date, end=end_date,␣
 ↪progress=False)['Adj Close']
stocks_data.head(), gold_data.head(), vix_data.head()
```

[164]:
```
(Ticker           AMZN    CYCC      GOOGL        NFLX       NPV       PTLC
 Date
 2017-01-03  37.683498  1641.0  40.400501  127.489998  9.640063  22.482380
 2017-01-04  37.859001  1584.0  40.388500  129.410004  9.662382  22.675312
 2017-01-05  39.022499  1608.0  40.651001  131.809998  9.721887  22.665012
 2017-01-06  39.799500  1611.0  41.260502  131.070007  9.692138  22.721207
 2017-01-09  39.846001  1800.0  41.359001  130.949997  9.766520  22.674374,
 Date
 2017-01-03    110.470001
 2017-01-04    110.860001
 2017-01-05    112.580002
 2017-01-06    111.750000
 2017-01-09    112.669998
 Name: Adj Close, dtype: float64,
 Date
 2017-01-03    12.85
 2017-01-04    11.85
 2017-01-05    11.67
 2017-01-06    11.32
 2017-01-09    11.56
 Name: Adj Close, dtype: float64)
```

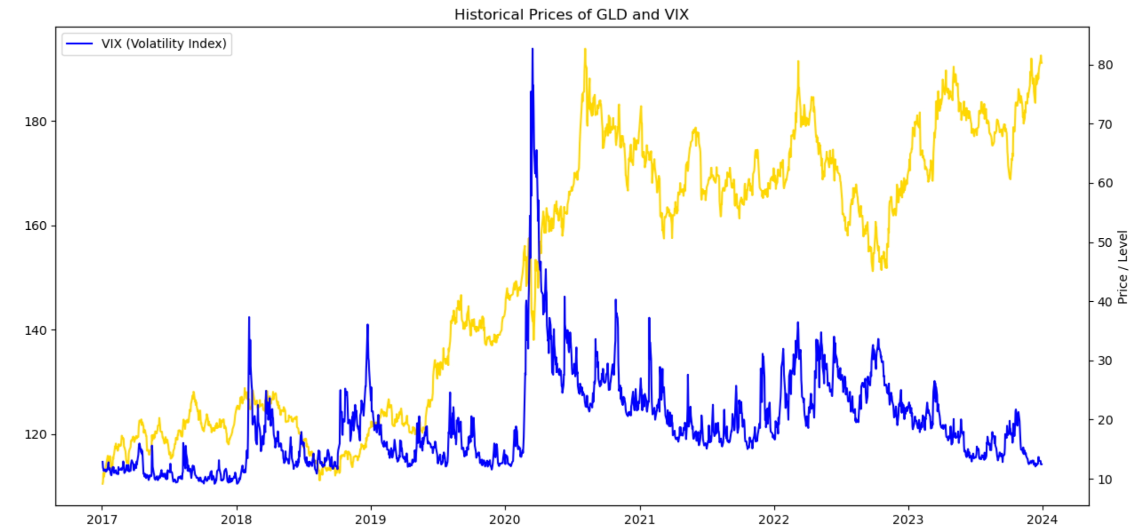
[165]:
```python
# Calculate daily returns for the stocks, gold, and VIX
stock_daily_returns = stocks_data.pct_change().dropna()
gold_daily_returns = gold_data.pct_change().dropna()
vix_daily_returns = vix_data.pct_change().dropna()

# Annualize the daily returns to get a sense of the yearly performance
# approximately 252 trading days in a year
stock_annual_returns = (1 + stock_daily_returns).resample('Y').prod() - 1
gold_annual_returns = (1 + gold_daily_returns).resample('Y').prod() - 1
vix_annual_returns = (1 + vix_daily_returns).resample('Y').prod() - 1

# Simulate the $1 portfolio across the selected stocks for simplicity
# Here, I assume equal weighting for each stock in the portfolio
portfolio_daily_returns = stock_daily_returns.mean(axis=1)
```

```
portfolio_annual_returns = (1 + portfolio_daily_returns).resample('Y').prod() -
 ↪1

annual_returns = pd.DataFrame({
    'Portfolio': portfolio_annual_returns,
    'Gold': gold_annual_returns,
    'VIX': vix_annual_returns
})

annual_returns
```

[165]:

Date	Portfolio	Gold	VIX
2017-12-31	0.134611	0.119308	-0.140856
2018-12-31	-0.047909	-0.019410	1.302536
2019-12-31	0.297390	0.178557	-0.457907
2020-12-31	0.315459	0.248146	0.650943
2021-12-31	0.093736	-0.041489	-0.243077
2022-12-31	-0.440453	-0.007721	0.258420
2023-12-31	0.179076	0.126916	-0.425473

[166]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(15, 7))

# Plot GLD data
plt.plot(gold_data.index, gold_data, label='GLD (Gold ETF)', color='gold')
# plt.plot(stocks_data.index, stocks_data, label='stock', color='red')

# Plot VIX data
plt.twinx()
plt.plot(vix_data.index, vix_data, label='VIX (Volatility Index)', color='blue')
plt.title('Historical Prices of GLD and VIX')
plt.xlabel('Date')
plt.ylabel('Price / Level')
plt.legend(loc='upper left')

plt.show()
```



[167]:
```
import yfinance as yf
import pandas as pd
import numpy as np

start_date = '2017-05-01'
end_date = '2024-02-01'

stock_symbols = ['GOOGL', 'CYCC', 'NPV', 'AMZN', 'PTLC', 'NFLX']
gold_symbol = 'GLD'
vix_symbol = '^VIX'
stocks_data = yf.download(stock_symbols, start=start_date, end=end_date,␣
 ↪progress=False)['Adj Close']
gold_data = yf.download(gold_symbol, start=start_date, end=end_date,␣
 ↪progress=False)['Adj Close']
vix_data = yf.download(vix_symbol, start=start_date, end=end_date,␣
 ↪progress=False)['Adj Close']
daily_returns = stocks_data.pct_change().fillna(0)

# Assuming equal weight
weights = np.full(len(stock_symbols), 1 / len(stock_symbols))
portfolio_daily_return = daily_returns.dot(weights)

# Calculate the indicator: difference between the normalized values of GLD and␣
 ↪VIX
indicator = (gold_data / gold_data.mean()) - (vix_data / vix_data.mean())

# Generate trading signals based on the indicator: 1 for long, 0 for hold
signals = np.where(indicator > 0, 1, 0)
```

```python
# Apply the signals to the portfolio's daily returns
trading_returns = portfolio_daily_return * signals

# cumulative returns
signal_cumulative_returns = (1 + trading_returns).cumprod()

# Buy-and-hold strategy
buy_and_hold_cumulative_returns = (1 + portfolio_daily_return).cumprod()

comparison = pd.DataFrame({
    'Signal-Based': signal_cumulative_returns,
    'Buy-and-Hold': buy_and_hold_cumulative_returns
})

comparison
```

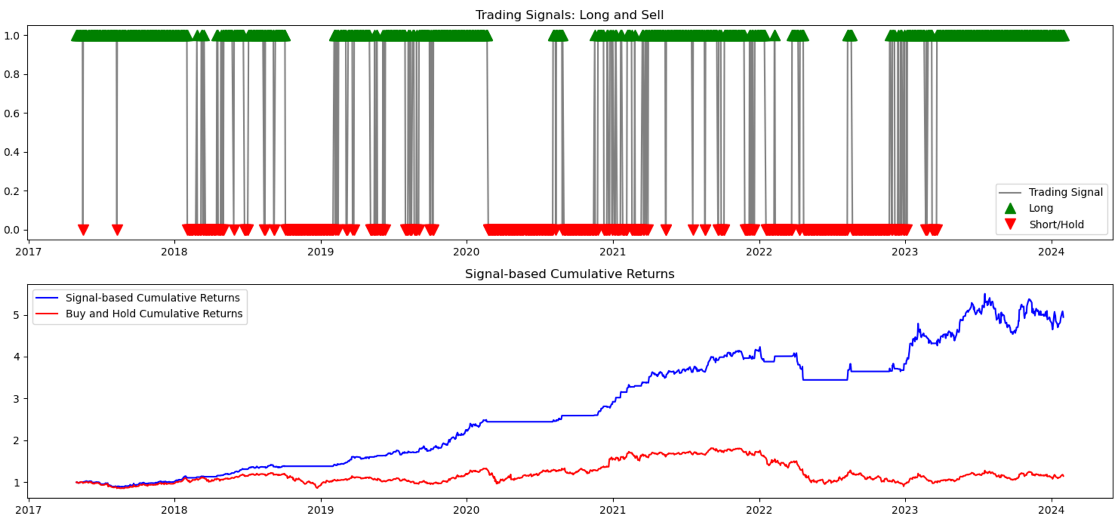
[167]:

```
            Signal-Based  Buy-and-Hold
Date
2017-05-01      1.000000      1.000000
2017-05-02      1.008387      1.008387
2017-05-03      0.998085      0.998085
2017-05-04      0.992450      0.992450
2017-05-05      0.984348      0.984348
…                    …             …
2024-01-25      4.948815      1.151569
2024-01-26      4.982716      1.159458
2024-01-29      5.083900      1.183003
2024-01-30      5.018424      1.167767
2024-01-31      4.943985      1.150446

[1700 rows x 2 columns]
```

[187]:

```python
import matplotlib.pyplot as plt

signals_df = pd.DataFrame(signals, index=stocks_data.index, columns=['Signal'])
signal_cumulative_returns_df = pd.DataFrame(signal_cumulative_returns,␣
 ↪index=stocks_data.index, columns=['Cumulative Returns'])

plt.figure(figsize=(15, 7))

#Long (1) as green, sell (0) as red
plt.subplot(2, 1, 1)
plt.plot(signals_df.index, signals_df['Signal'], label='Trading Signal',␣
 ↪color='gray')
plt.plot(signals_df[signals_df['Signal'] == 1].index,␣
 ↪signals_df['Signal'][signals_df['Signal'] == 1], '^', label='Long',␣
 ↪color='green', markersize=10)
```

```
plt.plot(signals_df[signals_df['Signal'] == 0].index, signals_df['Signal'][signals_df['Signal'] == 0], 'v', label='Short/Hold', color='red', markersize=10)
plt.title('Trading Signals: Long and Sell')
plt.legend()

# Plot the signal-based cumulative returns
plt.subplot(2, 1, 2)
plt.plot(signal_cumulative_returns_df.index, signal_cumulative_returns_df['Cumulative Returns'], label='Signal-based Cumulative Returns', color='blue')
plt.plot(buy_and_hold_cumulative_returns, label='Buy and Hold Cumulative Returns', color="red")
plt.title('Signal-based Cumulative Returns')
plt.legend()

plt.tight_layout()
plt.show()
```



[169]:
```
trading_returns = portfolio_daily_return * signals
trading_returns_percentage = trading_returns * 100
trading_returns_percentage.name = 'Trading Returns (%)'
trading_returns_percentage.to_csv('trading_returns.csv', index=True)
print(trading_returns_percentage)
```

```
Date
2017-05-01    0.000000
2017-05-02    0.838702
2017-05-03   -1.021645
2017-05-04   -0.564590
```

```
2017-05-05   -0.816389
                  …
2024-01-25    1.333816
2024-01-26    0.685030
2024-01-29    2.030713
2024-01-30   -1.287917
2024-01-31   -1.483310
Name: Trading Returns (%), Length: 1700, dtype: float64
```

[170]:
```
spy_returns.corr(trading_returns_percentage)
```

[170]:
```
0.20344650814113435
```

[171]:
```
factors_df = pd.read_csv('ff_research.csv', index_col=0)
factors_df.index = pd.to_datetime(factors_df.index, format='%Y%m%d')
factors_df
```

[171]:

	Mkt-RF	SMB	HML	RMW	CMA	RF
2017-05-01	0.21	0.25	-0.13	-0.17	-0.50	0.003
2017-05-02	0.03	-0.47	-0.21	0.40	-0.35	0.003
2017-05-03	-0.19	-0.52	0.22	-0.04	0.13	0.003
2017-05-04	0.02	-0.13	-0.36	0.36	-0.71	0.003
2017-05-05	0.46	0.11	0.00	-0.22	0.65	0.003
…	…	…	…	…	…	…
2024-01-25	0.46	0.20	0.56	-0.19	0.55	0.022
2024-01-26	-0.02	0.35	-0.27	0.22	-0.02	0.022
2024-01-29	0.85	0.89	-0.59	-1.13	-0.31	0.022
2024-01-30	-0.13	-0.96	0.84	1.00	0.13	0.022
2024-01-31	-1.74	-0.89	-0.30	-0.21	0.37	0.022

[1700 rows x 6 columns]

[172]:
```
CVNA = yf.download('CVNA', start='2017-05-01', end='2024-02-01')['Adj Close']
COST = yf.download('CVNA', start='2017-05-01', end='2024-02-01')['Adj Close']
cvna_daily_return = CVNA.pct_change().fillna(0)
cost_daily_return = COST.pct_change().fillna(0)
cvna_daily_return.name = "cvna"
cost_daily_return.name = "cost"
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
```

[173]:
```
print(trading_returns_percentage)
print(CVNA)
print(COST)
print(factors_df)
combined_data = pd.concat([trading_returns_percentage, cvna_daily_return,
 ↪cost_daily_return, factors_df], axis=1)
```

```
combined_data
```

```
Date
2017-05-01    0.000000
2017-05-02    0.838702
2017-05-03   -1.021645
2017-05-04   -0.564590
2017-05-05   -0.816389
                 …
2024-01-25    1.333816
2024-01-26    0.685030
2024-01-29    2.030713
2024-01-30   -1.287917
2024-01-31   -1.483310
Name: Trading Returns (%), Length: 1700, dtype: float64
Date
2017-05-01    10.770000
2017-05-02    10.100000
2017-05-03     8.720000
2017-05-04     9.980000
2017-05-05    10.920000
                 …
2024-01-25    41.000000
2024-01-26    41.799999
2024-01-29    44.919998
2024-01-30    44.139999
2024-01-31    43.060001
Name: Adj Close, Length: 1700, dtype: float64
Date
2017-05-01    10.770000
2017-05-02    10.100000
2017-05-03     8.720000
2017-05-04     9.980000
2017-05-05    10.920000
                 …
2024-01-25    41.000000
2024-01-26    41.799999
2024-01-29    44.919998
2024-01-30    44.139999
2024-01-31    43.060001
Name: Adj Close, Length: 1700, dtype: float64
            Mkt-RF   SMB   HML   RMW   CMA     RF
2017-05-01    0.21  0.25 -0.13 -0.17 -0.50  0.003
2017-05-02    0.03 -0.47 -0.21  0.40 -0.35  0.003
2017-05-03   -0.19 -0.52  0.22 -0.04  0.13  0.003
2017-05-04    0.02 -0.13 -0.36  0.36 -0.71  0.003
2017-05-05    0.46  0.11  0.00 -0.22  0.65  0.003
```

```
…              …    …    …    …    …     …
2024-01-25    0.46  0.20  0.56 -0.19  0.55  0.022
2024-01-26   -0.02  0.35 -0.27  0.22 -0.02  0.022
2024-01-29    0.85  0.89 -0.59 -1.13 -0.31  0.022
2024-01-30   -0.13 -0.96  0.84  1.00  0.13  0.022
2024-01-31   -1.74 -0.89 -0.30 -0.21  0.37  0.022

[1700 rows x 6 columns]
```

[173]:

```
            Trading Returns (%)      cvna      cost  Mkt-RF   SMB   HML   RMW  \
2017-05-01             0.000000  0.000000  0.000000    0.21  0.25 -0.13 -0.17
2017-05-02             0.838702 -0.062210 -0.062210    0.03 -0.47 -0.21  0.40
2017-05-03            -1.021645 -0.136634 -0.136634   -0.19 -0.52  0.22 -0.04
2017-05-04            -0.564590  0.144495  0.144495    0.02 -0.13 -0.36  0.36
2017-05-05            -0.816389  0.094188  0.094188    0.46  0.11  0.00 -0.22
…                           …         …         …       …     …     …     …
2024-01-25             1.333816 -0.024506 -0.024506    0.46  0.20  0.56 -0.19
2024-01-26             0.685030  0.019512  0.019512   -0.02  0.35 -0.27  0.22
2024-01-29             2.030713  0.074641  0.074641    0.85  0.89 -0.59 -1.13
2024-01-30            -1.287917 -0.017364 -0.017364   -0.13 -0.96  0.84  1.00
2024-01-31            -1.483310 -0.024468 -0.024468   -1.74 -0.89 -0.30 -0.21

             CMA     RF
2017-05-01 -0.50  0.003
2017-05-02 -0.35  0.003
2017-05-03  0.13  0.003
2017-05-04 -0.71  0.003
2017-05-05  0.65  0.003
…             …      …
2024-01-25  0.55  0.022
2024-01-26 -0.02  0.022
2024-01-29 -0.31  0.022
2024-01-30  0.13  0.022
2024-01-31  0.37  0.022

[1700 rows x 9 columns]
```

[189]:

```python
combined_data[['Trading Returns (%)','cvna', 'cost','Mkt-RF', 'RF']].corr()
```

[189]:

```
                     Trading Returns (%)      cvna      cost    Mkt-RF  \
Trading Returns (%)             1.000000  0.186368  0.186368  0.214614
cvna                            0.186368  1.000000  1.000000  0.448296
cost                            0.186368  1.000000  1.000000  0.448296
Mkt-RF                          0.214614  0.448296  0.448296  1.000000
RF                              0.009322  0.033140  0.033140 -0.010049

                           RF
```

```
Trading Returns (%)   0.009322
cvna                  0.033140
cost                  0.033140
Mkt-RF               -0.010049
RF                    1.000000
```

[190]:

```python
import statsmodels.api as sm
Y = combined_data['Trading Returns (%)']
X = combined_data[['cvna', 'cost','Mkt-RF', 'RF']]
X = sm.add_constant(X)

model = sm.OLS(Y, X).fit()

print(model.summary())
```

```
                             OLS Regression Results
===============================================================================
Dep. Variable:     Trading Returns (%)   R-squared:                       0.056
Model:                             OLS   Adj. R-squared:                  0.055
Method:                  Least Squares   F-statistic:                     33.72
Date:                 Sun, 17 Mar 2024   Prob (F-statistic):           3.64e-21
Time:                         16:37:03   Log-Likelihood:                -2333.2
No. Observations:                 1700   AIC:                             4674.
Df Residuals:                     1696   BIC:                             4696.
Df Model:                            3
Covariance Type:             nonrobust
===============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0805      0.033      2.421      0.016       0.015       0.146
cvna           0.8223      0.193      4.259      0.000       0.444       1.201
cost           0.8223      0.193      4.259      0.000       0.444       1.201
Mkt-RF         0.1275      0.020      6.222      0.000       0.087       0.168
RF             1.0678      3.480      0.307      0.759      -5.757       7.893
==============================================================================
Omnibus:                      295.781   Durbin-Watson:                   2.006
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3933.997
Skew:                           0.383   Prob(JB):                         0.00
Kurtosis:                      10.413   Cond. No.                     3.75e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 1.95e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

[176]:
```python
coefs = pd.DataFrame({
    'Coefficients': model.params,
    'Standard Error': model.bse,
    't Stat': model.tvalues,
    'P-value': model.pvalues,
    'Lower 95%': model.conf_int()[0],
    'Upper 95%': model.conf_int()[1]
})

print(coefs)
```

```
        Coefficients  Standard Error    t Stat       P-value  Lower 95%  \
const       0.080489        0.033253  2.420527  1.560249e-02   0.015268
cvna        0.822334        0.193080  4.259033  2.165702e-05   0.443634
cost        0.822334        0.193080  4.259033  2.165702e-05   0.443634
Mkt-RF      0.127466        0.020486  6.221973  6.171428e-10   0.087285
RF          1.067766        3.479747  0.306852  7.589940e-01  -5.757284

        Upper 95%
const    0.145709
cvna     1.201035
cost     1.201035
Mkt-RF   0.167647
RF       7.892816
```