RELATIONSHIP BETWEEN ESG AND FINANCIAL PERFORMANCE OF PUBLICLY LISTED FIRMS ON THE S&P 500

by

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PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN FINANCE

In the Master of Science in Finance Program
of the
Faculty
of
Business Administration

SIMON FRASER UNIVERSITY

Fall 2019

Approval

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Title of Project:	**Relationship between ESG and financial performance of publicly listed firms on the S&P 500.**

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Abstract

This research paper examines the relation between the Environmental, Social and Governance (ESG) factors and the financial performance of the company. We have included the Return on Asset, Tobin's Q, Earnings per Share, Weighted Average Cost of Capital, Market capitalization and the Free Cash Flow of the firms. We have considered a sample of around 400 companies listed on the US stock market.

After running a regression between the ESG Score and the other factors we found mixed results. We found a positive correlation between the Free cash flow, Earnings per Share and the Market Capitalization of the firm and a negative correlation between the Return on Asset, Tobin's Q and the Weighted Average Cost of Capital of the firm.

Keywords: ESG, Financial Performance, Corporate Social Responsibility

Acknowledgements

We would like to thank Professor Carlos Da Costa for his guidance throughout the course of our research. He guided us on the structure of the data and was always available to give us valuable feedback when needed.

We would also like to thank Dr. Victor Song for his support.

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1. Introduction

The purpose of this research paper is to analyse if there is any correlation between the ESG score of a company and its financial performance. ESG refers to the Environment Social and Governance factors that are used by investors to screen potential investment opportunities. ESG has been increasingly used by investors primarily in North America but majority of the investors are using it as a negative screener. In this paper our purpose was to understand if there is indeed any correlation between the financial performance of the company and their ESG score. Earlier research has found a positive relationship between environmental factors and the economic performance of a firm(Quan, Wu, Li, & Ying, 2018). The existing research has found mixed results with respect to correlation between ESG and the financial performance of a company. We have selected a sample of 450 companies from the S&P 500 which is a good representation of the stock market in the USA. The USA does not have any standard mandatory requirement for ESG disclosures like Europe. Although 80% of the companies provide voluntary disclosures regarding their ESG performance, it is very difficult to compare their performance with other international firms due to the lack of a common standard. Considering the recent climate change discussions, the US congress is debating on whether to make the ESG disclosures mandatory or not. (Temple-West, 2019).

In Germany, a similar research was done by considering each ESG factor in isolation and comparing them with various financial metrics (Velte, 2017). Our research is an extension of that research where we have taken the data from 2013-2017 and are examining the firms in the United States. We believe that the results can be different as firms in Europe have stricter ESG disclosure requirements in comparison to the firms listed in the US.

2.Research Background and Hypothesis Development

2.1About ESG

Environmental, social and governance factors cover wide spectrum of issues that are traditionally not part of financial or economic analysis but are extremely important and relevant to financial decisions. This might include steps taken by corporations on climate change, how they are managing resources like water, wind etc, how they manage their supply chains, how they treat their employees. It also deals with the health & safety policies of organizations and it says a lot about the culture of organizations to build trust and foster innovation.

'ESG' – the term was coined in 2005 in a study titled "Who Cares Wins" by UN global compact. ESG investing is a type of 'sustainable investing' which considers return on investment as well as evaluate the long-term impact of business practices on society, the environment and the performance of business itself (governance) (Kell, 2018). Robust ESG policies and practices can protect brand name, improve talent acquisition and retention, promote customer loyalty and reduce the risk of lawsuits against companies. Today evidence is increasingly piling up that ESG performance is directly linked with financial performance and thus a quarter of global assets are manager under Socially Responsible Investing (SRI)

2.2 Our Approach to ESG

We believe that company disclosure and transparency is important for driving accurate investor information, regulatory guidance and public disclosure. ESG data was collected from EIKON (Software product provided by Refinitiv to monitor and analyse financial information) which has standardized ESG data for nearly 70% of global market cap. These ESG scores are a reflection of the official disclosure on environmental, social and governance factors. ESG scores of companies are based on multiple factors and purely based on data disclosed by companies i.e. EIKON doesn't use, create or collect data that is not publicly disclosed. (Refinitiv, n.d.)

2.3 Hypothesis Development

Hypothesis 1: WACC

Hypothesis 1 (H1): A negative correlation between ESG rating and Weighted Average Cost of Capital

It is actively sought to demonstrate connection between ESG score and financial performance. In last decade, multiple studies have been done on this topic. One factor we have considered is the WACC (Weighted Average Cost of Capital).We also compare the WACC of a firm to its ESG score as previous research has proved the positive effects of Socially Responsible Investing (Sahut & Pasquini-Descomps, 2015). As per a recent research considered in Malaysia there is a significant relationship between the ESG score and the WACC of a firm (Atan, Said, Alam, & Zamri, 2018). The cost of financing is expected to reduce if the ESG score has been increasing. The WACC of a firm is calculated by taking a weighted average of its cost of debt and equity financing.

Hypothesis 2: Market Cap

Hypothesis 2 (H2): A positive correlation between ESG rating and Market Capitalization

Our second hypothesis is with regard to the overall market cap of firms. Analysing the size of a company is also very important as the big corporations are expected to have a relatively better ESG performance. We have considered the market capitalization of the companies in order to examine this. The market capitalization of the firm is calculated by multiplying the market price of a company and its numbers of shares. First, we expect a positive ESG-Market capitalization relationship in firms of American market. As described above, most studies in advanced economies as well as developing economies like China and India demonstrate a positive relationship between ESG and firms market capital and financial performance. Managers in developing countries are focused more on reducing operational costs, they are equally focused on creating value using social, environmental and corporate governance capabilities. Investors in developing markets understand the potential positive effect of ESG and reflect this in their firm valuation. (Laijawala, 2019).

Hypothesis 3: Cash Flow

Hypothesis 3 (H3): A positive correlation between ESG rating and Free Cash Flow over time

The Free Cash Flow of a firm is calculated as:

Net Income + Non-Cash Expenses – Increase in Working Capital – Capital Expenditures

The Free Cash Flow of the company is another measure of a company's profitability, but it excludes some factors such as non-cash expenses. This metric has been used in previous research conducted in the UK and a positive correlation was found on further analysis. (Okpa, Agele, Jude Awele Nkwo, & Richard Nyam Okarima, 2019)

Hypothesis 4: Return on Asset, Earnings per Share and Tobin's Quotient

Hypothesis 4 (H4): A positive correlation between ESG rating and the Profitability of the company

We have used the return on the firm's asset as our metric to measure the financial performance of the company. The return on assets is a common metric which has been widely used in previous studies to measure the financial performance of the firm (López , Garcia, & Rodriguez, 2007). The ROA is an accounting-based measure which is calculated by dividing the net income of the firm by its total assets. As Return on Asset is an accounting based measure, we have also considered Tobin's Q which is a market-based measure and has been widely used in existing literature (Choi & Wang, 2009). Tobin's Q is calculated as the total market value of the firm divided by the total asset value of the firm. This measure is used to estimate whether a given business is overvalued or undervalued. This measure can also be applied to the whole market as well. When the Tobin's ratio is between 0 and 1, it costs more to replace a firm's assets than the firm is worth whereas when Tobin's ratio is above 1, it implies that the firm is worth more than the cost of its assets. Because Tobin's premise is that firms should be worth what their assets are worth, anything above 1.0

theoretically indicates that a company is overvalued. Therefore, as ESG stat improves, Tobin's ratio will tend to move towards 1. The Earnings per share(EPS) is calculated as a company's net income divided by the outstanding number of shares. It is a widely used method in equity research and a key metric to determine a company's profitability. (Siew, 2012)

3. Data

We believe that company disclosure and transparency is important for driving accurate investor information, regulatory guidance and public disclosure .We have obtained all the financial data from Bloomberg. All the ESG data has been obtained from Thomson Reuters via DataStream. Our study consists of 449 listed firms on the US stock market. The companies were shortlisted on the basis of the availability of data which excludes the companies that were not trading during 2013-2017 or did not have sufficient ESG coverage. We have taken quarterly data from 2013-2017 as we believe that this period is a good representation of the increasing trend of ESG investing.

ESG Scores.

The ESG score is calculated by Refinitiv by assigning weights to various Environmental, Social and Governance factors. The Social score has the most weightage (35.5%) followed by Environmental and Governance factors. Each of the sub-categories also have a specified weight which is then multiplied by the scores to get the total category and eventually the total ESG scores. Refinitiv has over 150 content research analysts on the ESG team who cover over 400 ESG factors and over 7000 companies worldwide. Refinitiv updates these databases on a continuous basis. Although, the ESG scores are recalculated on a weekly basis, no significant changes are seen in the ESG scores as the companies usually disclose their ESG data once a year which is why we are using quarterly data for this paper. ESG scores of companies are based on multiple factors and purely based on data disclosed by companies i.e. EIKON doesn't use, create or collect data that is not publicly disclosed.

4. Results

4.1 Descriptive Statistics

Below table shows the descriptive statistics of the sample used for research. The mean of ESG is 62.18 whereas the range of ESG varies from 12.07 to 94.51. The sample has good variation in WACC which has a range from 0.76 to 16.65 with the average of 7.36

Table 1: Descriptive Statistics

	RETURN_ON_ASSET	CUR_MKT_CAP	WACC	ESGRank	Tobins_Q_Ratio	EPS	FCF
count	4788.000000	4788.000000	4788.000000	4788.000000	4788.000000	4788.000000	4788.000000
mean	2.219992	3.171217	7.365036	62.183367	0.499373	-0.164896	6.117454
std	1.447550	0.046938	2.169771	16.100081	0.323344	0.894186	1.611531
min	-2.279139	3.028389	0.764481	13.070000	-0.150888	-6.027838	-1.305135
25%	1.220411	3.136222	5.952479	51.845000	0.240196	-0.694057	5.144249
50%	2.289515	3.170001	7.407922	64.700000	0.503363	-0.161503	6.037762
75%	3.246055	3.203438	8.754228	74.360000	0.741398	0.362660	7.100478
max	7.318731	3.289311	16.654661	94.510000	1.299683	4.372474	12.618962

Correlation of Measures: At first, we calculated the correlation of measures and developed the heat map.

Figure 1: Heat Map of Correlation of Measures

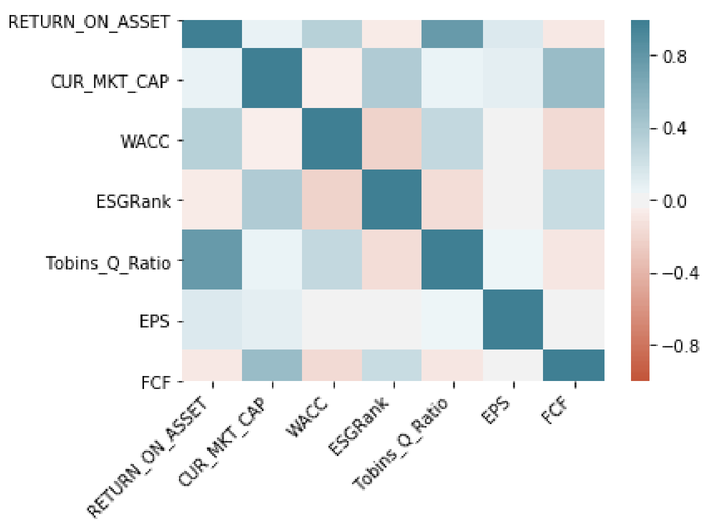


Table 2 – Correlation of measures

	RETURN_ON_ASSET	CUR_MKT_CAP	WACC	ESGRank	Tobins_Q_Ratio	EPS	FCF
RETURN_ON_ASSET	1.000000	0.064990	0.333975	-0.069762	0.765935	0.139575	-0.085145
CUR_MKT_CAP	0.064990	1.000000	-0.041122	0.370680	0.048546	0.093603	0.504708
WACC	0.333975	-0.041122	1.000000	-0.213463	0.268948	0.037431	-0.158923
ESGRank	-0.069762	0.370680	-0.213463	1.000000	-0.150304	-0.035973	0.248834
Tobins_Q_Ratio	0.765935	0.048546	0.268948	-0.150304	1.000000	0.040368	-0.101106
EPS	0.139575	0.093603	0.037431	-0.035973	0.040368	1.000000	0.038347
FCF	-0.085145	0.504708	-0.158923	0.248834	-0.101106	0.038347	1.000000

4.2 Regression Results

We worked on 2 data sources i.e. .Bloomberg and Thomson Reuters. We collected financial data of S&P500 companies from Bloomberg. The financial parameters used in this paper are Return on Asset, Market Cap, Weighted Average Cost of Capital (WACC), Earning Per Share (EPS) and Free Cash Flow (FCF). The frequency of collected data is quarterly and the time period chosen is 2013 to 2017 (20 quarters).

We ran the regression model with ESG Rank as the dependent variable and 6 independent variables. The independent variables are Return on Asset, Market Capitalization, WACC, Tobin's Q Ratio, EPS and FCF

The R^2 of regression model is 19.6%.

4.3 Data Consistency

To satisfy the regression assumptions and be able to trust the results, the residuals should have a constant variance. In econometrics, an extremely common test for heteroskedasticity is the White test. White test allows the independent variable to have a nonlinear and interactive effect on the error variance.

As in the Breusch-Pagan test, because the values for ε_i^2

aren't known in practice, the $\hat{\varepsilon}_i^2$ are calculated from the residuals and used as proxies for

ε_i^2

The White test is based on the estimation of the following:

$$\hat{\varepsilon}_i^2 = \alpha_0 + \alpha_1 X_{i1} + \ldots + \alpha_p X_{ip} + \alpha_{p+1} X_{ip}^2 + \ldots \alpha_{2p} X_{ip}^2 + \alpha_{2p+1}\left(X_{i1} X_{i2}\right) + \ldots + u_i$$

1. Estimate model using OLS:
   $$Y_i = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_p X_{ip} + \varepsilon_i$$

2. Obtain the predicted *Y* values after estimating the model

3. Estimate the model using OLS:
   $$\hat{\varepsilon}_i^2 = \delta_0 + \delta_1 \hat{Y}_i + \delta_2 \hat{Y}_i^2$$

4. Retain the R-squared value from this regression:
   $$R_{\hat{\varepsilon}^2}^2$$

5. Calculate the F-statistic or the chi-squared statistic:

$$F = \frac{\frac{R_{\hat{\varepsilon}^2}^2}{1}}{\frac{\left(1 - R_{\hat{\varepsilon}^2}^2\right)}{n-2}} \text{ or } \chi^2 = nR_{\hat{\varepsilon}^2}^2$$

{'LM Statistic': 285.15869720186186,
'LM-Test p-value': 3.65465296539775e-56,
'F-Statistic': 33.618309792511205,
'F-Test p-value': 5.9591710899977516e-58}

As the p-value is <0.05, our data doesn't have constant variance

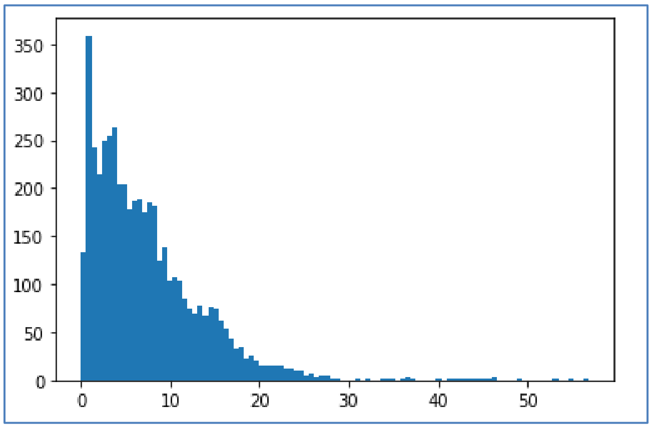
Our data was not normally distributed. One of the method to fix non-normally distributed data is the Box Cox Transformation. A seemingly simple way to transform data to be closer to a normal distribution.

We performed Box-Cox transformation on our data and the model accuracy improved.

Below is the plot of Return on Asset without Box cox transformation and after performing Box Cox transformation.

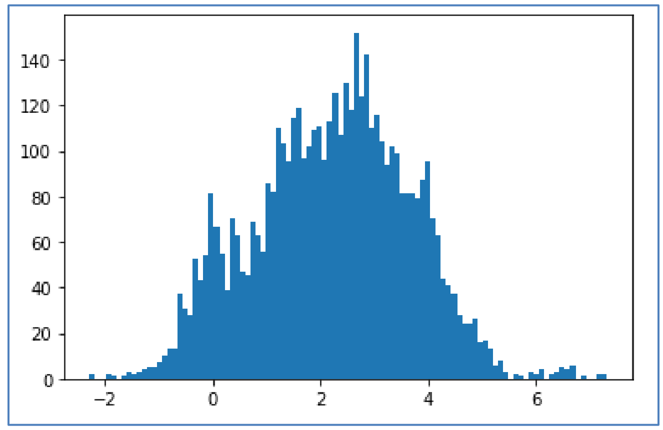
Return on Asset plot

Figure 2



Return On Asset before Box Cox Transformation

Figure 3



Return On Asset after Box Cox Transformation

Table 3: Revised Correlation Table

	RETURN_ON_ASSET	CUR_MKT_CAP	WACC	ESGRank	Tobins_Q_Ratio	EPS	FCF
RETURN_ON_ASSET	1.000000	0.035528	0.376607	-0.082079	0.808116	0.215051	-0.120786
CUR_MKT_CAP	0.035528	1.000000	-0.113404	0.515519	0.026738	0.248443	0.706357
WACC	0.376607	-0.113404	1.000000	-0.213410	0.351809	0.059971	-0.103578
ESGRank	-0.082079	0.515519	-0.213410	1.000000	-0.141787	0.107320	0.422169
Tobins_Q_Ratio	0.808116	0.026738	0.351809	-0.141787	1.000000	0.032448	-0.196544
EPS	0.215051	0.248443	0.059971	0.107320	0.032448	1.000000	0.246150
FCF	-0.120786	0.706357	-0.103578	0.422169	-0.196544	0.246150	1.000000

Table 4: Summary of Regression Results

OLS Regression Results

Dep. Variable:	ESGRank	**R-squared:**	0.308
Model:	OLS	**Adj. R-squared:**	0.307
Method:	Least Squares	**F-statistic:**	355.1
Date:	Sun, 01 Dec 2019	**Prob (F-statistic):**	0.00
Time:	21:06:02	**Log-Likelihood:**	-19216.
No. Observations:	4788	**AIC:**	3.845e+04
Df Residuals:	4781	**BIC:**	3.849e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-436.7366	18.655	-23.411	0.000	-473.309	-400.164
RETURN_ON_ASSET	1.3587	0.243	5.588	0.000	0.882	1.835
CUR_MKT_CAP	158.7896	6.110	25.990	0.000	146.812	170.767
WACC	-0.9641	0.098	-9.844	0.000	-1.156	-0.772
Tobins_Q_Ratio	-9.5950	1.081	-8.877	0.000	-11.714	-7.476
EPS	-0.6582	0.238	-2.768	0.006	-1.124	-0.192
FCF	0.6753	0.180	3.751	0.000	0.322	1.028

Omnibus:	179.674	**Durbin-Watson:**	0.241
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	199.685
Skew:	-0.498	**Prob(JB):**	4.35e-44
Kurtosis:	3.084	**Cond. No.**	1.07e+03

4.3 Results v/s Hypotheses

Hypothesis 1 (H1): A negative correlation between ESG rating and Weighted Average Cost of Capital

Our first hypothesis suggests that there is negative correlation between ESG and WACC. Regression results of model with normalized data gives us -21.3% correlation which supports our hypothesis. Our results are consistent with number of prior studies which documents that as companies are more focused on their ESG performance, the cost of capital goes down as there is more confidence shown by investors in company.

Hypothesis 2 (H2): A positive correlation between ESG rating and Market Capitalization

Our second hypothesis assumes that there is positive correlation between ESG and market capitalization of an organization. Investing in good companies is intuitively appealing. Who doesn't want to make money while doing good? The question here is that do stocks that rank high on ESG metrics outperform? Our regression results suggested a positive correlation of 51.5% between ESG and market capitalization. (Table 4)

A possible explanation of ESG and market capitalization is that cheap stocks have structural issues that make achieving high ESG scores less of a priority for the companies. Also, smaller companies have fewer resources to focus on ESG parameters. Indeed, the average market capitalization of the top 10% of the highest-ranking ESG stocks is almost twice that of the bottom 10%. (Source: Factor Research)

Hypothesis 3 (H3): A positive correlation between ESG rating and Free Cash Flow over time

Our 3rd hypothesis suggested positive correlation between Cash Flow and ESG.

Financial forecasting such as revenue, operating expenses, asset book value and cash flow can be done considering the impact of ESG factors. ESG factors can influence assets' anticipated cash flow in positive as well as negative way. Our research shows that FCF and ESG are related positively by 42.2%. This correlation was initially suggested at 24.8% and it increased to 42.2% after box cox transformation. Thus hypothesis 3 is supported.

Hypothesis 4 (H4): A positive correlation between ESG rating and the Profitability of the company

In the given sample, ESG and Tobin's ratio is negatively corelated. our results indicate that strong ESG rating may have had negative effects on stock market valuations of banks during the crisis, as companies with stronger governance are found to be associated with lower Tobin's Qs and stock returns. The correlation is numbered at -14.17%. The correlation between the Return on Asset and the ESG Score is -8.21% and the correlation between the EPS and the ESG Score is 10.73%

5. Limitations:-

USA does not have any regulation in place regarding ESG disclosures which may lead to unavailability of some information which may impact the ESG scores. Also, we cover only a small period (2013-2017) which may not be reflective of future performance due to changes in regulations that have or might happen post 2017. The Tobin Q ratio can be misrepresentative as theoretically a Tobin's Q ratio greater than 1 implies that a stock is overvalued. As we find a negative correlation between the ESG score and the Tobin's Q ratio, it can be a good or a bad thing for the firm depending on the initial Tobin's Q ratio.

We also believe that if we consider the t+1 values for the dependent variables, we might obtain a positive correlation. Prior studies have indicated that the ESG score might take some time to have an impact on the financial performance of the firm. (Wang & Qian, 2011).

6. Conclusion:-

Based on the results discussed above, our results are mixed which is in line with earlier empirical studies. We were expecting to find a positive relation between the ESG score and the financial performance of the firm but found a negative correlation with some of the factors. This might be due to the limitations of our research as discussed above. We believe that if the bill to make ESG disclosures mandatory for US firms gets approved in the congress then the scope of the study might be higher as we would be able to do the same study across different countries due to uniformity in the data available to us. Based on the results that we have got currently; it seems like although ESG is mainly being used as a screener for stocks it might become a very important factor to take into consideration for many investors in the future.

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8. Appendix

Python code for the model:

In [66]:

```
import pandas as pd

import numpy as np



from statsmodels.stats.diagnostic import het_breuschpagan

from statsmodels.stats.diagnostic import het_white

import pandas as pd

import statsmodels.api as sm

from statsmodels.formula.api import ols

from scipy import stats

import matplotlib.pyplot as plt
```

In [67]:

```
# Load the dataset - change name of sample.xlsx to the original filename

df = pd.read_excel("sample.xlsx")

df=df.rename(columns={"ESG Rank":"ESGRank"})

df=df[:-1]

df["ESGRank"]=df["ESGRank"].ffill()

keep=["RETURN_ON_ASSET","CUR_MKT_CAP","WACC","Tobins_Q_Ratio","EPS"
,"FCF"]
```

In [68]:

```
for i in keep:
    df=df[df[i]>0]
```

In [69]:

```
df["ESGRank"].isnull().values.any()
```

Out[69]:

```
False
```

In [70]:

```
import seaborn as sns
corr = df.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```

In [71]:

```
df.corr()
```

In [72]:

```
# Correlation of RETURN_ON_ASSET with ESG Rank
df["RETURN_ON_ASSET"].corr(df["ESGRank"])
```

Out[72]:

-0.0697615861720758

In [73]:

```
# Correlation of CUR_MKT_CAP with ESG Rank
df["CUR_MKT_CAP"].corr(df["ESGRank"])
```

Out[73]:

0.37068006039787016

In [74]:

```
# Correlation of WACC with ESG
df["WACC"].corr(df["ESGRank"])
```

Out[74]:

-0.21346330207493724

In [75]:

```
# Correlation of Toblin with ESG
df["Tobins_Q_Ratio"].corr(df["ESGRank"])
```

Out[75]:

-0.15030390531935545

In [76]:

Correlation of EPS with ESG

df["EPS"].corr(df["ESGRank"])

Out[76]:

-0.035973405545663398

In [77]:

Correlation of FCF with ESG

df["FCF"].corr(df["ESGRank"])

Out[77]:

0.24883430554995228

In [78]:

from sklearn.model_selection import train_test_split

Use three features (variables) for training

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X =
df[["RETURN_ON_ASSET","CUR_MKT_CAP","WACC","Tobins_Q_Ratio","EPS","FCF"]]

Target variable

y = df["ESGRank"]

Splitting the dataset into training and testing sets for training and evaluating the model

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25)

In [79]:

from sklearn.linear_model import LinearRegression

Create linear regression object

model = LinearRegression()

In [80]:

y_train

Name: ESGRank, Length: 3591, dtype: float64

In [81]:

Fit (train) the model on training dataset

model.fit(X_train,y_train)

Out[81]:

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

In [82]:

Generate predictions by trained model on test set

y_pred = model.predict(X_test)

In [83]:

from sklearn.metrics import mean_squared_error, r2_score

Measure mean squared error between original test set and predictions generated by the model

mean_squared_error(y_test,y_pred)

Out[83]:

211.78616434114832

In [84]:

Variance Score

r2_score(y_test,y_pred)

Out[84]:

0.19650913429747652

In [85]:

Coefficient values of the three features of the model

model.coef_

Out[85]:

array([4.34313959e-01, 9.25034251e-05, -1.44975502e+00, -2.54028258e+00,

-6.64310532e-01, 1.99973835e-04])

In [86]:

Intercept value of the regression model

model.intercept_

Out[86]:

73.31233384932418

In [87]:

f ='ESGRank~RETURN_ON_ASSET+CUR_MKT_CAP+WACC+Tobins_Q_Ratio+EPS+FCF'

statecrime_model = ols(formula=f, data=df).fit()

In [88]:

labels = ["LM Statistic", "LM-Test p-value", "F-Statistic", "F-Test p-value"]

white_test = het_white(statecrime_model.resid, statecrime_model.model.exog)

print(dict(zip(labels, white_test)))

{'LM Statistic': 354.8144778020224, 'LM-Test p-value': 7.30394735748643e-59, 'F-Statistic': 14.110052014648701, 'F-Test p-value': 2.0362479531703015e-61}

In [ ]:

In [103]:

import pandas as pd

import numpy as np

from statsmodels.stats.diagnostic import het_breuschpagan

from statsmodels.stats.diagnostic import het_white

import pandas as pd

import statsmodels.api as sm

from statsmodels.formula.api import ols

from scipy import stats

```
import matplotlib.pyplot as plt

import statsmodels.formula.api as smf

In [104]:

# Load the dataset - change name of sample.xlsx to the original filename

df = pd.read_excel("sample.xlsx")

df=df.rename(columns={"ESG Rank":"ESGRank"})

df=df[:-1]

df["ESGRank"]=df["ESGRank"].ffill()

keep=["RETURN_ON_ASSET","CUR_MKT_CAP","WACC","Tobins_Q_Ratio","EPS"
,"FCF"]

In [105]:

for i in keep:

    df=df[df[i]>0]

In [106]:

df["ESGRank"].isnull().values.any()

Out[106]:

False

In [107]:

for i in keep:



    print(i,"---------------")
```

```
    print(df[[i]].sort_values([i]))

    plt.hist(df[i],bins=100)

    plt.show()



    transform = np.asarray(df[[i]].values)



    dft=stats.boxcox(transform)[0]

    df[i]=dft

    print(df[i])

    plt.hist(dft,bins=100)

    plt.show()
```

In [110]:

```
# Correlation of RETURN_ON_ASSET with ESG Rank

df["RETURN_ON_ASSET"].corr(df["ESGRank"])
```

Out[110]:

-0.08207886100437892

In [111]:

```
# Correlation of CUR_MKT_CAP with ESG Rank

df["CUR_MKT_CAP"].corr(df["ESGRank"])
```

Out[111]:

0.5155191002602946

In [112]:

```
# Correlation of Variable 3 with ESG Rank
df["WACC"].corr(df["ESGRank"])
```

Out[112]:

-0.21340967115073806

In [113]:

```
# Correlation of Toblin with ESG
df["Tobins_Q_Ratio"].corr(df["ESGRank"])
```

Out[113]:

-0.14178738958402112

In [114]:

```
# Correlation of EPS with ESG
df["EPS"].corr(df["ESGRank"])
```

Out[114]:

0.10731961629182116

In [115]:

```
# Correlation of FCF with ESG
df["FCF"].corr(df["ESGRank"])
```

Out[115]:

0.4221687263875777

In [116]:

```
from sklearn.model_selection import train_test_split
# Use three features (variables) for training
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = df[["RETURN_ON_ASSET","CUR_MKT_CAP","WACC","Tobins_Q_Ratio","EPS","FCF"]]
# Target variable
y = df["ESGRank"]

# Splitting the dataset into training and testing sets for training and evaluating the model
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25)
```

In [117]:

```
from sklearn.linear_model import LinearRegression
# Create linear regression object
model = LinearRegression()
```

In [118]:

```
y_train
```

```
Name: ESGRank, Length: 3591, dtype: float64
```

In [119]:

```
# Fit (train) the model on training dataset
```

model.fit(X_train,y_train)

Out[119]:

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

In [120]:

Generate predictions by trained model on test set

y_pred = model.predict(X_test)

In [121]:

from sklearn.metrics import mean_squared_error, r2_score

Measure mean squared error between original test set and predictions generated by the model

mean_squared_error(y_test,y_pred)

Out[121]:

177.32916662898788

In [122]:

Variance Score

r2_score(y_test,y_pred)

Out[122]:

0.3162458087493448

In [123]:

Coefficient values of the three features of the model

model.coef_

Out[123]:

array([1.42371466, 160.29408511, -0.88558598, -10.0067275 ,

-0.88968188,   0.65738367])

In [124]:

Intercept value of the regression model

model.intercept_

Out[124]:

-442.0923839163218

In [128]:

f

='ESGRank~RETURN_ON_ASSET+CUR_MKT_CAP+WACC+Tobins_Q_Ratio+EPS+FCF'

statecrime_model = ols(formula=f, data=df).fit()

In [129]:

labels = ["LM Statistic", "LM-Test p-value", "F-Statistic", "F-Test p-value"]

white_test = het_white(statecrime_model.resid, statecrime_model.model.exog)

print(dict(zip(labels, white_test)))

{'LM Statistic': 321.15950243200126, 'LM-Test p-value': 4.305784462844918e-52, 'F-Statistic': 12.675453898555347, 'F-Test p-value': 3.876558056725906e-54}

In [130]:

lm1 = smf.ols(formula=f, data=df).fit()

In [131]:

```
lm1.summary()
```

In [ ]: