financial_risk_eda

July 29, 2025

1 CS 6220 Final Project: Predicting Firms' Financial Risk

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[1]:
```python
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
import warnings
warnings.filterwarnings('ignore')
```

2 Load Parquet Files

[2]:
```python
# Step 1: Import required libraries
import pandas as pd
import os
```

[3]:
```python
# Step 2: Check if the Parquet files exist in the current directory
train_file = "20231124_Financial_Risk_Project_train (1).parquet" # We will only␣
↪use this file for final project because test_file has no FinancialRisk␣
↪measurement
# test_file = "20231124_Financial_Risk_Project_test_public (1).parquet"

print("Train file exists:", os.path.exists(train_file))
# print("Test file exists:", os.path.exists(test_file))
```

```
Train file exists: True
```

[4]:
```python
# Step 3: Load the parquet files
train_df = pd.read_parquet(train_file)
# test_df = pd.read_parquet(test_file)

print("Train shape:", train_df.shape)
# print("Test shape:", test_df.shape)

train_df.head()
```

```
Train shape: (415, 73)
```

[4]:
```
                                                    url  \
ticker
FICO    https://seekingalpha.com/article/4649507-fair-…
RXRX    https://seekingalpha.com/earnings/earnings-cal…
BLDR    https://seekingalpha.com/article/4645938-build…
JKHY    https://seekingalpha.com/article/4649242-jack-…
OC      https://seekingalpha.com/article/4643409-owens…

                                         call_transcript    VWAP  \
ticker
FICO    Fair Isaac Corporation (FICO) Q4 2023 Earnings…  700.83
RXRX    Earnings Call Transcripts | Seeking Alpha\n\n\…    6.67
BLDR    Builders FirstSource, Inc. (BLDR) Q3 2023 Earn…   88.34
JKHY    Jack Henry & Associates, Inc. (JKHY) Q1 2024 E…  150.47
OC      Owens Corning (OC) Q3 2023 Earnings Call Trans…   95.47

       exchangeCountry        securityType         CIK  \
ticker
FICO               USA  Common or ordinary  0000814547
RXRX               USA  Common or ordinary  0001601830
BLDR               USA  Common or ordinary  0001316835
JKHY               USA  Common or ordinary  0000779152
OC                 USA  Common or ordinary  0001370946

                                 name  securityID incorporationCountry  \
ticker
FICO           Fair Isaac Corporation   138240101                  USA
RXRX    Recursion Pharmaceuticals Inc   384740101                  USA
BLDR          Builders FirstSource Inc  1630360101                  USA
JKHY     Henry (Jack) & Associates Inc   118110101                  USA
OC                       Owens Corning    82140601                  USA

                   exchangeName  … Working Capital  \
ticker                           …
FICO    New York Stock Exchange  …        5.063632
RXRX        Nasdaq Stock Market  …        2.528944
BLDR    New York Stock Exchange  …       11.272943
```

```
JKHY        Nasdaq Stock Market  …        0.843418
OC      New York Stock Exchange  …       15.414013

                                     businessDescription   close  \
ticker
FICO    Fair Isaac Corporation develops analytic, soft…  598.58
RXRX    Recursion Pharmaceuticals, Inc. operates as a …    7.71
BLDR    Builders FirstSource, Inc., together with its …   64.88
JKHY    Jack Henry & Associates, Inc., a financial tec…  175.56
OC      Owens Corning engages in manufacture and sale …   85.30

        dividendFactor  fiscalDint  floatShares  outstandingShares  \
ticker
FICO          1.000000    20221231   24272216.0         25154000.0
RXRX          1.000000    20221231  117933131.0        174072906.0
BLDR          1.000000    20221231  146461116.0        148994000.0
JKHY          0.989936    20221231   72430647.0         72910225.0
OC            0.980838    20221231   94098317.0         94700000.0

        shortInterestFloat  FinancialSector  FinancialRisk
ticker
FICO              0.033322                0            0.0
RXRX              0.130693                0            0.0
BLDR              0.040739                0            0.0
JKHY              0.030052                0            0.0
OC                0.038574                0            0.0

[5 rows x 73 columns]
```

[5]:
```python
# Use the already loaded parquet data
df = train_df.copy()
print(f"Dataset shape: {df.shape}")
df.head()
```

```
Dataset shape: (415, 73)
```

[5]:
```
                                                     url  \
ticker
FICO    https://seekingalpha.com/article/4649507-fair-…
RXRX    https://seekingalpha.com/earnings/earnings-cal…
BLDR    https://seekingalpha.com/article/4645938-build…
JKHY    https://seekingalpha.com/article/4649242-jack-…
OC      https://seekingalpha.com/article/4643409-owens…

                                         call_transcript    VWAP  \
ticker
FICO    Fair Isaac Corporation (FICO) Q4 2023 Earnings…  700.83
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```

```
BLDR    Builders FirstSource, Inc. (BLDR) Q3 2023 Earn…   88.34
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OC      Owens Corning (OC) Q3 2023 Earnings Call Trans…   95.47

       exchangeCountry        securityType        CIK  \
ticker
FICO               USA  Common or ordinary  0000814547
RXRX               USA  Common or ordinary  0001601830
BLDR               USA  Common or ordinary  0001316835
JKHY               USA  Common or ordinary  0000779152
OC                 USA  Common or ordinary  0001370946

                                   name  securityID incorporationCountry  \
ticker
FICO            Fair Isaac Corporation   138240101                  USA
RXRX    Recursion Pharmaceauticals Inc   384740101                  USA
BLDR          Builders FirstSource Inc  1630360101                  USA
JKHY     Henry (Jack) & Associates Inc   118110101                  USA
OC                       Owens Corning    82140601                  USA

                  exchangeName  … Working Capital  \
ticker                          …
FICO    New York Stock Exchange  …        5.063632
RXRX        Nasdaq Stock Market  …        2.528944
BLDR    New York Stock Exchange  …       11.272943
JKHY        Nasdaq Stock Market  …        0.843418
OC      New York Stock Exchange  …       15.414013

                                      businessDescription   close  \
ticker
FICO    Fair Isaac Corporation develops analytic, soft…  598.58
RXRX    Recursion Pharmaceuticals, Inc. operates as a …    7.71
BLDR    Builders FirstSource, Inc., together with its …   64.88
JKHY    Jack Henry & Associates, Inc., a financial tec…  175.56
OC      Owens Corning engages in manufacture and sale …   85.30

        dividendFactor  fiscalDint  floatShares  outstandingShares  \
ticker
FICO          1.000000    20221231   24272216.0         25154000.0
RXRX          1.000000    20221231  117933131.0        174072906.0
BLDR          1.000000    20221231  146461116.0        148994000.0
JKHY          0.989936    20221231   72430647.0         72910225.0
OC            0.980838    20221231   94098317.0         94700000.0

        shortInterestFloat  FinancialSector  FinancialRisk
ticker
FICO              0.033322                0            0.0
```

```
RXRX              0.130693                0            0.0
BLDR              0.040739                0            0.0
JKHY              0.030052                0            0.0
OC                0.038574                0            0.0

[5 rows x 73 columns]
```

2.1 Data Cleaning

[6]:
```
# Drop irrelevant features
irrelevant_cols = ['url', 'exchangeCountry', 'CIK', 'securityID',
                   'incorporationCountry', 'exchangeName', 'exchangeID',␣
 ↪'businessDescription', 'FinancialSector']

# Drop FinancialSector because the variable describes which company is a␣
 ↪finance company and we should not know this for the purpsoe of this project
df.drop(columns=irrelevant_cols, inplace=True, errors='ignore')

# Drop FinancialSector variable?

# Drop columns with more than 20% missing values
missing_threshold = 0.2
df.dropna(axis=1, thresh=(1 - missing_threshold) * len(df), inplace=True)

# Separate numerical and categorical columns
num_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()
cat_cols = df.select_dtypes(include=['object']).columns.tolist()
```

2.2 Exploratory Data Analysis (EDA)

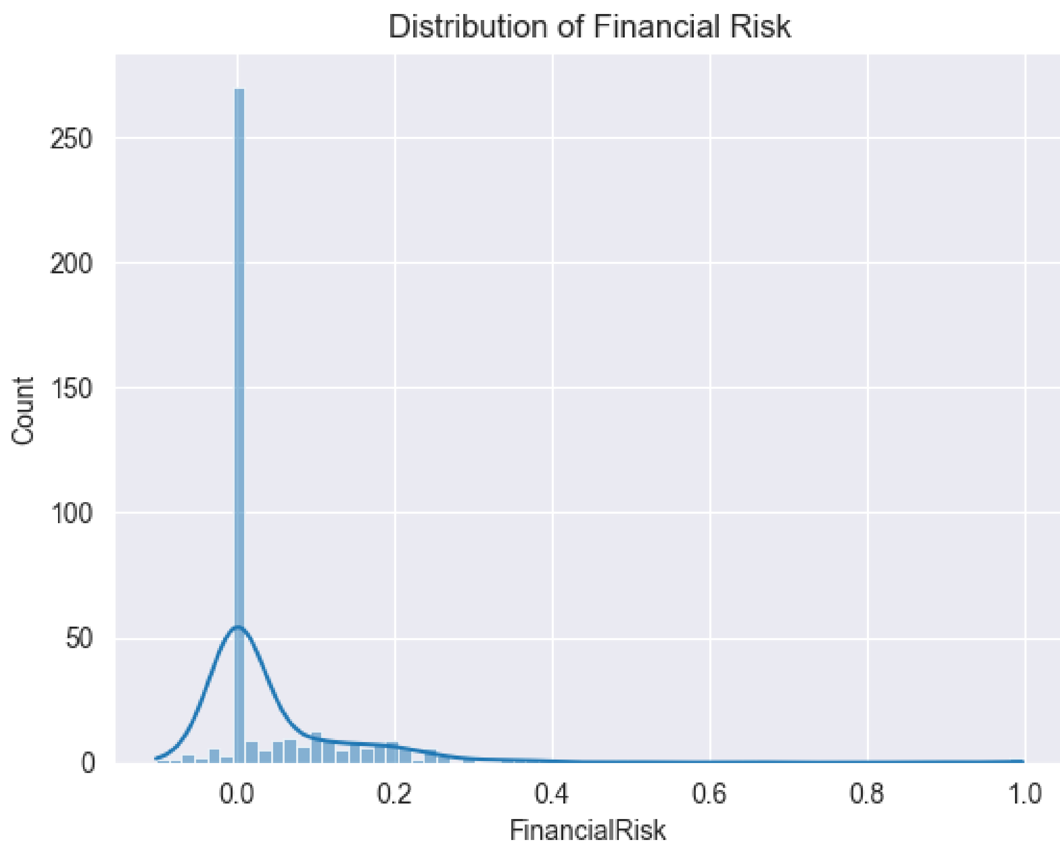
[7]:
```
df.describe()
```

[7]:
```
              VWAP  Accrual Ratio       Assets         B/P        CF/P  \
count   415.000000     415.000000   415.000000  415.000000  415.000000
mean    116.474308      -0.018919   200.850240    0.527509    0.112481
std     216.885791       0.176063   408.857675    0.467866    0.195024
min       0.199900      -3.202525     1.228840   -0.636664   -0.775506
25%      24.995000      -0.030362    37.962225    0.170290    0.035302
50%      57.950000      -0.005417    78.088405    0.454349    0.079560
75%     130.317500       0.018226   183.633250    0.763030    0.166526
max    2648.960000       0.261432  4042.049341    3.750665    1.727142

       Capital Expenditure        Cash  Debt/Equity  Depreciation  \
count           415.000000  415.000000   397.000000    415.000000
mean              2.303081   18.136927     1.914057      1.930943
std               4.525536   70.680449     7.141619      3.588728
min               0.000000    0.000000     0.000000      0.000000
```

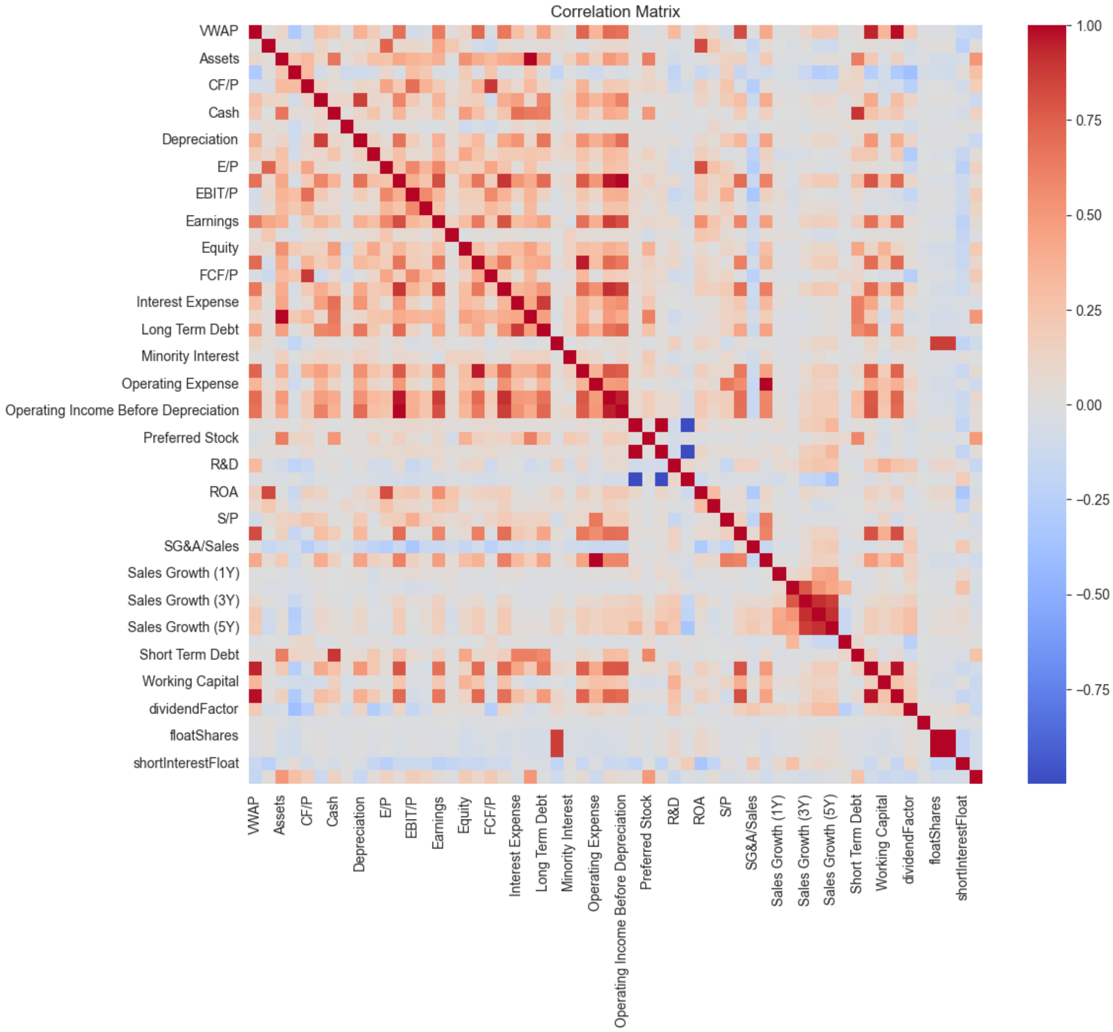
```
25%               0.123280     2.487505     0.337896      0.123215
50%               0.701300     5.497844     0.738463      0.810170
75%               2.418535    13.397640     1.463662      2.658760
max              57.515690  1309.060835   116.069725     54.195690

         Dividend  …  Short Term Debt          TEV  Working Capital  \
count  415.000000  …       415.000000   399.000000       415.000000
mean     1.604028  …         9.638088   132.510298         5.553125
std      2.162034  …        48.195878   215.511729        17.098716
min      0.000000  …         0.000000   -63.167179      -105.669178
25%      0.000000  …         0.180620    37.830784         0.000000
50%      1.036192  …         1.153693    75.609645         0.000000
75%      2.111366  …         4.958480   153.935241         6.529998
max     19.611487  …       882.360527  2924.920173       189.206644

             close  dividendFactor    fiscalDint   floatShares  \
count   415.000000      415.000000  4.150000e+02  4.150000e+02
mean    110.817879        0.978670  2.022126e+07  5.162328e+08
std     190.034596        0.025503  6.180495e+02  1.397186e+09
min       1.830000        0.863362  2.022103e+07  1.305533e+07
25%      27.245000        0.968785  2.022123e+07  7.171691e+07
50%      61.350000        0.985036  2.022123e+07  1.518589e+08
75%     130.060000        1.000000  2.022123e+07  3.686314e+08
max    2460.840000        1.000000  2.023010e+07  1.592372e+10

       outstandingShares  shortInterestFloat  FinancialRisk
count       4.150000e+02          414.000000     415.000000
mean        5.584309e+08            0.039076       0.049077
std         1.497614e+09            0.039058       0.117747
min         1.365940e+07            0.002825      -0.102909
25%         7.712301e+07            0.015174       0.000000
50%         1.665872e+08            0.026484       0.000000
75%         3.947026e+08            0.049398       0.060544
max         1.594342e+10            0.287963       0.998330

[8 rows x 56 columns]
```

[8]:

```
# Check distribution of target
sns.histplot(df['FinancialRisk'], kde=True)
plt.title('Distribution of Financial Risk')
plt.show()

# Log-transform target
df['FinancialRisk_log'] = np.log1p(df['FinancialRisk'])
```



[9]:
```
# Correlation matrix
plt.figure(figsize=(12, 10))
corr = df[num_cols].corr()
sns.heatmap(corr, cmap='coolwarm', center=0)
plt.title('Correlation Matrix')
plt.show()
```



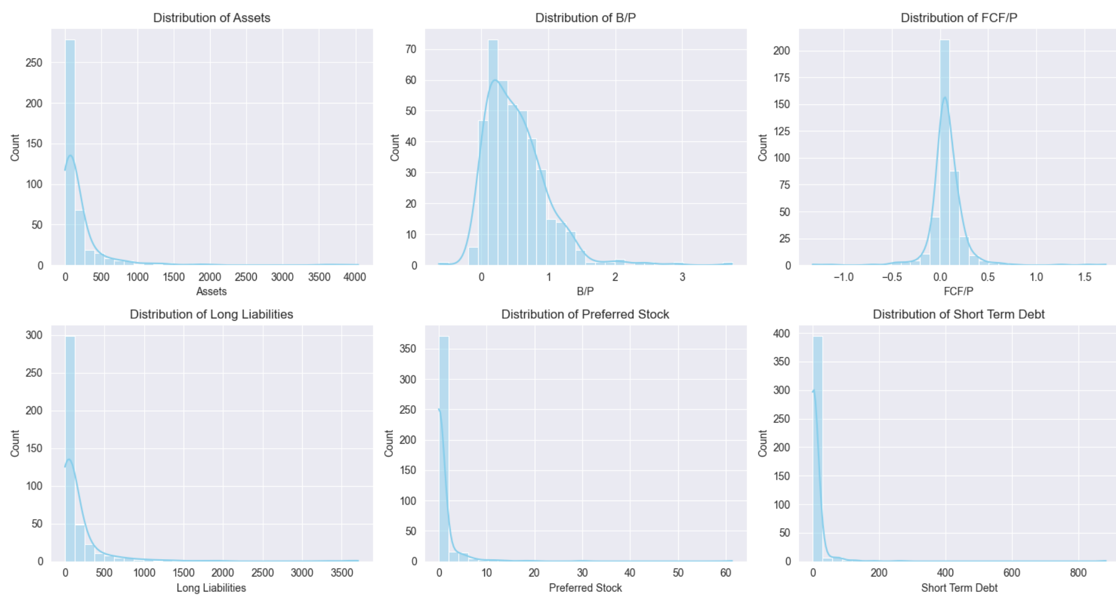
[10]:
```python
# Distribution of some variables with the highest correlation score

# Get correlation with the outcome variable
target_corr = corr['FinancialRisk'].drop('FinancialRisk')

# Select features with |correlation| > 0.2
selected = target_corr[abs(target_corr) > 0.2]

# Print feature names and their correlation scores
print("Selected Features and Correlation Scores:\n")
for feature, score in selected.items():
    print(f"{feature}: {score:.3f}")
```

```
Selected Features and Correlation Scores:

Assets: 0.509
```

```
B/P: 0.289
FCF/P: 0.214
Long Liabilities: 0.514
Preferred Stock: 0.495
Short Term Debt: 0.264
```

[11]:

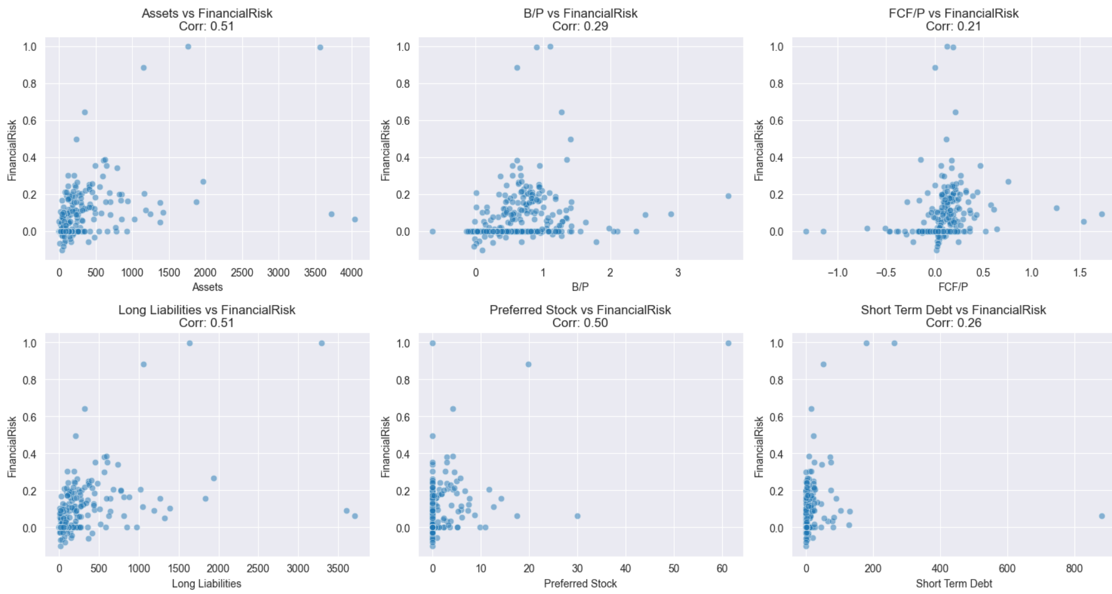
```python
# Set up the plot grid
# Plot the variables distribution (histogram) using for loops
num_feats = len(selected)
cols = 3
rows = (num_feats + cols - 1) // cols

plt.figure(figsize=(5 * cols, 4 * rows))

for i, col in enumerate(selected.index, 1):  # use selected.index instead of selected
    plt.subplot(rows, cols, i)
    sns.histplot(df[col], kde=True, bins=30, color='skyblue')
    plt.title(f'Distribution of {col}')

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



[12]:

```python
# Scatter plots between the highest correlated variable with outcome variable (FinancialRisk

# Scatter plots between selected features and FinancialRisk
```

```python
num_feats = len(selected)
cols = 3
rows = (num_feats + cols - 1) // cols

plt.figure(figsize=(5 * cols, 4 * rows))

for i, col in enumerate(selected.index, 1):
    plt.subplot(rows, cols, i)
    sns.scatterplot(data=df, x=col, y='FinancialRisk', alpha=0.5)
    plt.title(f'{col} vs FinancialRisk\nCorr: {selected[col]:.2f}')
    plt.xlabel(col)
    plt.ylabel('FinancialRisk')

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



2.3 Baseline Model: Linear Regression

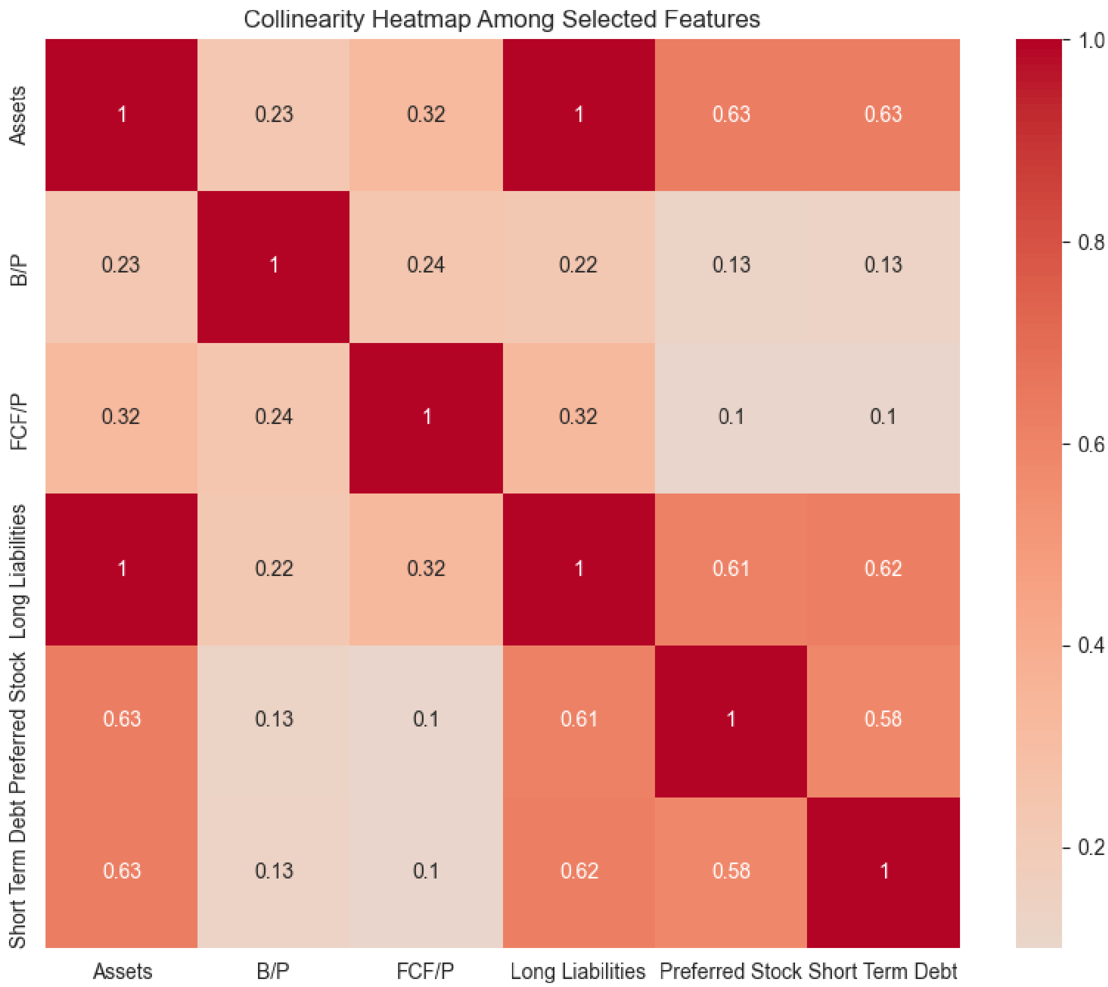
[13]:
```python
# Baseline Model: Linear Regression
selected_features = ['Assets', 'Cash', 'Debt/Equity', 'B/P', 'SG&A/Sales', 'Long Liabilities']
print('Columns in DataFrame:', df.columns.tolist())
missing_features = [col for col in selected_features if col not in df.columns]
if missing_features:
    print('The following features are missing from the data:', missing_features)
else:
    print('All selected features are present in the data.')
```

```python
if 'FinancialRisk_log' not in df.columns:
    print('FinancialRisk_log column is missing. Please make sure the previous␣
 ↪cell has been executed.')
else:
    print('FinancialRisk_log column exists.')
print('Missing value count for selected features:')
print(df[selected_features].isnull().sum())
# Convert selected features to numeric type
for col in selected_features:
    df[col] = pd.to_numeric(df[col], errors='coerce')
# Remove all rows with missing values in selected features or target
df_clean = df.dropna(subset=selected_features + ['FinancialRisk_log']).copy()
print('Shape after dropping missing:', df_clean.shape)
# Continue with modeling
X = df_clean[selected_features]
y = df_clean['FinancialRisk_log']
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, X.columns)
    ])
from sklearn.linear_model import LinearRegression
model = Pipeline(steps=[('preprocessor', preprocessor),
                        ('regressor', LinearRegression())])
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
from sklearn.metrics import mean_squared_error, r2_score
r2 = r2_score(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred) ** 0.5
print(f'R² Score: {r2:.2f}')
print(f'RMSE: {rmse:.2f}')
```

```
Columns in DataFrame: ['call_transcript', 'VWAP', 'securityType', 'name',
'Accrual Ratio', 'Assets', 'B/P', 'CF/P', 'Capital Expenditure', 'Cash',
'Debt/Equity', 'Depreciation', 'Dividend', 'E/P', 'EBIT', 'EBIT/P', 'EBIT/TEV',
'Earnings', 'Earnings Growth (1Y)', 'Equity', 'FCF', 'FCF/P', 'Income Tax',
'Interest Expense', 'Long Liabilities', 'Long Term Debt', 'Market Cap',
```

```
'Minority Interest', 'Operating Cash Flow', 'Operating Expense', 'Operating
Income', 'Operating Income Before Depreciation', 'Operating Margin', 'Preferred
Stock', 'Profit Margin', 'R&D', 'R&D/Sales', 'ROA', 'ROE', 'S/P', 'SG&A',
'SG&A/Sales', 'Sales', 'Sales Growth (1Y)', 'Sales Growth (2Y)', 'Sales Growth
(3Y)', 'Sales Growth (4Y)', 'Sales Growth (5Y)', 'Sales Variability', 'Short
Term Debt', 'TEV', 'Working Capital', 'close', 'dividendFactor', 'fiscalDint',
'floatShares', 'outstandingShares', 'shortInterestFloat', 'FinancialRisk',
'FinancialRisk_log']
All selected features are present in the data.
FinancialRisk_log column exists.
Missing value count for selected features:
Assets              0
Cash                0
Debt/Equity        18
B/P                 0
SG&A/Sales          7
Long Liabilities    0
dtype: int64
Shape after dropping missing: (390, 60)
R² Score: -0.08
RMSE: 0.08
```

[14]:
```python
# Test Co-linearity between the highly correlated variables

# Correlation heatmap of selected features
plt.figure(figsize=(10, 8))
sns.heatmap(df[selected.index].corr(), annot=True, cmap='coolwarm', center=0)
plt.title("Collinearity Heatmap Among Selected Features")
plt.show()
```



[15]:
```
# Further examines multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
import pandas as pd

X = df[selected.index].dropna()
X = add_constant(X)

vif_data = pd.DataFrame()
vif_data['Feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]

print(vif_data)
# Baseline model might have low performance because Asset and Long Liabilities␣
 ↪are strongly correlated with each other
```

```
             Feature         VIF
0              const    2.703747
1             Assets  143.285350
2                B/P    1.101047
3              FCF/P    1.182681
4   Long Liabilities  137.109055
5    Preferred Stock    1.878595
6    Short Term Debt    1.873132
```

[16]:
```
# Drop Assets or Long Liabilities (drop asset) because it is highly correlated␣
↪with each other
reduced_features = selected.index.drop('Assets')
```

2.4 Modeling 2: Regularization Techniques

Using Lasso, Ridge, and elastic net + stepwise selection

Try the regularization models with all the features

[17]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV

full_features = df.drop(columns=['FinancialRisk',␣
↪'Assets','FinancialRisk_log'])  # Drop target
X = full_features.select_dtypes(include=[np.number]).dropna() # Keep only␣
↪numerical features
y = df.loc[X.index, 'FinancialRisk']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42)
```

[18]:
```
# Train regularized models
# Lasso
lasso = LassoCV(cv=5, random_state=42)
lasso.fit(X_train, y_train)

# Ridge
ridge = RidgeCV(alphas=[0.1, 1.0, 10.0], cv=5)
ridge.fit(X_train, y_train)

# ElasticNet
elastic = ElasticNetCV(cv=5, random_state=42)
elastic.fit(X_train, y_train)

#  Evaluation function
def evaluate(model, name):
```

```python
    preds = model.predict(X_test)
    r2 = r2_score(y_test, preds)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    print(f"{name} Performance:")
    print(f"  R²: {r2:.3f}")
    print(f"  RMSE: {rmse:.3f}")
    print("-" * 30)
    return r2, rmse

# Run evaluations
lasso_r2, lasso_rmse = evaluate(lasso, "Lasso")
ridge_r2, ridge_rmse = evaluate(ridge, "Ridge")
elastic_r2, elastic_rmse = evaluate(elastic, "Elastic Net")

# For Lasso, Ridge, ElasticNet
models = {'Lasso': lasso, 'Ridge': ridge, 'ElasticNet': elastic}

for name, model in models.items():
    print(f"{name} Coefficients:")
    for feat, coef in zip(X.columns, model.coef_):
        print(f"{feat}: {coef:.4f}")
    print("-" * 40)
```

```
Lasso Performance:
  R²: 0.393
  RMSE: 0.068
------------------------------
Ridge Performance:
  R²: -0.481
  RMSE: 0.106
------------------------------
Elastic Net Performance:
  R²: 0.389
  RMSE: 0.068
------------------------------
Lasso Coefficients:
VWAP: -0.0031
Accrual Ratio: -0.0000
B/P: 0.0096
CF/P: 0.0000
Capital Expenditure: -0.0000
Cash: -0.0000
Debt/Equity: 0.0000
Depreciation: -0.0000
Dividend: -0.0000
E/P: 0.0001
EBIT: -0.0000
EBIT/P: 0.0000
```

```
EBIT/TEV: 0.0000
Earnings: -0.0000
Earnings Growth (1Y): 0.0000
Equity: -0.0000
FCF: -0.0000
FCF/P: 0.0000
Income Tax: -0.0000
Interest Expense: -0.0217
Long Liabilities: 0.0501
Long Term Debt: -0.0000
Market Cap: -0.0000
Minority Interest: -0.0000
Operating Cash Flow: -0.0000
Operating Expense: -0.0000
Operating Income: -0.0000
Operating Income Before Depreciation: -0.0000
Operating Margin: 0.0000
Preferred Stock: 0.0153
Profit Margin: 0.0000
R&D: -0.0000
R&D/Sales: -0.0000
ROA: -0.0000
ROE: -0.0000
S/P: -0.0000
SG&A: -0.0000
SG&A/Sales: 0.0078
Sales: -0.0000
Sales Growth (1Y): 0.0000
Sales Growth (2Y): -0.0000
Sales Growth (3Y): -0.0000
Sales Growth (4Y): -0.0000
Sales Growth (5Y): -0.0000
Sales Variability: -0.0000
Short Term Debt: 0.0000
TEV: -0.0000
Working Capital: -0.0000
close: -0.0000
dividendFactor: -0.0000
fiscalDint: -0.0000
floatShares: -0.0000
outstandingShares: -0.0000
shortInterestFloat: 0.0000
----------------------------------------
Ridge Coefficients:
VWAP: -0.0215
Accrual Ratio: -0.0012
B/P: 0.0160
CF/P: -0.0225
```

```
Capital Expenditure: -0.0020
Cash: -0.0322
Debt/Equity: 0.0084
Depreciation: -0.0248
Dividend: -0.0000
E/P: 0.0324
EBIT: 0.0146
EBIT/P: 0.0286
EBIT/TEV: -0.0110
Earnings: -0.0040
Earnings Growth (1Y): 0.0059
Equity: -0.0200
FCF: 0.0026
FCF/P: 0.0179
Income Tax: -0.0046
Interest Expense: -0.0544
Long Liabilities: 0.0626
Long Term Debt: -0.0273
Market Cap: 0.0033
Minority Interest: -0.0028
Operating Cash Flow: 0.0017
Operating Expense: 0.0041
Operating Income: 0.0015
Operating Income Before Depreciation: 0.0174
Operating Margin: -0.0010
Preferred Stock: 0.0140
Profit Margin: -0.0012
R&D: -0.0006
R&D/Sales: 0.0019
ROA: -0.0371
ROE: -0.0041
S/P: -0.0239
SG&A: 0.0009
SG&A/Sales: 0.0131
Sales: 0.0037
Sales Growth (1Y): 0.0020
Sales Growth (2Y): -0.0113
Sales Growth (3Y): -0.0064
Sales Growth (4Y): 0.0102
Sales Growth (5Y): 0.0036
Sales Variability: -0.0036
Short Term Debt: 0.0494
TEV: 0.0250
Working Capital: 0.0009
close: 0.0040
dividendFactor: 0.0019
fiscalDint: -0.0002
floatShares: -0.0041
```

```
outstandingShares: -0.0052
shortInterestFloat: -0.0081
----------------------------------------
ElasticNet Coefficients:
VWAP: -0.0032
Accrual Ratio: -0.0000
B/P: 0.0091
CF/P: 0.0000
Capital Expenditure: -0.0000
Cash: -0.0000
Debt/Equity: 0.0000
Depreciation: -0.0000
Dividend: -0.0000
E/P: 0.0007
EBIT: -0.0000
EBIT/P: 0.0000
EBIT/TEV: 0.0000
Earnings: -0.0000
Earnings Growth (1Y): 0.0000
Equity: -0.0000
FCF: -0.0000
FCF/P: 0.0000
Income Tax: -0.0000
Interest Expense: -0.0199
Long Liabilities: 0.0474
Long Term Debt: -0.0000
Market Cap: -0.0000
Minority Interest: -0.0000
Operating Cash Flow: -0.0000
Operating Expense: -0.0000
Operating Income: -0.0000
Operating Income Before Depreciation: -0.0000
Operating Margin: 0.0000
Preferred Stock: 0.0163
Profit Margin: 0.0000
R&D: -0.0000
R&D/Sales: -0.0000
ROA: -0.0007
ROE: -0.0000
S/P: -0.0000
SG&A: -0.0000
SG&A/Sales: 0.0081
Sales: -0.0000
Sales Growth (1Y): 0.0000
Sales Growth (2Y): -0.0000
Sales Growth (3Y): -0.0000
Sales Growth (4Y): -0.0000
Sales Growth (5Y): -0.0000
```

```
Sales Variability: -0.0000
Short Term Debt: 0.0000
TEV: -0.0000
Working Capital: -0.0000
close: -0.0000
dividendFactor: -0.0000
fiscalDint: -0.0000
floatShares: -0.0000
outstandingShares: -0.0000
shortInterestFloat: 0.0000
----------------------------------------
```

Lasso and Elastic Net outperforms Ridge because the former two models can perform feature selection by shrinking coefficients to exactly zero when there are many features

Try the regularization models by only using features with correlation > 0.2

[19]:
```
X = df[reduced_features].dropna()

y = df.loc[X.index, 'FinancialRisk']
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42)
```

[20]:
```
from sklearn.linear_model import LassoCV, RidgeCV, ElasticNetCV

# Lasso
lasso = LassoCV(cv=5, random_state=42)
lasso.fit(X_train, y_train)

# Ridge
ridge = RidgeCV(alphas=[0.1, 1.0, 10.0], cv=5)
ridge.fit(X_train, y_train)

# Elastic Net
elastic = ElasticNetCV(cv=5, random_state=42)
elastic.fit(X_train, y_train)
```

[20]:
```
ElasticNetCV(cv=5, random_state=42)
```

[21]:
```
from sklearn.metrics import r2_score, mean_squared_error
import numpy as np

def evaluate(model, X_test, y_test, name="Model"):
    preds = model.predict(X_test)
    r2 = r2_score(y_test, preds)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    print(f"{name} Performance:")
    print(f"  R²: {r2:.3f}")
```

```python
    print(f"  RMSE: {rmse:.3f}")
    print("-" * 30)

evaluate(lasso, X_test, y_test, "Lasso")
evaluate(ridge, X_test, y_test, "Ridge")
evaluate(elastic, X_test, y_test, "Elastic Net")


# For Lasso, Ridge, ElasticNet
models = {'Lasso': lasso, 'Ridge': ridge, 'ElasticNet': elastic}

for name, model in models.items():
    print(f"{name} Coefficients:")
    for feat, coef in zip(X.columns, model.coef_):
        print(f"{feat}: {coef:.4f}")
    print("-" * 40)
```

```
Lasso Performance:
  R²: 0.250
  RMSE: 0.086
------------------------------
Ridge Performance:
  R²: 0.368
  RMSE: 0.079
------------------------------
Elastic Net Performance:
  R²: 0.239
  RMSE: 0.087
------------------------------
Lasso Coefficients:
B/P: 0.0053
FCF/P: 0.0000
Long Liabilities: 0.0264
Preferred Stock: 0.0226
Short Term Debt: 0.0000
----------------------------------------
Ridge Coefficients:
B/P: 0.0207
FCF/P: 0.0006
Long Liabilities: 0.0409
Preferred Stock: 0.0391
Short Term Debt: -0.0200
----------------------------------------
ElasticNet Coefficients:
B/P: 0.0042
FCF/P: 0.0000
Long Liabilities: 0.0256
Preferred Stock: 0.0217
```

```
Short Term Debt: 0.0000
----------------------------------------
```

2.5 Modeling 3: non-linear models

Using Random Forest to check if non-linear models can outperform regression models (because we have a lot of variables)

[22]:
```
from sklearn.ensemble import RandomForestRegressor
# Train test split
full_features = df.drop(columns=['FinancialRisk', 'Assets',␣
↪'FinancialRisk_log'])  # Drop target
X = full_features.select_dtypes(include=[np.number]).dropna() # Keep only␣
↪numerical features
y = df.loc[X.index, 'FinancialRisk']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

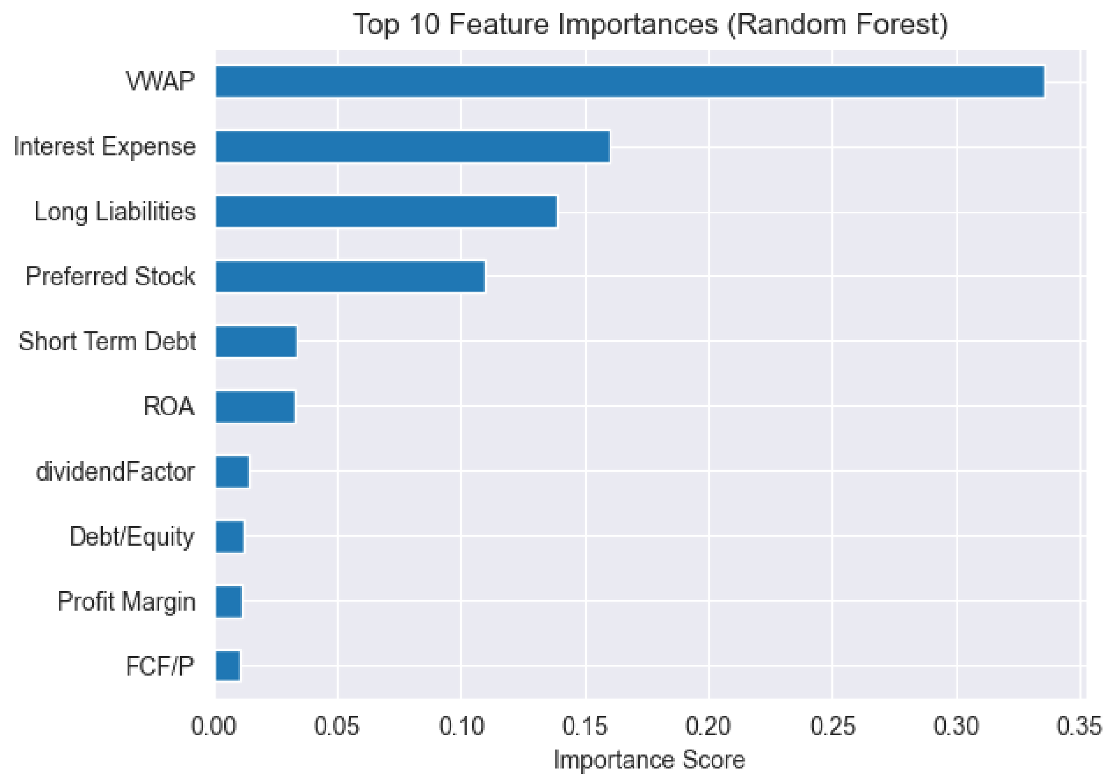
[23]:
```
# Fit model
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
```

[23]:
```
RandomForestRegressor(random_state=42)
```

[24]:
```
# Check performance
y_pred = rf.predict(X_test)

r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(f"Random Forest R²: {r2:.4f}")
print(f"Random Forest RMSE: {rmse:.4f}")
```

```
Random Forest R²: -0.1234
Random Forest RMSE: 0.0927
```

[25]:
```
# Check feature importance for rf model
import pandas as pd
import matplotlib.pyplot as plt

feature_importances = pd.Series(rf.feature_importances_, index=X.columns)
feature_importances.nlargest(10).plot(kind='barh')
plt.title("Top 10 Feature Importances (Random Forest)")
plt.xlabel("Importance Score")
plt.gca().invert_yaxis()
plt.show()
```



`# Findings`

Compare performance between the 3 models

2.6 Base Model: Linear Regression

R^2: -0.08 RMSE: 0.08

2.7 Regularization Model (With all features)

Ridge: R^2: 0.393 RMSE: 0.068

Lasso: R^2: -0.481 RMSE: 0.106

Elastic Net: R^2: 0.389 RMSE: 0.068

2.8 Regularization Model (With features > 0.2 correlation)

Ridge: R^2: 0.25 RMSE: 0.086

Lasso: R^2: 0.368 RMSE: 0.079

Elastic Net: R^2: 0.239 RMSE: 0.087

2.9 Non-linear model (Random Forest)

R^2: -0.1234 RMSE: 0.0927

Best model is Ridge Model with all features included