

**DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE - EM1405**

**by Professor Andrea Albarelli**

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

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# 1. Outline

# 1. Outline

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- central banks aim to keep inflation at a stable rate of approx. 2% per year
- economic shocks/risky fiscal policy lead to unexpected hikes in consumer prices and therefore inflation
- aiming to stabilize inflation, central banks decrease the incentives for banks and companies to borrow money by steadily increasing their rates to straddle liquidity and calm price hikes
- as exemplified by the following papers, there is no clear census on what stocks/assets perform better in these times of decreasing liquidity or even if they perform good/bad at all

# 1. Outline

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**“[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

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**“[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

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## 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?

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## 2. Data



## 2. Data

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### 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	2023-04-01	14

## 2. Data

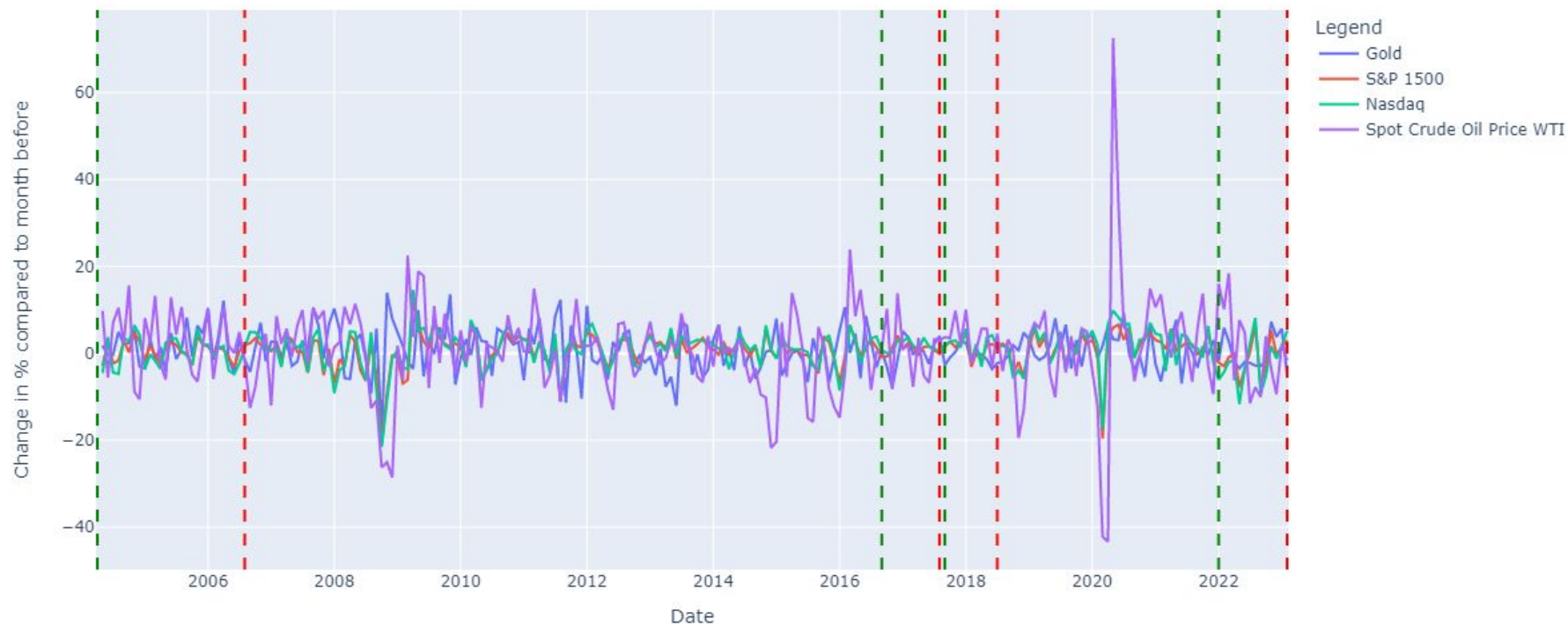
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### Weaknesses

- rather short periods (9 months minimum)
- rather few periods; limited data possibilities (checking for rolling improvement with was initial idea, impractical due to only 3(or 4) periods)
- current period hasn't concluded
- no comparison of results to random timeframes (stocks always performing better than other securities/assets?)
- 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



## 2. Data

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### 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

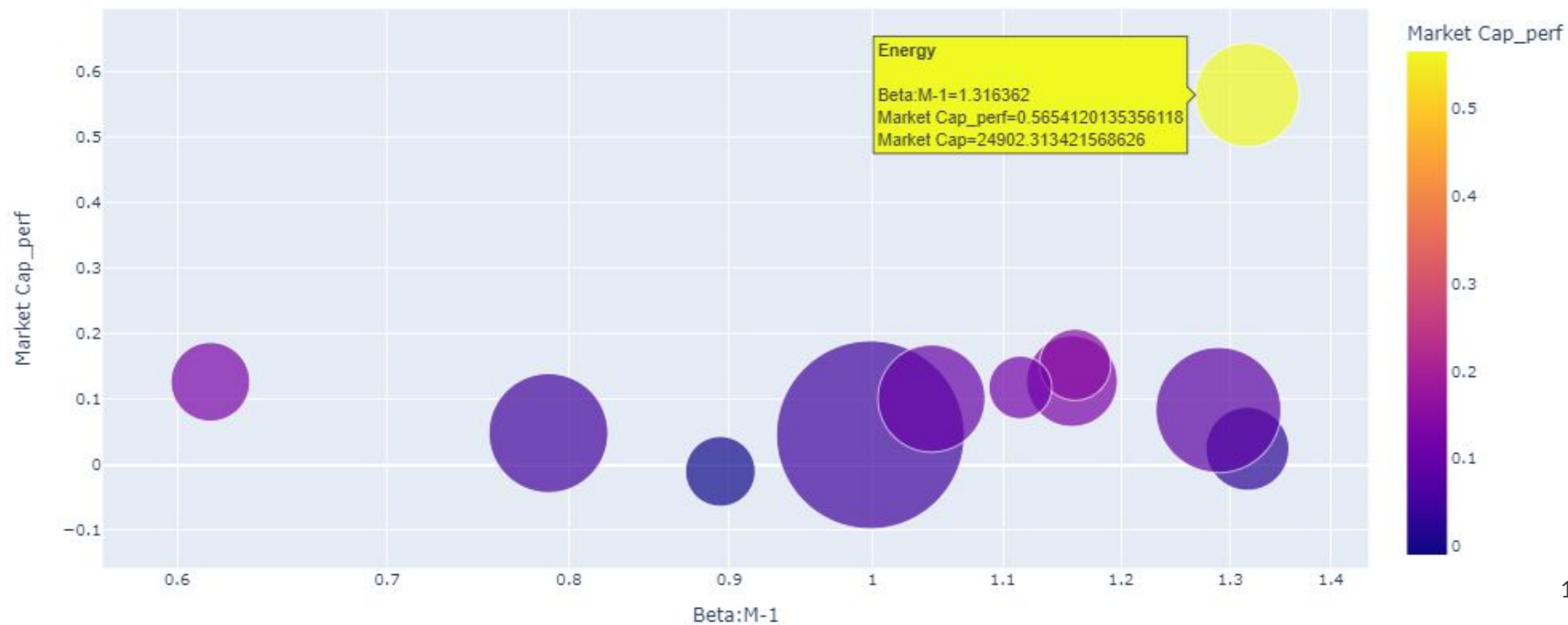
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### Cleaning & Preprocessing

- 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

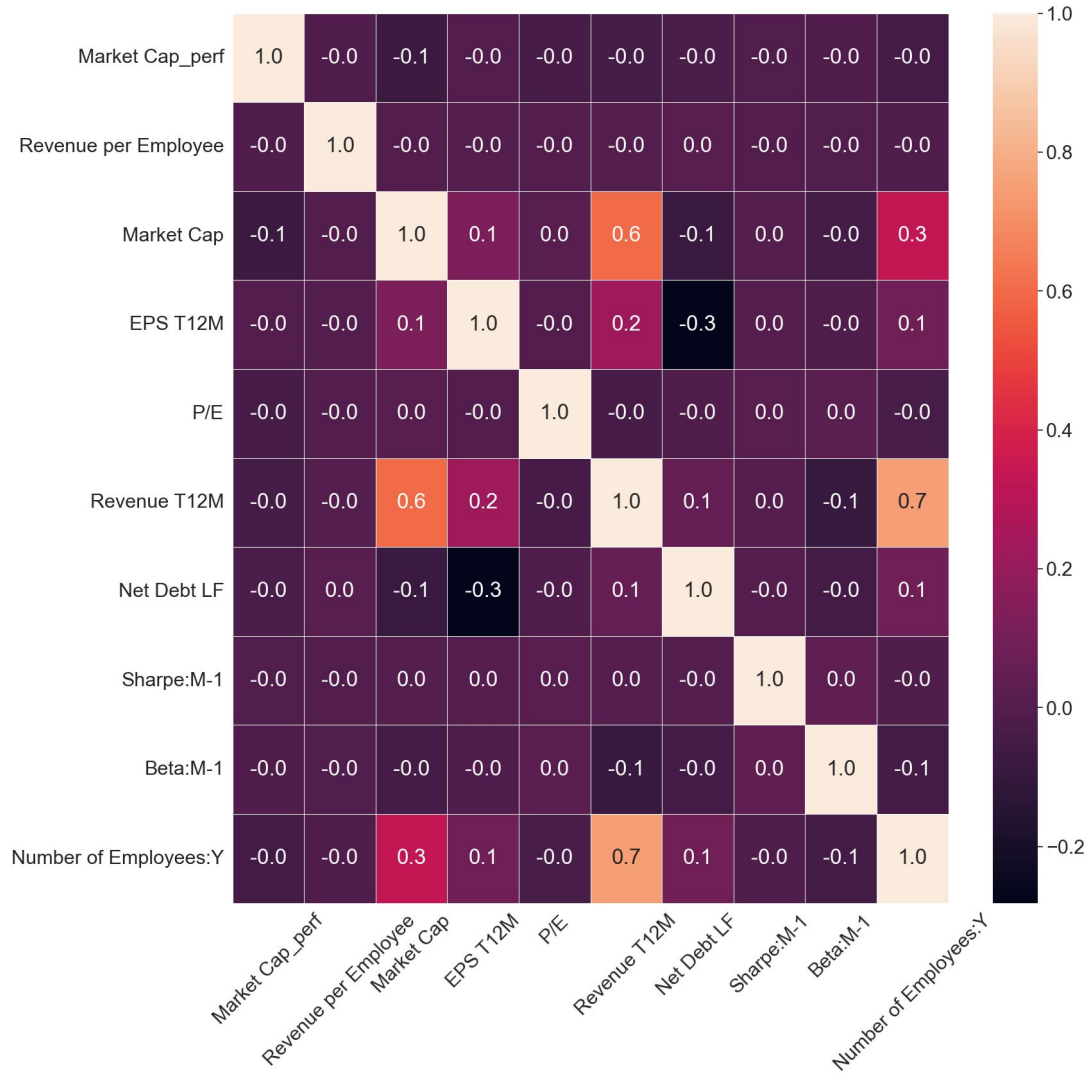
## 2. Data

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





## 2. Data



## 2. Data: “Top 10”

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- 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	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	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	7.510413e+05	1.242710e+10	5.520000	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	

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# 3. Machine Learning

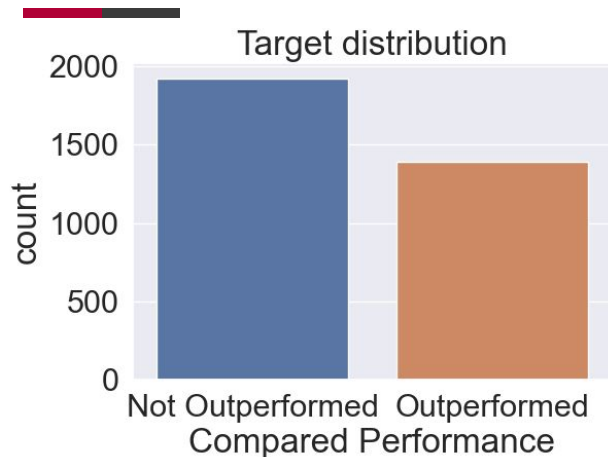
Github

### 3. Machine Learning

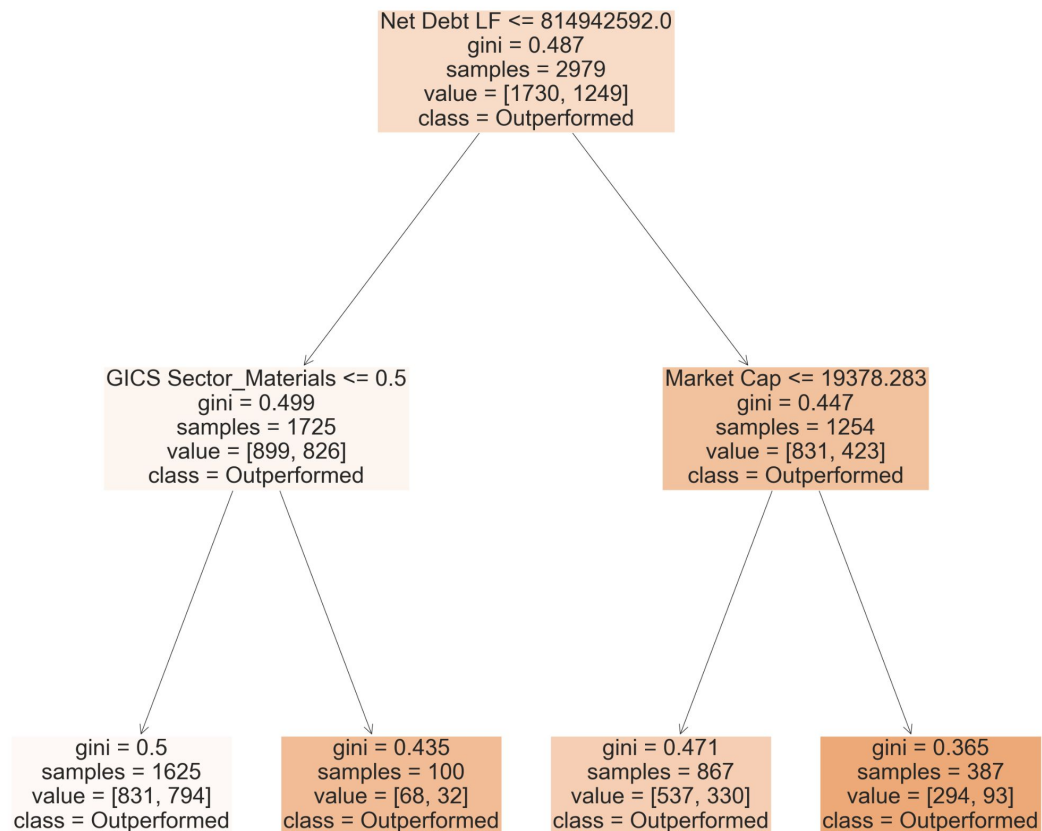
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- **target** label is determined:
  - companies with a **higher return** than the mean are labeled “**Outperformed**”
  - companies with a **lower return** than the mean or an equal return are labeled “**Not Outperformed**”
- differentiation between **three data cases**:
  - a case where the data consists of **only the concluded periods**
  - a case where the data consists of **all data**, including the ongoing period
  - a case where the **training data** consists of the **concluded**, 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**

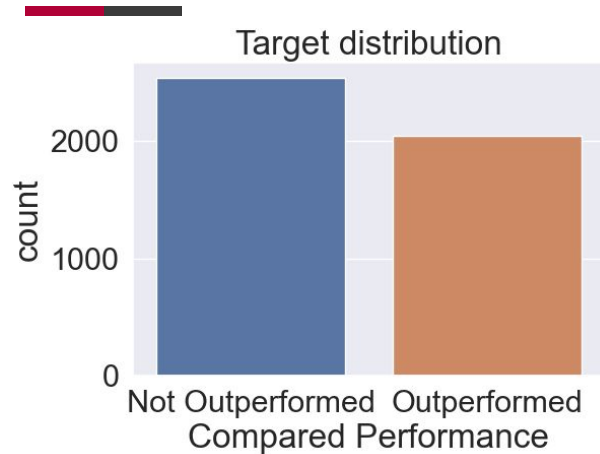
### 3. Machine Learning: DT concluded data



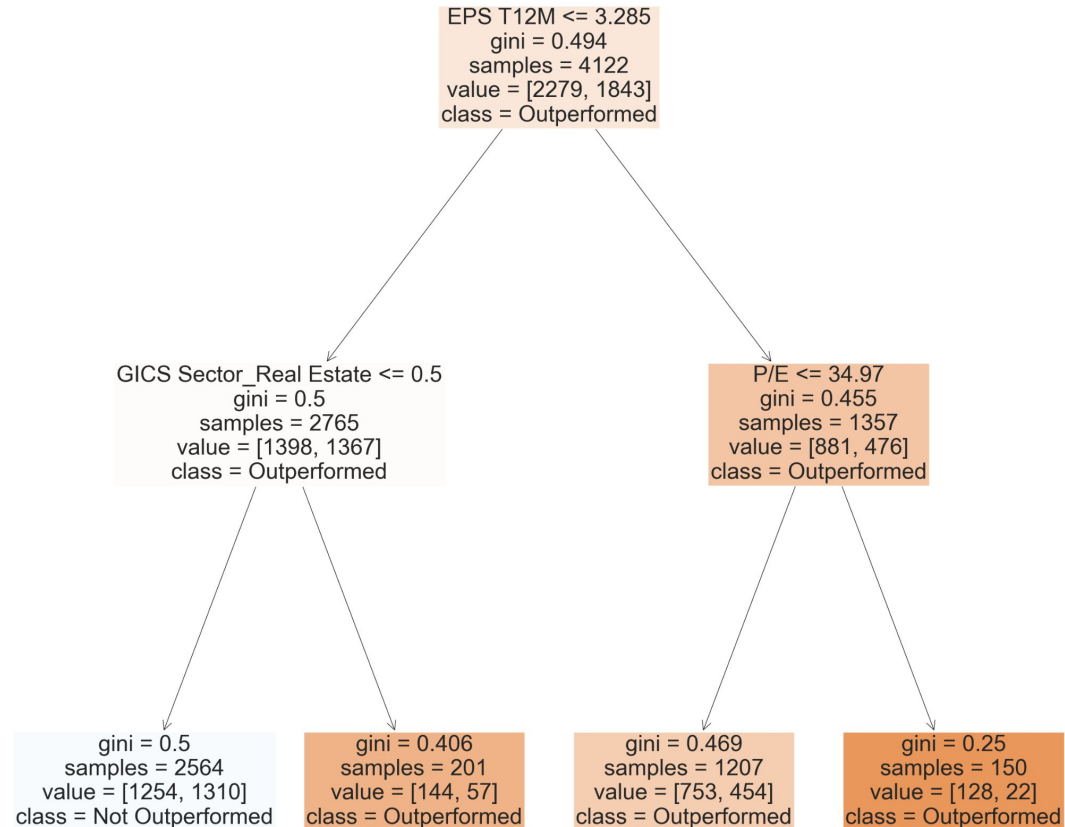
```
Train Accuracy : 0.5807317891910037
Train Confusion Matrix:
[[1730   0]
 [1249   0]]
Test Accuracy : 0.5770392749244713
Test Confusion Matrix:
[[191   0]
 [140   0]]
```



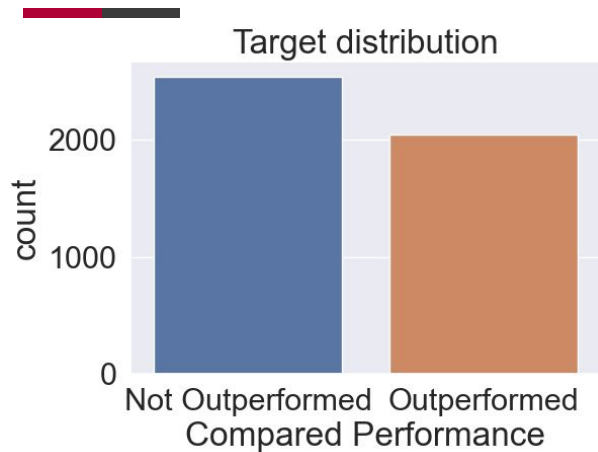
### 3. Machine Learning: DT all data



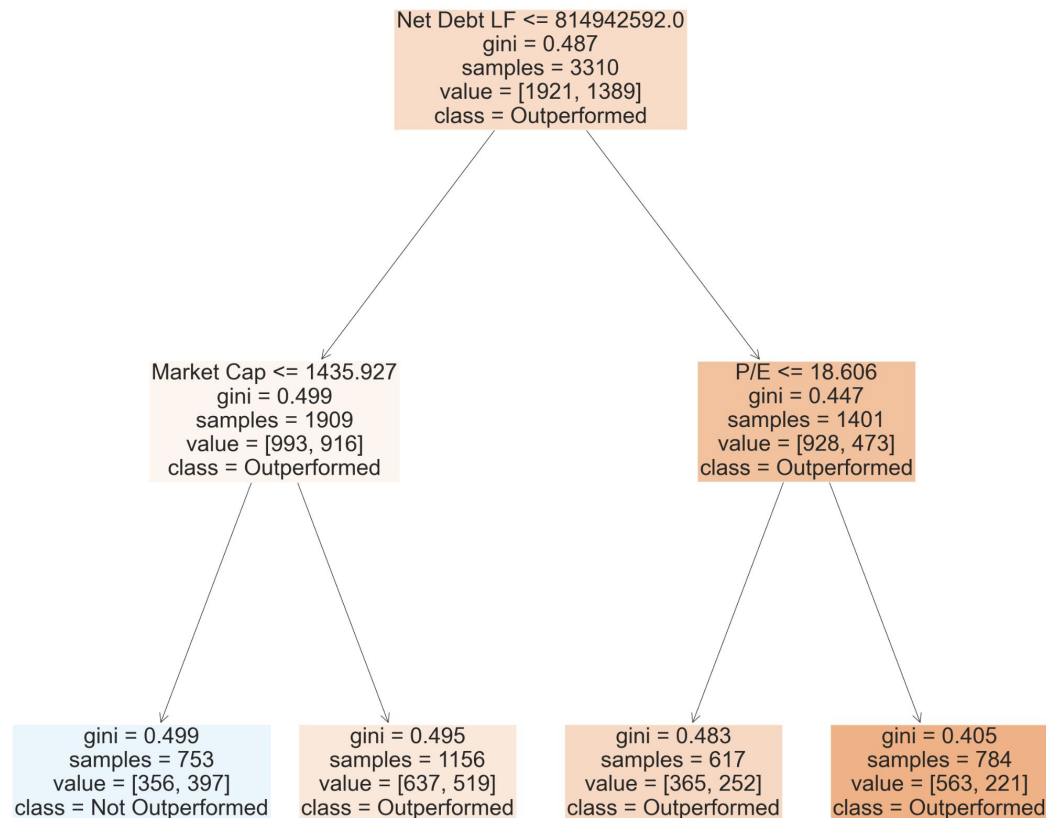
```
Train Accuracy : 0.5664725861232411
Train Confusion Matrix:
[[1025 1254]
 [ 533 1310]]
Test Accuracy : 0.5327510917030568
Test Confusion Matrix:
[[104 152]
 [ 62 140]]
```



### 3. Machine Learning: DT concluded=train, current=test



```
Train Accuracy : 0.592749244712991
Train Confusion Matrix:
[[1565  356]
 [ 992  397]]
Test Accuracy : 0.5062992125984253
Test Confusion Matrix:
[[571  85]
 [542  72]]
```

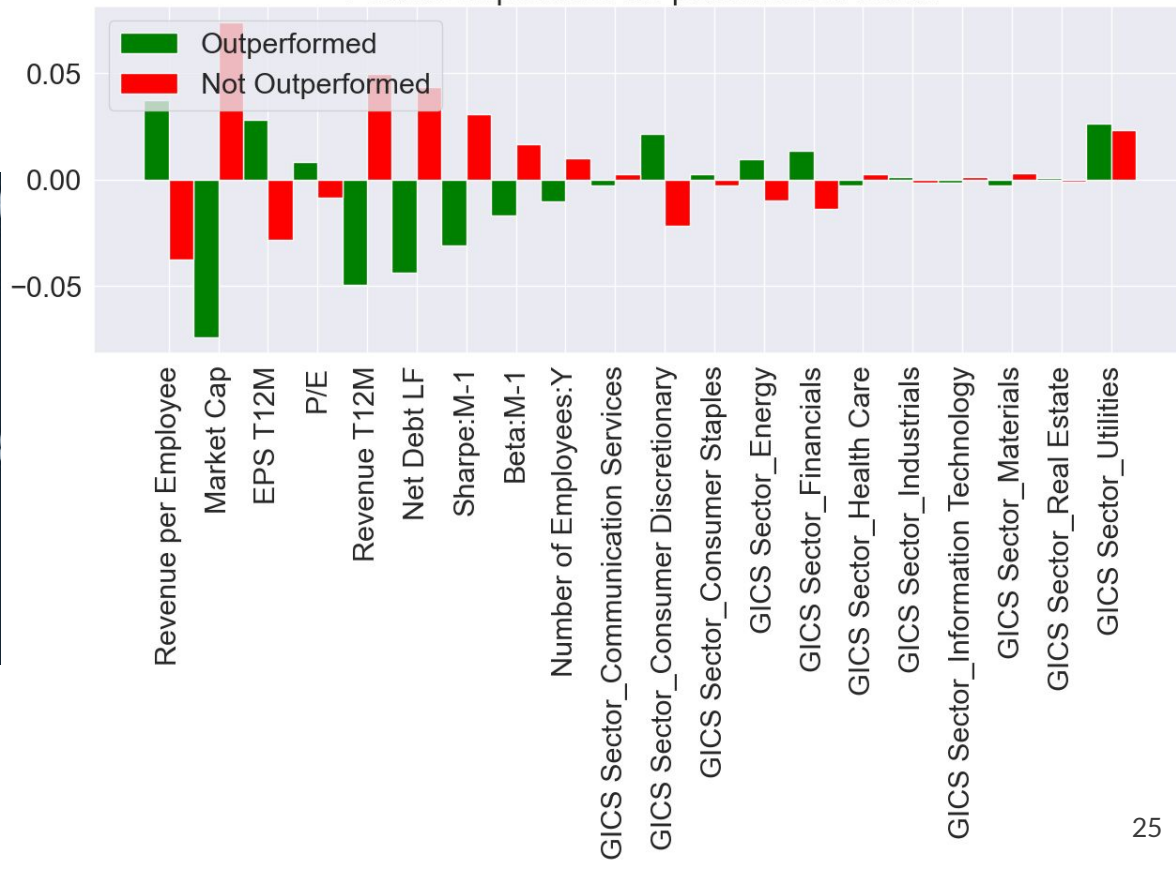




### 3. Machine Learning: RF concluded data

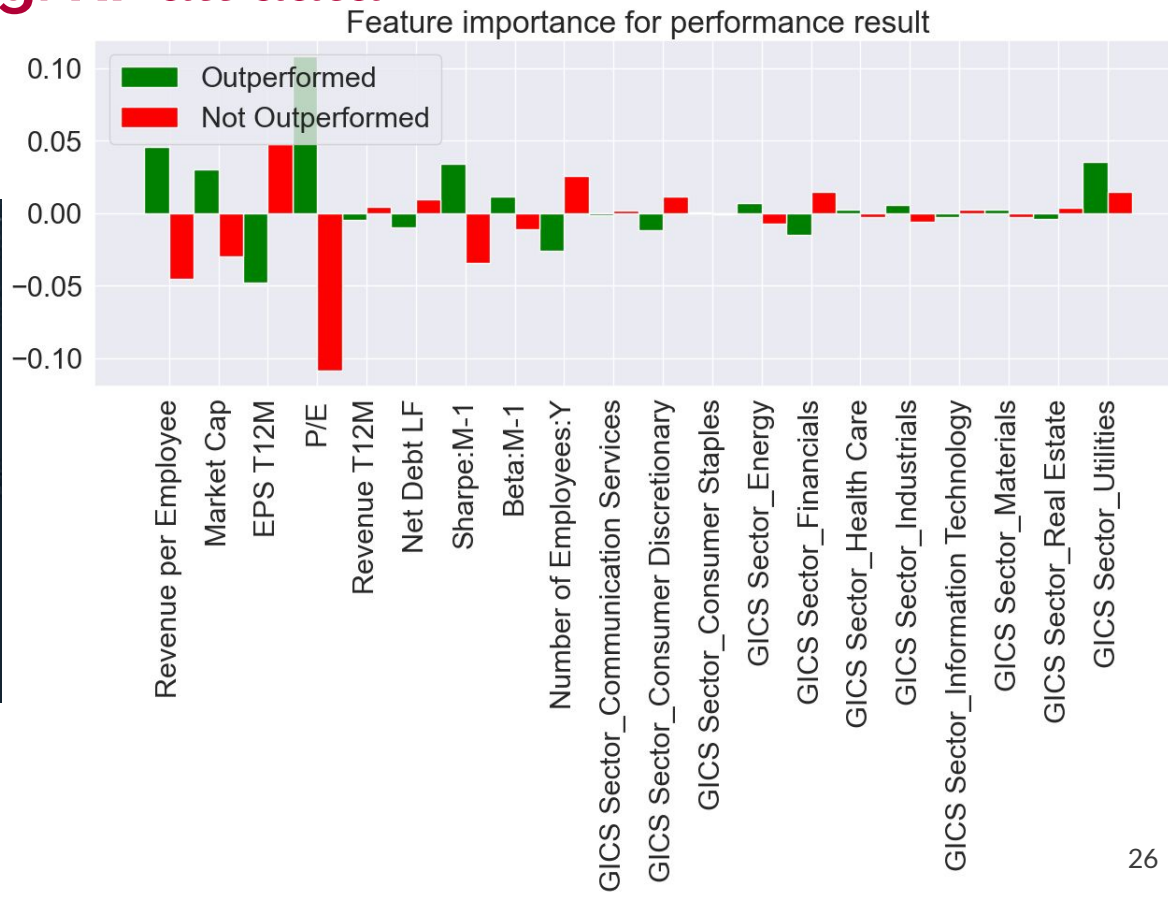
```
Train Accuracy : 0.9519
Train Confusion Matrix:
[[1694  15]
 [ 128 1142]]
Test Accuracy : 0.67673
Test Confusion Matrix:
[[169  43]
 [ 64  55]]
```

Feature importance for performance result



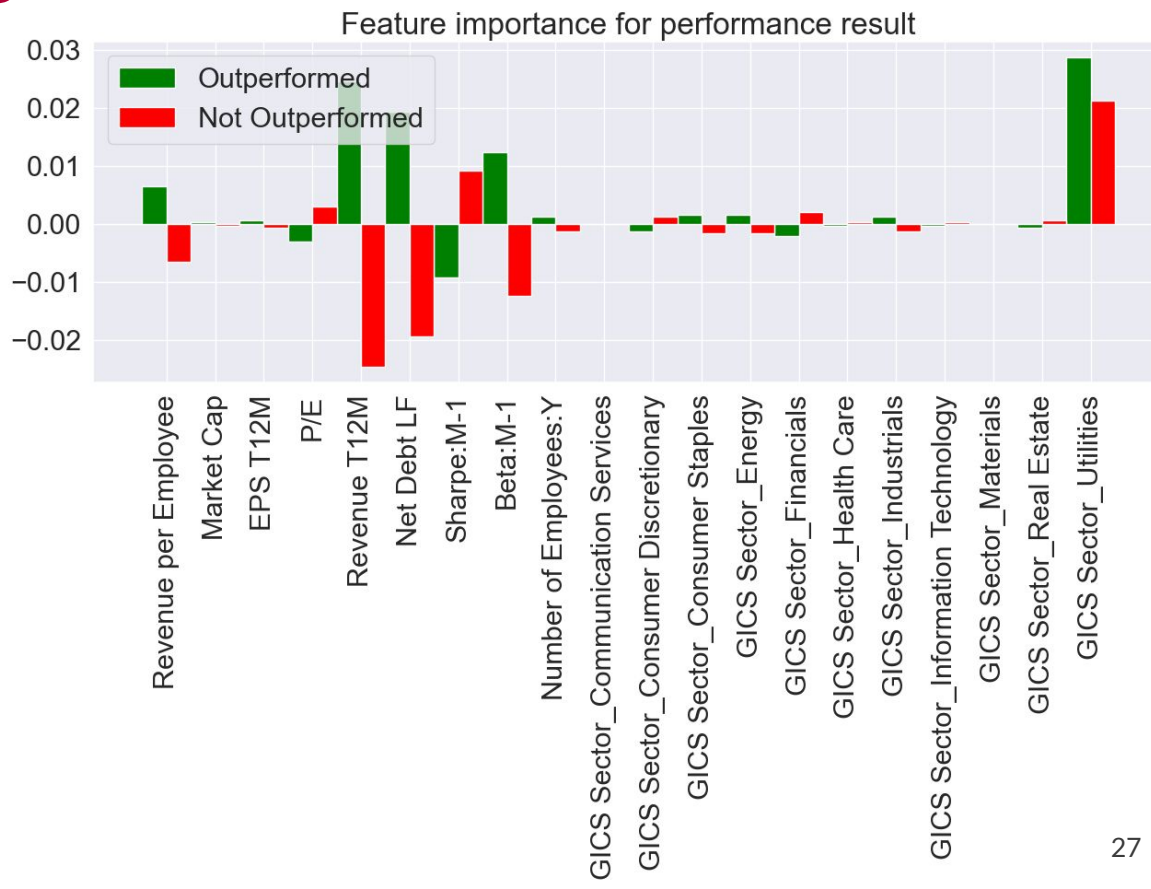
### 3. Machine Learning: RF all data

```
Train Accuracy : 0.9267
Train Confusion Matrix:
[[2156  114]
 [ 188 1664]]
Test Accuracy : 0.61135
Test Confusion Matrix:
[[186  79]
 [ 99  94]]
```



### 3. Machine Learning: RF concluded=train, current=test

```
Train Accuracy : 0.5815
Train Confusion Matrix:
[[1916   5]
 [1380   9]]
Test Accuracy : 0.51811
Test Confusion Matrix:
[[652   4]
 [608   6]]
```



### 3. Machine Learning: RF predictor implementation

	Name	Start	Last	Duration	Gold	Nasdaq	Spot Crude Oil Price WTI	S&P 1500
0	Period 1	2004-04-01	2006-08-01	27	1.626804	1.047715	1.991006	1.148445
1	Period 2	2016-09-01	2017-08-01	10	1.000984	1.201220	1.063302	1.135936
2	Period 3	2017-09-01	2018-07-01	9	0.957095	1.206716	1.424729	1.124224
3	Period 4	2022-01-01	2023-04-01	14	1.125556	0.841070	0.954698	0.899495

	Name	Start	Last	Duration	all_Grid	concluded_Grid	current_test_Grid
0	Period 1	2004-04-01	2006-08-01	27	1.588451	1.725495	1.181392
1	Period 2	2016-09-01	2017-08-01	10	1.300215	1.398202	1.221751
2	Period 3	2017-09-01	2018-07-01	9	1.328033	1.419703	1.455724
3	Period 4	2022-01-01	2023-04-01	14	1.170977	0.801176	1.005071

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# 4. Conclusion

## 4. Conclusion

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→ 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. Conclusion

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### 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)?

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## 5. Sources



# Data Sources

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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

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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, Zaghun 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!**

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