Investigating periods of increasing interest rates for the S&P 1500

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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

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

“[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.

“[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.

1. Outline

Findings

- gold seen as good long-term investment, but not short-term
- profits in general lower for higher rates
- evidence of positive relationship between inflation and stock returns
- risky assets and those of energy/industry sector seem to be better

Resulting research questions

➔ Do companies with certain features perform better?

➔ Can those better performing companies be predicted?

2. Data

2. Data

Basics

- S&P 1500 members included at start of period
- Start: first effective fed rate increase
- End: first effective fed rate stagnant/decrease

Comparative Data (monthly):

- S&P 500
- Nasdaq
- Gold
- Crude Oil
- 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	2023-03-01	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 (stocks always performing better?)
- no consideration of initial crisis or crisis within period

2. Data

Indices/Assets monthly change in %

2. Data

Total performance to FED/CPI/Unemployment Rate
Total Indices/Asset change in %
700
600
500
400
300
200
100
0
Rates for FED/CPI/Unemployment
14
12
10
8
6
4
2
0
2006
2008
2010
2012
2014
2016
2018
2020
2022
Date
Legend
S&P 1500
Nasdaq
Gold
Spot Crude Oil Price WTI
FED Rate
CPI
Rate of Unemployment

2. Data

Target & Features

Target:
Performance of company by change in Market Cap:

- **“Outperformed”** for higher than mean
- **“Not Outperformed”**

Features:

- Market Cap - Size by market valuation
- Sector
- Revenue T12M
- Number of Employees
- **Profitability Ratios**
  - EPS T12M - Profit per Share
  - P/E - Price to EPS
- **Risk Ratios**
  - Net Debt - Ability to pay off debt
  - Sharpe M - Return to Risk
  - Beta M - Compared Volatility
  - Revenue per Employee

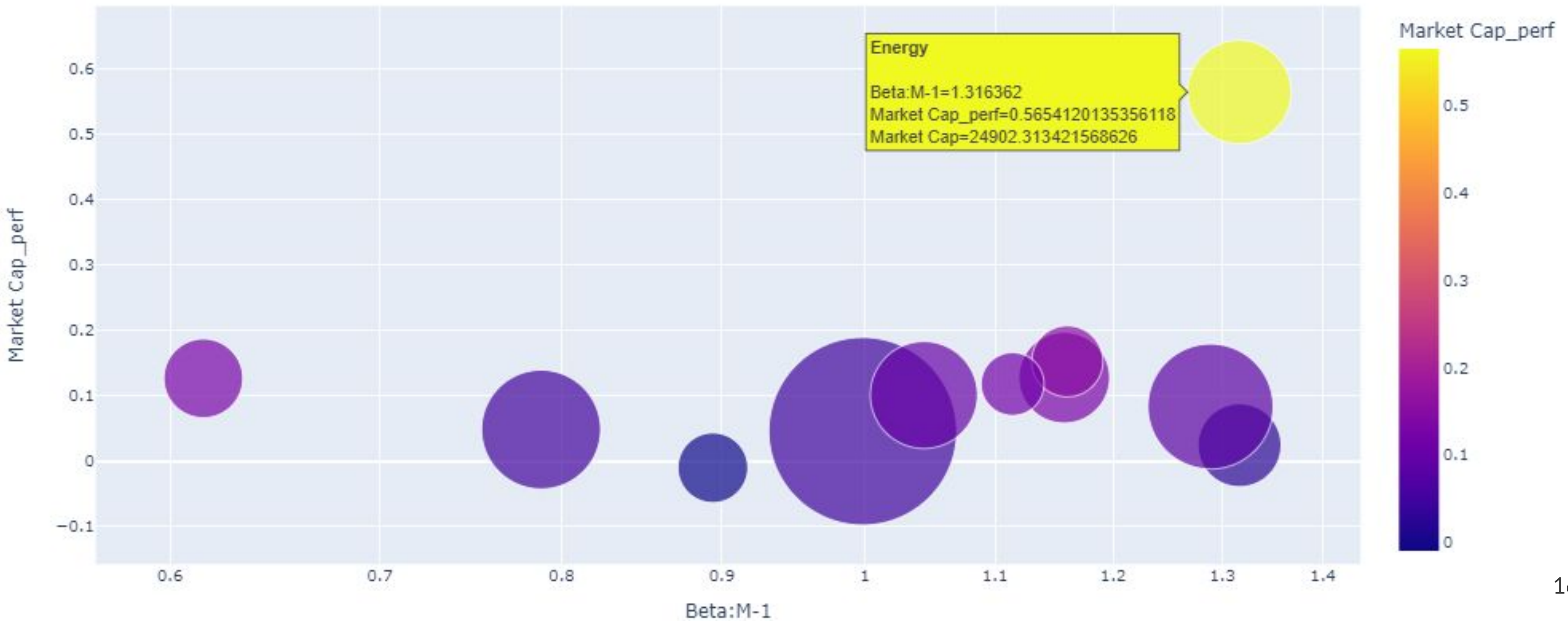
2. Data

Cleaning & Preprocessing

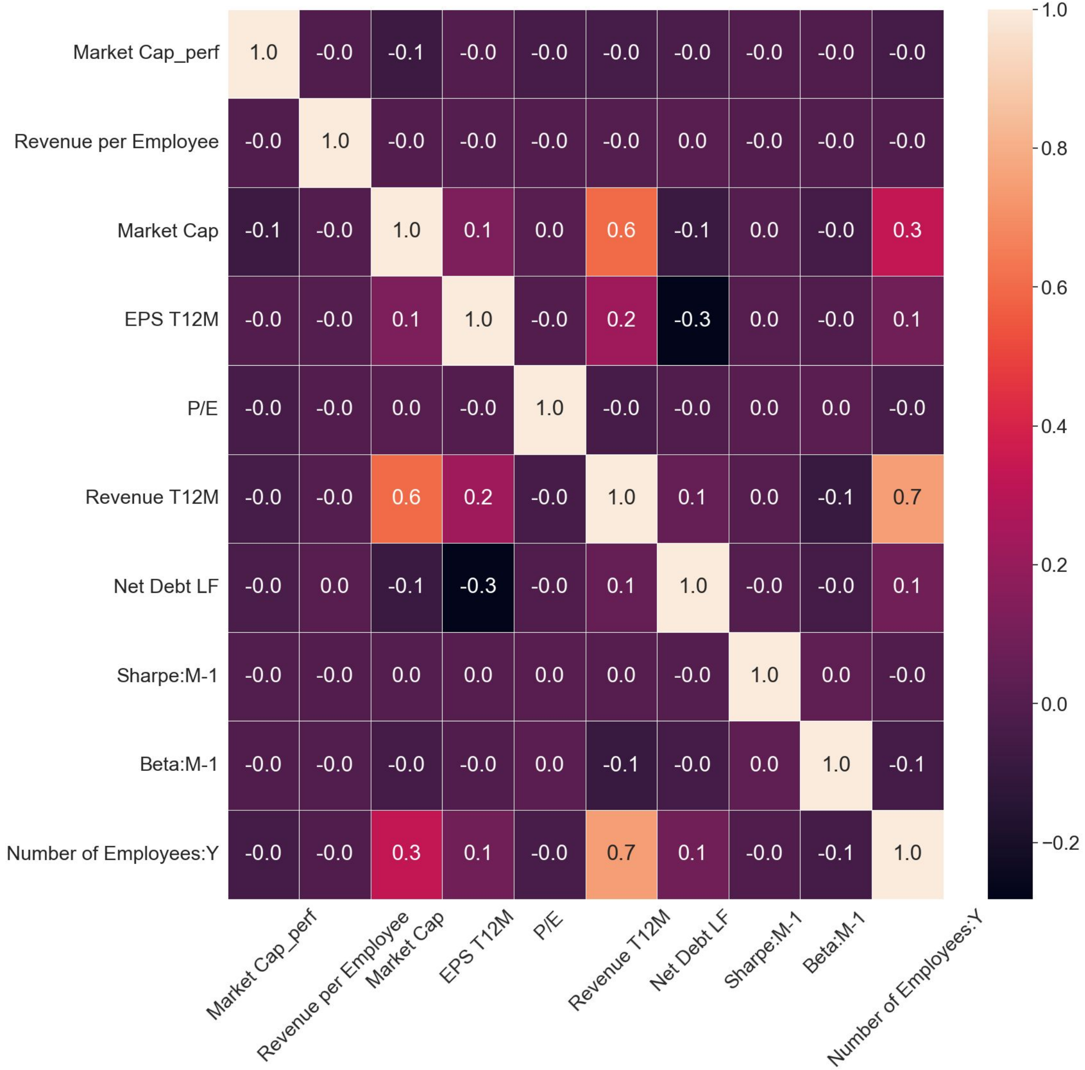
- transforming to correct data-types
- dropping all observations with nan values
- creating dummies (one-hot encoding) for the sector feature
- adding a new feature: Revenue per Employee
- adding the base for the target feature: Market Cap_perf
- dropping Price and Market Cap_last

2. Data

ALL DATA: Risk/Compared Volatility to SP1500 compared to Return/Performance by GICS Sector



2. Data


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

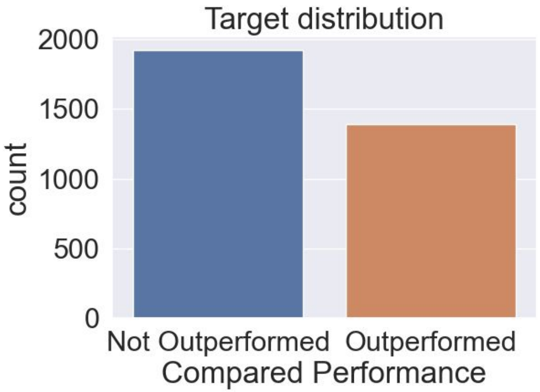
	Market Cap_perf	Revenue per Employee	Market Cap	EPS T12M	P/E	Revenue T12M	Net Debt LF	Sharpe:M-1	Beta:M-1	Number of Employees:Y
count	2837.000000	2.837000e+03	2.837000e+03	2837.000000	2837.000000	2.837000e+03	2.837000e+03	2837.000000	2837.000000	2.837000e+03
mean	0.161105	8.693829e+05	1.766405e+10	12.960799	31.557441	9.433643e+09	2.782123e+09	2.127500	1.171152	2.410013e+04
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+04
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+00
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+03
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+03
75%	0.294830	7.316413e+05	1.242718e+10	3.320000	29.636232	6.790800e+09	2.440245e+09	3.246132	1.439695	1.740000e+04
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+06

3. Machine Learning

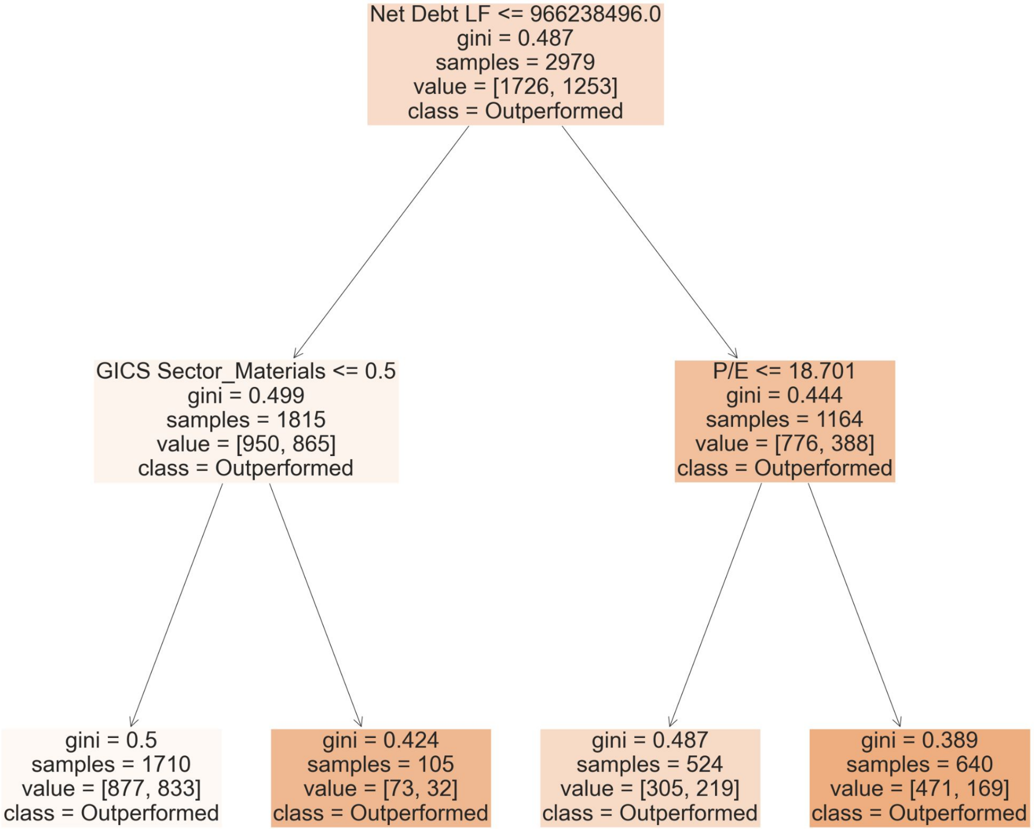
3. Machine Learning

- **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 data cases**:
  - a case where the data consists of **only the former/ 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 **hyperparameter-tuning using GridSearchCV**

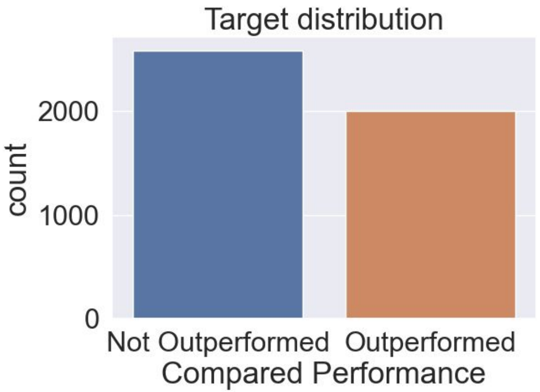
3. Machine Learning: DT former data



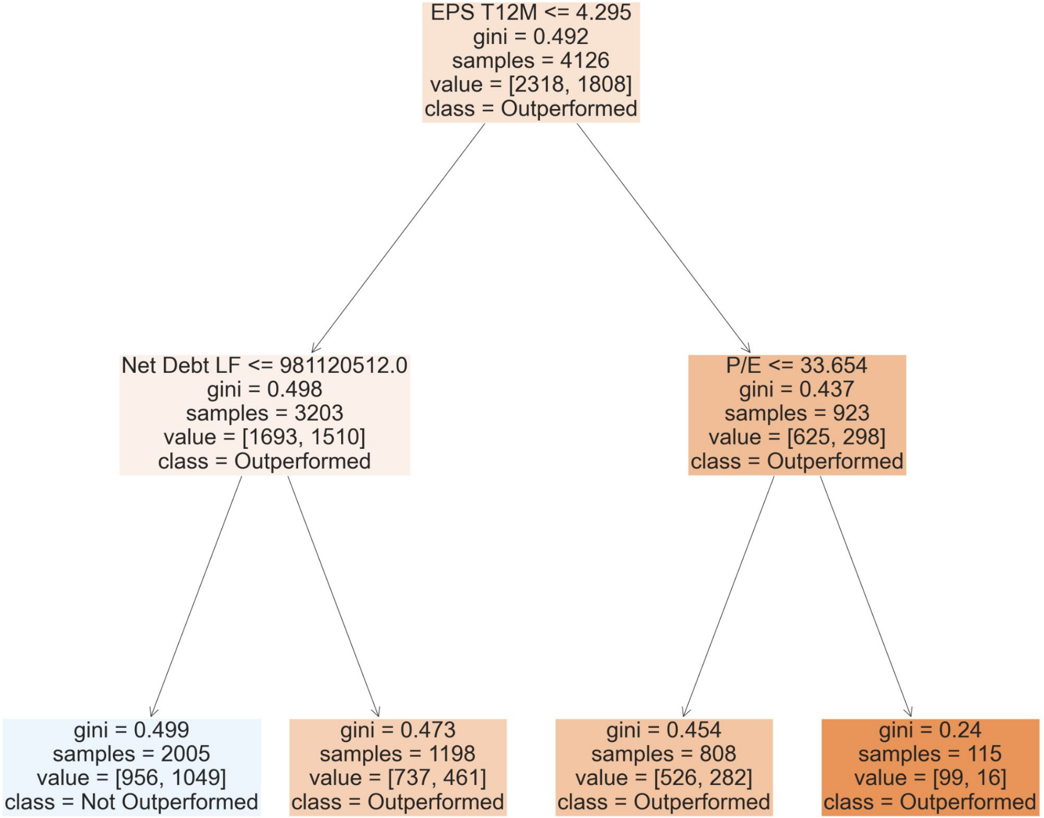

```
Train Accuracy : 0.5793890567304465
Train Confusion Matrix:
[[1726    0]
 [1253    0]]
Test Accuracy : 0.5891238670694864
Test Confusion Matrix:
[[195   0]
 [136   0]]
```



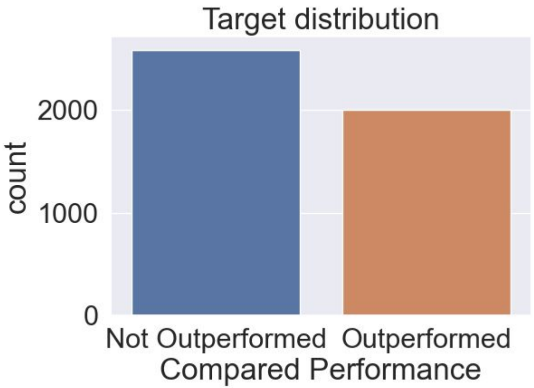
3. Machine Learning: DT all data



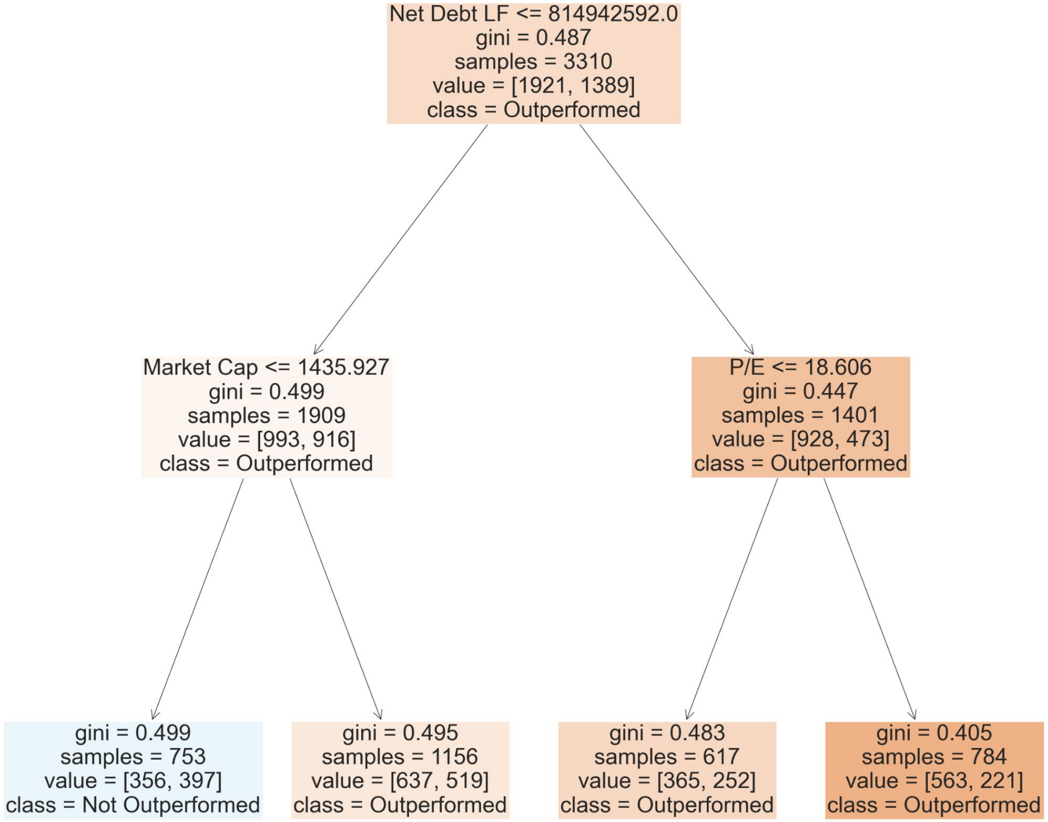

```
Train Accuracy : 0.5843431895298109
Train Confusion Matrix:
[[1362  956]
 [ 759 1049]]
Test Accuracy : 0.5490196078431373
Test Confusion Matrix:
[[146 119]
 [ 88 106]]
```



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

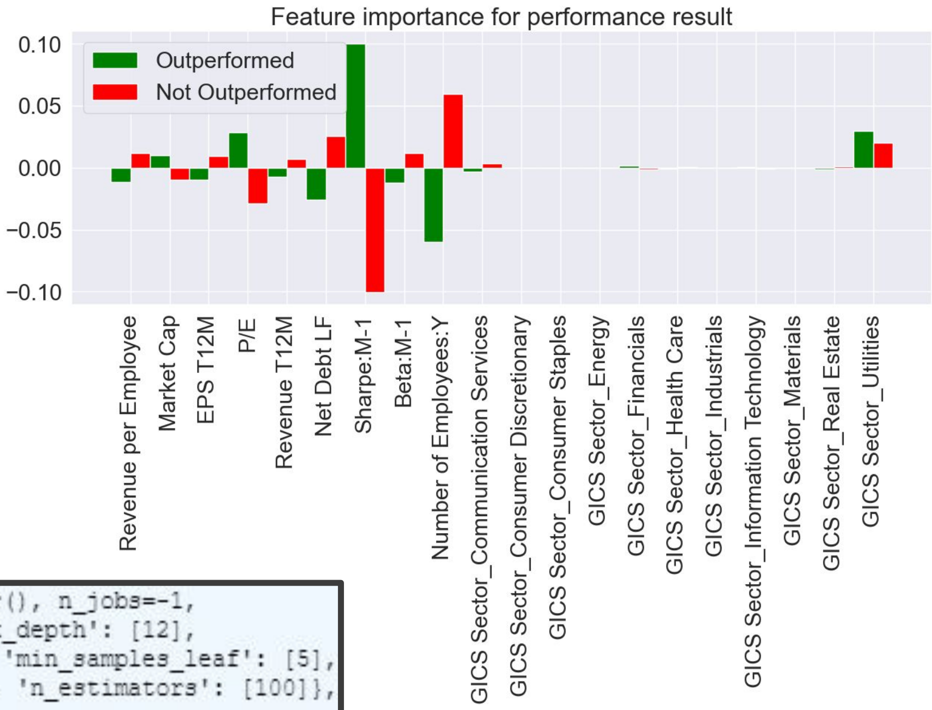



```
Train Accuracy : 0.592749244712991
Train Confusion Matrix:
[[1565  356]
 [ 992  397]]
Test Accuracy : 0.5090196078431373
Test Confusion Matrix:
[[567  75]
 [551  82]]
```



3. Machine Learning: RF former data

```
Train Accuracy : 0.8563276267203076
Train Confusion Matrix:
[[1667   59]
 [ 369  884]]
Test Accuracy : 0.6374622356495468
Test Confusion Matrix:
[[159  36]
 [ 84  52]]
```




```
GridSearchCV(cv=4, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [False], 'max_depth': [12],
                         'max_features': ['sqrt'], 'min_samples_leaf': [5],
                         'min_samples_split': [25], 'n_estimators': [100]},
             verbose=3)
```

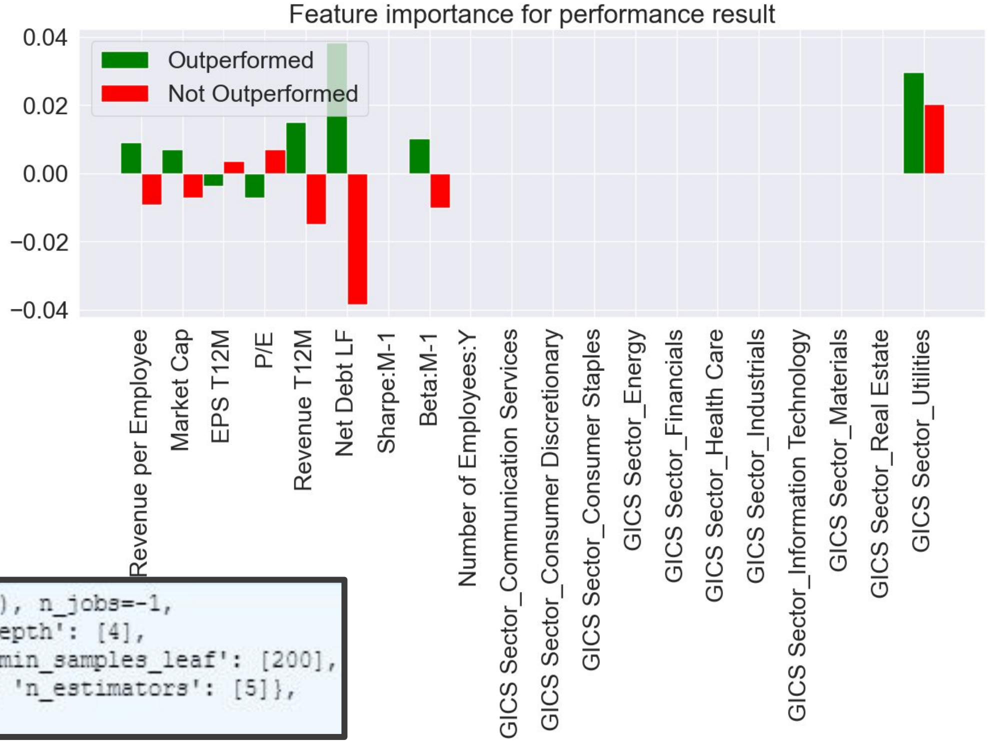
3. Machine Learning: RF all data

```
Train Accuracy : 0.9878699660359049
Train Confusion Matrix:
[[2263   10]
 [  40 1809]]
Test Accuracy : 0.6834061135371179
Test Confusion Matrix:
[[196  66]
 [ 79 117]]
```


```
GridSearchCV(cv=4, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [False], 'max_depth': [20],
                         'max_features': ['sqrt'], 'min_samples_leaf': [5],
                         'min_samples_split': [5], 'n_estimators': [50]},
             verbose=3)
```

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

```
Train Accuracy : 0.6036253776435045
Train Confusion Matrix:
[[1727  194]
 [1118  271]]
Test Accuracy : 0.5086614173228347
Test Confusion Matrix:
[[615  41]
 [583  31]]
```




```
GridSearchCV(cv=4, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_depth': [4],
                         'max_features': ['sqrt'], 'min_samples_leaf': [200],
                         'min_samples_split': [100], 'n_estimators': [5]},
             verbose=3)
```

3. Machine Learning: RF predictor implementation

Name	Start	Last	Duration	Gold	Nasdaq	Spot Crude Oil Price WTI
Period 1	2004-04-01	2006-08-01	27	1.626804	1.047715	1.991006
Period 2	2016-09-01	2017-08-01	10	1.000984	1.201220	1.063302
Period 3	2017-09-01	2018-07-01	9	0.957095	1.206716	1.424729
Period 4	2022-01-01	2023-03-01	13	1.094375	0.788331	0.880558

Name	Start	Last	Duration	S&P 1500	all_Grid	former_Grid	current_test_Grid
Period 1	2004-04-01	2006-08-01	27	1.148445	1.598761	1.733503	1.422722
Period 2	2016-09-01	2017-08-01	10	1.135936	1.319970	1.383332	1.181492
Period 3	2017-09-01	2018-07-01	9	1.124224	1.349438	1.436288	1.317974
Period 4	2022-01-01	2023-03-01	13	0.874502	1.269982	0.846276	0.806864

4. Results

4. Results

- ➔ Do companies with certain feature values perform better?

  Kind off, certain features can be good indicators whether or not a company will perform better or worse during periods of inflation.

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

  Yes, they can be approximately predicted based on the data from 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)?

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!