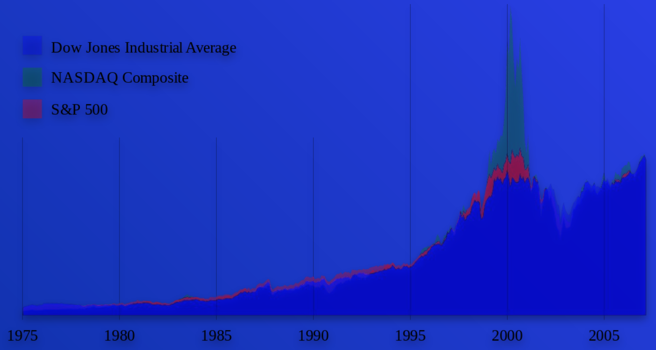
How to Beat the Market!



Results may vary
Past performance does not guarantee future results

Team Presentation

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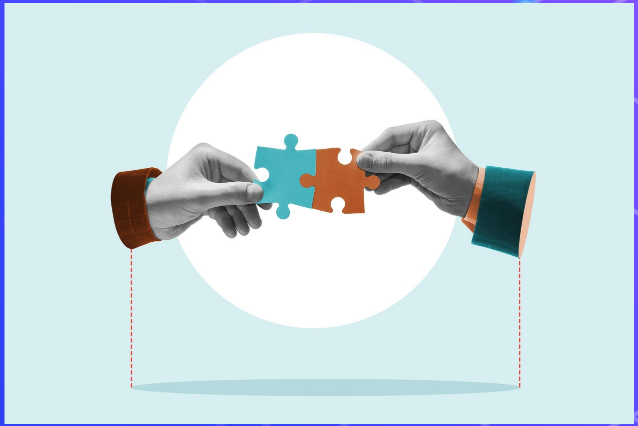
Motivation- M&A activity

- **Problem Statement:** Within industry, the preprocessing and analysis of financial statements is not standardized or automated in any fashion
    - This is particularly true in the context of Mergers and Acquisitions in the middle market
    - Calculations performed by hand, <10 companies analyzed per month

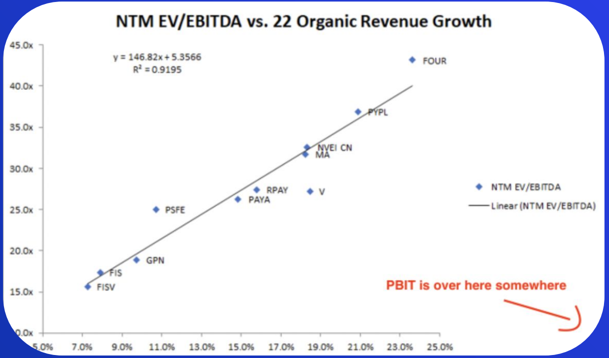
- **Proposed Solution:** To define a structured set of data (with financial metrics/multiples), and a standard method for preprocessing and analyzing middle market firms financials
    - Understanding Investor Priorities from the perspective of an acquisitive firm
    - Tying together pricing and valuation metrics used by both institutional and private investors



The Goal and Scope:

- **Project Goal:** Analyzing public financial data to understand relationships between metrics and company's valuation.
  - What do investors care about in a given Industry?

- **Project Scope:** Exploring correlations, predicting multiples, and providing insights for investment decisions.
  - Understanding Investor Priorities: Investigating what metrics investors prioritize within specific industries to guide strategic investment decisions.



Finance Background

<u>What is a valuation multiple?</u>

- Financial metric used to assess a company's worth relative to its financial performance.
- Provides a simple way to compare companies within the same industry or across different sectors.

1. EV/EBITDA
2. P/E
3. EV/Sales
4. EV/EBIT
5. Book Value
6. P/FCF
7. EV/UFCF
8. ....

EBITDA MULTIPLES (EV/EBITDA) BASED ON GROWTH & RISK

Lower Risk

Higher Risk

WACC (discount rate)	Revenue Growth (average in next 3 years): 0%	5%	10%	20%	40%
8%	9,0 x	13,6 x	15,5 x	19,7 x	30,4 x
10%	7,3 x	10,1 x	11,4 x	14,4 x	22,0 x
12%	6,1 x	8,0 x	9,0 x	11,3 x	17,2 x
14%	5,3 x	6,7 x	7,5 x	9,4 x	14,0 x
16%	4,6 x	5,7 x	6,4 x	8,0 x	11,8 x
18%	4,2 x	5,0 x	5,6 x	6,9 x	10,2 x
20%	3,8 x	4,5 x	5,0 x	6,1 x	8,9 x

Data Collection and Preprocessing

Source of data:

-

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XPF Table	XPF TYPE	XPF NAME	XPF LABEL	COMMENTS
co_afntind2	2	SALE_FN	Sales/Turnover (Net) Footnote	
co_afntind1	2	COGS_FN	Cost of Goods Sold Footnote	
co_afntind2	2	XRD_FN	Research and Development Expense Footnote	
co_afntind2	2	XRENT_FN	Rental Expense Footnote	
co_afntind1	2	DP_FN	Depreciation and Amortization Footnote	
co_afntind2	2	XINT_FN	Interest and Related Expense - Total Footnote	
-----	0	-----	-----	Comb of inc tax fnotes
co_afntind2	2	TXFED_FN	Income Taxes � Federal Footnote	Part of AFTNT7
co_afntind2	2	TXFO_FN	Income Taxes - Foreign Footnote	Part of AFTNT7
co_afntind2	2	TXS_FN	Income Taxes � State Footnote	Part of AFTNT7
co_afntind2	2	TXO_FN	Income Taxes - Other Footnote	Part of AFTNT7
co_afntind1	2	ITCI_FN	Investment Tax Credit (Income Account) Footnote	
co_afntind2	2	TXT_FN	Income Taxes - Total Footnote	
-----	0	-----	-----	Comb of IB, NI fnotes
co_afntind1	2	IB_FN	Income Before Extraordinary Items Footnote	part of AFTNT10
co_afntind2	2	NI_FN	Net Income (Loss) Footnote	part of AFTNT10
co_afntind2	2	NIADJ_FN	Net Income Adjusted for Common/Ordinary Stock (Capital) Equivalents Footnote	
-----	0	-----	-----	comb of EPSP fnotes
co_afntind1	2	EPSPI_FN	Earnings Per Share (Basic) � Including Extraordinary Items Footnote	part of AFTNT12
co_afntind1	2	EPSPX_FN	Earnings Per Share (Basic) � Excluding Extraordinary Items Footnote	part of AFTNT12
co_afntind1	2	CAPX_FN	Capital Expenditures Footnote	
-----	0	-----	-----	comb of MRC fnotes
co_afntind2	2	MRC1_FN	Rental Commitments � Minimum � 1st Year Footnote	part of AFTNT14
co_afntind2	2	MRC2_FN	Rental Commitments � Minimum � 2nd Year Footnote	part of AFTNT14
co_afntind2	2	MRC3_FN	Rental Commitments � Minimum � 3rd Year Footnote	part of AFTNT14
co_afntind2	2	MRC4_FN	Rental Commitments � Minimum � 4th Year Footnote	part of AFTNT14
co_afntind2	2	MRC5_FN	Rental Commitments � Minimum � 5th Year Footnote	part of AFTNT14
co_afntind1	2	DPACT_FN	Depreciation Depletion and Amortization (Accumulated) Footnote	
co_afntind1	2	AP_FN	Accounts Payable - Trade Footnote	
co_afntind2	2	TXP_FN	Income Taxes Payable Footnote	
co_afntind1	2	EIEAC_FN	Equity Interest in Earnings of Associated Companies Footnote	

```python
filtered_data = MiddleMarket_data.loc[MiddleMarket_data['ebitda'] > 0, ['tic','mkvalt','ebitda','dvc','ob','conm','fdate','lt','fyr','xrd','cogs',
                                                                          'oibdp','capx','at','revt', 'xsga','ppent','csho','ppegt', 'che','ceq','lct',
                                                                          'prcl_c','prch_c','Avg_Price','Market_Cap','oiadp','invt','sich','emp','txt','xint','act']]
#filtered_data
filtered_data.columns = ['Ticker', 'MarkCap','EBITDA', 'Dividends', 'Operating Income',
                         'Company Name', 'Fiscal Date', 'Long-Term Debt', 'Fiscal Year',
                         'Research and Development Expenses', 'Cost of Goods Sold',
                         'Operating Income Before Depreciation', 'Capital Expenditures', 'Total Assets',
                         'Revenue', 'Selling, General, and Administrative Expenses', 'Property, Plant, and Equipment Net',
                         'Common Shares Outstanding', 'Gross Property, Plant, and Equipment', 'Cash and Equivalents',
                         'Common Equity', 'Current Liabilities', '52-Week Low Price', '52-Week High Price','Avg_Price',
                         'Market_Cap','OpInc After Dep','Inventory','SP Index Code','Employees','Taxes','Interest Expense','Current Assets']
filtered_data.reindex()
```

Python

	Ticker	MarkCap	EBITDA	Dividends	Operating Income	Company Name	Fiscal Date	Long-Term Debt	Fiscal Year	Research and Development Expenses	...	52-Week High Price	Avg_Price	Market_Cap	OpInc After Dep	Inventory	SP Index Code	Employees	Taxe
0	AIR	1476.9063	101.800	0.100	750.0	AAR CORP	2021-07-22	565.300	5	NaN	...	47.99	28.2750	1000.228125	65.500	591.000	5080.0	4.700	18.20
1	AIR	1706.5540	149.300	0.000	850.0	AAR CORP	2022-07-22	539.400	5	NaN	...	45.49	38.1950	1351.759245	116.200	604.100	5080.0	4.500	26.60
2	AIR	1749.6408	179.300	0.000	740.0	AAR CORP	2023-07-21	734.000	5	NaN	...	52.83	43.2900	1511.513640	151.400	624.700	5080.0	5.000	31.40

Data Collection and Preprocessing

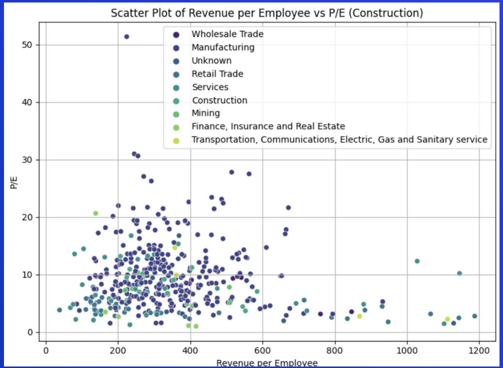
- <u>Adding financial metrics, ratios, and growth rates</u>

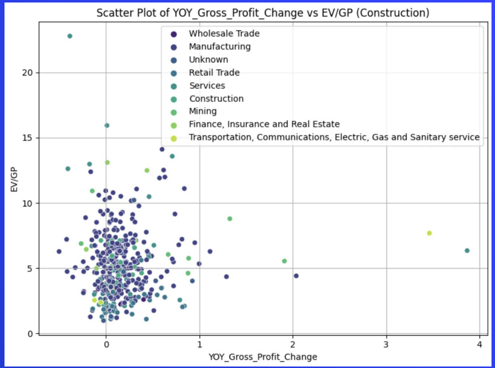
```python
# Define a function to map SP Index Codes to divisions
def map_sp_index_to_division(sp_index_code):
    if sp_index_code >= 100 and sp_index_code <= 999:
        return 'Agriculture, Forestry and Fishing'
    elif sp_index_code >= 1000 and sp_index_code <= 1499:
        return 'Mining'
    elif sp_index_code >= 1500 and sp_index_code <= 1799:
        return 'Construction'
    elif sp_index_code >= 2000 and sp_index_code <= 3999:
        return 'Manufacturing'
    elif sp_index_code >= 4000 and sp_index_code <= 4999:
        return 'Transportation, Communications, Electric, Gas and Sanitary service'
    elif sp_index_code >= 5000 and sp_index_code <= 5199:
        return 'Wholesale Trade'
    elif sp_index_code >= 5200 and sp_index_code <= 5999:
        return 'Retail Trade'
    elif sp_index_code >= 6000 and sp_index_code <= 6799:
        return 'Finance, Insurance and Real Estate'
    elif sp_index_code >= 7000 and sp_index_code <= 8999:
        return 'Services'
    elif sp_index_code >= 9100 and sp_index_code <= 9729:
        return 'Public Administration'
    elif sp_index_code >= 9900 and sp_index_code <= 9999:
        return 'Nonclassifiable'
    else:
        return 'Unknown'

# Add a new column 'Division' based on 'SP Index Code'
filtered_data['Division'] = filtered_data['SP Index Code'].apply(map_sp_index_to_division
```

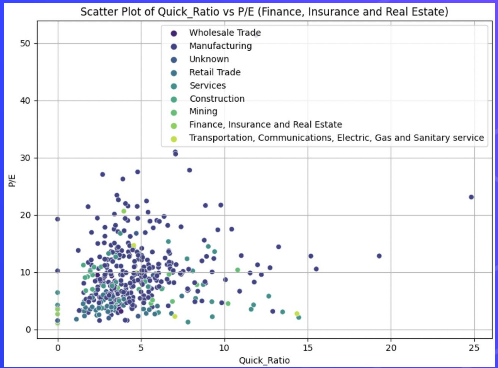
```python
iltered_data['EBIT - Capex'] = filtered_data['Operating Income'] + filtered_data['Interest Expense'] + filtered_data['Taxes'] - filtered_data['Capital Expenditure
filtered_data['Enterprise_Value'] = filtered_data['Market_Cap'] + filtered_data['Long-Term Debt'] - filtered_data['Cash and Equivalents']
filtered_data['EV/EBITDA'] = filtered_data['Enterprise_Value'] / filtered_data['EBITDA']
filtered_data['EPS'] = filtered_data['Operating Income Before Depreciation'] / filtered_data['Common Shares Outstanding']
filtered_data['P/E'] = filtered_data['Avg_Price'] / filtered_data['EPS']
filtered_data['Debt_to_Equity'] = filtered_data['Long-Term Debt'] / filtered_data['Common Equity']
filtered_data['ROE'] = filtered_data['Operating Income Before Depreciation'] / filtered_data['Common Equity']
filtered_data['Current_Ratio'] = filtered_data['Total Assets'] / filtered_data['Current Liabilities']
filtered_data['Quick_Ratio'] = (filtered_data['Total Assets'] - filtered_data['Inventory']) / filtered_data['Current Liabilities']

filtered_data['Interest_Coverage_Ratio'] = filtered_data['EBITDA'] / filtered_data['Interest Expense']
filtered_data['Gross_Margin'] = (filtered_data['Revenue'] - filtered_data['Cost of Goods Sold']) / filtered_data['Revenue']
filtered_data['Operating_Margin'] = filtered_data['Operating Income Before Depreciation'] / filtered_data['Revenue']
filtered_data['Gross Profit'] = filtered_data['Revenue'] - filtered_data['Cost of Goods Sold']
filtered_data['Gross Profit Margin'] = (filtered_data['Gross Profit'] / filtered_data['Revenue'])
filtered_data['EV/GP'] = filtered_data['Enterprise_Value'] / filtered_data['Gross Profit']
filtered_data['EBITDA - Capex'] = filtered_data['EBITDA'] - filtered_data['Capital Expenditures']
filtered_data['EBITDA - Capex Margin'] = (filtered_data['EBITDA - Capex'] / filtered_data['EBITDA'])
filtered_data['EV/EBITDA-Capex'] = filtered_data['Enterprise_Value'] / filtered_data['EBITDA - Capex']
filtered_data['Free Cash Flow'] = (filtered_data['EBITDA']
                                  - filtered_data['Taxes']
                                  - filtered_data['Interest Expense']
                                  + (filtered_data['Current Assets'] - filtered_data['Current Liabilities'])
                                  - filtered_data['Capital Expenditures'])
filtered_data['FCF_Positive'] = (filtered_data['Free Cash Flow'] > 0).astype(int)
filtered_data['FCF Yield'] = filtered_data['Free Cash Flow'] / filtered_data['Market_Cap']
filtered_data['Invested_Capital'] = filtered_data['Long-Term Debt'] + filtered_data['Common Equity']
filtered_data['EBIT'] = filtered_data['Operating Income'] + filtered_data['Interest Expense'] + filtered_data['Taxes']
filtered_data['EV_EBIT'] = filtered_data['Enterprise_Value'] / filtered_data['EBIT']
filtered_data['ROIC'] = filtered_data['EBIT'] / filtered_data['Invested_Capital']
filtered_data['EBIT Margin (%)'] = (filtered_data['EBIT'] / filtered_data['Revenue'])
filtered_data['EBIT_Positive'] = (filtered_data['EBIT'] > 0).astype(int)
filtered_data['Revenue per Employee'] = filtered_data['Revenue'] / filtered_data['Employees']
filtered_data['Total Debt Service'] = filtered_data['Long-Term Debt'] + filtered_data['Interest Expense']
filtered_data['Debt_Coverage_Ratio'] = filtered_data['Operating Income Before Depreciation'] / filtered_data['Total Debt Service']
filtered_data['Dividend (y/n)'] = (filtered_data['Dividends'] > 0).astype(int)
 tered_data['Price_Range_Ratio'] = (filtered_data['52-Week High Price'] - filtered_data['52-Week Low Price']) / filtered_data['52-Week Low Price']
```

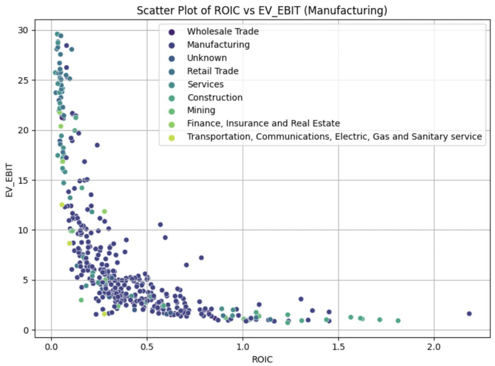
```python
grouped_data = filtered_data.sort_values(by=['Ticker', 'Fiscal Year']).groupby('Ticker')

filtered_data['YOY_Gross_Margin_Change'] = grouped_data['Gross_Margin'].pct_change()
filtered_data['YOY_EBIT_Margin_Change'] = grouped_data['EBIT Margin (%)'].pct_change()
filtered_data['YOY_Operating_Margin_Change'] = grouped_data['Operating_Margin'].pct_change()
filtered_data['YOY_Gross_Profit_Change'] = grouped_data['Gross Profit'].pct_change()
filtered_data['YOY_Revenue_Change'] = grouped_data['Revenue'].pct_change()
filtered_data['YOY_EBIT_Change'] = grouped_data['EBIT'].pct_change()
filtered_data['YOY_EBIT - Capex Change'] = grouped_data['EBIT - Capex'].pct_change()
filtered_data
```

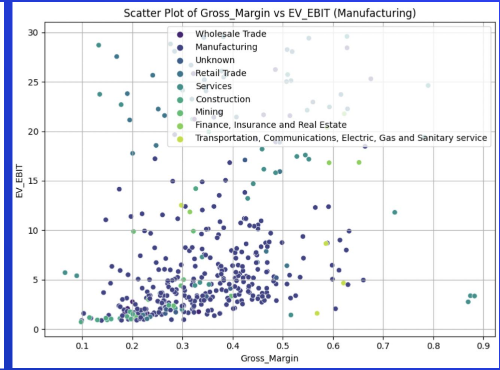
Exploratory Data Analysis



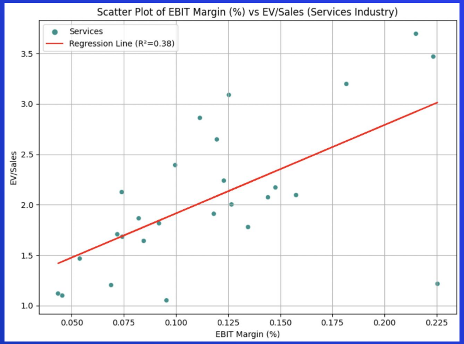


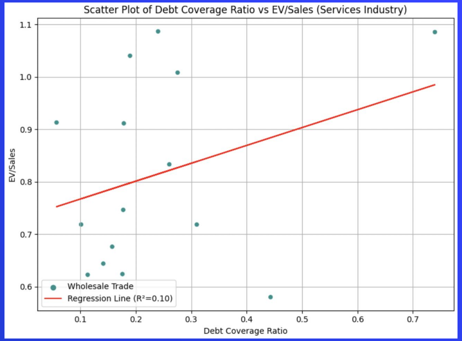


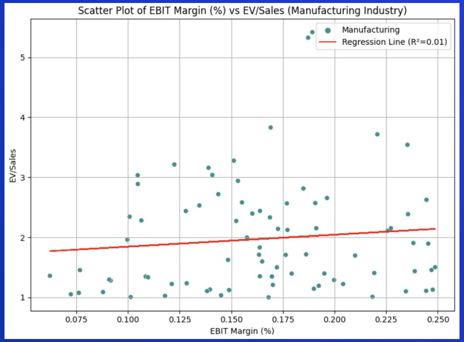


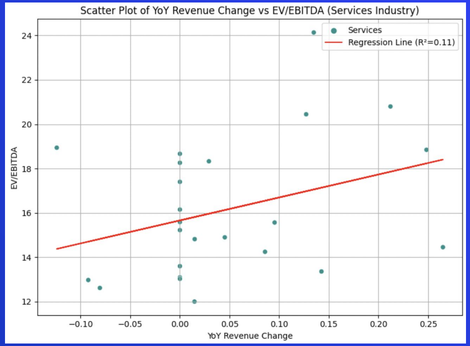


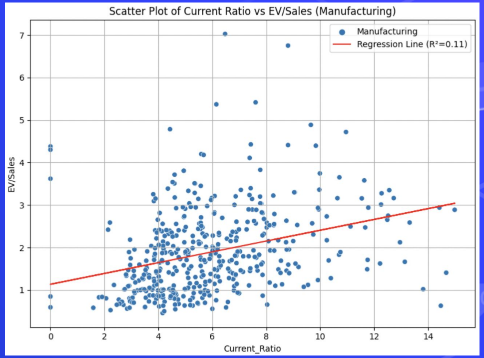
Exploratory Data Analysis cntd











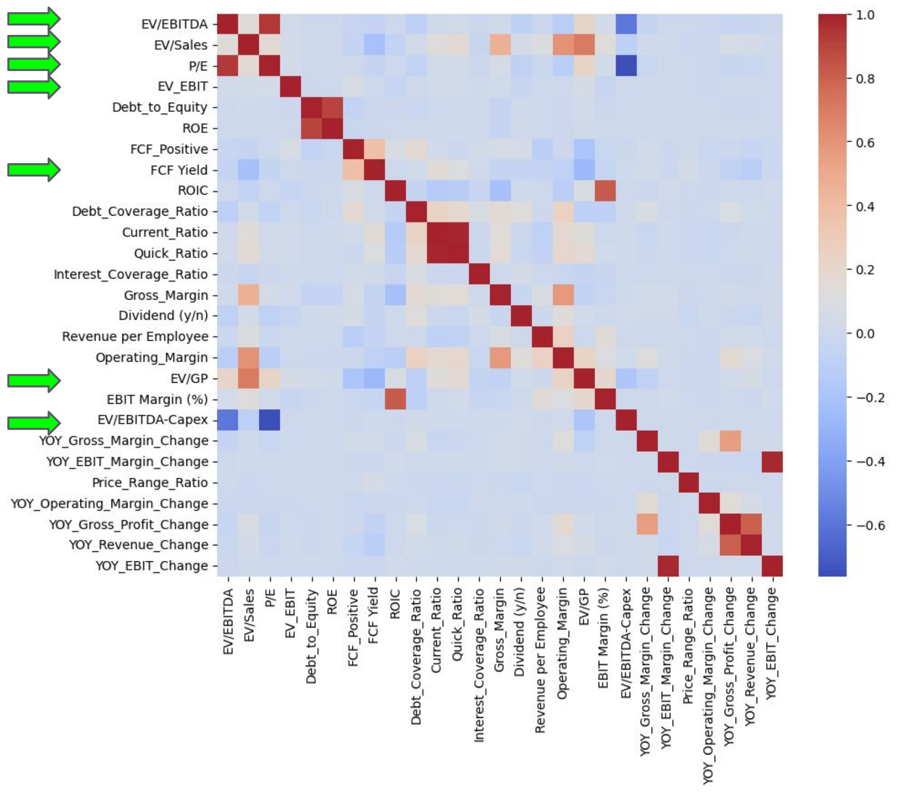
Industry Level Analysis

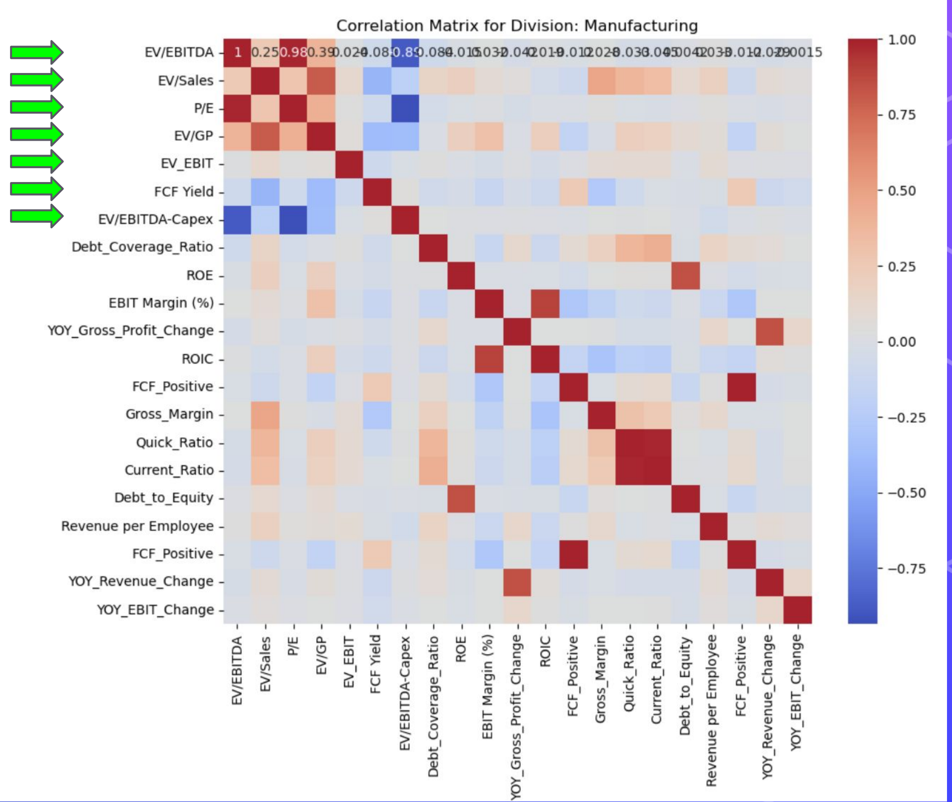
```
Division
Manufacturing                              753
Retail Trade                               412
Services                                   317
Construction                               119
Wholesale Trade                            103
Unknown_Nonclassifiable                     55
Finance, Insurance and Real Estate          55
Mining_Trans_Comm_Gas_Sanitary              51
```

Feature Selection- Multiples

```
Number of correlations with |value| > 0.3
EV/EBITDA: 14
EV/Sales: 29
P/E: 15
EV/GP: 25
EV_EBIT: 13
FCF Yield: 19
EV/EBITDA-Capex: 3
```

Feature Selection- Multiples





Feature Importance- Metrics

Division: Construction

Multiple: EV/EBITDA

OLS Regression Results

Dep. Variable:	EV/EBITDA	R-squared:	0.699
Model:	OLS	Adj. R-squared:	0.662
Method:	Least Squares	F-statistic:	18.76
Date:	Mon, 06 May 2024	Prob (F-statistic):	8.54e-22
Time:	17:49:14	Log-Likelihood:	-334.51
No. Observations:	119	AIC:	697.0
Df Residuals:	105	BIC:	735.9
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	16.4562	3.841	4.284	0.000	8.840	24.072
Debt_Coverage_Ratio	-7.2383	5.291	-1.368	0.174	-17.729	3.252
ROE	-18.8543	4.862	-3.878	0.000	-28.494	-9.214
EBIT Margin (%)	-2.0618	1.919	-1.075	0.285	-5.866	1.742
YOY_Gross_Profit_Change	-11.3433	3.366	-3.370	0.001	-18.017	-4.669
ROIC	1.3264	1.008	1.315	0.191	-0.673	3.326
FCF_Positive	-1.9021	0.565	-3.368	0.001	-3.022	-0.782
FCF_Positive	-1.9021	0.565	-3.368	0.001	-3.022	-0.782
Gross_Margin	8.2427	14.562	0.566	0.573	-20.630	37.116
Quick_Ratio	-4.3678	3.181	-1.373	0.173	-10.675	1.939
Current_Ratio	5.5941	3.051	1.833	0.070	-0.456	11.645
Debt_to_Equity	3.0080	0.780	3.858	0.000	1.462	4.554
Revenue per Employee	0.0008	0.001	0.785	0.434	-0.001	0.003
FCF_Positive	-1.9021	0.565	-3.368	0.001	-3.022	-0.782
FCF_Positive	-1.9021	0.565	-3.368	0.001	-3.022	-0.782
YOY_Revenue_Change	12.6295	4.374	2.887	0.005	3.957	21.302
YOY_EBIT_Change	2.3348	1.611	1.449	0.150	-0.859	5.529

Omnibus:	33.615	Durbin-Watson:	1.841
Prob(Omnibus):	0.000	Jarque-Bera (JB):	81.242
Skew:	1.081	Prob(JB):	2.28e-18
Kurtosis:	6.422	Cond. No.	2.55e+22

Multiple: EV/Sales

OLS Regression Results

Dep. Variable:	EV/Sales	R-squared:	0.703
Model:	OLS	Adj. R-squared:	0.667
Method:	Least Squares	F-statistic:	19.14
Date:	Mon, 06 May 2024	Prob (F-statistic):	4.19e-22
Time:	17:49:14	Log-Likelihood:	-31.981
No. Observations:	119	AIC:	91.96
Df Residuals:	105	BIC:	130.9
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.5717	0.302	-1.892	0.061	-1.171	0.028
Debt_Coverage_Ratio	-0.4278	0.416	-1.028	0.307	-1.253	0.398
ROE	-1.1562	0.383	-3.022	0.003	-1.915	-0.398
EBIT Margin (%)	0.6149	0.151	4.073	0.000	0.316	0.914
YOY_Gross_Profit_Change	-0.5080	0.265	-1.918	0.058	-1.033	0.017
ROIC	-0.2698	0.079	-3.400	0.001	-0.427	-0.112
FCF_Positive	-0.0430	0.044	-0.968	0.335	-0.131	0.045
FCF_Positive	-0.0430	0.044	-0.968	0.335	-0.131	0.045
Gross_Margin	6.2668	1.146	5.469	0.000	3.995	8.539
Quick_Ratio	-1.1394	0.250	-4.552	0.000	-1.636	-0.643
Current_Ratio	1.2375	0.240	5.154	0.000	0.761	1.714
Debt_to_Equity	0.1880	0.061	3.064	0.003	0.066	0.310
Revenue per Employee	0.0001	7.99e-05	1.485	0.141	-3.98e-05	0.000
FCF_Positive	-0.0430	0.044	-0.968	0.335	-0.131	0.045
FCF_Positive	-0.0430	0.044	-0.968	0.335	-0.131	0.045
YOY_Revenue_Change	0.6618	0.344	1.923	0.057	-0.021	1.344
YOY_EBIT_Change	0.0817	0.127	0.644	0.521	-0.170	0.333

Omnibus:	22.778	Durbin-Watson:	1.209
Prob(Omnibus):	0.000	Jarque-Bera (JB):	38.425
Skew:	0.863	Prob(JB):	4.53e-09
Kurtosis:	5.184	Cond. No.	2.55e+22

Feature Importance- Metrics

Division: Finance, Insurance and Real Estate

```
Multiple: EV/Sales
                            OLS Regression Results
==============================================================================
Dep. Variable:                EV/Sales   R-squared:                       0.576
Model:                             OLS   Adj. R-squared:                  0.441
Method:                  Least Squares   F-statistic:                     4.279
Date:                 Mon, 06 May 2024   Prob (F-statistic):           0.000173
Time:                         17:49:14   Log-Likelihood:                -176.36
No. Observations:                   55   AIC:                             380.7
Df Residuals:                       41   BIC:                             408.8
Df Model:                           13
Covariance Type:             nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                    -1.1875      4.061     -0.292      0.771      -9.389       7.014
Debt_Coverage_Ratio     -13.9303     12.791     -1.089      0.282     -39.763      11.902
ROE                      -2.1126      0.660     -3.200      0.003      -3.446      -0.779
EBIT Margin (%)           4.4523      1.901      2.342      0.024       0.612       8.292
YOY_Gross_Profit_Change  -1.0150      4.678     -0.217      0.829     -10.462       8.432
ROIC                     -6.7307     21.826     -0.308      0.759     -50.808      37.347
FCF_Positive             -0.7657      1.003     -0.763      0.450      -2.791       1.260
FCF_Positive             -0.7657      1.003     -0.763      0.450      -2.791       1.260
Gross_Margin             19.3049      7.522      2.567      0.014       4.114      34.496
Quick_Ratio               1.6883     20.028      0.084      0.933     -38.759      42.136
Current_Ratio            -0.4344     19.877     -0.022      0.983     -40.576      39.707
Debt_to_Equity            0.2989      0.092      3.254      0.002       0.113       0.484
Revenue per Employee      0.0012      0.001      1.312      0.197      -0.001       0.003
FCF_Positive             -0.7657      1.003     -0.763      0.450      -2.791       1.260
FCF_Positive             -0.7657      1.003     -0.763      0.450      -2.791       1.260
YOY_Revenue_Change       -4.1435      7.810     -0.531      0.599     -19.915      11.628
YOY_EBIT_Change           0.2179      1.846      0.118      0.907      -3.511       3.947
==============================================================================
Omnibus:                      20.894   Durbin-Watson:                   1.322
Prob(Omnibus):                 0.000   Jarque-Bera (JB):               36.916
Skew:                          1.191   Prob(JB):                     9.64e-09
Kurtosis:                      6.230   Cond. No.                     1.34e+22
==============================================================================
```

Division: Manufacturing

```
Multiple: EV/Sales
                            OLS Regression Results
==============================================================================
Dep. Variable:                EV/Sales   R-squared:                       0.411
Model:                             OLS   Adj. R-squared:                  0.400
Method:                  Least Squares   F-statistic:                     39.59
Date:                 Mon, 06 May 2024   Prob (F-statistic):           5.60e-76
Time:                         17:49:14   Log-Likelihood:                -1427.5
No. Observations:                  753   AIC:                             2883.
Df Residuals:                      739   BIC:                             2948.
Df Model:                           13
Covariance Type:             nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                    -0.7061      0.485     -1.457      0.146      -1.658       0.245
Debt_Coverage_Ratio      -0.0739      0.201     -0.367      0.714      -0.469       0.322
ROE                       0.8404      0.119      7.089      0.000       0.608       1.073
EBIT Margin (%)           0.4671      0.108      4.332      0.000       0.255       0.679
YOY_Gross_Profit_Change  -1.1569      0.493     -2.346      0.019      -2.125      -0.189
ROIC                     -0.3896      0.166     -2.346      0.019      -0.716      -0.064
FCF_Positive             -0.1542      0.111     -1.391      0.165      -0.372       0.063
FCF_Positive             -0.1542      0.111     -1.391      0.165      -0.372       0.063
Gross_Margin              5.5401      0.502     11.041      0.000       4.555       6.525
Quick_Ratio               0.3815      0.096      3.987      0.000       0.194       0.569
Current_Ratio            -0.1974      0.088     -2.250      0.025      -0.370      -0.025
Debt_to_Equity           -0.0309      0.007     -4.525      0.000      -0.044      -0.018
Revenue per Employee      0.0020      0.000      5.725      0.000       0.001       0.003
FCF_Positive             -0.1542      0.111     -1.391      0.165      -0.372       0.063
FCF_Positive             -0.1542      0.111     -1.391      0.165      -0.372       0.063
YOY_Revenue_Change        2.1496      0.636      3.381      0.001       0.901       3.398
YOY_EBIT_Change           0.0110      0.023      0.472      0.637      -0.035       0.057
==============================================================================
Omnibus:                     568.195   Durbin-Watson:                   1.100
Prob(Omnibus):                 0.000   Jarque-Bera (JB):            12569.776
Skew:                          3.187   Prob(JB):                         0.00
Kurtosis:                     21.974   Cond. No.                     2.24e+21
==============================================================================
```

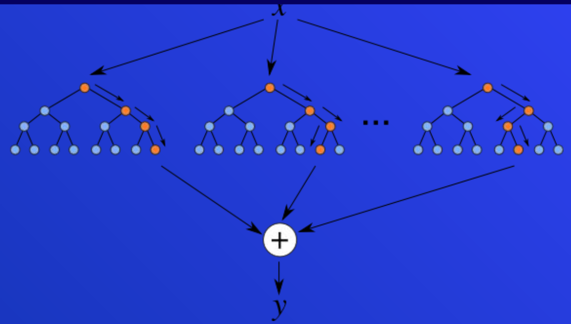
Feature Importance - Code demo

Machine Learning Approach

Handling Nonlinearity:
Captures complex nonlinear relationships between input features and target variables. Financial data often exhibits nonlinear patterns.

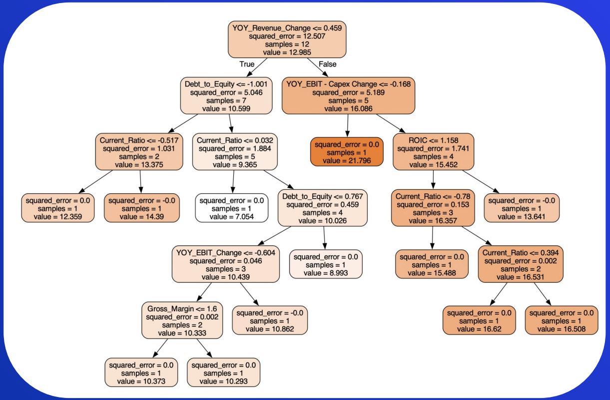
Feature Importance:
Allows us to identify which financial metrics have the most significant impact on valuation multiples..

Robustness to Overfitting:
Random Forest is less prone to overfitting compared to other machine learning algorithms, making it suitable for datasets with a large number of features and observations.

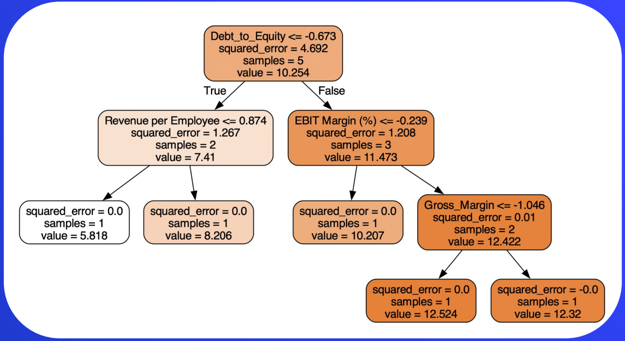


Some Random Forest Results

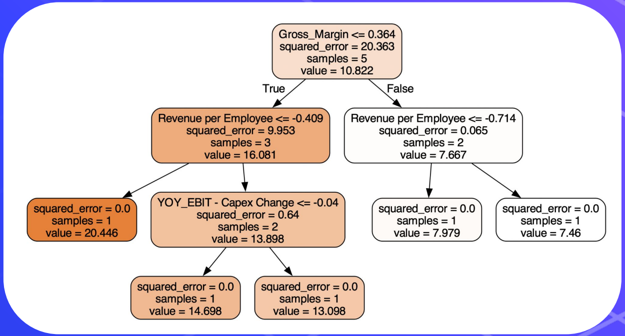
Construction

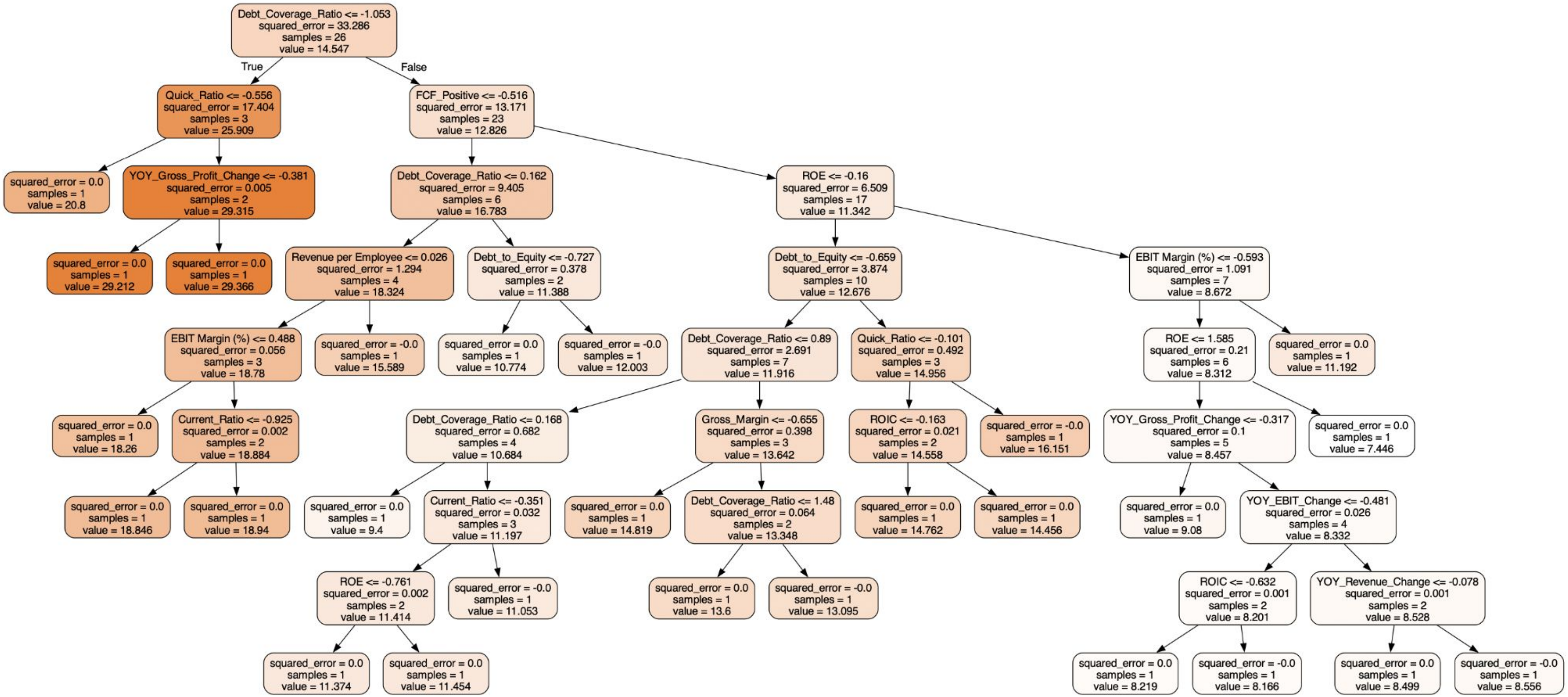


Mining



Financial




Debt_Coverage_Ratio <= -1.053
squared_error = 33.286
samples = 26
value = 14.547
True
False
Quick_Ratio <= -0.556
squared_error = 17.404
samples = 3
value = 25.909
FCF_Positive <= -0.516
squared_error = 13.171
samples = 23
value = 12.826
squared_error = 0.0
samples = 1
value = 20.8
YOY_Gross_Profit_Change <= -0.381
squared_error = 0.005
samples = 2
value = 29.315
Debt_Coverage_Ratio <= 0.162
squared_error = 9.405
samples = 6
value = 16.783
ROE <= -0.16
squared_error = 6.509
samples = 17
value = 11.342
squared_error = 0.0
samples = 1
value = 29.212
squared_error = 0.0
samples = 1
value = 29.366
Revenue per Employee <= 0.026
squared_error = 1.294
samples = 4
value = 18.324
Debt_to_Equity <= -0.727
squared_error = 0.378
samples = 2
value = 11.388
Debt_to_Equity <= -0.659
squared_error = 3.874
samples = 10
value = 12.676
EBIT Margin (%) <= -0.593
squared_error = 1.091
samples = 7
value = 8.672
EBIT Margin (%) <= 0.488
squared_error = 0.056
samples = 3
value = 18.78
squared_error = -0.0
samples = 1
value = 15.589
squared_error = 0.0
samples = 1
value = 10.774
squared_error = -0.0
samples = 1
value = 12.003
Debt_Coverage_Ratio <= 0.89
squared_error = 2.691
samples = 7
value = 11.916
Quick_Ratio <= -0.101
squared_error = 0.492
samples = 3
value = 14.956
ROE <= 1.585
squared_error = 0.21
samples = 6
value = 8.312
squared_error = 0.0
samples = 1
value = 11.192
squared_error = 0.0
samples = 1
value = 18.26
Current_Ratio <= -0.925
squared_error = 0.002
samples = 2
value = 18.884
Debt_Coverage_Ratio <= 0.168
squared_error = 0.682
samples = 4
value = 10.684
Gross_Margin <= -0.655
squared_error = 0.398
samples = 3
value = 13.642
ROIC <= -0.163
squared_error = 0.021
samples = 2
value = 14.558
squared_error = -0.0
samples = 1
value = 16.151
YOY_Gross_Profit_Change <= -0.317
squared_error = 0.1
samples = 5
value = 8.457
squared_error = 0.0
samples = 1
value = 7.446
squared_error = 0.0
samples = 1
value = 18.846
squared_error = 0.0
samples = 1
value = 18.94
squared_error = 0.0
samples = 1
value = 9.4
Current_Ratio <= -0.351
squared_error = 0.032
samples = 3
value = 11.197
squared_error = 0.0
samples = 1
value = 14.819
Debt_Coverage_Ratio <= 1.48
squared_error = 0.064
samples = 2
value = 13.348
squared_error = 0.0
samples = 1
value = 14.762
squared_error = 0.0
samples = 1
value = 14.456
squared_error = 0.0
samples = 1
value = 9.08
YOY_EBIT_Change <= -0.481
squared_error = 0.026
samples = 4
value = 8.332
ROE <= -0.761
squared_error = 0.002
samples = 2
value = 11.414
squared_error = -0.0
samples = 1
value = 11.053
squared_error = 0.0
samples = 1
value = 13.6
squared_error = -0.0
samples = 1
value = 13.095
ROIC <= -0.632
squared_error = 0.001
samples = 2
value = 8.201
YOY_Revenue_Change <= -0.078
squared_error = 0.001
samples = 2
value = 8.528
squared_error = 0.0
samples = 1
value = 11.374
squared_error = 0.0
samples = 1
value = 11.454
squared_error = 0.0
samples = 1
value = 8.219
squared_error = -0.0
samples = 1
value = 8.166
squared_error = 0.0
samples = 1
value = 8.499
squared_error = -0.0
samples = 1
value = 8.556

Conclusions

Navigating Market Complexity:

- Financial markets inherently unpredictable, challenging to outperform/predict consistently.
- Findings dependent on industry/sector we're looking at

Information is hard to get:

- Accomplishing this analysis for middle market firms would require proprietary financial information that we may not have access to
- Reliable forward looking estimates, essential, but difficult to obtain.
- Precision impact

All industries are different and all companies are different.

Website

https://cillianfisher.github.io/FinalWebsite/

Thanks!

Any questions?