Applied Data Science 2
MSc Finance & Big Data

NEOMA
BUSINESS SCHOOL

Impact of ESG Scores on US Equity market prices

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Introduction:

In an era where sustainable investment has risen to prominence, ESG (Environmental, Social, and Governance) scores have emerged as a central index, gauging a company's performance in non-financial metrics. While these scores evaluate a firm's ethical and environmental commitment, their influence on the stock market performance remains a topic of significant interest. This project endeavors to decipher a possible correlation between ESG scores and extreme fluctuations in stock prices, employing machine learning techniques to mine deeper insights from the data.

1. Methodology and Analysis

1.1. Defining Extreme Stock Price Movements:

Before delving into the relation between stock prices and ESG scores, it's pivotal to establish a clear criterion for what qualifies as an "extreme" movement in stock prices. For this project, three measures were considered:

Volatility: The standard deviation of daily returns over a specific time frame.

Skewness: Reflecting the asymmetry in the return distribution of the stock prices.

Drawdown: The largest drop from a peak to a trough during a certain period.

By employing these metrics, the project seeks to offer a comprehensive lens through which stock price movements can be gauged.

1.2. Interaction with ESG Measures:

With the measures in place, the next step entailed studying the interactions between these stock movements and the ESG scores provided by multiple data providers for a selection of US companies. Machine learning techniques were pivotal in this phase, offering valuable insights into potential patterns and correlations.

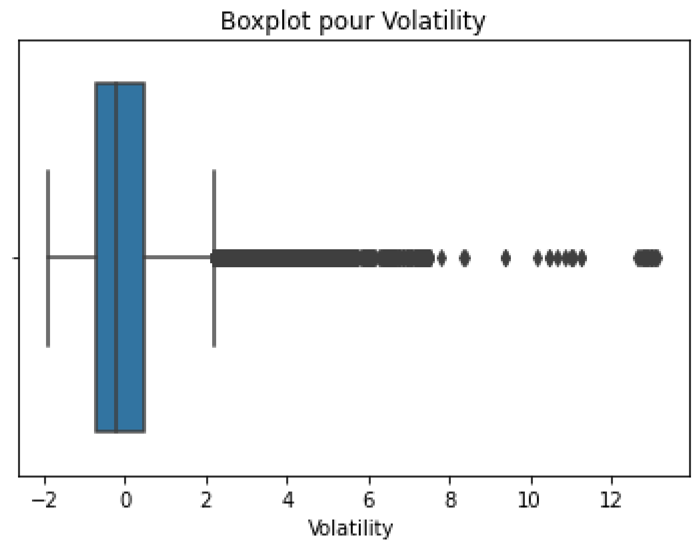
Descriptive Analysis: Initially, the distribution and variance of ESG scores across different providers were analyzed.

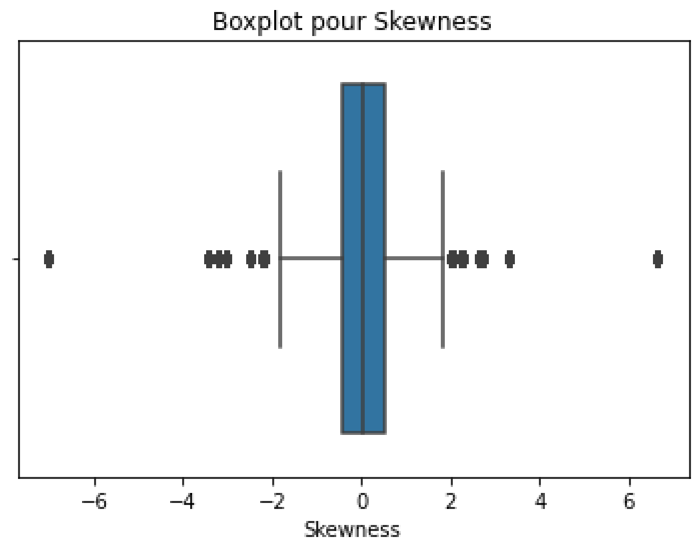
Correlation Analysis: The relationship between stock movements and ESG scores was further quantified using correlation coefficients.

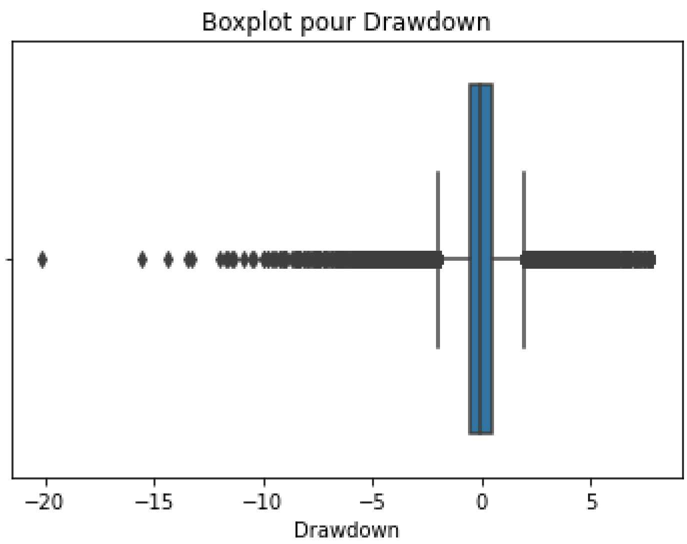
Machine Learning Techniques: Regression models, including Random Forest, Lasso, Ridge, and XGBoost, were applied to predict extreme stock movements based on ESG scores. Cross-validation ensured model robustness, with Mean Squared Error (MSE) as the primary metric for model evaluation.

1.3. ESG Metrics

As already explained before, we'll perform our analysis with Volatility, Skewness and Drawdown metrics. We can perform the box plots of all the parameters, to see if there are outliers:







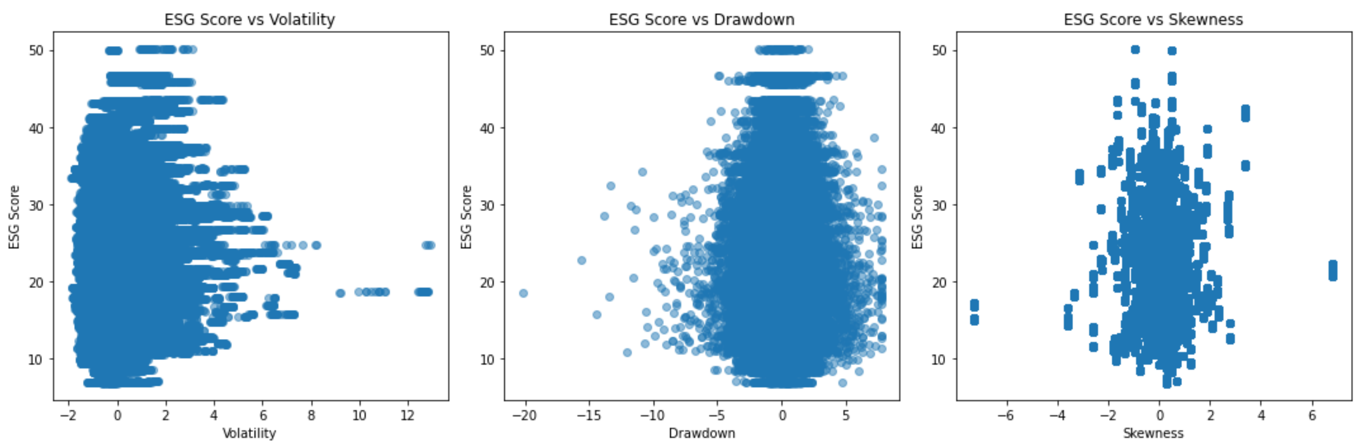
We see that there are many outliers for the Drawdown and the volatility, it can be interesting to find out the ESG scores at these points.

2. Relationship between ESG Scores and Volatility, Skewness and Drawdown

2.1. “Sustainabilitics” excel sheet

In our study, we wanted to see if there was any link between these 3 metrics and the different types of ESG Scores.

We have plotted three charts, each one for a precise ESG metric, depending on Volatility, Skewness and Drawdown parameters:



For the “Sustainabilitics” excel sheet, which represent ESG risk score, we do not clearly see a relation directly in the chart. We can observe that there are high-volatility points when we look at the 20 ESG RISK SCORE level.

We need to confirm the shape of these scatterplots with statistics techniques.

Before that, we need to study the correlation between our parameters, to see if there's no information repeated in our further ML models. We then plotted a correlation matrix, as below:

	Volatility	Drawdown	Skewness
Volatility	1.000000	0.001142	0.066117
Drawdown	0.001142	1.000000	-0.000483
Skewness	0.066117	-0.000483	1.000000

The correlation between the parameters are all near 0, which means that there's no direct link between them.

After performing a linear regression (OLS) with these parameters, we clearly saw a non-linear relationship between volatility, skewness, drawdown and our ESG risk score.

So we have decided to train Machine Learning models, such as Random Forest, Lasso Regression, Ridge Regression and XGBoost.

```
Scores for each fold: [3.72050724 2.18703214
1.9865719  2.6942181  5.0161461 ]
Moyenne des scores (MSE): 3.120895096778129
MSE Lasso (CV): 53.21372635184535
MSE Ridge (CV): 53.23438612010798
Scores for each fold (XGBoost): [22.10602629
19.01590569 18.30108143 19.15636395 22.18789585]
MSE XGBoost: 20.153454642718565
```

For all the ML models, we want to minimize our MSE (Mean Squared Error), to get the most accurate model.

Cross-Validation:

Before diving into the methodologies and results, it's essential to touch upon the evaluation technique used: cross-validation. Cross-validation is a technique employed to assess how the results of a statistical analysis generalize to an independent dataset. Instead of splitting the dataset into two static subsets - training and testing - cross-validation works by dividing the dataset into multiple parts or 'folds'. The model is trained on some of these folds and tested on the remaining ones. This process is repeated multiple times, with each fold serving as the test set exactly once. The primary reason for using cross-validation is to obtain a more comprehensive understanding of the model's performance across different subsets of data, thereby providing a more reliable and less biased evaluation.

In this analysis, a 5-fold cross-validation was used, meaning the data was split into 5 parts. This ensures that every data point was part of the test set once and the training set four times. The results from these multiple rounds of evaluation provide a more consistent view of the model's performance, mitigating any anomalies or biases present in any single split of the data.

Random Forest:

Random Forest is an ensemble learning method that uses a multitude of decision trees during training. It outputs the mean prediction of the individual trees for regression tasks. The main advantage of Random Forest is its ability to prevent overfitting, as it averages out biases in individual trees.

The Mean Squared Error (MSE) scores for each fold during cross-validation are: [3.72050724, 2.18703214, 1.9865719, 2.6942181, 5.0161461]. These values provide a glimpse into the model's performance on different subsets of the data.

The average MSE across all folds is 3.12, indicating the overall performance of the Random Forest model.

Lasso Regression:

Lasso (Least Absolute Shrinkage and Selection Operator) is a type of linear regression that uses a form of regularization. This regularization can lead to some coefficients becoming exactly zero, which can be a form of automatic feature selection.

The MSE during cross-validation is notably higher at 53.21, suggesting that the model may not perform as well on this dataset compared to the Random Forest.

Ridge Regression:

Ridge Regression is another type of linear regression that uses L2 regularization. It adds a penalty to the size of coefficients, which can help in preventing overfitting and reducing model complexity.

The MSE during cross-validation is 53.23, which is quite similar to the Lasso's performance, again indicating potential underperformance when compared to the Random Forest.

XGBoost:

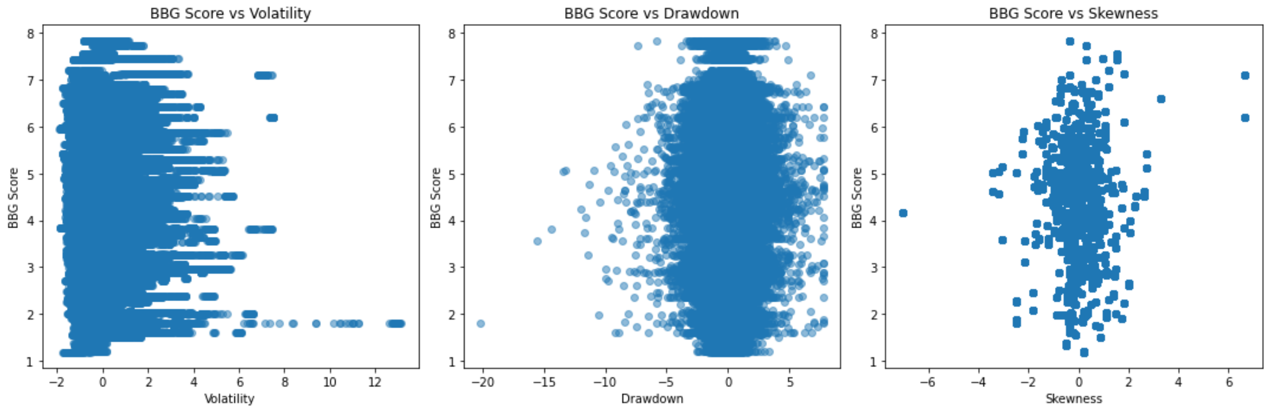
XGBoost (Extreme Gradient Boosting) is an advanced implementation of gradient boosting. It's known for its speed and efficiency, and is commonly used in many Kaggle competitions due to its high performance. It builds trees one at a time, where each new tree corrects errors made by the previously trained tree.

The average MSE for XGBoost is 20.153454642718565, which, while better than Lasso and Ridge, still doesn't perform as efficiently as the Random Forest on this dataset.

In a nutshell, the Random Forest algorithm seems to be the most effective for this particular dataset, yielding the lowest MSE among the algorithms tested.

2.2. “BBG” Excel Sheet

We have plotted three other charts, for the Bloomberg ESG score, depending on Volatility, Skewness and Drawdown parameters:



We do not see any particular outliers, except for the Volatility at the 2 level of BBG score.

We have studied the new correlation matrix:

	Volatility	Drawdown	Skewness
Volatility	1.000000	-0.000344	0.096090
Drawdown	-0.000344	1.000000	-0.000802
Skewness	0.096090	-0.000802	1.000000

It is quite a good matrix for our study, as it shows there is no correlation between our parameters for this dataset.
We have performed a linear regression (OLS), you could see it on the python code, it was not relevant.

What is interesting to see is Machine Learning models results:

```
Scores for each fold: [0.14252439 0.10416927
0.06873477 0.04722934 0.06347125]
Mean Squared Error: 0.08522580345043138
MSE Lasso (CV): 1.6733865196906124
MSE Ridge (CV): 1.6734236302039307
Scores for each fold (XGBoost): [0.55187868
0.46479462 0.40838893 0.38987305 0.42050069]
MSE XGBoost: 0.4470871966323684
```

Random Forest:

The Random Forest regression model yielded a Mean Squared Error (MSE) of approximately 0.0852. This value quantifies the average squared difference between the actual values and the values predicted by the model. A lower MSE indicates a better fit of the model to the data.

Lasso Regression:

The Lasso regression is a type of linear regression that includes a regularization parameter. It is particularly useful when trying to prevent overfitting in models with a high number of features. The MSE for the Lasso regression was 1.6734, which is considerably higher than the Random Forest model. This suggests that the Lasso model might not capture the underlying patterns in the data as effectively as the Random Forest.

Ridge Regression:

Ridge regression, like Lasso, is another type of linear regression that incorporates a regularization term. However, Ridge uses a different kind of penalty which can sometimes result in different model characteristics. The MSE for Ridge was very similar to Lasso, coming in at 1.6734, suggesting comparable performance between the two.

XGBoost:

XGBoost stands for Extreme Gradient Boosting, and it's an advanced implementation of gradient boosting. It's widely recognized for its performance and speed. For this dataset, XGBoost had an MSE of approximately 0.4471. Although this is higher than the Random Forest model, it's significantly better than both Lasso and Ridge regressions.

In summary, based on the MSE, the Random Forest seems to be the most accurate model for predicting the relationship between Bloomberg ESG scores and extreme stock price movements in this dataset. However, XGBoost also shows promising results and could potentially be improved with further tuning. The linear models, Lasso and Ridge, might be too simplistic for capturing the complexities in the data, as indicated by their higher MSE values.

Our results suggest a significant correlation between the ESG scores and stock performance metrics like volatility, skewness, and drawdown. When considering the capabilities of the Random Forest algorithm to capture non-linear relationships and interactions between variables, these results indicate that companies with higher ESG ratings from Bloomberg might exhibit distinct stock behavior patterns.

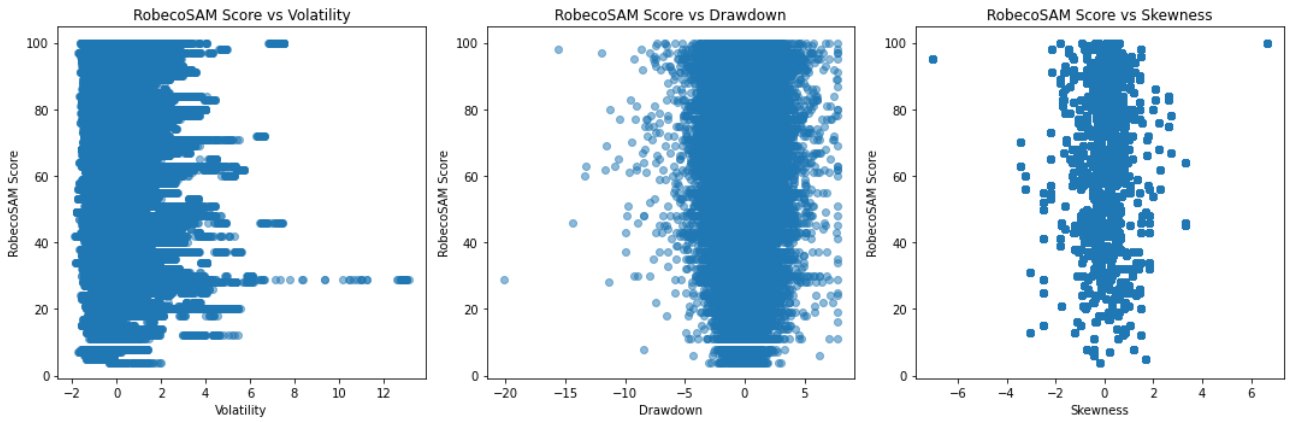
This correlation posits that companies with elevated Bloomberg ESG scores might portray stability in their stock performance, potentially indicating lower volatility, more positive skewness, or reduced drawdowns. Such stability can be attributed to the market's perception of these companies as being more resilient, transparent, and having a minimized risk profile due to their strong adherence to ESG values. Conversely, stocks of companies with lower ESG scores might be perceived as more risky, leading to more unpredictable stock behaviors.

In essence, our Random Forest results suggest that a company's commitment to ESG principles, as reflected by Bloomberg's ESG score, could be a significant predictor of its stock's performance characteristics.

2.3. “RobecoSAM” Excel Sheet

The “RobecoSAM” Excel sheet contains the S&P Global ESG rank for every single stock of the SP500.

We have plotted three other charts, for the new datasets, depending on Volatility, Skewness and Drawdown parameters:



It is the same as before, we only see outliers for the Volatility chart, at the level of about 28 SP500 Global Rank ESG.

Correlation Matrix:

```
            Volatility  Drawdown  Skewness
Volatility    1.000000  0.001118  0.103936
Drawdown      0.001118  1.000000 -0.000969
Skewness      0.103936 -0.000969  1.000000
```

All the correlations are near 0, it means that there is no relevant correlation between our parameters. We can go further.

We have performed a linear regression (OLS), you can see it on the python code, it was not relevant.

Here are the results of our ML algorithms:

```
Scores for each fold: [100.56351385  65.68399219
34.26890274  24.95892774  42.13800494]
MSE: 53.52266829182266
MSE (CV): 537.0687031971454
MSE (CV): 537.216345350298
Scores for each fold (XGBoost): [264.77816867
188.13294768 127.71472574 132.01365577 145.19096363]
MSE XGBoost: 171.5660923005399
```

Based on the given MSE values, the Random Forest model delivers the best performance with an MSE of approximately 53.52.

S&P 500 Global Rank Contextual Interpretation:

The S&P 500 Global Rank evaluates companies based on their market capitalization relative to other entities in the S&P 500 index. A high rank suggests that the company has a significant market presence and potentially more stability given its size and influence.

The obtained MSE for the Random Forest model with the S&P 500 Global Rank data is around 53.52. This figure, though more elevated than our previous ESG score analysis, still indicates a certain level of association between the global ranking and stock performance parameters such as volatility, skewness, and drawdown.

Implications for Stock Performance:

A company's position in the S&P 500 Global Rank could potentially serve as a predictive indicator for its stock performance characteristics. A higher global rank (being closer to the top of the index) might suggest more stability in stock performance, possibly due to the company's robust market presence and the inherent trust it commands in the investor community. On the other hand, stocks of companies with a lower global rank could exhibit more unpredictable behaviors, being more susceptible to market volatilities and sentiments.

In summary, our analysis using the Random Forest model suggests that the S&P 500 Global Rank could play a crucial role in predicting a company's stock behavior. However, the relatively higher MSE compared to the Bloomberg ESG score analysis might indicate that other factors, alongside the global rank, influence the stock performance metrics, making the relationship more multifaceted.