ESG Ratings as a Risk Measure

Chris Kozak

Rutgers University

Abstract

Environmental, Social, and Governance guidelines have been an increasingly popular metric for investors. Established literature dictates that the better a company performs in Environmental, Social, and Governance ratings, the less risky and more profitable for investors. This study basis the research conducted on these opinions and seeks to test the stated conclusion using hypothetical portfolios. By constructing portfolios solely based on Environmental, Social, and Governance scores the study investigates how portfolios have historically performed within the last year and a half. The study seeks to provide insight into where the current research may be lacking and to test some contested opinions on the topic of Environmental, Social, and Governance. More research is needed to validate the ways in which Environmental, Social, and Governance regulation scores affect the risk measures used in risk management measurements.

Introduction

Environmental, Social, and Governance (henceforth ESG) is a set of standards that inform investors on the risk practices of a company. Companies with good ESG ratings pursue practices that protect against risks associated with the three sectors mentioned. Environmentally, companies with good ESG ratings will pursue practices that avoid negatively impacting the environment. For the social aspect, companies ensure relations with those who interact with the company (employees, customers, or communities in surrounding areas) are healthy. Finally, the governance portion entails consistently treating members of the company and investors/shareholders fairly which includes diversity and transparency. This measure has become increasingly popular as corporate responsibility has become a new metric that investors utilize when making financial decisions. If an ESG driven investor were looking at tobacco or defense industries, for example, they would typically avoid these investments in favor of ones more dedicated to ESG standards. With the recent surge in ESG utilization, questions about the validity of ESG usage arise and are essential to answer. One of the most important measures to validate is how well ESG ratings can serve risk management. This paper aims to explore how well ESG ratings can be used to measure risk as a case study.

Literature Review

Understanding the implications of risk measures is vital to drawing conclusions on financial decisions. Value at risk (VaR), the efficient frontier, and returns on investments are some of the key metrics used to measure the risk of an investment. VaR is a risk measure that informs an investor of their risk in a strategy with a single number. VaR is calculated by finding the distributions of returns or dollar amount for an investment, selecting a confidence level (95% for example) and then taking the corresponding lower quantile value associated with that confidence level as the VaR. While there are a myriad of ways to calculate VaR, this study focuses on utilizing historical data to create a distribution of past returns to make a decision about what the VaR is. The efficient frontier is a visual representation of how risky a portfolio or stock is relative to its return. The farther into the "northwest" portion of an efficient frontier an investment strategy is the better its performance overall. Being in the northwest section equates to having minimal risk for larger returns, relative to the specific scenario being modeled. Returns are the profits or losses one makes when performing various strategies with higher returns being more favorable (Hull, 2012).

An analysis of ESG companies provides a useful foundation to investigating how ESG on the whole interacts with risk measurement. According to Jeremy Galbreath, higher ESG rated companies generally have better risk management (Galbreath, 2013). Companies that perform well on ESG rating scales are more likely to have more attention paid to their risk departments and thus less risk. For a company to have a high ESG rating, it must comply with regulations put forth by a government and thus must adhere to guidelines strictly requiring a more robust risk management approach. While Galbreath does not definitively outline the effectiveness in using ESG as a broader way to measure risk, he does help establish a foundational understanding that is utilized throughout this study. His sentiments are echoed throughout the available literature as many studies indicate that higher ESG ratings tend to lower risk in various forms. One such versions of this lowered risk is shown through how "green stocks" outperform "brown stocks" in both returns and in tail-risk protection (Xiong, 2021). Stocks whose ESG ratings (based on Sustainalytics' rating system) were good saw significantly more returns than stocks with poor ESG ratings. The former can be labeled as "green stocks" while the latter can be called "brown stocks." This most likely stems from the fact that higher rated ESG companies have lower systematic volatility and less volatile earnings (Giese et al., 2019). This lower volatility is associated with the better risk management inherent in highly rated ESG companies (Giese et al., 2019).

Studying the measures of risk while incorporating ESG ratings is increasingly becoming more valuable. Analyzing the construction of efficient frontiers, ESG ratings have been shown to inform investors on how to garner better Sharpe ratios (Pedersen et al., 2021). The incorporation of green stocks into portfolios has been shown to reduce the risk while simultaneously increasing the returns on investments. However, these broad sweeping statements have seen some complications recently with the energy crisis of 2022. While green stocks have been steadily outperforming brown stocks for close to a decade, the energy crisis of early 2022 saw a shift in this tend (Bauer et al., 2022). Brown stocks outperformed the counterpart green stocks for the first time in a decade. This crisis showed that there are scenarios in which brown stocks outperform green stocks, but there has not been enough time passed nor research done to definitively conclude how this crisis has impacted the performance of green and brown stocks in the long run. For this study the assumptions was made that the decade long precedent of green stocks outperforming brown stocks continued past the outlier case of the 2022 energy crisis. VaR estimations are also reduced when a company has higher ESG ratings. Specifically when companies publicly engage in pursuing ESG practices, they report lower VaR (Hoepner et al., 2018). ESG disclosure and higher ESG scores showed a reduction in idiosyncratic risk and VaR with the benefit of also improving downside tail risk (Reber et al., 2022). These conclusions help inform the hypothesis that ESG ratings serve as a useful tool in risk assessment and perform well.

The fund flow into better ESG rated companies also increased suggesting a general move for investors to add these types of companies into their portfolios. This increase in funding follows from the established ideas on how engaging in corporate social responsibility (CSR), which is typical for well rated ESG stocks, can increase funding while acting as insurance (Landi et al., 2022). In general, when corporations dedicate resources to CSR and ESG practices, they are rewarded by shareholders and the society they serve (Suchman, 1995). Investors look for less risky investments, and when companies involved themselves with CSR they exhibit behaviors investors associate with less risky investments (Landi et al., 2022). Better CSR and ESG leads investors to believe risk is inherently well managed and thus are more open to increasing the portion of their portfolios dedicated to those stocks. This engagement can act similar to insurance against reputation risk as well. The effective period of this so-called insurance is not extensive with successive drops in reputation, but in isolated events it can help prevent large downward movements in value for companies (Shiu & Yang, 2017). Thus, maintaining a high ESG rating acts as a protective barrier against negative shocks to stock price and garners more capitol when compared to lower ESG performing stocks.

Methodology

The data collected was taken from the Yahoo Finance API via python. Using built-in functions data was extracted from the S&P500 from all stocks with available ESG rating data. After extracting the relevant data there were 432 available stocks from the 500 on the S&P500. Once these stocks had been downloaded they were then sorted by ascending order of total ESG score (the sum of each component score). Yahoo Finance utilizes Sustainalytics to rate companies, and the scale that they use ranges from 0-100 with 0 being the best possible ESG rating and 100 being the worst. The stocks collected ranged from 6.8 to 46 in total ESG score with a median value of 21. Other descriptive statistics on the collected S&P500 data can be found in Table 1. Data was extracted from January 1, 2022 to April 1, 2023. This date range was chosen because the farthest back ESG rating update from Sustainalytics occurred in January 2022 and the current ESG rating was prioritized over a large dataset. The ending bound was arbitrarily chose as a “neat” cut-off point that also included a fairly large amount of data.

The stocks were then divided into 3 equal sized bins with descriptive statistics found in Tables 2 through 4. Each bin was to be considered the best, middle, and worst third of the collected data respectively. From these large bins, a smaller subset of stocks were chosen to create portfolios solely based on total ESG scores. By taking the median of each bin and finding 11 stocks within the range the respective medians three portfolios were created to represent the ESG groupings of the bins. From this point forward the best ESG portfolio will be referred to as portfolio 1, the middle as portfolio 2, and the worst as portfolio 3. These 33 stocks were the focus for the remainder of the analysis. All following results were obtained by looking at the adjusted returns for these stocks.

For each portfolio an efficient frontier and historical 95% VaR were constructed. For the efficient frontiers, annualized returns and annualized covariances were put into an optimizer that created 20 portfolios with various allocations to each stock. The portfolios were then plotted along with each individual stock in a Markowitz risk-return space showing where the portfolios would lie given various allocations of stocks. The minimum variance (risk) portfolio values were highlighted as these portfolios show the safest strategy to pursue if these hypothetical investments were to be made. An adjustment to portfolio 3 was made to account for the recent failure of Silicon Valley Bank. In the original portfolio Silicon Value Bank Financial Group (SIVB) was included and skewed both the risk and returns of the portfolio to an extremely significant degree. To account for this recent shock to this portfolio SIVB was removed and the analysis was continued with no other changes.

95% VaR models were also produced using daily historical log returns from January 1, 2022 to April 1, 2023. Using the allocations prescribed in the minimum variance portfolio for each stock, daily returns were calculated for the stocks and then for the entire portfolio. This data then formed a distribution where the lower 5% quantile value was equivalent to the 95% VaR. This value was then extracted in terms of the log return.

Results

The results from this case study show some interesting deviations from the original hypothesized results. Based on the literature available on the topic of ESG and risk, portfolio 1 should have performed better than 2 and 3 but it in fact performed worse in every metric measured. When discussing the efficient frontiers, focusing on the minimum risk portfolios gives insight into what a potential investor would chose in each of these scenarios. Efficient frontier graphs shown in figures one through three display how the graphs of portfolios 2 and 3 are noticeably better in both risk and return than portfolio 1 . Portfolio 2 performed marginally better than portfolio 1, but portfolio 3 performed much better than both. In fact, portfolio 1 had a negative return while simultaneously having the most risk.

The same trend is seen when looking at the 95% VaRs as well. For Portfolios 2 and 3 the VaR was essentially the same while portfolio 1 had a 0.03% lower VaR. Once again, the worse the ESG score the better the portfolio looks to investors. This difference may not seem to be a large amount, but for larger investment portfolios any increase in the value that could be lost is a significant measure to take into account. With an ESG driven portfolio that has higher risk and lower returns this case study shows a deviation from established opinions on ESG ratings as a risk metric.

Discussion

This case study, while small in scale, demonstrates how there may be need for more in-depth research into the effectiveness of using ESG ratings as a risk measure. The original hypothesis that portfolio 1 would perform noticeably better than portfolios 2 or 3 was supported by a variety of sources yet failed to be verified when tested on current data. There is thus a pressing need to reevaluate how effective these ratings can be used to hedge against risk and how important ESG ratings of a company can be to portfolio managers. One of the main findings of this case study points to the conclusion that the worse a company performs on an ESG scale, the more enticed investors should be. Having lower risk and nearly 20% more returns than a portfolio of green stocks shows a clear sign of outperformance. This leads to questions on why ESG stocks and portfolios have been garnering more and more funding when they may be underperforming. A possible explanation of this discrepancy could be the lack of diversity present in the stocks, as well as some remnants of the effects of the energy crisis of 2022.

The underperformance of green stocks and the portfolio constructed in this case study may stem from a lack of diversification. When building a portfolio, it is best to hedge riskier investments with “safer” investments. These investments may often This means, for an investor, utilizing a broad range of industries to ensure that negative impacts in one sector do not infect other stocks and cause cascading losses. When investors construct portfolios with the same guidelines as this study constructed portfolio 1, this hedging may become increasingly more difficult. While brown stocks are unappealing to ESG driven investors, the incorporation of them into portfolios may prove to be a useful strategy to guard against correlated losses that could be present in green stock only portfolios. While this case study does not prove that ESG stocks have lower performance, the random nature of the stock choice does show some evidence that the broad reaching opinions present in the present literature may need reevaluation.

Another question arises when one considers how the appeal of ESG stocks to investors comes from the idea that they are less risky. As mentioned, companies with good ESG ratings are thought to innately have better risk management. This logic seems applicable, the better a company performs on a risk measurement scale the better their risk management should be. However, as seen through the efficient frontiers of this case study, this conclusion does not lead to less risk for investors. A possible explanation for this discrepancy could be that the rating system for ESG rating organizations have not been standardized (Dorfleitner et al., 2015). The way Sustainalytics performs its ESG ratings differs from Bloomberg’s which differs from Morningstar and so on. Perhaps if other ratings were readily available to study, this case study could have incorporated multiple rating organizations to garner a mean score for companies. This mean score could have provided a more informed score that used varied metrics to measure the same risk measurements. Another explanation stems from the same ideas previously mentioned regarding the lack of diversity. Issues of one company in undiversified portfolios spread to other companies thereby increasing risk throughout. The disconnect between established literature on highly rated ESG companies and this case study, therefore, have no clear solution. One field to explore would be an examination of standardized practices when rating companies.

The conflicting results between this study and the literature reviewed provides interesting avenues to explore. There is a definite need for more comprehensive studies on how ESG ratings impact how investors should construct portfolios, how companies should value these ratings, and how risk managers should factor these ratings into their assessments. If this study were to be replicated a similar approach to how one can look at regime switching models. For one such study, a group of stocks were examined relatively soon after they were added or dropped from the DS400, a corporate social responsibility driven index. When companies were added to the DS400, they generally saw increased returns while being removed from this index led to a decrease in returns (Ramchander et al., 2012). Adapting this model to account for changes in ESG rating could prove to be a useful forecasting tool when looking at returns or even volatility. In essence, if one were to adapt the process modeling a regime switching approach to the changes in ESG ratings, meaningful conclusions about the direct impact of a company's score could be achieved. There are currently few studies that implement this type of approach and the ones that do are typically not definitive in their conclusions. While a quasi-regime switching model showed a direct impact on VaR and cashflow in the short term, conclusions were limited aside from the fact that companies need to dedicate more time to understanding how to use CSR practices in their ESG efforts (Yang et al., 2022). This type of data was not readily available in python, but other ESG rating companies separate from Yahoo Finance would be able to provide records of such data.

While not the focus of this case study, models that stratify portfolios based on their concentration of high rated ESG measures should also be explored as well. The portfolio construction used in this study was adapted from a similar approach in another where the number of highly rated ESG stocks would act as a way to stratify the data into various classes. The best ESG rated classes were shown to have lower risks and had significantly accurate forecasts in long horizons of three years (Capelli et al., 2021). The caveat to this approach was that the short horizon forecasting was not significant, and so more research is needed to evaluate the utility of ESG ratings in forecasting volatility.

Summary

The literature on ESG as a risk measure supports the initial claim that good ESG ratings provide a useful means of mitigating risk, however this case study disagrees with this conclusion. The evidence provided shows a surprisingly lacking performance of highly rated ESG stocks in both risk metrics and returns metrics. Based on the efficient frontier calculated minimum risk portfolio, the better the ESG score the more risky and less profitable an investment is. Moreover, when investing in a portfolio based solely on the ESG rating, the VaR of the portfolio is inversely related to how good the ESG score is. Some of these conclusions are certainly affected by the lack of diversity in the portfolios and there may be some remaining effects of the 2022 energy crisis that may have affected the data collected. Further research is needed to fully validate the utility of ESG as a risk measure. This study reaches the conclusion that a diversified approach to hypothetical investment strategies is essential when developing strategies to validate ESG ratings as a risk measure. Diversification helps to avoid possible correlations that could be present in the findings of this case study and can more accurately reflect the behavior of investors in the market.

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Tables

Table 1

S&P500 ESG descriptive statistics

	index	Total-Score	E-Score	S-Score	G-Score
count	432.000000	432.000000	432.000000	432.000000	432.000000
mean	215.500000	21.211111	5.549074	8.966667	6.702778
std	124.851912	7.144239	5.273015	3.697588	2.212733
min	0.000000	6.800000	0.000000	1.100000	3.100000
25%	107.750000	15.800000	1.500000	6.600000	5.200000
50%	215.500000	21.000000	3.550000	8.700000	6.200000
75%	323.250000	25.925000	8.800000	11.325000	7.700000
max	431.000000	46.000000	24.600000	20.700000	15.500000

Table 2:

Bin 1 descriptive statistics

	index	Total-Score	E-Score	S-Score	G-Score
count	143.000000	143.000000	143.000000	143.000000	143.000000
mean	228.132867	13.606294	2.474126	5.686713	5.450350
std	126.499526	2.202822	2.039563	2.107473	1.343994
min	4.000000	6.800000	0.000000	1.100000	3.100000
25%	120.000000	12.050000	1.000000	4.000000	4.600000
50%	239.000000	13.900000	2.200000	5.600000	5.300000
75%	336.000000	15.700000	3.400000	7.250000	6.050000
max	428.000000	16.800000	11.600000	10.500000	11.600000

Table 3:

Bin 2 descriptive statistics

	index	Total-Score	E-Score	S-Score	G-Score
count	143.000000	143.000000	143.000000	143.000000	143.000000
mean	209.713287	20.632168	4.254545	9.451748	6.935664
std	122.856817	2.099014	3.691248	2.655843	2.101790
min	5.000000	17.000000	0.000000	1.500000	3.100000
25%	102.500000	18.750000	1.250000	7.750000	5.600000
50%	206.000000	21.000000	3.000000	9.300000	6.400000
75%	313.000000	22.400000	7.100000	11.200000	8.150000
max	431.000000	23.900000	15.800000	16.400000	12.800000

Table 4:

Bin 3 descriptive statistics

	index	Total-Score	E-Score	S-Score	G-Score
count	143.000000	143.000000	143.000000	143.000000	143.00000
mean	210.000000	29.232867	9.843357	11.717483	7.67972
std	125.276539	4.215494	5.847156	3.336447	2.43370
min	0.000000	24.000000	0.200000	2.100000	3.30000
25%	107.500000	25.950000	4.550000	9.350000	5.80000
50%	196.000000	28.400000	10.100000	11.300000	7.30000
75%	316.500000	31.750000	14.350000	13.900000	8.80000
max	430.000000	43.200000	24.600000	20.700000	15.50000

Figures

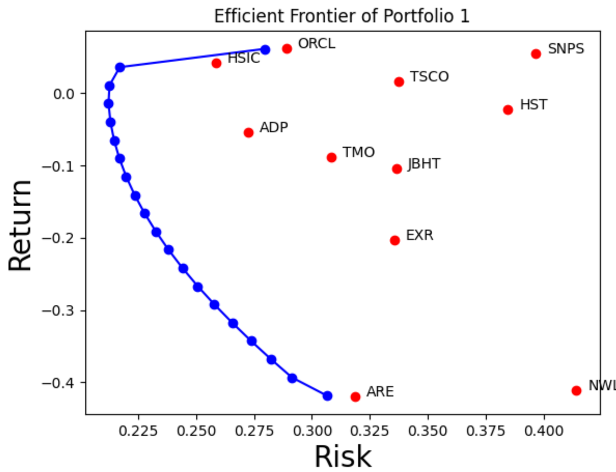


Figure 1

risk, return = (0.2122, -0.0149)

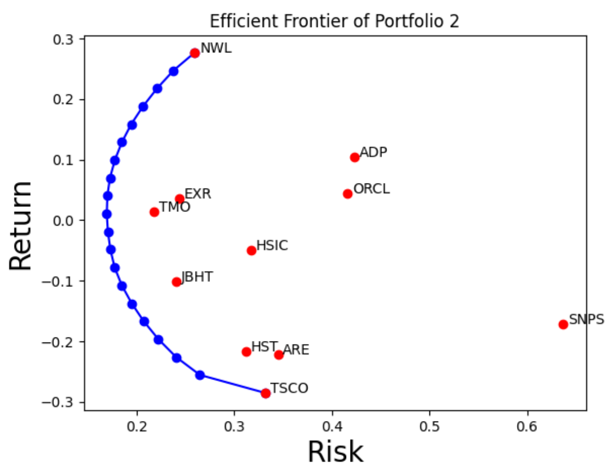


Figure 2

risk, return = (0.1698, 0.0104)

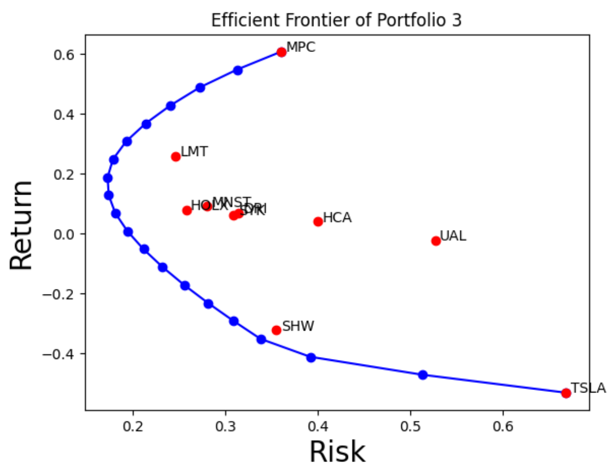
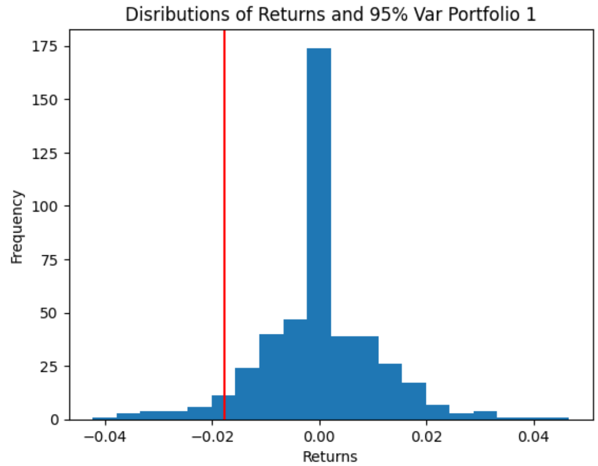


Figure 3

risk, return = (0.1733, 0.1878)



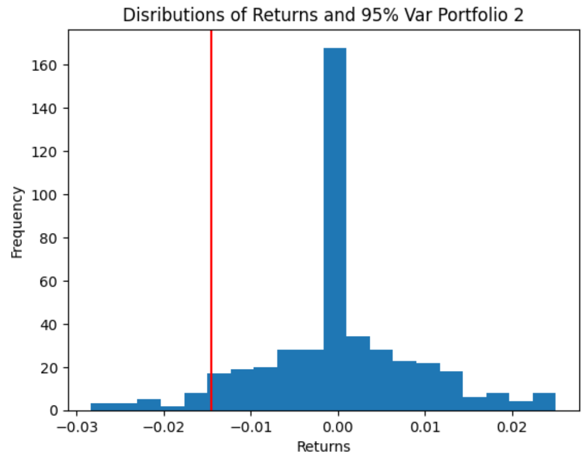


Figure 4

VaR on Returns: -0.0176994

Figure 5

VaR on Returns: -0.0145524

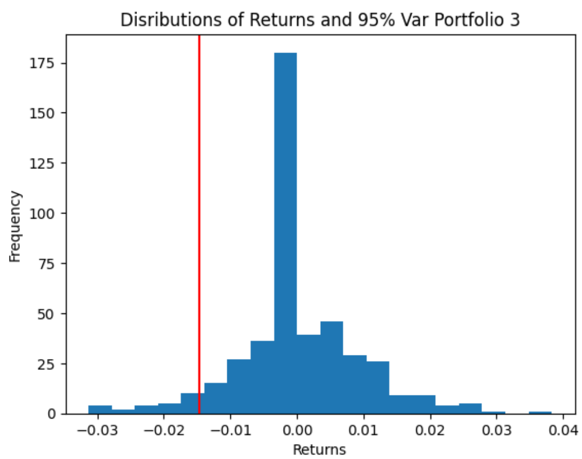


Figure 6

VaR on Returns: -0.0146814

Appendix

In [288]:
```
import numpy as np
import yfinance as yf
import pandas as pd
import os
import requests
import pandoc
```

In [287]:
```
!pip3 install yesg
!pip3 install pandoc
import yesg
```

...

In [7]:
```
SP_500 = pd.read_csv("constituents_csv.csv")
#Reading in ticker info
```

In [103]:
```
tickers = SP_500['Symbol']
Ratings = pd.DataFrame(SP_500['Name'])
Ratings['Symbol'] = SP_500.Symbol
dataframes = []

for i in tickers:
    try:
        df = yesg.get_esg_short(i)
        dataframes.append(df)
    except: continue
Ratings = pd.concat(dataframes, ignore_index = True)
Ratings.reindex
Ratings.head(10)
#Seeing which stocks on the S&P500 have data for ESG ratings and pulling them into one dataframe
```

...

In [269]:
```
Ratings
```

...

In [110]:
```
Ratings2 = Ratings.astype({'Total-Score': 'float', 'E-Score': 'float',
                           'S-Score': 'float', 'G-Score': 'float'})
Ratings2 = Ratings2.sort_values('Total-Score', ascending = True)
Ratings2 = Ratings2.reset_index()
Bin1 = pd.DataFrame(Ratings2.iloc[:143])
Bin2 = pd.DataFrame(Ratings2.iloc[144:287])
Bin3 = pd.DataFrame(Ratings2.iloc[288:431])
#Reformatting meta detaframe, sorting by ascending values, splitting large dataset into smaller chunk:
```

In [270]:
```
a = Ratings2.describe()
x = Bin1.describe()
y = Bin2.describe()
z = Bin3.describe()
display(a,x,y,z)
#getting basic descriptive stats for each bin
```

...

In [129]:
```
Bin1.loc[Bin1['Total-Score'] == 13.9]     #find stocks around median for ESG ratings for each bin
port1 = pd.DataFrame(Bin1.iloc[66:77])
tickers1 = port1.Ticker.values.tolist()
port1
```

...

In [271]:
```
Bin2.loc[Bin2['Total-Score'] == 21]
port2 = pd.DataFrame(Bin2.iloc[66:77])
tickers2 = port2.Ticker.values.tolist()
port2
```

...

In [280]:
```
port3 = pd.DataFrame(Bin3.iloc[66:77])
tickers3 = port3.Ticker.values.tolist()
port3
```

...

In [236]:
```
#Lets start building an efficient frontier based on bins
tickers_df1 = yf.download(tickers1,
                      start='2022-01-01',
                      end='2023-04-02',
                      progress=False, auto_adjust=True)

from math import log

returns = tickers_df1['Close'].applymap(log).diff()[1:]
prices = tickers_df1['Close']
stats = returns.agg(['mean', 'std', 'var'])
correl = returns.corr()
display(stats, correl)
```

...

In [272]:
```
tickers_df2 = yf.download(tickers2,
                      start='2022-01-01',
                      end='2023-04-02',
                      progress=False, auto_adjust=True)

from math import log

returns2 = tickers_df2['Close'].applymap(log).diff()[1:]
prices2 = tickers_df2['Close']
stats2 = returns2.agg(['mean', 'std', 'var'])
correl2 = returns2.corr()
display(stats2, correl2)
```

...

In [281]:
```
tickers_df3 = yf.download(tickers3,
                      start='2022-01-01',
                      end='2023-04-02',
                      progress=False, auto_adjust=True)

from math import log

returns3 = tickers_df3['Close'].applymap(log).diff()[1:]

stats3 = returns3.agg(['mean', 'std', 'var'])
correl3 = returns3.corr()
display(stats3, correl3)
```

...

In [282]:
```
#Annualizing data

#Port1

annual_returns1 = stats.transpose()['mean'] * 252
annual_covar1 = returns.cov() * 252

#Port2

annual_returns2 = stats2.transpose()['mean'] * 252
annual_covar2 = returns2.cov() * 252

#Port3

annual_returns3 = stats3.transpose()['mean'] * 252
annual_covar3 = returns3.cov() * 252


display(annual_covar1,annual_covar2,annual_covar3)
display(annual_returns1,annual_returns2,annual_returns3)
```

...

In [154]:
```
import sys
!{sys.executable} --version
# !{sys.executable} -m pip install cvxpy
# !{sys.executable} -m pip install PyPortfolioOpt

import math
import numpy as np
from datetime import datetime
import pandas as pd
import yfinance as yf
from yahoofinancials import YahooFinancials
import matplotlib.pyplot as plt
from IPython.display import display

%matplotlib inline
```

```
Python 3.10.8
```

In [198]:
```
#Used from Quiz 1 Answer Sheet

from numpy import array, dot
from qpsolvers import solve_qp

class create_efficient_frontier():
    def __init__(self, returns, covar):
        self.returns = np.array(returns)
        self.covar = np.array(covar)
        self.n =len(self.covar)
        self.tickers = list(returns.index)

    def get_portfolio(self, return_target):
        """for a given target return create lowest variance long-only portfolio"""
        P, q = self.covar, np.array([0.] * self.n)
        G, h = None,None
        A = np.array([annual_returns, np.array([1.0] * self.n)])
        b = np.array([return_target, 1.0])
        lb, ub = np.array([0.] * self.n),np.array([1.] * self.n)

        self.portfolio = solve_qp(P, q, G, h, A, b, lb, ub,solver='osqp')
        return {"portfolio":self.portfolio, "risk_ret":self.risk_return()}  # return (allocation , ri

    def risk_return(self):
        """return the risk and return for this portfolio"""
        return np.sqrt(self.portfolio.dot(self.covar.dot(self.portfolio))),\
            self.returns.dot(self.portfolio)
```

In [250]:
```
#EF from best best ESG portfolio
import math
annual_returns = annual_returns1
annual_covar = annual_covar1
ef = create_efficient_frontier(annual_returns, annual_covar)
min_return, max_return = min(annual_returns) + .001, max(annual_returns) - .001
frontier = np.array([ef.get_portfolio(r)['risk_ret']
                     for r in np.linspace(min_return, max_return, 20)]).T

# plot the efficient frontier in the Markowitz risk-return space

plt.plot(frontier[0], frontier[1], 'o-', color='blue') # plot the efficient frontier
for n, r, s in zip(annual_returns1.index, annual_returns1, np.sqrt(np.diag(annual_covar1))):
    plt.plot([s], [r], 'o', color='red')
    plt.text(s+0.005, r, n)
plt.title('Efficient Frontier of Portfolio 1')
plt.xlabel('Risk', fontsize=20)
plt.ylabel('Return', fontsize=20)
plt.show()
```

...

In [251]:
```
#Looking at allocations

min_var_risk = min(frontier[0])
min_var_portfoio_number = [i for i, risk in enumerate(frontier[0]) if risk == min_var_risk][0]

print("min variance portfolio:")
print(f"efficient frontier portfolio # = {min_var_portfoio_number}")

print(f"(risk, return) = ({frontier[0][min_var_portfoio_number]:0.4f}, {frontier[1][min_var_portfoio_

frontier_portfolios = np.array([ef.get_portfolio(r)['portfolio']
                     for r in np.linspace(min_return, max_return, 20)])

ticker_list = list(annual_returns.index)
allocation1 = pd.DataFrame(frontier_portfolios[min_var_portfoio_number], index=ticker_list, columns=[
display(allocation1)
```

...

In [274]:
```
#EF from best middle ESG portfolio
import math
annual_returns = annual_returns2
annual_covar = annual_covar2
ef = create_efficient_frontier(annual_returns, annual_covar)
min_return, max_return = min(annual_returns), max(annual_returns)
frontier = np.array([ef.get_portfolio(r)['risk_ret']
                     for r in np.linspace(min_return, max_return, 20)]).T

# plot the efficient frontier in the Markowitz risk-return space

plt.plot(frontier[0], frontier[1], 'o-', color='blue') # plot the efficient frontier
for n, r, s in zip(annual_returns1.index, annual_returns, np.sqrt(np.diag(annual_covar))):
    plt.plot([s], [r], 'o', color='red')
    plt.text(s+0.005, r, n)
plt.title('Efficient Frontier of Portfolio 2')
plt.xlabel('Risk', fontsize=20)
plt.ylabel('Return', fontsize=20)
plt.show()
```

...

In [275]:
```
min_var_risk = min(frontier[0])
min_var_portfoio_number = [i for i, risk in enumerate(frontier[0]) if risk == min_var_risk][0]

print("min variance portfolio:")
print(f"efficient frontier portfolio # = {min_var_portfoio_number}")

print(f"(risk, return) = ({frontier[0][min_var_portfoio_number]:0.4f}, {frontier[1][min_var_portfoio_n

frontier_portfolios = np.array([ef.get_portfolio(r)['portfolio']
                     for r in np.linspace(min_return, max_return, 20)])

ticker_list = list(annual_returns.index)
allocation2 = pd.DataFrame(frontier_portfolios[min_var_portfoio_number], index=ticker_list, columns=[
display(allocation2)
```

...

In [283]:
```
#EF from best worst ESG portfolio including SVB
import math
annual_returns = annual_returns3
annual_covar = annual_covar3
ef = create_efficient_frontier(annual_returns, annual_covar)
min_return, max_return = min(annual_returns), max(annual_returns)
frontier = np.array([ef.get_portfolio(r)['risk_ret']
                     for r in np.linspace(min_return, max_return, 15)]).T

# plot the efficient frontier in the Markowitz risk-return space

plt.plot(frontier[0], frontier[1], 'o-', color='blue') # plot the efficient frontier
for n, r, s in zip(annual_returns.index, annual_returns, np.sqrt(np.diag(annual_covar))):
    plt.plot([s], [r], 'o', color='red')
    plt.text(s+0.005, r, n)
plt.title('Efficient Frontier of Portfolio 3')
plt.xlabel('Risk', fontsize=20)
plt.ylabel('Return', fontsize=20)
plt.show()

#this includes SVB
```

...

In [284]:
```
#Removing SVB and recalculating returns, vol, etc

SVB_ind = port3.index[(port3['Ticker'] == 'SIVB')]
port3 = port3.drop(SVB_ind)
port3

tickers3 = port3.Ticker.values.tolist()


tickers_df3 = yf.download(tickers3,
                      start='2022-01-01',
                      end='2023-04-02',
                      progress=False, auto_adjust=True)

from math import log

returns3 = tickers_df3['Close'].applymap(log).diff()[1:]
prices3 = tickers_df3['Close']
stats3 = returns3.agg(['mean', 'std', 'var'])
correl3 = returns3.corr()
display(stats3, correl3)

annual_returns3 = stats3.transpose()['mean'] * 252
annual_covar3 = returns3.cov() * 252
```

...

In [286]:
```
#EF from worst ESG portfolio without SVB
import math
annual_returns = annual_returns3
annual_covar = annual_covar3
ef = create_efficient_frontier(annual_returns, annual_covar)
min_return, max_return = min(annual_returns), max(annual_returns)
frontier = np.array([ef.get_portfolio(r)['risk_ret']
                     for r in np.linspace(min_return, max_return, 20)]).T

# plot the efficient frontier in the Markowitz risk-return space

plt.plot(frontier[0], frontier[1], 'o-', color='blue') # plot the efficient frontier
for n, r, s in zip(annual_returns.index, annual_returns, np.sqrt(np.diag(annual_covar))):
    plt.plot([s], [r], 'o', color='red')
    plt.text(s+0.005, r, n)
plt.title('Efficient Frontier of Portfolio 3')
plt.xlabel('Risk', fontsize=20)
plt.ylabel('Return', fontsize=20)
plt.show()

#this DOES NOT includes SVB
```

...

In [256]:
```
min_var_risk = min(frontier[0])
min_var_portfoio_number = [i for i, risk in enumerate(frontier[0]) if risk == min_var_risk][0]

print("min variance portfolio:")
print(f"efficient frontier portfolio # = {min_var_portfoio_number}")

print(f"(risk, return) = ({frontier[0][min_var_portfoio_number]:0.4f}, {frontier[1][min_var_portfoio_n

frontier_portfolios = np.array([ef.get_portfolio(r)['portfolio']
                     for r in np.linspace(min_return, max_return, 20)])

ticker_list = list(annual_returns.index)
allocation3 = pd.DataFrame(frontier_portfolios[min_var_portfoio_number], index=ticker_list, columns=[
display(allocation3)
```

...

In [267]:
```
### For Portfolio 1 (Best ESG)


### We use the minimum variance portfolio to calculate these VaR's
returns_p1 = prices.resample('D').last().pct_change()
returns_p1 = returns_p1[1:]
display(returns_p1)
p1_returns = returns_p1.dot(allocation1)

var_level = 0.05
portfolio_var1 = np.percentile(p1_returns, var_level*100)

plt.hist(p1_returns, bins=20)
plt.axvline(x=portfolio_var1, color='r', linestyle='-')
plt.title("Disributions of Returns and 95% Var Portfolio 1")
plt.ylabel('Frequency')
plt.xlabel('Returns')
plt.show()

print("The 95% VaR for porfolio 1 in terms of returns is: ", portfolio_var1)
```

...

In [265]:
```
### For Portfolio 2 (Middle ESG)


### We use the minimum variance portfolio to calculate these VaR's
returns_p2 = prices2.resample('D').last().pct_change()
returns_p2 = returns_p2[1:]
display(returns_p2)
p2_returns = returns_p2.dot(allocation2)

var_level = 0.05
portfolio_var2 = np.percentile(p2_returns, var_level*100)

plt.hist(p2_returns, bins=20)
plt.axvline(x=portfolio_var2, color='r', linestyle='-')
plt.title("Disributions of Returns and 95% Var Portfolio 2")
plt.ylabel('Frequency')
plt.xlabel('Returns')
plt.show()

print("The 95% VaR for porfolio 2 in terms of returns is: ", portfolio_var2)
```

...

In [266]:
```
### For Portfolio 3 (Worst ESG)


### We use the minimum variance portfolio to calculate these VaR's
returns_p3 = prices3.resample('D').last().pct_change()
returns_p3 = returns_p3[1:]
display(returns_p3)
p3_returns = returns_p3.dot(allocation3)

var_level = 0.05
portfolio_var3 = np.percentile(p3_returns, var_level*100)

plt.hist(p3_returns, bins=20)
plt.axvline(x=portfolio_var3, color='r', linestyle='-')
plt.title("Disributions of Returns and 95% Var Portfolio 3")
plt.ylabel('Frequency')
plt.xlabel('Returns')
plt.show()

print("The 95% VaR for porfolio 3 in terms of returns is: ", portfolio_var3)
```

...

In [ ]:
```


plt.plot(frontier[0], frontier[1], 'o-', color='blue') # plot the efficient frontier
for n, r, s in zip(annual_returns1.index, annual_returns1, np.sqrt(np.diag(annual_covar1))):
    plt.plot([s], [r], 'o', color='red')
    plt.text(s+0.005, r, n)

plt.title('Efficient Frontier of Portfolio 1')
plt.xlabel('Risk', fontsize=20)
plt.ylabel('Return', fontsize=20)
```