Investigating periods of increasing interest rates for the S&P 1500: Patterns and possible strategies

by Luca Reichelt, 999786

Università Ca'Foscari Venezia

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1. Outline

1. Outline

- central banks aim to keep inflation at a stable rate of approx. 2% per year
- economic shocks often lead to unexpected hikes in consumer prices and therefore inflation
- central banks decrease the incentives for banks and companies to borrow money by steadily increasing their rates, aiming to stabilize inflation

Questions regarding the period of increasing interest rates:

➔ Do companies with certain feature values perform better?

➔ Therefore, can better performing companies be determined and predicted?

1. Outline

“[Gold is generally assumed to be a great hedge against (long-term) inflation.]”

- see Ghosh, Dipak, et al. "Gold as an inflation hedge?." Studies in Economics and Finance 22.1 (2004): 1-25.

“In terms of investment policy implication, our results suggest that US investors will have a good hedge against inflation by holding stock asset and real estate, and not by holding gold.”

- see Salisu, Afees A., Ibrahim D. Raheem, and Umar B. Ndako. "The inflation hedging properties of gold, companies and real estate: A comparative analysis." Resources Policy 66 (2020): 101605.

“[C]orporate profitability is the highest when inflation is modest (0-4 percent), and it is very low when inflation is very low (deflation) or very high (over 10 percent).”

- see Park, Sangkyun. "companies as a Hedge against Inflation: Does Corporate Profitability Keep Up with Inflation?."

1. Outline

“[I]nvestors are better off by holding a portfolio of stocks with higher long-run betas as part of asset selection and allocation strategy. Stocks that outperform inflation tend to be drawn from the Energy and industrial sectors. ”

- see Bampinas, Georgios, and Theodore Panagiotidis. "Hedging inflation with individual US companies: A long-run portfolio analysis." The North American Journal of Economics and Finance 37 (2016): 374-392.

“[There is e]vidence of a positive relationship between current stock market returns and current inflation. This result confirms that stock returns act as a hedge against inflation.”

- see Choudhry, Taufiq. "Inflation and rates of return on stocks: evidence from high inflation countries." Journal of International Financial Markets, Institutions and Money 11.1 (2001): 75-96.

2. Data

2. Data

- S&P 1500 members included at start and end
- start: first effective fed rate increase
- end: first effective fed rate stagnant/decrease
- MC change as target variable (“Outperformed” for higher than mean of change else “Not Outperformed”)
- features (as of start):
  - Market Cap
  - EPS T12M
  - P/E
  - Revenue T12M
  - GICS Sector
  - Net Debt
  - Sharpe Monthly
  - Beta Monthly
  - Number of Employees
  - Revenue per Employee

As well as some **comparative** monthly data such as:

- Gold
- Crude Oil
- Nasdaq
- Nasdaq
- CPI (Consumer Price Index)
- Rate of Unemployment

2. Data

Periods

	Name	Start	Last	Duration
0	Period 1	2004-04-01	2006-08-01	27
1	Period 2	2016-09-01	2017-08-01	10
2	Period 3	2017-09-01	2018-07-01	9
3	Period 4	2022-01-01	2023-02-01	13

2. Data

Weaknesses

- rather short periods (9 months minimum)
- rather few periods
- current period hasn’t concluded
- no comparison of results to random timeframes

2. Data

Indices/Assets monthly change in %
Change in % compared to month before
60
40
20
0
−20
−40
2006
2008
2010
2012
2014
2016
2018
2020
2022
Date
Legend
Gold
S&P 1500
Nasdaq
Spot Crude Oil Price WTI

2. Data

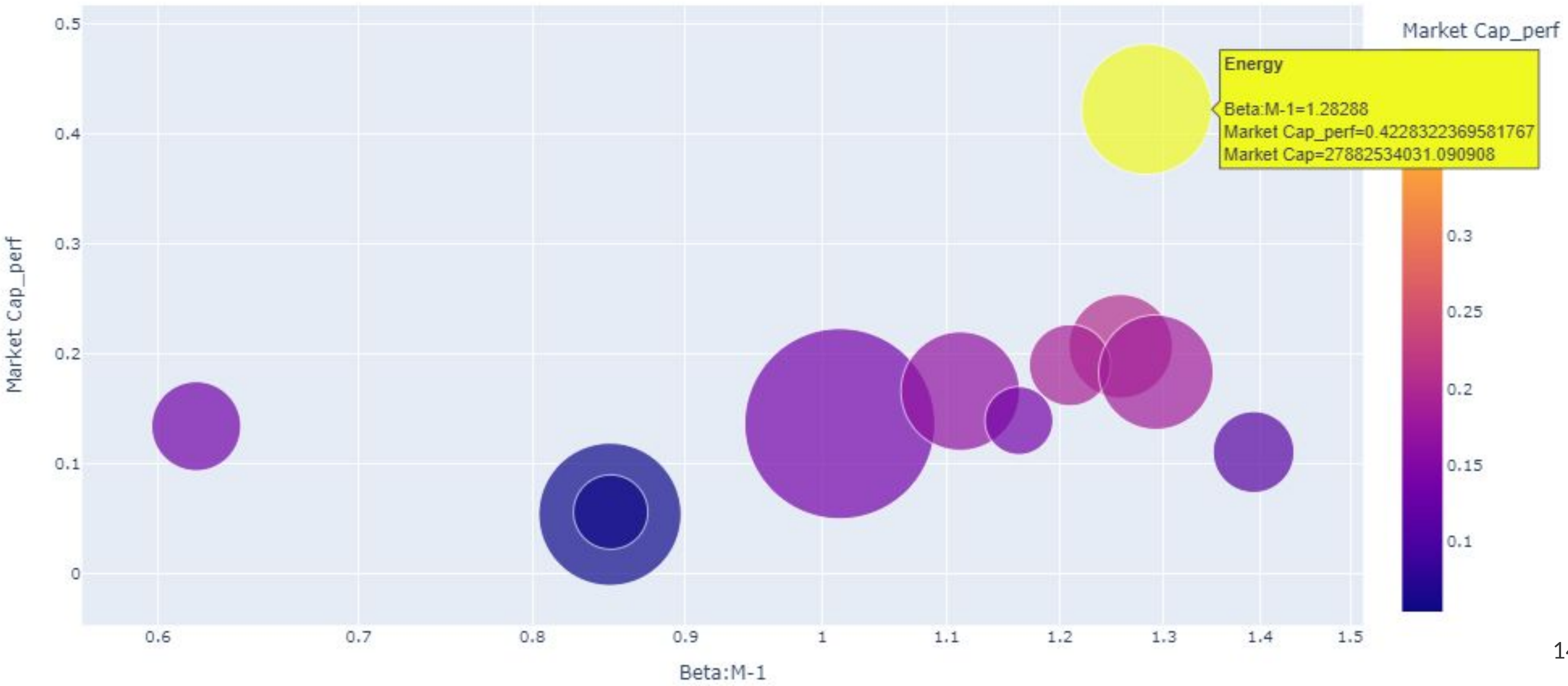
Total performance to FED/CPI/Unemployment Rate

2. Data

Cleaning & Preprocessing

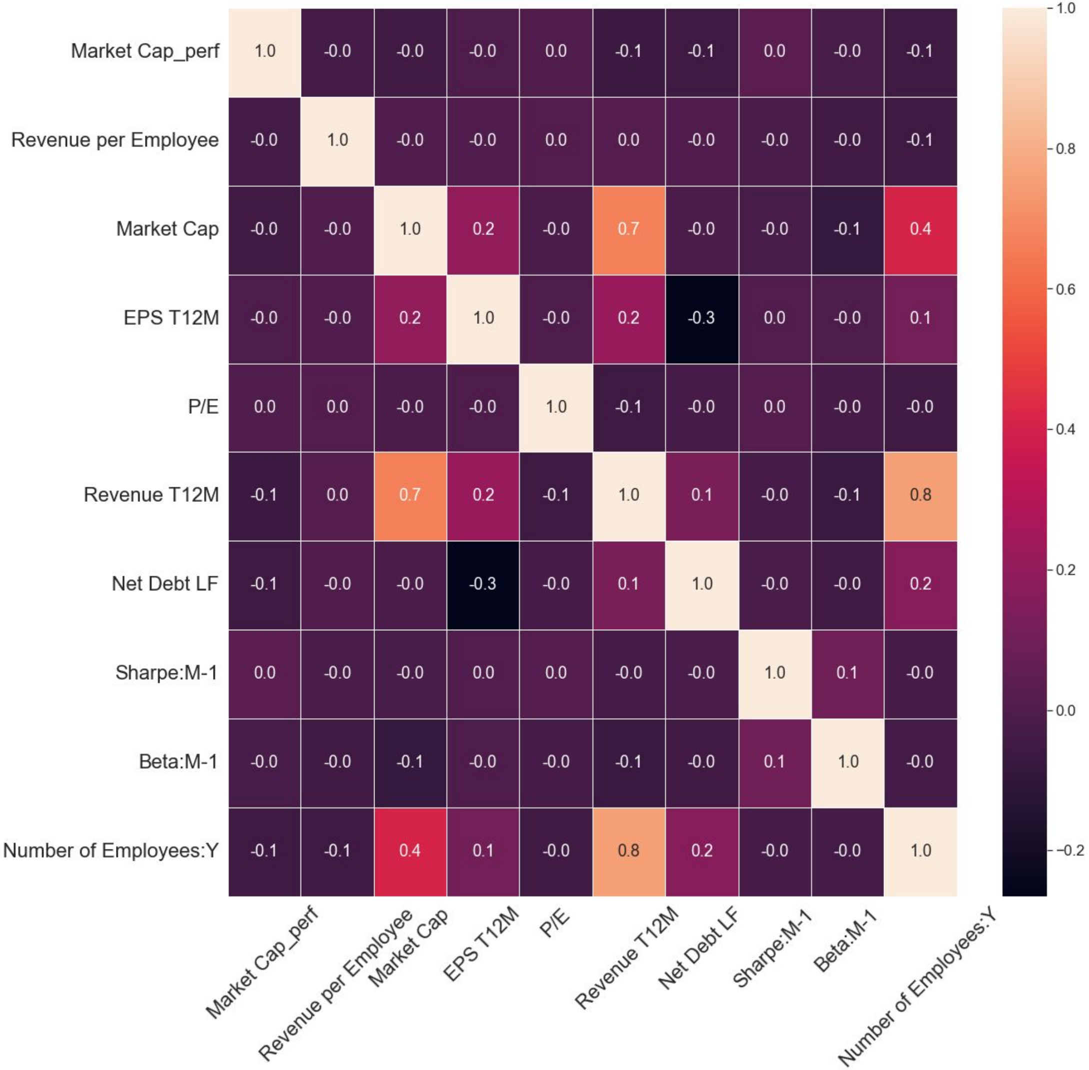
- adaptation/remodeling of various APIs to fit the Dataframe
- transforming to correct datatypes
- dropping all rows with nan values
- creating dummies (one-hot encoding) for the sector feature
- adding a new feature: Revenues per Employee
- adding the base for the target feature: Market Cap_perf
- dropping Price and Market Cap_last

2. Data



Market Cap_perf
Energy
Beta:M-1=1.28288
Market Cap_perf=0.4228322369581767
Market Cap=27882534031.090908
0.5
0.4
0.3
0.2
0.1
0
0.6
0.7
0.8
0.9
1
1.1
1.2
1.3
1.4
1.5
Beta:M-1
0.3
0.25
0.2
0.15
0.1

2. Data


Market Cap_perf
Revenue per Employee
Market Cap
EPS T12M
P/E
Revenue T12M
Net Debt LF
Sharpe:M-1
Beta:M-1
Number of Employees:Y
1.0 -0.0 -0.0 -0.0 0.0 -0.1 -0.1 0.0 -0.0 -0.1
-0.0 1.0 -0.0 -0.0 0.0 0.0 -0.0 -0.0 -0.0 -0.1
-0.0 -0.0 1.0 0.2 -0.0 0.7 -0.0 -0.0 -0.1 0.4
-0.0 -0.0 0.2 1.0 -0.0 0.2 -0.3 0.0 -0.0 0.1
0.0 0.0 -0.0 -0.0 1.0 -0.1 -0.0 0.0 -0.0 -0.0
-0.1 0.0 0.7 0.2 -0.1 1.0 0.1 -0.0 -0.1 0.8
-0.1 -0.0 -0.0 -0.3 -0.0 0.1 1.0 -0.0 -0.0 0.2
0.0 -0.0 -0.0 0.0 0.0 -0.0 -0.0 1.0 0.1 -0.0
-0.0 -0.0 -0.1 -0.0 -0.0 -0.1 -0.0 0.1 1.0 -0.0
-0.1 -0.1 0.4 0.1 -0.0 0.8 0.2 -0.0 -0.0 1.0
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

2. Data: "Top 10"

- Top10 performing companies for all concluded periods
- Energy sector strongly overrepresented
- Real Estate and Utilities are both not once in Top10

All

Industrials	505
Consumer Discretionary	441
Financials	417
Information Technology	349
Health Care	304
Materials	191
Real Estate	179
Consumer Staples	142
Utilities	120
Communication Services	101
Energy	88

Top 10

Industrials	7
Energy	5
Consumer Discretionary	5
Materials	3
Information Technology	3
Financials	3
Health Care	2
Communication Services	1
Consumer Staples	1

2. Data: “Top 10” vs. All

Top 10

	Market Cap_perf	Revenue per Employee	Market Cap	EPS T12M	P/E	Revenue T12M	Net Debt LF	Sharpe:M-1	Beta:M-1	Number of Employees:Y
count	30.000000	3.000000e+01	3.000000e+01	30.000000	30.000000	3.000000e+01	3.000000e+01	30.000000	30.000000	30.000000
mean	1.954413	5.078052e+05	2.441349e+09	0.984556	35.399076	1.444729e+09	2.619570e+08	6.904675	0.993617	4609.333333
std	0.693458	4.032231e+05	6.085325e+09	1.919795	23.022050	1.550357e+09	1.138929e+09	30.388213	0.938778	5805.966499
min	1.304530	1.283391e+05	2.782508e+08	-6.720000	9.326661	2.055270e+08	-3.371000e+09	-2.827769	-1.657429	178.000000
25%	1.500476	1.768069e+05	5.714091e+08	0.405000	19.404363	3.251750e+08	-8.340650e+07	-1.973641	0.667566	922.250000
50%	1.862673	3.971350e+05	9.707596e+08	1.050000	28.241244	7.713390e+08	4.667550e+07	-0.880110	1.025435	1929.500000
75%	2.207235	6.760008e+05	1.644764e+09	1.735000	38.376455	2.016746e+09	3.241035e+08	1.632434	1.338787	6742.750000
max	5.033335	1.654904e+06	3.378525e+10	4.370000	100.730191	5.526000e+09	3.476000e+09	162.272899	3.457157	26000.000000

All

	Market Cap_perf	Revenue per Employee	Market Cap	EPS T12M	P/E	Revenue T12M	Net Debt LF	Sharpe:M-1	Beta:M-1	Number of Employees:
count	2837.000000	2.837000e+03	2.837000e+03	2837.000000	2837.000000	2.837000e+03	2.837000e+03	2837.000000	2837.000000	2.837000e+0
mean	0.161105	8.693829e+05	1.766405e+10	12.960799	31.557441	9.433643e+09	2.782123e+09	2.127500	1.171152	2.410013e+0
std	0.357638	2.531066e+06	5.086190e+10	383.184299	52.917709	2.617835e+10	1.640547e+10	14.993197	0.639499	8.250902e+0
min	-0.756240	2.241154e+04	1.272757e+08	-28.993488	1.186686	6.438100e+07	-1.924410e+11	-6.599870	-5.586384	9.000000e+0
25%	-0.039069	2.413852e+05	1.384998e+09	0.960000	16.143771	8.185460e+08	8.842000e+06	-1.798663	0.800994	1.918000e+0
50%	0.123482	3.791714e+05	3.383413e+09	1.950000	20.998204	2.215573e+09	5.608190e+08	-0.024635	1.107392	6.100000e+0
75%	0.294850	7.316413e+05	1.242718e+10	3.520000	29.636232	6.790800e+09	2.440245e+09	3.246132	1.439695	1.740000e+0
max	5.033335	5.176925e+07	8.473556e+11	15514.000732	1232.898177	4.900120e+11	4.879700e+11	536.800751	6.549999	2.300000e+0

3. Machine Learning

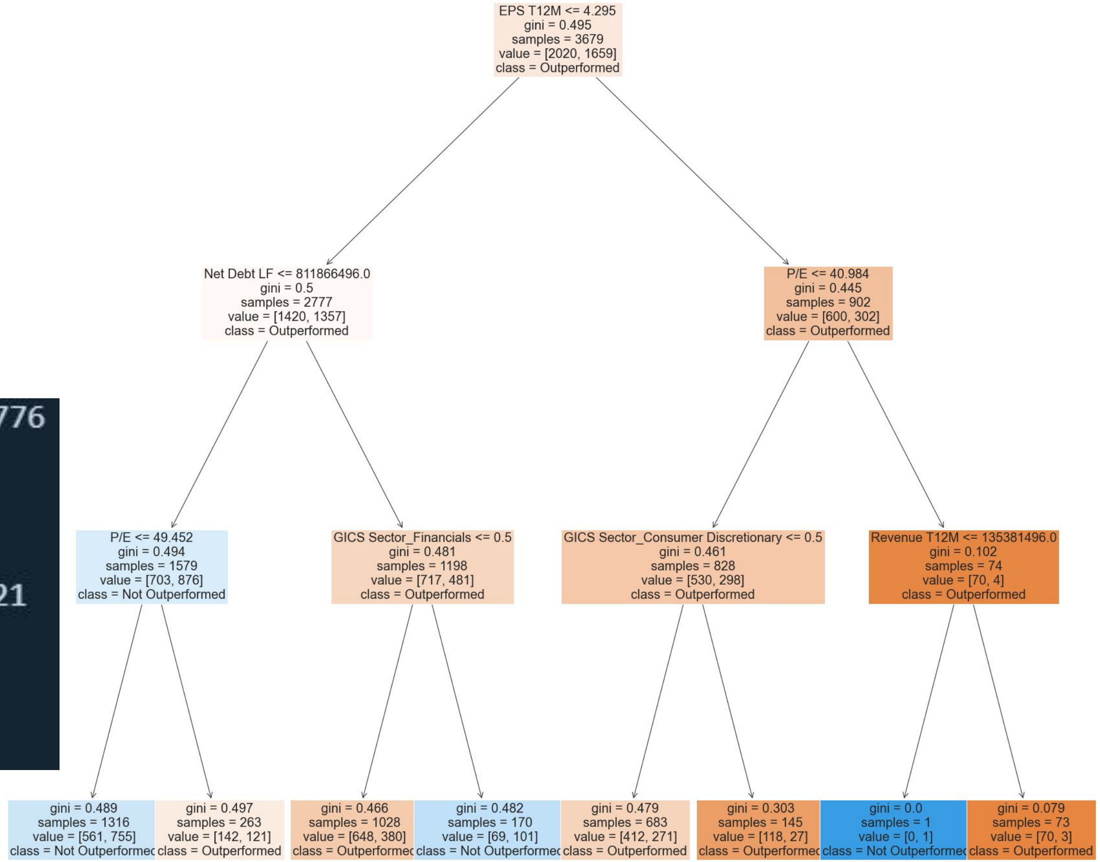
3. Machine Learning

- target label is determined:
    - companies with a higher return than the mean are labeled "Outperformed"
    - companies with a lower return than the mean or an equal return are labeled "Not Outperformed"
- differentiation between three cases:
    - a case where the data consists of only the former, already concluded periods
    - a case where the data consists of all data, including the ongoing period
    - a case where the training data consists of the former, concluded periods and the test data consists of the current, ongoing period
- the features will be evaluated using
    - simple DecisionTree with a max_depth of 3
    - RandomForest with hyperparametertuning using GridSearchCV

3. Machine Learning: DT all data

```
X_train : (3679, 20)
y_train : (3679,)
X_test : (409, 20)
y_test : (409,)
```

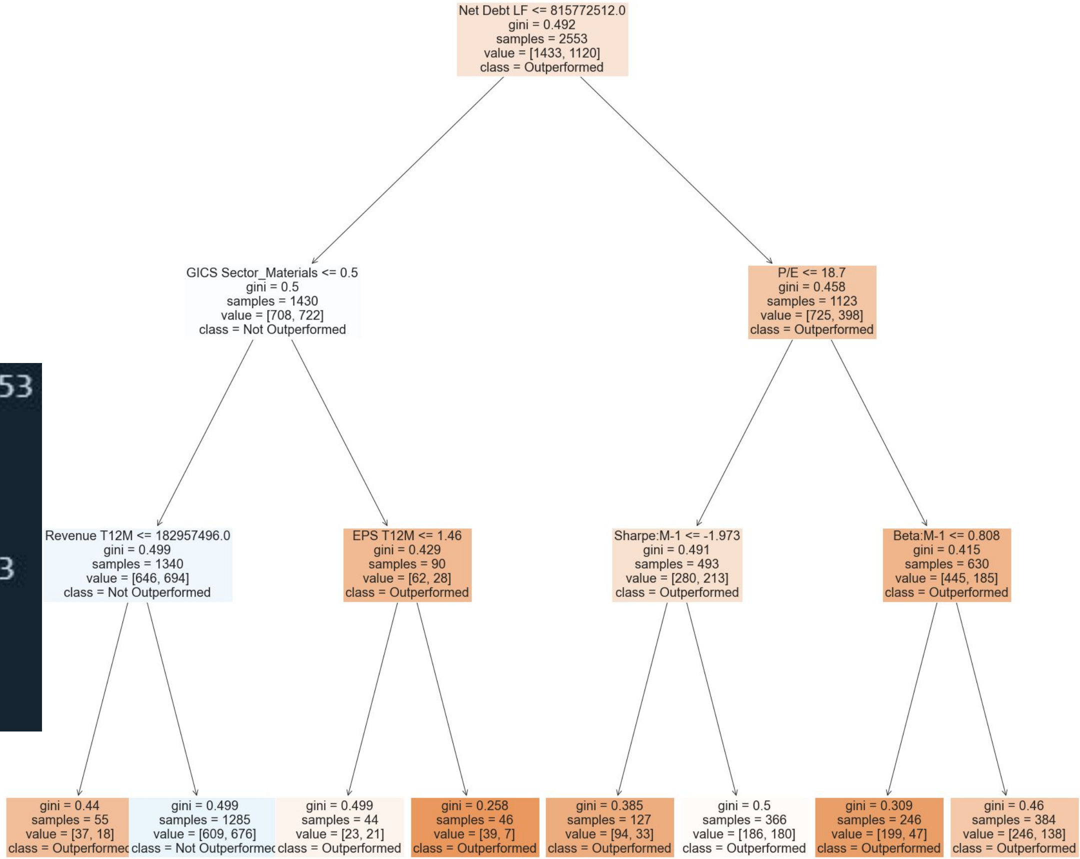
```
Train Accuracy : 0.6107637945093776
Train Confusion Matrix:
[[1390  630]
 [ 802  857]]
Test Accuracy : 0.5916870415647921
Test Confusion Matrix:
[[142  66]
 [101 100]]
```



3. Machine Learning: DT former data

```
X_train : (2553, 20)
y_train : (2553,)
X_test : (284, 20)
y_test : (284,)
```

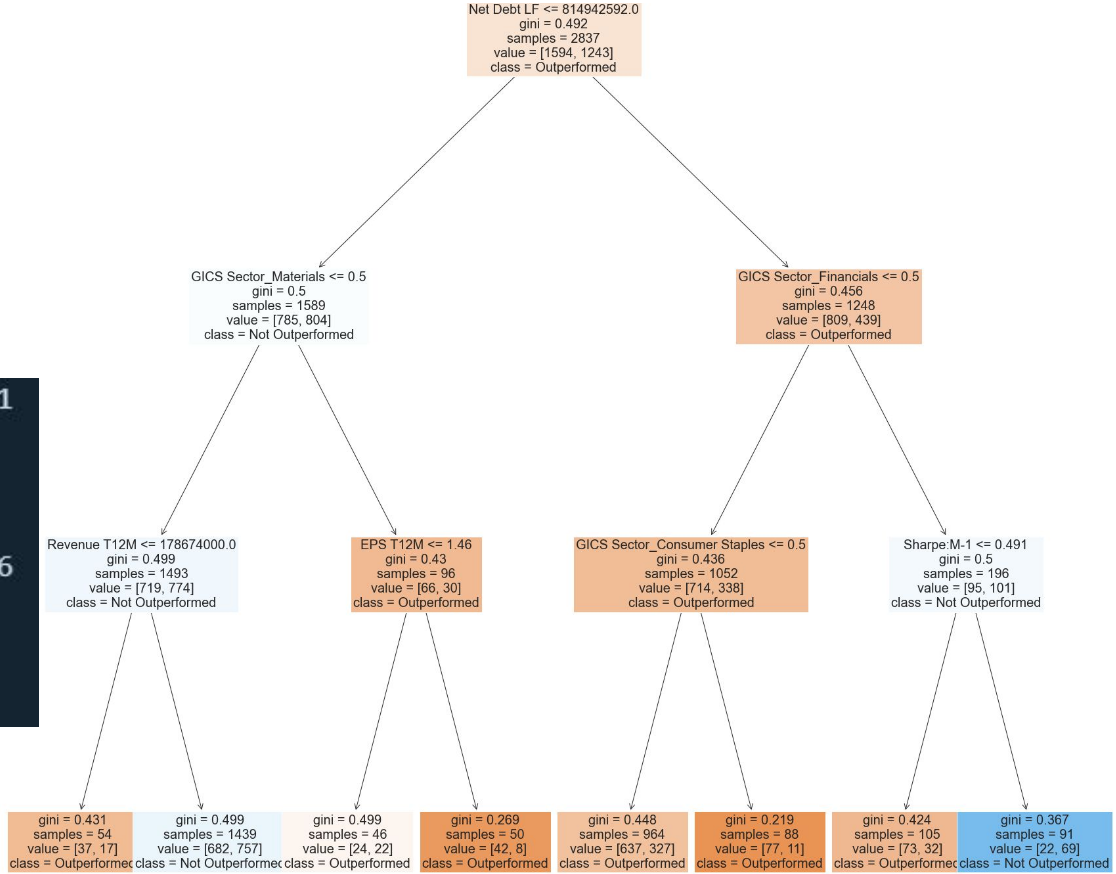
```
Train Accuracy : 0.5875440658049353
Train Confusion Matrix:
[[824 609]
 [444 676]]
Test Accuracy : 0.5950704225352113
Test Confusion Matrix:
[[91 70]
 [45 78]]
```



3. Machine Learning: DT former=train, current=test

```
X_train : (2837, 20)
y_train : (2837,)
X_test : (1251, 20)
y_test : (1251,)
```

```
Train Accuracy : 0.6048642932675361
Train Confusion Matrix:
[[890 704]
 [417 826]]
Test Accuracy : 0.49960031974420466
Test Confusion Matrix:
[[322 338]
 [288 303]]
```



3. Machine Learning RF all data

```
Train Accuracy : 0.9233487360695841
Train Confusion Matrix:
[[1902  118]
 [ 164 1495]]
Test Accuracy : 0.6112469437652812
Test Confusion Matrix:
[[131  77]
 [ 82 119]]
```

```
GridSearchCV
GridSearchCV(cv=4, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [False], 'max_depth': [12],
                         'max_features': ['auto'], 'min_samples_leaf': [5],
                         'min_samples_split': [5], 'n_estimators': [50]},
             verbose=3)
```

3. Machine Learning RF former data

```
Train Accuracy : 0.8511555033294164
Train Confusion Matrix:
[[1299  134]
 [ 246  874]]
Test Accuracy : 0.5809859154929577
Test Confusion Matrix:
[[117  44]
 [ 75  48]]
```

```
GridSearchCV

GridSearchCV(cv=4, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [False], 'max_depth': [16],
                         'max_features': ['sqrt'], 'min_samples_leaf': [5],
                         'min_samples_split': [50], 'n_estimators': [25]},
             verbose=3)
```

3. Machine Learning RF former=train, current=test

```
Train Accuracy : 0.9400705052878966
Train Confusion Matrix:
[[1404   29]
 [ 124  996]]
Test Accuracy : 0.5809859154929577
Test Confusion Matrix:
[[122  39]
 [ 80  43]]
```

```
GridSearchCV

GridSearchCV(cv=4, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_depth': [20],
                         'max_features': ['sqrt'], 'min_samples_leaf': [5],
                         'min_samples_split': [10], 'n_estimators': [100]},
             verbose=3)
```

3. Machine Learning RF Implementation

	Name	Start	Last	Duration	Gold	S&P 1500	Nasdaq	Spot Crude Oil Price WTI	all_Grid	former_Grid	current_test_Grid
0	Period 1	2004-04-01	2006-08-01	27	1.626804	1.148445	1.047715	1.991006	1.499838	1.588331	1.696985
1	Period 2	2016-09-01	2017-08-01	10	1.002506	1.135936	1.201220	1.063302	1.291162	1.333193	1.373152
2	Period 3	2017-09-01	2018-07-01	9	0.956180	1.124224	1.206716	1.424729	1.319101	1.371090	1.393592
3	Period 4	2022-01-01	2023-02-01	13	1.022434	0.897279	0.797209	0.923216	1.208731	0.897760	0.887757

4. Results

4. Results

- ➔ Do companies with certain feature values perform better?

  Yes, better performing companies can be identified by certain features.

- ➔ Therefore, can better performing companies be determined and predicted?

  Yes, they can be approximately predicted based on past periods.

4. Results

Potential further research questions:

How much more can the classifier be refined(label data more precisely to detect the very best)?

Can these better performing companies simply be explained by some kick-off event such as an energy crisis (energy companies profit/less energy dependent companies perform better in comparison)?

(Back to weaknesses:) Do companies with these features simply perform better in general?

5. Sources

Data Sources

Bloomberg Finance L.P.

https://www.spglobal.com/spdji/en/indices/equity/sp-composite-1500/#overview

https://fred.stlouisfed.org/series/FEDFUNDS#

https://fred.stlouisfed.org/series/CORESTICKM159SFRBATL

https://fred.stlouisfed.org/series/UNRATE

https://fred.stlouisfed.org/series/WTISPLC

https://www.investing.com/commodities/gold-historical-data

Scientific Sources

1. Bampinas, Georgios, and Theodore Panagiotidis. "Hedging inflation with individual US companies: A long-run portfolio analysis." The North American Journal of Economics and Finance 37 (2016): 374-392.
2. Choudhry, Taufiq. "Inflation and rates of return on stocks: evidence from high inflation countries." Journal of International Financial Markets, Institutions and Money 11.1 (2001): 75-96.
3. Ghosh, Dipak, et al. "Gold as an inflation hedge?." Studies in Economics and Finance 22.1 (2004): 1-25.
4. Salisu, Afees A., Ibrahim D. Raheem, and Umar B. Ndako. "The inflation hedging properties of gold, companies and real estate: A comparative analysis." Resources Policy 66 (2020): 101605.
5. Zaremba, Adam, Zaghum Umar, and Mateusz Mikutowski. "Inflation hedging with commodities: A wavelet analysis of seven centuries worth of data." Economics Letters 181 (2019): 90-94.

Thank you for your attention!