Unlocking A-Share Market Dynamics: Exploring ESG Impact on Volatility and Mean-Variance Portfolio

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1 Introduction

ESG is developed to evaluate the sustainability of corporate operations and their impact on social values from three dimensions: environment, society, and corporate governance. ESG criteria have gained substantial attention in recent years as investors increasingly prioritize sustainability and ethical considerations in their investment decisions. Understanding the relationship between ESG scores and stock market dynamics, particularly stock return volatility, is crucial for investors, policymakers, and corporate stakeholders.

According to Pedersen, ESG scores can provide information about company fundamentals on the one hand and influence investor preferences on the other (2020, p.572)[10]. Inspired by this, our article aims to study whether ESG indicators play a guiding role in stock selection and how to incorporate this indicator when building an investment portfolio in China's A-share market.

To verify ESG scores' impact on stock volatility, we use Ordinary Least Squares regression on listed companies in the Chinese A-share market. Then we incorporate ESG factors to construct investment portfolios. We modified the Markowitz Mean-Variance Model by introducing ESG score constraints and further explored the impact of ESG on Mean-Variance investors' preferences.

2 Literature Review

In recent years, investors have begun to consider the impact of non-financial factors in addition to the company's financial fundamentals when trading (Giese et al., 2019, p.69)[8]. The trading demand of investors unrelated to financial fundamentals have an impact on stock prices, and the sharp volatility of stock prices cause stock market risks. With the widespread adoption and deepening understanding of the ESG (Environmental, Social, and Governance) framework, ESG criteria has been integrated into investment portfolio construction process as an important non-financial factor. Research has shown that better ESG performance has the potential to increase firm value through lower firm risk (Aouadi et al., 2018, p.1030)[2]. Sassen et al. (2016, p.867)[11] suggest a significant negative correlation between ESG scores and stock return volatility in European markets, indicating that firms with superior ESG performance experience lower volatility in their stock prices. Similarly, Alareeni et al. (2020, p.1409)[1] document a similar pattern in the US market, attributing the lower volatility to enhanced corporate governance practices and environmental stewardship. Our first research question will verify the negative impact of ESG on stock return volatility in the Chinese A-share market using similar methods compared to previous research.

Incorporating Environmental, Social, and Governance (ESG) factors into portfolio construction is essential, with the mean-variance model playing a pivotal role. This model balances the competing goals of maximizing profit while minimizing risk. Markowitz addressed this core challenge by developing a parametric optimization model that is broad enough to apply to a wide range of real-world scenarios yet straightforward for theoretical examination and numerical solution (Steinbach, 2001, p.31)[13]. At the end of 2016, Global Survey showed large and experienced investors were increasingly focusing on ESG investment practices. State Street's Center for Applied Research surveyed 582 institutional investors who have implemented or plan to implement ESG strategies. Increasingly number of institutional investors in Americas, EMEA and Asia-Pacific, plan to utilize the impact of ESG in their investment strategies (Eccles et al., 2017, p.125)[6].

To employ ESG investment strategies of varying types and degrees, Drut[5] (2010) integrated the incorporation of ESG scores directly into investors' utility function. Their study clarified that taking ESG into consideration restricts their investment universe and the return will be penalized in a mean-variance framework. Based on the Pedersen et al's research (2019, p.573)[10], investors can be categorized into three groups: Type-U (ESG-unaware) investors, Type-A (ESG-aware) investors and Type-M (ESG-motivated) investors. Essentially, Type-M investors seek a portfolio that strikes an optimal balance between high expected returns, low risk, and elevated average ESG scores. Pedersen et al. demonstrated and explained that the increasingly widespread adoption of ESG affects portfolio selection and equilibrium asset prices.

Based on previous findings, we consider the inclusion of ESG metrics in the mean-variance model. We only focus on Type-M investors to study what role ESG specifically plays in people's investment behavior in different ESG-preferring investor populations, what can be achieved after considering ESG, and to quantify the costs and benefits caused by ESG metrics.

3 Research Questions

- Verify the impact of corporate ESG scores on stock return volatility in China's A-share market.
- Introduce ESG Scores to improve the Markowitz Mean Variance Model and study the impact of ESG on mean variance investors' preference.

4 Data

4.1 Data Description

The data in this article is mainly from CSMAR database, Sino-Securities Information Service Platform, and CFND database. In the first research question, we take the data of Chinese A-share listed companies from 2017 to 2022 from CSMAR as the research sample and analyzes the impact of ESG performance on the volatility of stock returns. The factor names and brief descriptions are shown in the table below.

In our factor selection process, we draw upon insights from prior research. For instance, Engelhardt (2021) advocates for incorporating various financial indicators to gauge company performance (p.7133)[7]. Additionally, we consider media oversight. The dissemination of information by multiple media outlets can mitigate information asymmetry in the market, indirectly enhancing the efficacy of ESG initiatives in influencing corporate value and temporarily stabilizing stock prices. However, indiscriminate exposure to media scrutiny may backfire. Managers might resort to earnings manipulation and financial statement embellishment under media pressure, potentially leading investors astray in their decision-making.

Control Variables	**Factor Description**
Volatility	The volatility of stock returns over the past 250 trading days
esgscore	esg score given by Sino-Securities Information Service Company
dummy audit	Credibility of audit reports
Director Ratio	number of directors/number of supervisors
TopTenHoldersRate	Shareholding ratio of top ten shareholders
DA	debt to total assets ratio
ROE	return on equity
media	log(number of media comments +1)
PB	price to book ratio
BM	book to market ratio
ATO	total asset turnover ratio
total asset log	log(value of total asset+1)
dummy year	represent the year effect
beta	systemic risks relative to the A-share market

[H]

Table 1: Factor Description

In the second research question, we take the stock return of Chinese A-share listed companies from 2009 to 2023 from CSMAR and ESG scores from Sino-Securities Index Information Service.

4.2 Data Processing

For the first research question, we refer to the approach of Yang Zhuqing and Liu Shaobo (2013, p.75)[12]. We use the standard deviation of the return rate of individual stocks taking into account cash dividend reinvestment on past 250 trading days of the company within a year to represent stock price volatility (2013, p.75). To facilitate the interpretation of the coefficient, we expand the volatility by 100 times on the original basis. Besides, we perform logarithmic operations when dealing with the total asset variable.

To address missing values, we excluded data from companies that did not disclose financial indicators. Regarding missing values for media supervision, we assigned a value of 0 to the media supervision variable. This approach was adopted because CFND's media supervision data reflects the frequency of a company's review by mainstream media outlets in a given year. Therefore, if data for certain companies are missing, it implies that they were not subject to review by domestic mainstream media.

5 Methodology

5.1 ESG Score's Impact on Stock Return's Volatility

To investigate how ESG factors influence stock returns' volatility, we construct a regression model to verify the correlation between ESG and return volatility. Based on previous literature, we carefully select 10 prevalent and significant influential factors, covering company operational factors, management structure, Beta coefficients and so on, as independent variables.

According to Zhou (2021)[14], companies that actively fulfill ESG responsibilities and disclose them are more likely to attract media attention, thereby disseminating company-specific information to investors and affecting stock price volatility. Hence, we account for media influence and incorporate the ESG scores provided by the Sino-Securities Index Information Service's ESG Rating Index. We set the dependent variable as stock return volatility and conducted regression analysis using these factors.

To eliminate the influence of macroeconomic factors on the market, we include 5 year-dummy variables from 2017 to 2021. We construct the model as

$$\begin{aligned}\text{Volit} = {} & \beta_0 + \beta_1 \cdot \text{ESG}_{it} + \beta_2 \cdot \text{Media}_{it} + \beta_3 \cdot \text{Contral\_Variable}_{1it} + \dots \\ & + \beta_n \cdot \text{Contral\_Variable}_{nit} + \alpha_1 \cdot \text{Dummy\_Year2017} + \alpha_2 \cdot \text{Dummy\_Year2018} \\ & + \alpha_3 \cdot \text{Dummy\_Year2019} + \alpha_4 \cdot \text{Dummy\_Year2020} + \alpha_5 \cdot \text{Dummy\_Year2021}\end{aligned} \tag{1}$$

The summary table of the regression results is listed below:

Dep. Variable:	Volatility	**R-squared:**	0.313
Model:	OLS	**Adj. R-squared:**	0.313
Method:	Least Squares	**F-statistic:**	500.1
Prob (F-statistic):	0.00	**Log-Likelihood:**	-68839.
No. Observations:	18666	**AIC:**	1.377e+05
Df Residuals:	18648	**BIC:**	1.379e+05
Df Model:	17	**Covariance Type:**	nonrobust

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
constant	43.6311	0.071	616.172	0.000	43.492	43.770
beta	1.3932	0.072	19.320	0.000	1.252	1.535
ATO	-0.2619	0.072	-3.619	0.000	-0.404	-0.120
dummy audit	0.0764	0.072	1.064	0.287	-0.064	0.217
Director Ratio	0.1069	0.073	1.458	0.145	-0.037	0.250
esg score	-0.7792	0.075	-10.321	0.000	-0.927	-0.631
TopTenHoldersRate	-0.1946	0.074	-2.639	0.008	-0.339	-0.050
DA	1.5958	0.084	18.985	0.000	1.431	1.761
ROE	-0.0318	0.071	-0.446	0.656	-0.172	0.108
media	2.7373	0.085	32.266	0.000	2.571	2.904
PB Volatility	-0.1463	0.071	-2.059	0.039	-0.286	-0.007
BM	-1.9708	0.090	-21.892	0.000	-2.147	-1.794
total asset log	-4.0610	0.108	-37.618	0.000	-4.273	-3.849
dummy 2017	-4.6162	0.086	-53.558	0.000	-4.785	-4.447
dummy 2018	-1.4974	0.088	-17.109	0.000	-1.669	-1.326
dummy 2019	-2.1202	0.088	-24.209	0.000	-2.292	-1.949
dummy 2020	0.1362	0.088	1.540	0.124	-0.037	0.310
dummy 2021	0.1001	0.089	1.124	0.261	-0.074	0.275

Omnibus:	2184.723	**Durbin-Watson:**	1.394
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	6569.424
Skew:	0.623	**Prob(JB):**	0.00
Kurtosis:	5.625	**Cond. No.**	3.07

Notes:

[1] Due to the relatively small values of volatility, we multiply the volatility by 100 to better study the effects of various variables on it.

[2] To optimize the performance of the model and balance the coefficients of each term due to the significant differences in the magnitudes of the independent variables, we standardize the independent variables.

[3] For variable media, we assign zero to all the companies that have no record.

From the coefficients obtained from the regression, we find the ESG score's coefficient is negative, and the statistical value of t is very small. With the upper bound of the confidence interval less than zero, it indicates a statistically significant negative correlation between ESG and volatility.

5.2 Modified Mean-Variance Portfolio incorporating ESG

Variable	Meaning
w	Weight of the portfolio
μ	Excepted return of the portfolio
γ	Risk aversion coefficient
δ	ESG preference coefficient
Σ	Covariance of portfolio
g	ESG score
g_{target}	Given target ESG score
μ_{target}	Given target expected return

Table 2: Meaning of Variables

In Table 2, we list the meaning of each variable.

5.2.1 Model: Mean-Variance meets sustainability goals

ESG assesses the sustainability of business operations and their impact on social values in three dimensions: environmental, social and corporate governance. Investors increasingly integrate ESG information into their decision-making processes. In the second part, this paper focuses on Type-M investors, characterized by their pursuit of portfolios that strike an optimal balance between high expected returns, low risk, and a consistently high average ESG score. Specifically, we address the investor's challenge of selecting a portfolio comprising N risky assets and a risk-free security. While traditional models predominantly consider the trade-off between portfolio return and risk, our enhanced model incorporates an ESG score factor into the objective function. Additionally, we introduce ESG preference coefficients to capture the influence of ESG considerations on portfolio construction.

$$\max_{w} \left\{ \underbrace{w^\top \mu - \frac{\gamma}{2} w^\top \Sigma w}_{\text{mean-variance}} + \underbrace{\delta \left(\frac{w^\top g}{w^\top 1} \right)}_{\text{ESG tilt}}, \text{ subject to } \begin{matrix} w^\top 1 = 1 \\ 0 \le w \le 1 \end{matrix} \right\} \tag{2}$$

In this equation, we use the average of Sino-Securities Index Information Service ESG scores of the stock in portfolios to represent ESG score factor. The ESG preference coefficient, denoted as θ, reflects the degree to which investors prioritize ESG performance. A higher θ signifies greater emphasis placed by investors on ESG criteria. The risk aversion coefficient, denoted as γ, to capture investors' attitude towards risk. Because it is not easy to short stocks in the Chinese market, the coefficients for each stock are specified to be between 0 and 1. This simplification facilitates the modeling process and ensures practical applicability within the context of the market dynamics under consideration.

5.2.2 Efficient Frontier and ESG-SR Frontier

Following the framework of the fundamental mean-variance model, we construct Efficient Frontier curves incorporating ESG factors. This attempt aims to elucidate the implications of ESG considerations on investment costs and benefits.

$$\min_{w}\left\{\sqrt{w^\top \Sigma w},\ \text{subject to}\ \begin{array}{ll} w^\top 1 = 1, 0 \le w \le 1 & \text{basic constraint} \\ w^\top \mu = \mu_{\text{target}}, & \text{return constraint} \\ w^\top g = g_{\text{target}} & \text{ESG constraint} \end{array}\right\} \tag{3}$$

However, considering investment return, risk, and ESG scores simultaneously on the basic Efficient Frontier curve is difficult. In the basic Efficient Frontier curve, the tangent portfolio has the largest Sharpe rate. To visualize the impact of ESG scores on the decision-making of M investors, we aim to depict the trade-off between investment return, risk, and ESG scores graphically. According to Pedersen's study[10] (2019, p.575), investors have the ability to evaluate the trade-offs between return, risk, and ESG score independently. This suggests that the optimal trade-off between investment return and risk can be identified for specific ESG scores, utilizing the Sharpe ratio as a guiding metric to select portfolios with the highest Sharpe ratio.

$$SR(g_{target}) = \max_{w}\left\{\frac{w^\top \mu}{\sqrt{w^\top \Sigma w}},\ \text{subject to}\ \left\{\begin{array}{l} w^\top 1 = 1 \\ 0 \le w \le 1 \\ w^\top g = g_{target} \end{array}\right\}\right\} \tag{4}$$

To ensure comprehensive consideration of ESG score coverage and the robustness of our findings, we partition the screened A-share stocks into 20 groups based on quartiles of their ESG scores. Subsequently, we randomly select one stock from each group, resulting in a total of 20 stocks to compose a new portfolio. By applying our formulated model, we derive the ESG-SR Frontier. Multiple iterations of random selections are conducted to generate diverse portfolios, facilitating the identification of common trends and characteristics among the resulting curves. Through this systematic approach, we aim to derive universally applicable conclusions that transcend specific stock selections and reflect broader market dynamics.

5.2.3 Effectiveness of ESG indicators

To assess the costs and benefits associated with the Environmental, Social, and Governance (ESG) indicator, we employ stock data spanning from 2009 to 2022. During this period, stocks are classified into 20 groups based on quartiles of their annual average ESG scores. Compute the weights of the corresponding portfolios separately using the modified mean-variance model.

6 Result and Discussion

6.1 Linear Regression

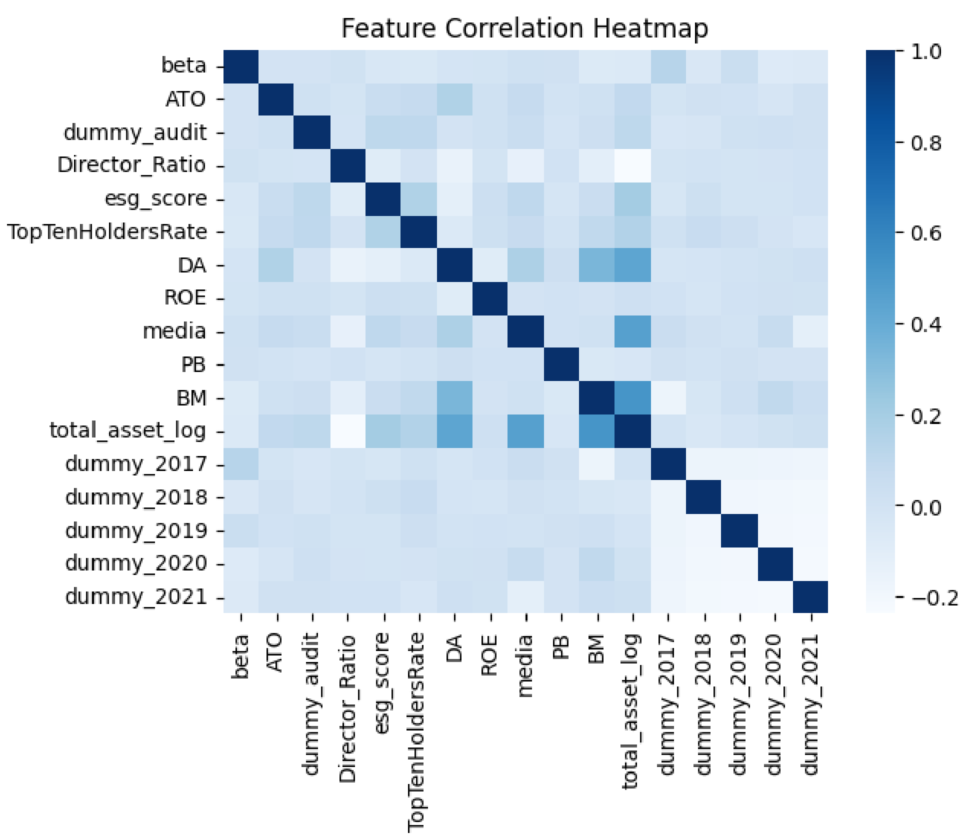

Figure 1: An example of multiple figures in one frame.

Through the independent variable correlation figure, we can see that there is relatively low collinearity among the independent variables. The advantage lies in its ability to avoid multicollinearity issues, allowing each variable to explain the variability of the target variable more independently. This contributes to enhancing the stability, interpretability, and generalization ability of the model.

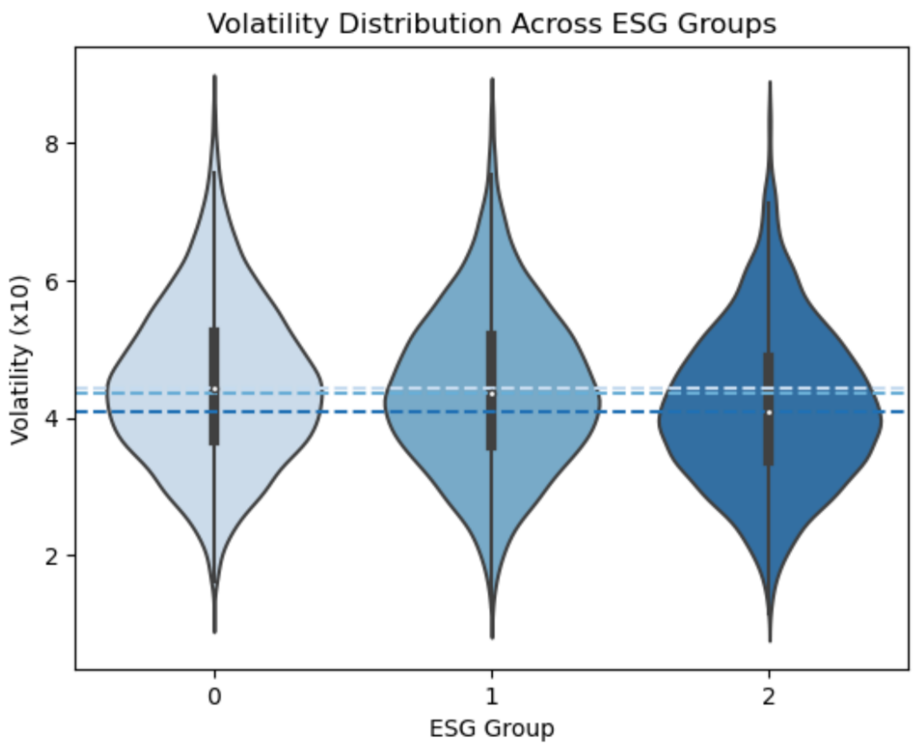

Figure 2: Feature Importance

We roughly grouped the data into three categories based on ESG scores to explore the distribution of stock return volatility within each group. The result is shown in Figure 2. It can be observed that the group with the highest ESG scores exhibits significantly lower volatility compared to the group with the lowest ESG scores. Furthermore, the group with the lowest ESG scores shows a more pronounced long and heavy tail effect in its distribution, indicating a greater number of high-volatility outliers. This further suggests that companies with lower ESG scores may experience larger stock price fluctuations and are more susceptible to idiosyncratic risks.

Therefore, we further confirmed that our OLS regression model is reliable. And from the regression result, we find that better ESG performance can exhibit significantly lower stock volatility. This finding offers the following insights:

1. For companies: From the perspective of firms, considering ESG factors in future operations can contribute to increased profitability, stability in stock prices, and enhanced market confidence. Using ESG ratings as a reference, companies can better focus on long-term development, optimize management structures, and generate higher returns while stabilizing market confidence, thus achieving optimal long-term benefits.

2. For investors: ESG scores may constitute an important factor in a stock's performance. Particularly for risk-averse investors, companies with higher ESG scores often demonstrate more sustainable business models, clear development strategies, and well-established management practices. Such companies' stock prices are proven to be more stable during long-term market fluctuations, enhancing their reliability for investors.

6.2 ESG-adjusted capital asset pricing model

Before delving into the specific findings, it is crucial to visually represent the relationship between ESG scores and stock returns. The graph spanning from 2015 to 2023 illustrates a notable increase in companies' focus on ESG, reflected in an overall upward trend in ESG scores. These scores exhibit a hump-shaped pattern concerning stock returns. A low ESG score indicates deficiencies in environmental, social, and governance practices, potentially leading to issues such as poor risk management and reputation harm. Such scores may indicate problems like environmental pollution, labor disputes, corruption, or mismanagement, heightening a firm's business risk and undermining investor confidence. Moreover, ESG-related challenges can tarnish a company's reputation, eroding consumer and investor trust in its offerings.

Conversely, excessively high ESG scores may also entail short-term drawbacks. For instance, improving ESG performance increases corporate costs and drains corporate resources. Margolis et al.[9] (2009) synthesized 251 studies on ESG and firms' financial performance, with 214 (nearly 85%) suggesting no positive correlation between firms' financial performance and ESG. Cornell[4] (2020) concluded that environmental investment does not yield immediate profits, potentially leading to short-term stock return reductions.

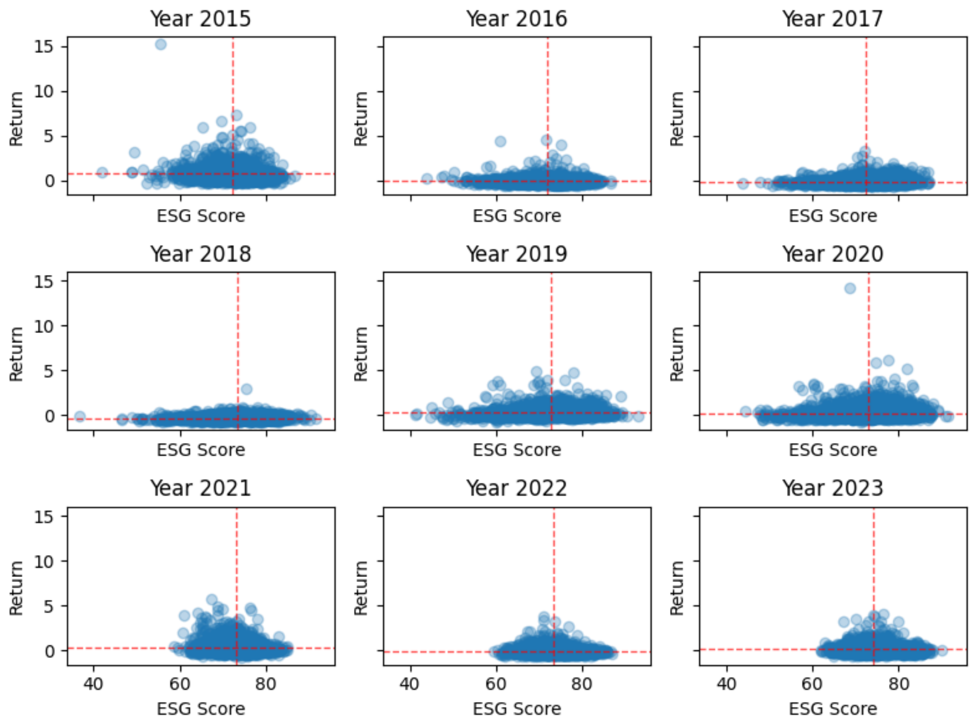

Figure 3: Visualization of relationship between ESG scores and stock returns, 2015-2017

6.2.1 Comparison of efficient frontier with/without esg constraints

The comparison of three different types of efficient frontier by using the 20 stocks of different levels of ESG is shown below.

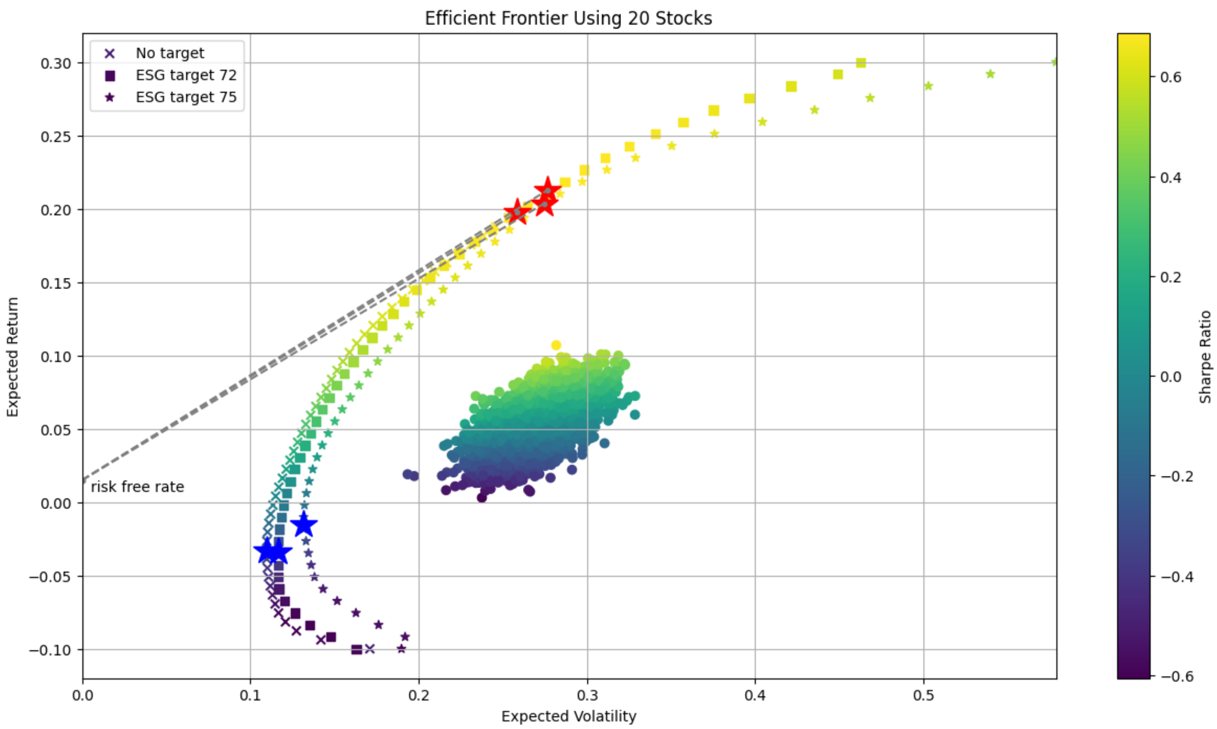

Figure 4: Efficient_frontier

Figure 4 illustrates the standard mean-variance frontier along with the associated tangent portfolio. The slope from the risk-free rate to the tangent portfolio represents the maximum Sharpe ratio (SR). This tangent portfolio is pivotal in maximizing the risk-adjusted returns given the available assets.

We delineate three distinct stylized frontiers. As investors seek heightened ESG scores, the frontier diverges from the unconstrained frontier, necessitating a trade-off wherein investors may need to reconcile potential diminution in returns and/or augmentation in volatility.

By utilizing equation 3, we can get the following result

Modification on equation 3	**sharpe ratio value**
No ESG constraint	0.7148029625436059
$g_{target} = 72$	0.7057171204466886
$g_{target} = 75$	0.6869058755944738

Table 3: Result of sharpe ratio of tangent portfolios

As Table 3 shows, the result is in accordance with the fact that restricting portfolios to have any ESG score other than that of the tangency portfolio must yield a lower maximum SR.

6.2.2 Analysis on ESG-SR frontier

In Figure 7, by utilizing Equation 4, for each level of ESG, we calculate the highest attainable Sharpe ratio (SR). We represent this association between ESG scores and the highest SR in terms of the ESG-SR frontier. The ESG-SR frontier is a useful way to illustrate the investment opportunity set when people care about risk, return, and ESG. (Risk and return can be summarized by the Sharpe ratio)

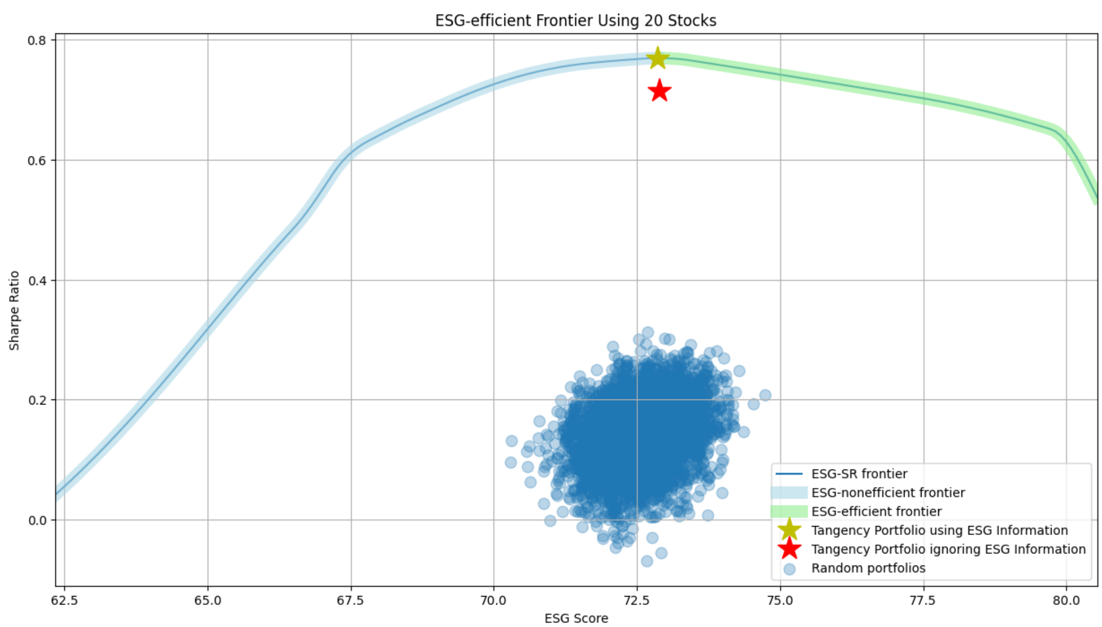

Figure 5: The ESG-SR frontier

Variable	**Meaning**
ESG-SR frontier	The association between ESG scores and the highest SR
ESG-nonefficient frontier	The ESG-nonefficient frontier offers investors the opportunity to enhance either their ESG scores or Sharpe ratios, or both, without sacrificing one for the other, so it is nonefficient.
ESG-efficient frontier	The ESG-efficient frontier offers optimal investment portfolios. However, due to the tradeoff between the Sharpe ratio and ESG scores, the ideal portfolio selection along this frontier varies based on one's preference for ESG criteria.
Tangency Portfolio using ESG information	The peak of the ESG-SR frontier.
Tangency Portfolio ignoring ESG information	The tangency portfolio constructed without considering ESG-related factors.
Random portfolios	Represents the relationship of sharpe ratio and ESG score among random portfolios.

Table 4: Meaning of variables in the legend of Figure 7

Tangency Portfolio Type	**Using ESG information**	**Ignoring ESG information**
ESG score	72.85803182579565	72.88156950765537
Sharpe Ratio	0.7690213207249059	0.7148029625436059
On ESG-SR frontier	True	False
On efficient-frontier without ESG constraint	False	True

Table 5: Comparison of Using/Ignoring ESG info

For diverse investor profiles, their portfolio options varies.

- Investors who prioritize both the Sharpe ratio (SR) and ESG factors should opt for a frontier portfolio positioned to the right of this portfolio on the ESG-efficient frontier, as the ESG-SR frontier exhibits an inverted U-shape, indicating an optimal range for portfolio selection.

- Investors who lack familiarity with ESG metrics may opt for portfolios positioned below the frontier, as Table 5 shows. This decision could stem from their reliance on a tangency portfolio computation that overlooks the pertinent insights embedded within ESG scores, thus conditioning on less comprehensive information.

Maximum SR that incorporates this ESG proxy is about 7.6% higher than the maximum SR that ignores such information.

6.2.3 Effect verification of modified mean-variance model

The 2023 returns for each of the 20 sets of portfolios using the modified mean-variance model are shown below.

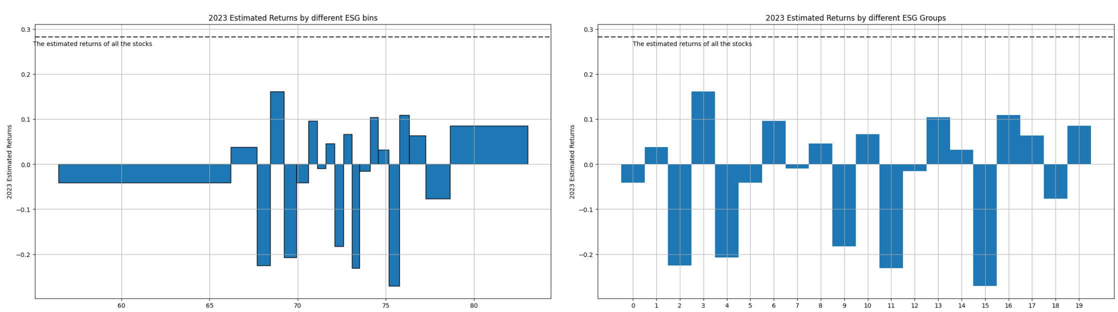

Figure 6: Returns of 20 sets portfolios

The dashed line in the figure represents the global optimal solution derived without constraining the ESG value. With an annual return of -0.037007 for the CSI in 2023, the modified mean-variance model is clearly valid. However, our analysis overlooks the impact of trading fees, restrictions on share quantities, as well as stop orders. Consequently, the calculated portfolio returns may be inflated. It is evident that the portfolio, when grouped by ESG, falls below the global optimal solution. This discrepancy arises because considering ESG performance restricts the choice to a specific range of stocks, potentially sacrificing a portion of investment returns. When grouped according to ESG, it can be seen that portfolios with intermediate ESG scores perform slightly better. This is consistent with the previous analysis of the relationship between ESG and stock returns.

However, due to the multitude of corporate factors influencing ESG and the relative immaturity of the ESG scoring system in China, there is significant variability in the volatility among grouped stock return categories based on ESG scores. Nonetheless, ESG will become an important factor influencing investors' investment behavior, and stocks of companies with good ESG performance will have more stable long-term returns.

7 Conclusion

In this project study, we aimed to investigate the impact of corporate ESG scores on stock return volatility in China's A-share market and to enhance the Markowitz Mean-Variance Model by introducing ESG scores to study their impact on Mean-Variance investors' preferences.

Regarding our first research question, we constructed regressions, and the results confirmed that companies with higher ESG scores tend to exhibit lower stock volatility. This finding has significant implications for both companies and investors. By using ESG ratings as a reference, companies can better optimize management structures, plan for long-term development, instill confidence in the market, and investors can choose more stable strategies and construct less volatile portfolios.

Furthermore, considering the impact of ESG on volatility, we posed our second research question. We incorporated ESG performance considerations and introduced ESG tilt to adjust the Markowitz Mean-Variance Model. Generally, our study indicated that both excessively low and high ESG scores could lead an undesirable outcome. Additionally, the ESG-derived efficient frontiers demonstrated that investors need to make a sacrifice between lower returns and higher volatility when seeking higher ESG scores. Based on those findings, we provided different investing options for diverse profile investors.

In conclusion, our study provides valuable insights into the relationship between the ESG scores and stock return and volatility in China's A-share market, highlighting the importance of considering ESG factors for both companies and investors, and proposing a mean-variance model that incorporates ESG factors for investors for consideration.

8 Limitations and Future Work

1. In exploring the regression model of ESG score's impact on individual stock volatility, we found that the feature importance of the constant term was relatively high. If there are significant biases or variances in the data, this influence may become more significant, as Figure7 showed, indicating that our model might be affected by outliers. In the future, it may be beneficial to introduce additional factors to fully explain stock volatility, or to employ other regularization models to further reduce the variance of the constant term.

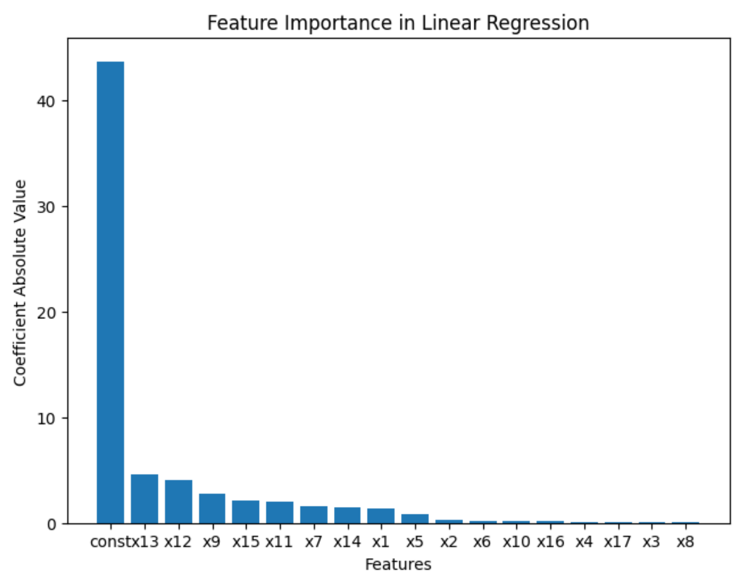

Figure 7: Feature Importance

2. We utilized the ESG ratings from Sino-Securities Index Information Service in our analysis, and the subjectivity of ESG rating agencies may have influenced the experimental results (Berg et al.,2022)[3]. Future studies might consider integrating ESG ratings from multiple agencies to mitigate rating errors and obtain more impartial results, thereby addressing the divergence of ESG ratings.

3. In constructing the Markowitz Mean-Variance Model, we simplified the model by restricting $w > 0$, i.e., we did not consider asset shorting. While short selling is often restricted but not entirely prohibited. Future research could explore introducing a lower limit L (a negative constant) on w or using $L = f(*)$ (using company information * to estimate its short-selling restrictions) to develop the model and Efficient Frontiers that are more aligned with the market.

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9 Appendix

9.1 Web Interface

We have developed a lightweight front-end interface tailored to deliver a user-friendly experience. Upon uploading a file, the interface seamlessly showcases the corresponding results derived from the ESG-adjusted Capital Asset Pricing Model (CAPM), which enhances user engagement and ensures accessibility to intricate financial analyses.

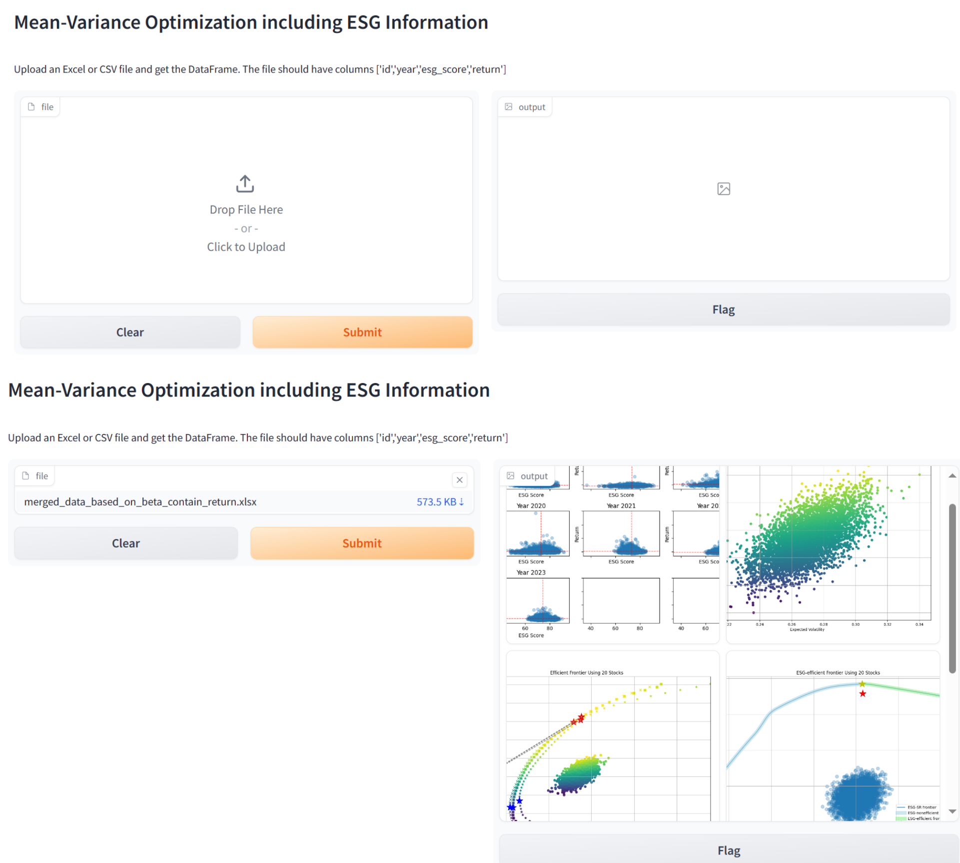

Figure 8: Demo of Web interface

9.2 Code

Coding for Research Question 1

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
import statsmodels.api as sm
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Data procession (scaling)
data = pd.read_excel("regression_raw_data.xlsx")
y = data['Volatility']*100
X = data.drop(columns=['Volatility'])
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_with_const = sm.add_constant(X_scaled)

# OLS Regression
model_ols = sm.OLS(y, X_with_const).fit()

# Check the Coefficients
coefficients = model_ols.params
print("Coefficients:", coefficients)
print(model_ols.summary())

# Calculate feature correlation matrix
correlation_matrix = X.corr()

# Correlation Heatmap
```

```
sns.heatmap(correlation_matrix, annot=False, cmap='Blues')
plt.title('Feature Correlation Heatmap')
plt.show()


coef_abs = np.abs(model_ols.params)
coef_abs_sorted = coef_abs.sort_values(ascending=False)
plt.bar(range(len(coef_abs)), coef_abs_sorted)
plt.xticks(range(len(coef_abs)), coef_abs_sorted.index)
plt.tight_layout()
plt.xlabel('Features')
plt.ylabel('Coefficient Absolute Value')
plt.title('Feature Importance in Linear Regression')
plt.show()

colors = sns.color_palette("Blues", 3)

# Expand Volatility by 10 times
filtered_data = data.copy()
filtered_data['Volatility'] *= 10

# Calculate lower and upper bounds
lower_bound = filtered_data['Volatility'].quantile(0)
upper_bound = filtered_data['Volatility'].quantile(0.999)

# Filter data based on upper and lower bounds
filtered_data = filtered_data[(filtered_data['Volatility'] >= lower_bound) &
    (filtered_data['Volatility'] <= upper_bound)]


```

```
quantiles = [0, 0.33, 0.67, 1]

# Use a custom list of quantiles to split the data into four groups
filtered_data['ESG_group'] = pd.qcut(filtered_data['esg_score'], q=quantiles,
    labels=False)

# Use Seaborn to draw a violin plot and specify the color
ax = sns.violinplot(x='ESG_group', y='Volatility', data=filtered_data,
    palette=colors)
plt.xlabel('ESG Group')
plt.ylabel('Volatility (x10)')
plt.title('Volatility Distribution Across ESG Groups')

group_medians = filtered_data.groupby('ESG_group')['Volatility'].median()
```

Code for Research Question 2

```
import pandas as pd
import numpy as np
from scipy.optimize import minimize
import matplotlib.pyplot as plt
import scipy.interpolate as sci
import gradio as gr
import tempfile

def main(file):
    df=pd.read_excel(file)
    N=20
    years = df['year'].unique()[-9:]

    fig, axes = plt.subplots(3, 3, figsize=(8, 6), sharex=True,sharey=True)
```

```
axes = axes.flatten()

for i, year in enumerate(years):
    data_year = df[df['year'] == year]
    ax = axes[i]
    ax.scatter(data_year['esg_score'], data_year['return'],alpha=0.3)
    ax.set_title(f'Year {year}')
    ax.set_xlabel('ESG Score')
    ax.set_ylabel('Return')

    mean_esg_score = data_year['esg_score'].mean()
    mean_return = data_year['return'].mean()
    ax.axhline(y=mean_return, color='red', linestyle='--', linewidth=1,
        alpha=0.7)
    ax.axvline(x=mean_esg_score, color='red', linestyle='--', linewidth=1,
        alpha=0.7)

plt.tight_layout()

with tempfile.NamedTemporaryFile(suffix='.png', delete=False) as temp_file1:
    plt.savefig(temp_file1.name)
    temp_file1.close()
    temp_file_path1 = temp_file1.name



df_pivot = df.pivot_table(index='year', columns='id', values='return')
df_pivot = df_pivot.dropna(axis=1)



average_esg_score_2017_2022 = df[df["year"] !=
```

```
    max(df["year"])].groupby('id')['esg_score'].mean()
average_esg_score_2023 = df[df['year'] ==
    max(df["year"])].groupby('id')['esg_score'].mean()


valid_ids = df_pivot.columns.tolist()
filtered_average_esg_score = average_esg_score_2017_2022.loc[valid_ids]
sorted_esg_score=filtered_average_esg_score.sort_values()

bins = pd.qcut(sorted_esg_score, q=N)

result = pd.DataFrame({
    'esg_score': sorted_esg_score,
    'quantile': bins
})


dfs = []
for _, group in result.groupby(bins):
    group = group.drop(columns=['quantile'])
    dfs.append(group)


sampled_df = pd.DataFrame(columns=dfs[0].columns)


for group_df in dfs:
    sampled_row = group_df.sample(n=1, random_state=40)
    sampled_df = pd.concat([sampled_df, sampled_row])

```

```
    esg_score_df=sampled_df
    esg_score_array=np.array(esg_score_df.values)

    selected_columns=esg_score_df.index.to_list()
    returns = df_pivot.loc[:, selected_columns]

    risk_aversion=10
    esg_coefficient=5/1000#2/1000
    risk_free=0.015

    returns_2017_to_2022 = returns[:-1]
    returns_2023 = returns.tail(1)

    expected_returns = returns_2017_to_2022.mean()
    minimum_expected_return = min(expected_returns)
    maximum_expected_return = max(expected_returns)
    print("expected return min 20 stocks",min(expected_returns))
    print("expected return max 20 stocks",max(expected_returns))
    covariance_matrix = returns_2017_to_2022.cov(ddof=0)

    def generate_ptfs(returns, N):
        ptf_rs = []
        ptf_stds = []
        ptf_esgs=[]
        for i in range(N):
            weights = np.random.random(len(returns.columns))
            weights /= np.sum(weights)
            ptf_rs.append(np.sum(returns.mean() * weights))
            ptf_stds.append(np.sqrt(np.dot(weights.T, np.dot(returns.cov(),
               weights))))
```

```
            ptf_esgs.append(np.dot(esg_score_array.T,weights)/np.sum(weights))
        ptf_rs = np.array(ptf_rs)
        ptf_stds = np.array(ptf_stds)
        ptf_sharpes = (ptf_rs-risk_free) / ptf_stds

        return ptf_rs, ptf_stds,ptf_sharpes,ptf_esgs

    def ptf_stats(weights):
        weights = np.array(weights)
        ptf_r = np.dot(expected_returns, weights)
        ptf_std = np.sqrt(np.dot(weights.T, np.dot(covariance_matrix, weights)))
        ptf_esg = (np.dot(esg_score_array.T, weights)/np.sum(weights))[0]
        return np.array([ptf_r, ptf_std, (ptf_r - risk_free) / ptf_std, ptf_esg])

    def objective_function(weights):
        return -np.dot(expected_returns, weights) + 1/2*risk_aversion*
            np.dot(np.dot(weights, covariance_matrix), weights)-
            esg_coefficient*np.dot(esg_score_array.T,weights)/np.sum(weights)

    def min_var(weights):
        return np.sqrt(np.dot(weights, np.dot(covariance_matrix, weights)))

    def sharpe_function(weights):
        return -np.dot(expected_returns, weights)/np.sqrt(np.dot(np.dot(weights,
            covariance_matrix), weights))

    def efficient_frontier(start_r, end_r, steps):
        target_rs = np.linspace(start_r, end_r, steps)
        target_stds = []
        for r in target_rs:
```

```
            cons= ({'type': 'eq', 'fun': lambda weights:
                np.dot(expected_returns, weights) - r},
                    {'type': 'eq', 'fun': lambda weights: np.sum(weights)-1})
            bnds = [(0, 1)] * len(expected_returns)
            res = minimize(min_var, x0=np.ones(len(expected_returns)) /
                len(expected_returns), bounds = bnds, constraints=cons)
            target_stds.append(res.fun)
        target_stds = np.array(target_stds)
        return target_rs, target_stds

    def efficient_frontier_with_esg(start_r, end_r, steps, esg_target_score):
        target_rs = np.linspace(start_r, end_r, steps)
        target_stds = []
        for r in target_rs:
            cons= ({'type': 'eq', 'fun': lambda weights:
                np.dot(expected_returns, weights) - r},
                    {'type': 'eq', 'fun': lambda weights: np.sum(weights)-1},
                    {'type': 'eq', 'fun': lambda weights:
                        np.dot(esg_score_array.T,weights)/np.sum(weights)-esg_target_score})
            bnds = [(0, 1)] * len(expected_returns)
            res = minimize(min_var, x0=np.ones(len(expected_returns)) /
                len(expected_returns), bounds = bnds, constraints=cons)
            target_stds.append(res.fun)
        target_stds = np.array(target_stds)
        return target_rs, target_stds


    optimizer = minimize(objective_function, x0=np.ones(len(expected_returns))
        / len(expected_returns),
                        bounds=[(0, 1)] *
```

```
                          len(expected_returns),constraints={'type': 'eq',
                          'fun': lambda weights: np.sum(weights)-1})

mle_weights=optimizer.x
print("The top five weights",sorted(mle_weights)[-5:])
print("objective function value: ",optimizer.fun)
print("Status:",optimizer.success)

def portfolio_metrics_test(weights, returns):
    portfolio_return = np.dot(weights, returns.mean())
    return portfolio_return

print("Test sample by 2023")
test_returns=portfolio_metrics_test(mle_weights, returns_2023)
print("MLE Portfolio by all stocks - Expected Return:
    {:.4f}".format(test_returns))

def objective_function_group_return(weights,return_df,esg_score_array):
    return -np.dot(return_df.mean(), weights) + 1/2*risk_aversion*
        np.dot(np.dot(weights, return_df.cov(ddof=0)), weights)-
        esg_coefficient*np.dot(esg_score_array.T,weights)/np.sum(weights)


test_returns_group=[]
for index,df in enumerate(dfs):
    esg_score_array_group=np.array(df.values) #128
    selected_columns_group=df.index.to_list()
    returns_group = df_pivot.loc[:, selected_columns_group]
    returns_group_2017_to_2022=returns_group[:-1]
    returns_group_2023=returns_group.tail(1)
```

```
        expected_returns_group_2017_to_2022=returns_group_2017_to_2022.mean()

        optimizer_group = minimize(objective_function_group_return,
            x0=np.ones(len(expected_returns_group_2017_to_2022)) /
            len(expected_returns_group_2017_to_2022),
                         args=(returns_group_2017_to_2022,esg_score_array_group),
                  bounds=[(0, 1)] *
                         len(expected_returns_group_2017_to_2022),constraints={'type':
                         'eq', 'fun': lambda weights: np.sum(weights)-1})

        mle_weights_group=optimizer_group.x

        test_returns_group.append(portfolio_metrics_test(mle_weights_group,
            returns_group_2023))

        print("Test sample by 2023 (group {})".format(index))
        print("MLE Portfolio by all stocks - Expected Return:
            {:.4f}".format(portfolio_metrics_test(mle_weights_group,
            returns_group_2023)))




    bin_upper_limits = np.array(sorted([interval.right for interval in
        set(bins.values)]))
    bin_lower_limits = np.array(sorted([interval.left for interval in
        set(bins.values)]))
    print(bin_lower_limits)
    print(bin_upper_limits)
    plt.figure(figsize=(15,8))
```

```
    plt.grid(True)
    plt.axhline(y=test_returns, color='black', linestyle='--', linewidth=2,
        alpha=0.7)
    plt.text(56, test_returns-0.01, 'The estimated returns of all the stocks',
        verticalalignment='top', horizontalalignment='left')
    plt.bar(bin_lower_limits, test_returns_group,
        width=(bin_upper_limits-bin_lower_limits), align='edge',
        edgecolor='black')
    plt.xlabel('ESG Bins')
    plt.ylabel('2023 Estimated Returns')
    plt.title('2023 Estimated Returns by different ESG bins')


    with tempfile.NamedTemporaryFile(suffix='.png', delete=False) as temp_file2:
        plt.savefig(temp_file2.name)
        temp_file2.close()
        temp_file_path2 = temp_file2.name


    plt.figure(figsize=(15,8))
    plt.grid(True)
    plt.axhline(y=test_returns, color='black', linestyle='--', linewidth=2,
        alpha=0.7)
    plt.text(0, test_returns-0.01, 'The estimated returns of all the stocks',
        verticalalignment='top', horizontalalignment='left')
    # plt.bar(bin_lower_limits, test_returns_group,
        width=(bin_upper_limits-bin_lower_limits), align='edge',
        edgecolor='black')
    x_values = range(len(test_returns_group))

```

```
    y_values = test_returns_group

    plt.bar(x_values, y_values, width=1)
    plt.xlabel('ESG Groups')
    plt.ylabel('2023 Estimated Returns')
    plt.title('2023 Estimated Returns by different ESG Groups')
    plt.xticks(x_values, x_values)


    with tempfile.NamedTemporaryFile(suffix='.png', delete=False) as temp_file3:
        plt.savefig(temp_file3.name)
        temp_file3.close()
        temp_file_path3 = temp_file3.name


    ptf_rs, ptf_stds, ptf_sharpes, ptf_esgs=
        generate_ptfs(returns_2017_to_2022, 5000)

    plt.figure(figsize=(15, 8))
    plt.scatter(ptf_stds, ptf_rs, c=ptf_sharpes, marker='o')
    plt.grid(True)
    plt.xlabel('Expected Volatility')
    plt.ylabel('Expected Return')
    plt.colorbar(label='Sharpe Ratio')
    plt.title('5000 Randomly Generated Portfolios In The Risk-Return Space')


    with tempfile.NamedTemporaryFile(suffix='.png', delete=False) as temp_file4:
        plt.savefig(temp_file4.name)
        temp_file4.close()
```

```
        temp_file_path4 = temp_file4.name



    opts = minimize(sharpe_function, x0=np.ones(len(expected_returns)) /
        len(expected_returns),
                        bounds=[(0, 1)] * len(expected_returns),constraints=[
                            {'type': 'eq', 'fun': lambda weights: np.sum(weights)
                                - 1},
                        ])

    opts_72 = minimize(sharpe_function, x0=np.ones(len(expected_returns)) /
        len(expected_returns),
                            bounds=[(0, 1)] * len(expected_returns),constraints=[
                                {'type': 'eq', 'fun': lambda weights:
                                    np.sum(weights) - 1},
                                {'type': 'eq', 'fun': lambda weights:
                                    np.dot(esg_score_array.T,weights)-72},
                            ])

    opts_75 = minimize(sharpe_function, x0=np.ones(len(expected_returns)) /
        len(expected_returns),
                            bounds=[(0, 1)] * len(expected_returns),constraints=[
                                {'type': 'eq', 'fun': lambda weights:
                                    np.sum(weights) - 1},
                                {'type': 'eq', 'fun': lambda weights:
                                    np.dot(esg_score_array.T,weights)-75},
                            ])


```

```
    opt_var = minimize(min_var, x0=np.ones(len(expected_returns)) /
        len(expected_returns),
                             bounds=[(0, 1)] * len(expected_returns),constraints=[
                                 {'type': 'eq', 'fun': lambda weights:
                                     np.sum(weights) - 1},
                             ])


    opt_var_72 = minimize(min_var, x0=np.ones(len(expected_returns)) /
        len(expected_returns),
                             bounds=[(0, 1)] * len(expected_returns),constraints=[
                                 {'type': 'eq', 'fun': lambda weights:
                                     np.sum(weights) - 1},
                                 {'type': 'eq', 'fun': lambda weights:
                                     np.dot(esg_score_array.T,weights)-72},])

    opt_var_75 = minimize(min_var, x0=np.ones(len(expected_returns)) /
        len(expected_returns),
                             bounds=[(0, 1)] * len(expected_returns),constraints=[
                                 {'type': 'eq', 'fun': lambda weights:
                                     np.sum(weights) - 1},
                                 {'type': 'eq', 'fun': lambda weights:
                                     np.dot(esg_score_array.T,weights)-75}] )


    target_rs, target_stds = efficient_frontier(minimum_expected_return,
        maximum_expected_return, 50)
    target_rs_esg_72,target_stds_esg_72 =
        efficient_frontier_with_esg(minimum_expected_return,
        maximum_expected_return, 50, 72)
```

```
target_rs_esg_75,target_stds_esg_75 =
    efficient_frontier_with_esg(minimum_expected_return,
    maximum_expected_return, 50, 75)

plt.figure(figsize=(15, 8))
plt.scatter(ptf_stds, ptf_rs, c=(ptf_rs - risk_free)/ptf_stds, marker='o')
plt.scatter(target_stds, target_rs, c=(target_rs - risk_free)/target_stds,
    marker='x',label='No target')
plt.scatter(target_stds_esg_72, target_rs_esg_72, c=(target_rs_esg_72 -
    risk_free)/target_stds_esg_72, marker=',',label="ESG target 72")
plt.scatter(target_stds_esg_75, target_rs_esg_75, c=(target_rs_esg_75 -
    risk_free)/target_stds_esg_75, marker='*',label="ESG target 75")

plt.plot(ptf_stats(opts['x'])[1], ptf_stats(opts['x'])[0], 'r*',
    markersize=20.0)
plt.plot(ptf_stats(opts_72['x'])[1], ptf_stats(opts_72['x'])[0], 'r*',
    markersize=20.0)
plt.plot(ptf_stats(opts_75['x'])[1], ptf_stats(opts_75['x'])[0], 'r*',
    markersize=20.0)

plt.plot(ptf_stats(opt_var['x'])[1], ptf_stats(opt_var['x'])[0], 'b*',
    markersize=20.0)
plt.plot(ptf_stats(opt_var_72['x'])[1], ptf_stats(opt_var_72['x'])[0],
    'b*', markersize=20.0)
plt.plot(ptf_stats(opt_var_75['x'])[1], ptf_stats(opt_var_75['x'])[0],
    'b*', markersize=20.0)

plt.plot([0, ptf_stats(opts["x"])[1]], [risk_free,
    ptf_stats(opts["x"])[0]], linestyle='--', color='grey',marker='.')
plt.plot([0, ptf_stats(opts_72["x"])[1]], [risk_free,
```

```
        ptf_stats(opts_72["x"])[0]], linestyle='--', color='grey',marker='.')
    plt.plot([0, ptf_stats(opts_75["x"])[1]], [risk_free,
        ptf_stats(opts_75["x"])[0]], linestyle='--', color='grey',marker='.')


    print("sharpe values of tangent
        portfolios",ptf_stats(opts["x"])[2],ptf_stats(opts_72["x"])[2],
        ptf_stats(opts_75["x"])[2])
    plt.text(0+0.005, risk_free, 'risk free rate', verticalalignment='top',
        horizontalalignment='left')

    plt.grid(True)
    plt.legend()
    plt.xlabel('Expected Volatility')
    plt.ylabel('Expected Return')
    plt.xlim(0, max(target_stds_esg_75))
    plt.colorbar(label='Sharpe Ratio')
    plt.title('Efficient Frontier Using {} Stocks'.format(N))

    with tempfile.NamedTemporaryFile(suffix='.png', delete=False) as temp_file5:
        plt.savefig(temp_file5.name)
        temp_file5.close()
        temp_file_path5 = temp_file5.name



    x_lower = min(esg_score_array)[0]
    x_upper = max(esg_score_array)[0]
    x_range = np.linspace(x_lower, x_upper, 200)
    print(x_lower)
```

```
print(x_upper)
# esg_target_val=60

sharpe_list=[]
for x in x_range:
    optimizer = minimize(sharpe_function, x0=np.ones(len(expected_returns))
        / len(expected_returns),
                          bounds=[(0, 1)] * len(expected_returns),constraints=[
                              {'type': 'eq', 'fun': lambda weights:
                                  np.sum(weights) - 1},
                              {'type': 'eq', 'fun': lambda weights:
                                  np.dot(esg_score_array.T,weights)-x},
                          ])
    sharpe_list.append(-optimizer.fun)
max_sharpe_index = sharpe_list.index(max(sharpe_list))
max_sharpe = max(sharpe_list)

plt.figure(figsize=(15, 8))

plt.plot(x_range,sharpe_list,label="ESG-SR frontier")
plt.plot(x_range[:max_sharpe_index+1], sharpe_list[:max_sharpe_index+1],
    linewidth=10, alpha=0.6,color='lightblue', label="ESG-nonefficient
    frontier")
plt.plot(x_range[max_sharpe_index+1:], sharpe_list[max_sharpe_index+1:],
    linewidth=10, alpha=0.6,color='lightgreen', label="ESG-efficient
    frontier ")

plt.plot(x_range[max_sharpe_index], max_sharpe, 'y*',
    markersize=20.0,label="Tangency Portfolio using ESG Information")

```

```
    plt.plot(ptf_stats(opts['x'])[3], ptf_stats(opts['x'])[2], 'r*',
        markersize=20.0,label="Tangency Portfolio ignoring ESG Information")
    plt.grid(True)
    plt.xlabel('ESG Score')
    plt.ylabel('Sharpe Ratio')
    plt.xlim(min(x_range),max(x_range))
    plt.scatter(ptf_esgs, ptf_sharpes, s=80,alpha=0.3,marker='o',label="Random
        portfolios")
    plt.legend()
    plt.title('ESG-efficient Frontier Using {} Stocks'.format(N))
    print("with ERG information",x_range[max_sharpe_index],max_sharpe)
    print("without ERG information",ptf_stats(opts['x'])[3],
        ptf_stats(opts['x'])[2])

    with tempfile.NamedTemporaryFile(suffix='.png', delete=False) as temp_file6:
        plt.savefig(temp_file6.name)
        temp_file6.close()
        temp_file_path6 = temp_file6.name

    return temp_file_path1,temp_file_path4,temp_file_path5,
        temp_file_path6,temp_file_path2,temp_file_path3


gr.Interface(
    main,
    inputs="file",
    outputs=gr.Gallery(),
    title="Mean-Variance Optimization including ESG Information",
    description="Upload an Excel or CSV file and get the DataFrame. The file
        should have columns ['id','year','esg_score','return']").launch()
```