

# Eco-Risk Alpha

## Measuring the Green Discount in Counterparty CVA

Letizia Cazzaniga, Angelique Girod, Marco Piazza, Jacopo Raffaeli

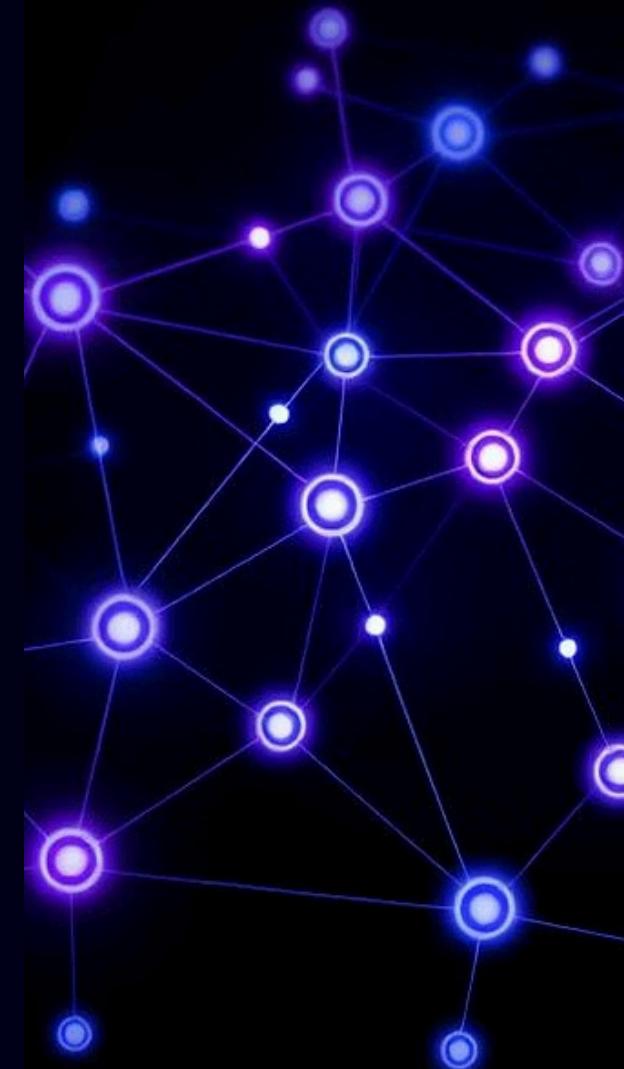
# Objective

## Predict CDS using Machine Learning

Train Linear and non linear models to explain credit-default-swap (CDS) spreads using ESG and fundamental risk factor variables.

## Translate in CVA

Translate those spreads into CVA (Credit Valuation Adjustment) value to quantify a potential "green credit premium"



# Data Analysis Pipeline



## Data Exploration and Pre-processing

Preliminary analysis of market data (**CDS spreads**) and risk factors, including **ESG scores** and corporate fundamentals. Data cleaning, missing value management, and normalization to prepare the dataset for modeling.



## Model Development and Selection

Implementation of **predictive models** (linear and non-linear) to explain CDS spreads. Evaluation of model performance and selection of the most robust framework for integrating ESG risk factors.



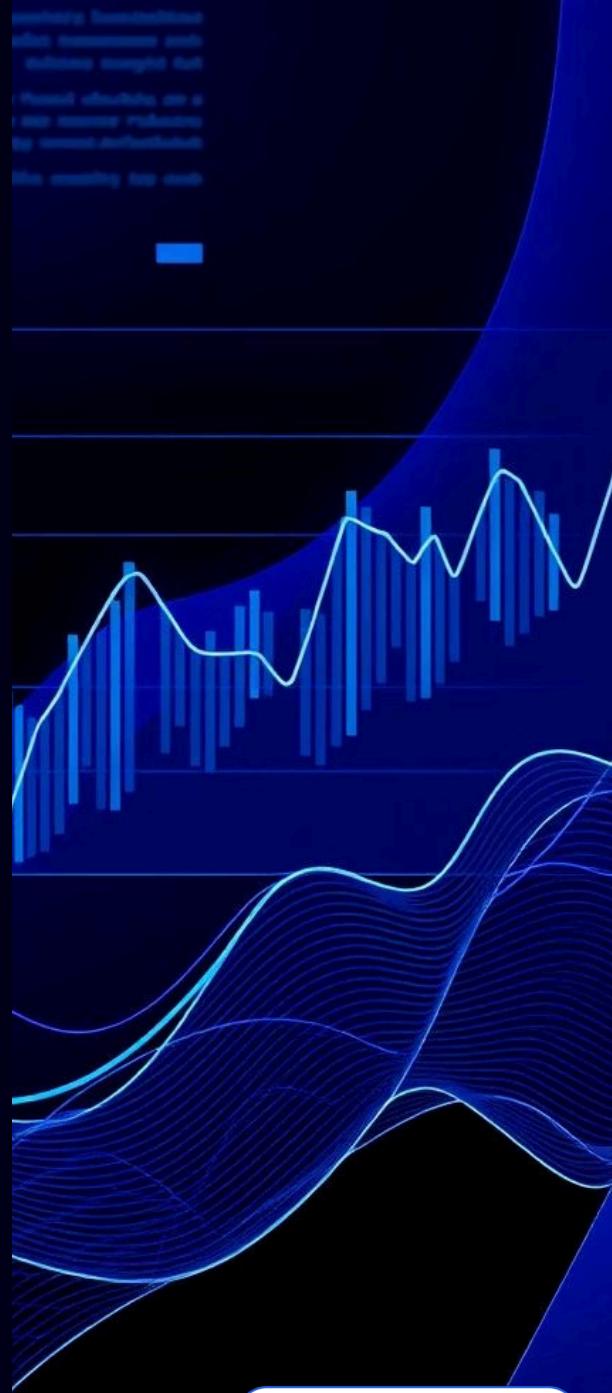
## CVA Quantification

Translation of model outputs into Credit Valuation Adjustment (CVA) to quantify the potential "**Green Credit Premium**," measuring the impact of ESG factors on counterparty default risk.

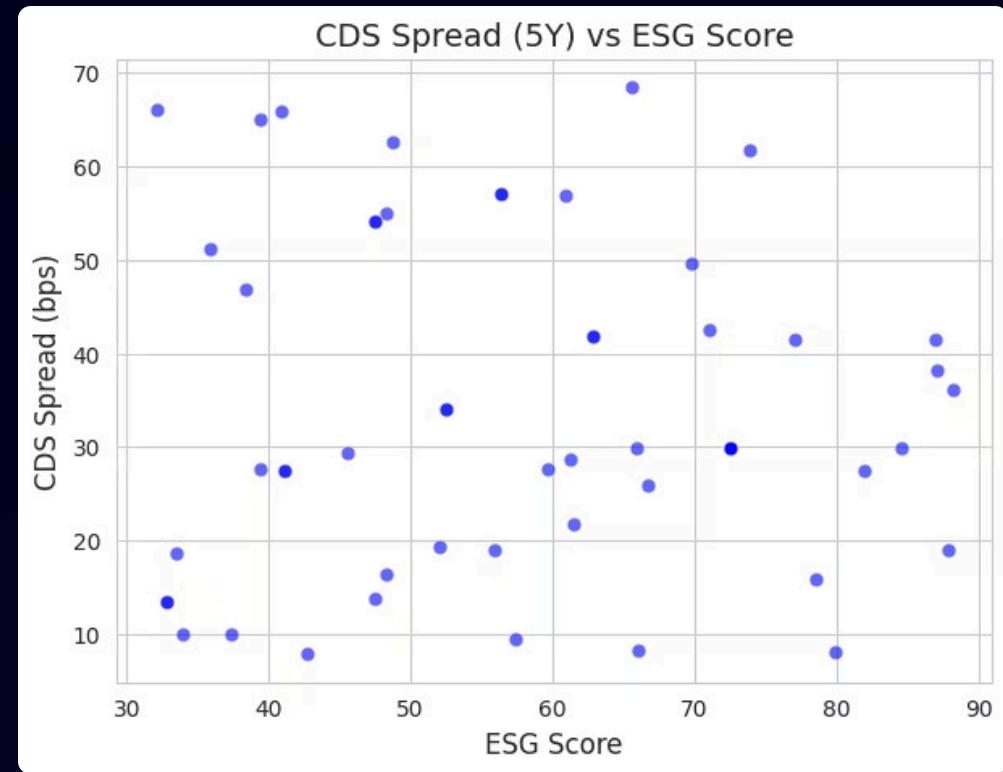
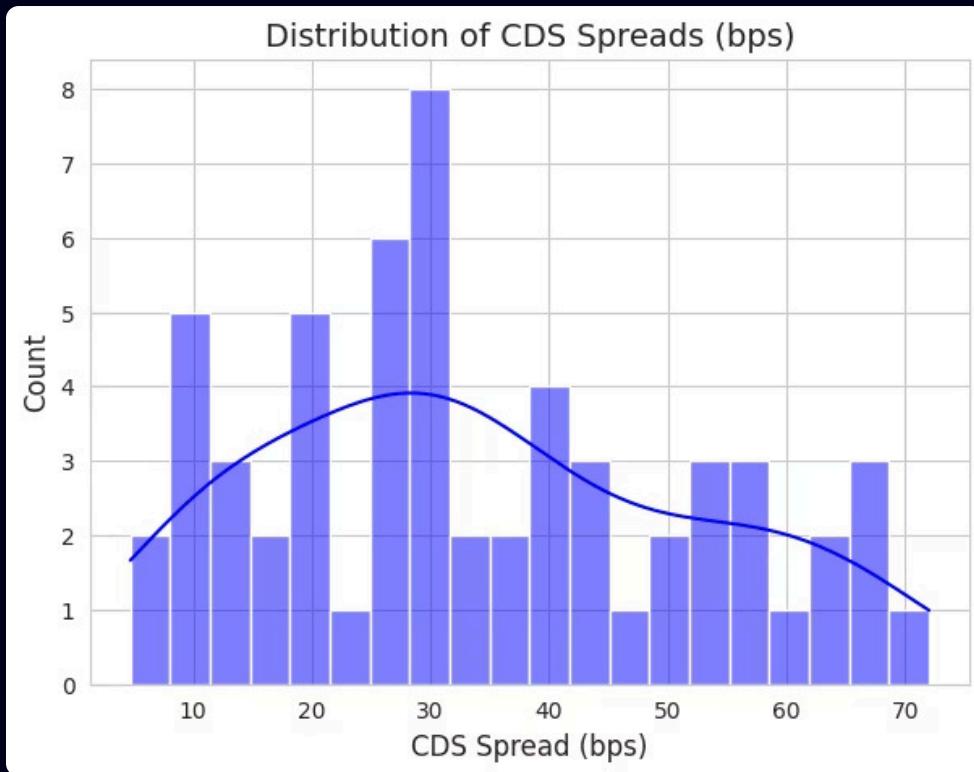


## Possible extensions

Extension of the framework simulating new synthetic data and stress test.

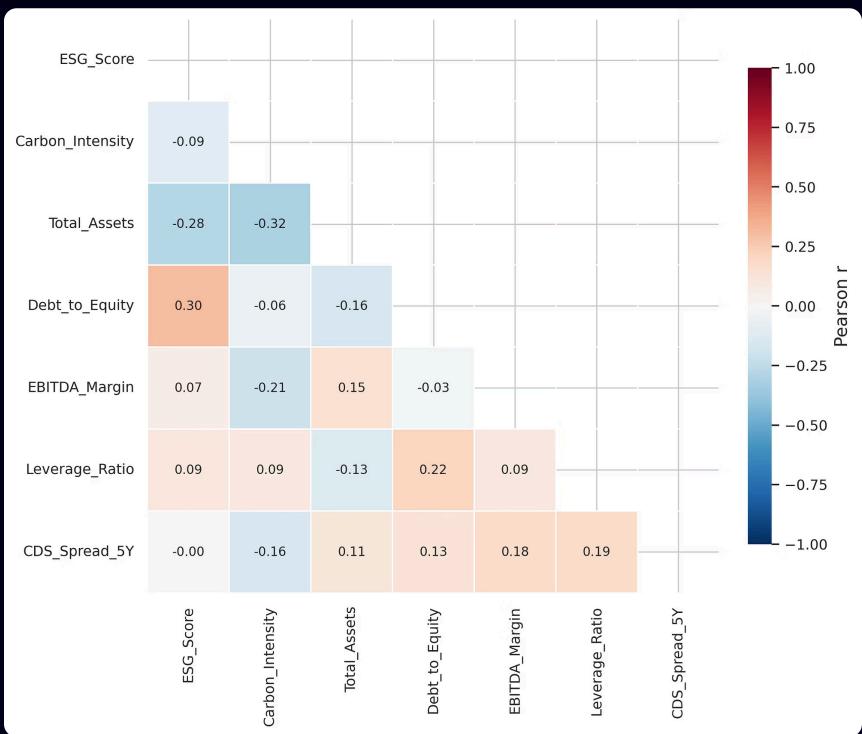


# Data Exploration

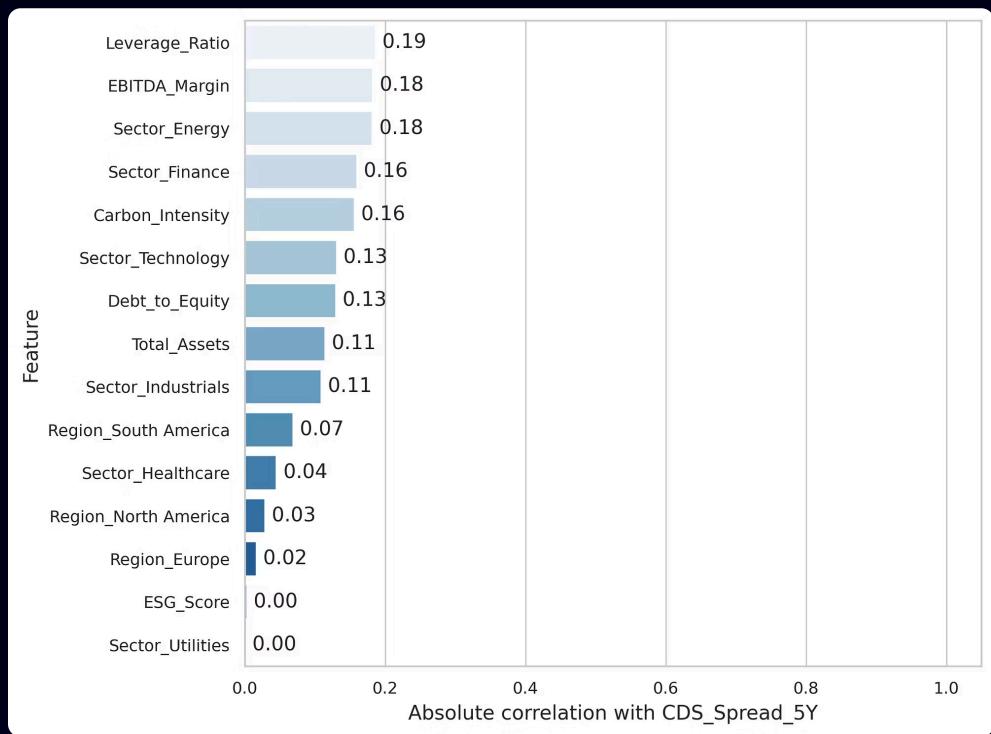


# Correlation matrix

Correlation matrix



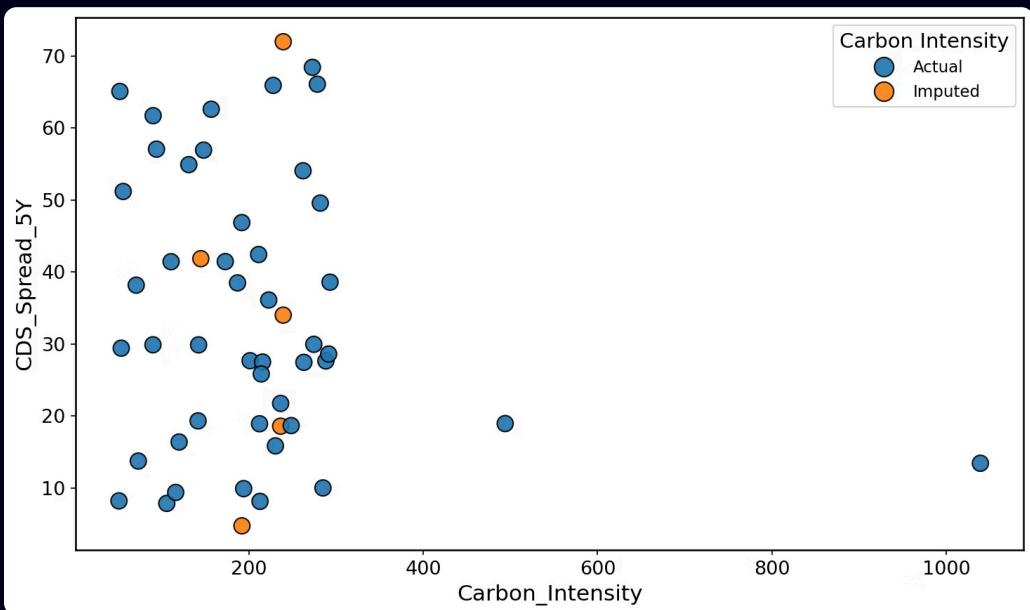
Correlation with target value



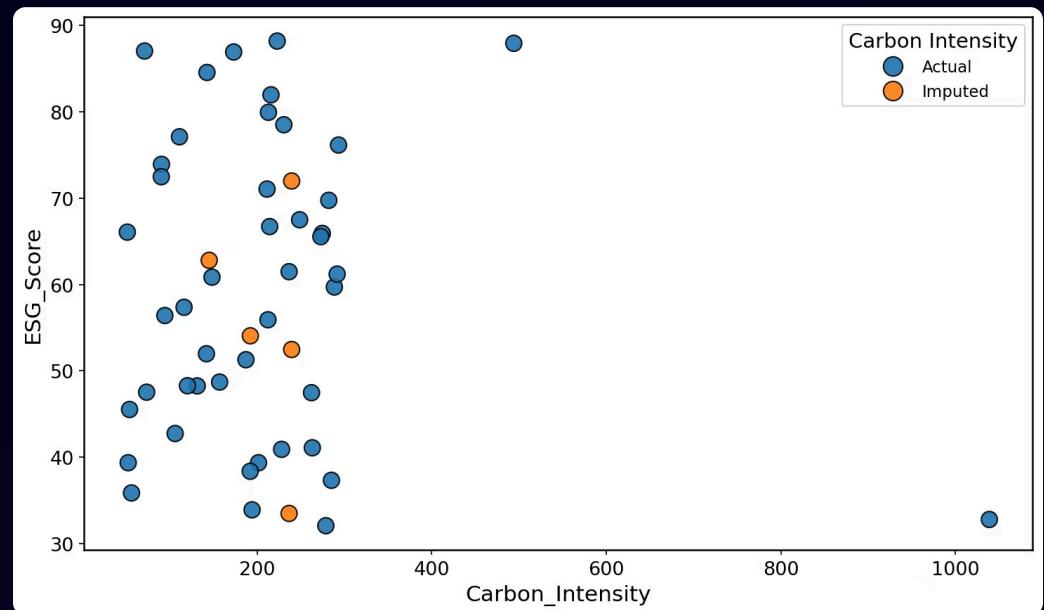
# Imputation of Missing Data

Sector-wise median Imputation was performed for missing data imputation

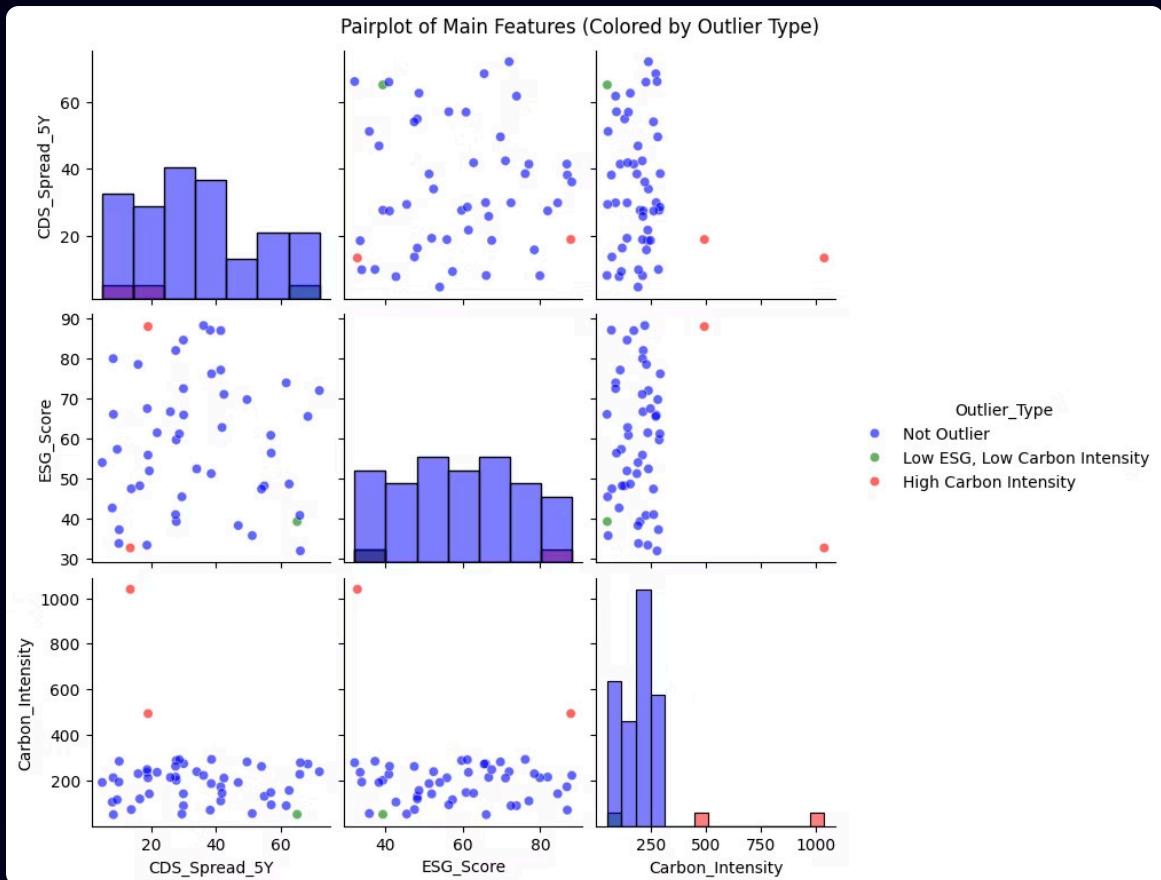
Carbon Intensity vs CDS scores



Carbon Intensity vs ESG scores



# Outlier Analysis

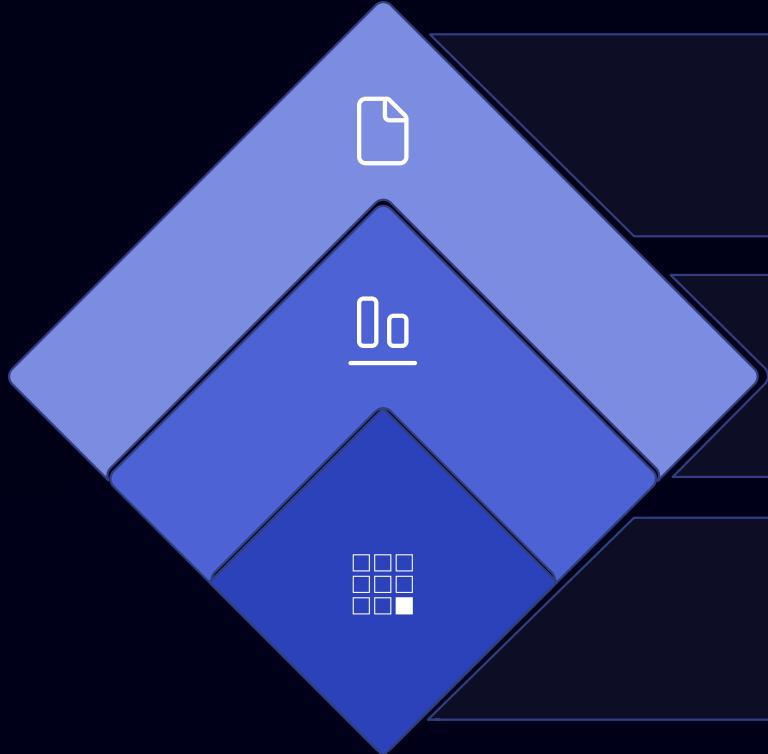


- Check of feature value consistency
- Outlier detection using **Isolation Forest**
- Three companies flagged as potential outliers



Maintained to align with the real world

# Feature Selection



## Sequential Feature Selection (SFS)

Iterative forward and backward

## Correlation

Correlation between features and target

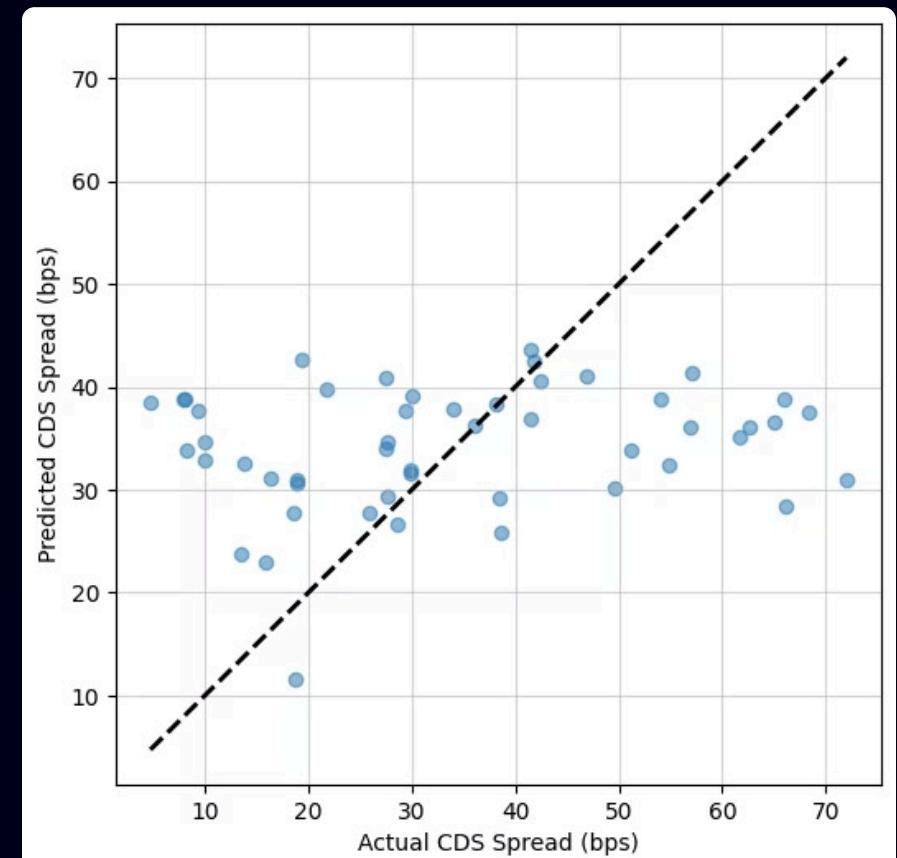
## Expert Selection

Manual domain-based choice

# Linear Models

Feature Selection	R <sup>2</sup> (Train)	RMSE (CV)
LR full dataset	0.2	24.75
LR with Lasso	0	19.3
SFS (Forward and Backward)	0.11	<b>18.74</b>
Correlation with target (N=3)	0.1	19.39

**SFS Forward / Backward**

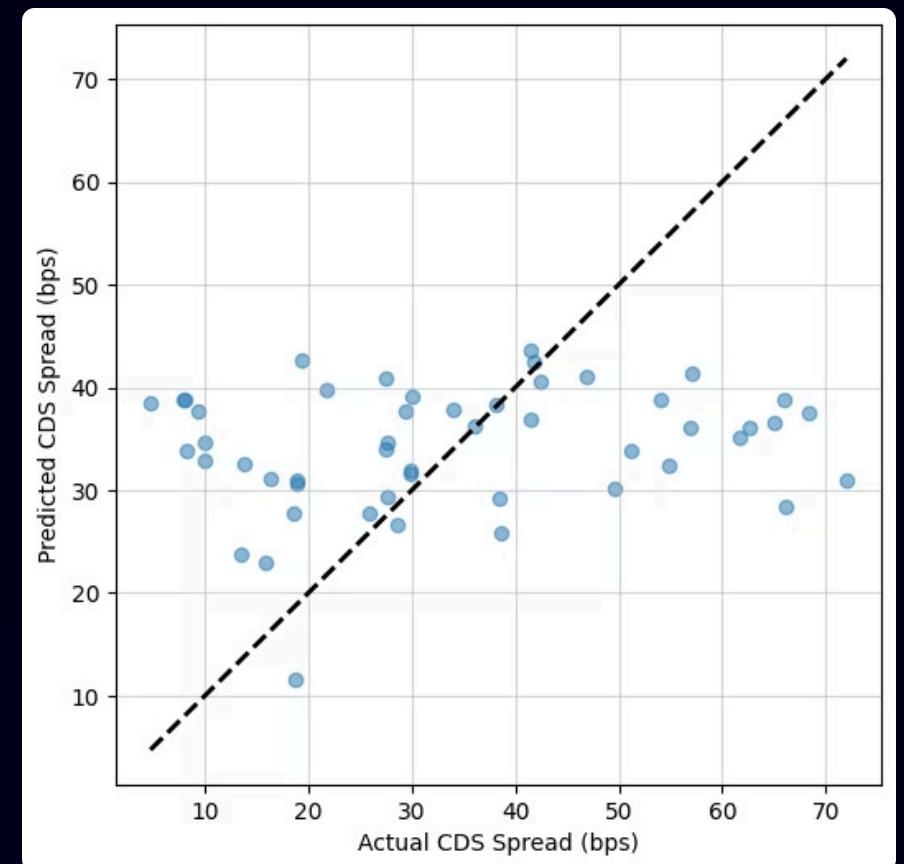


*\*\*evaluated on a Leave-One-Out procedure*

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**SFS Forward / Backward**



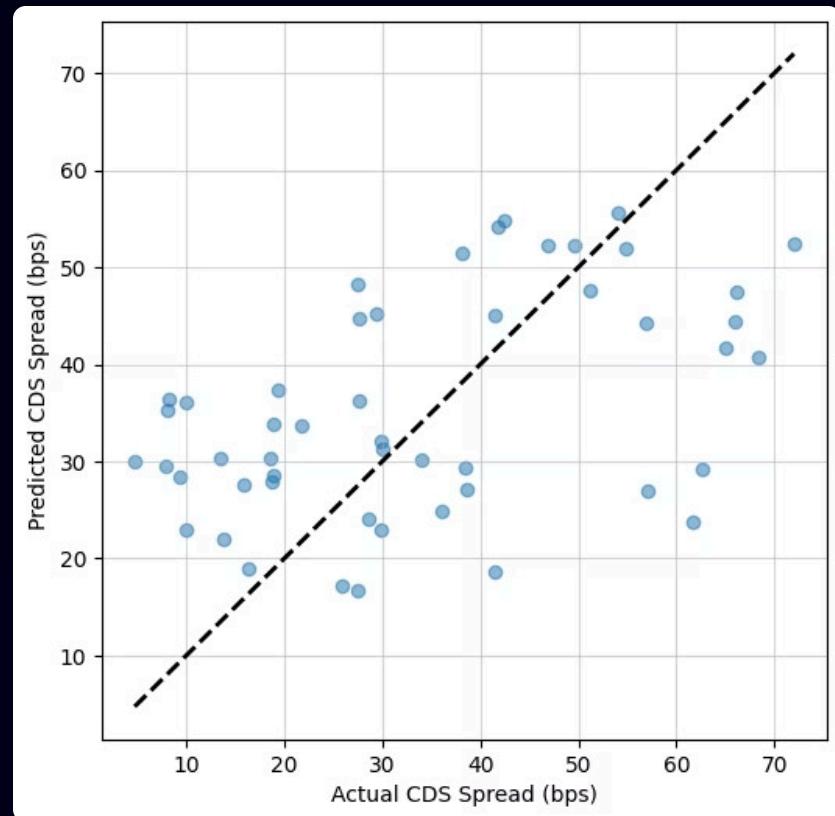
**Features selected:** Carbon Intensity, Leverage Ratio, Sector Energy

*\*\*evaluated on a Leave-One-Out procedure*

# Random Forest Model

Feature Selection	R <sup>2</sup> (Train)	RMSE (Test)
All features	0.84	20.44
All features (tuned hyperparameters)	0.77	19.68
SFS Forward	0.88	18.03
SFS Backward	<b>0.89</b>	17.1
SFS Forward (tuned hyperparameters)	0.77	17.48
SFS Backward (tuned hyperparameters)	0.78	<b>16.76</b>

**SFS Backward (tuned hyperparameters)**

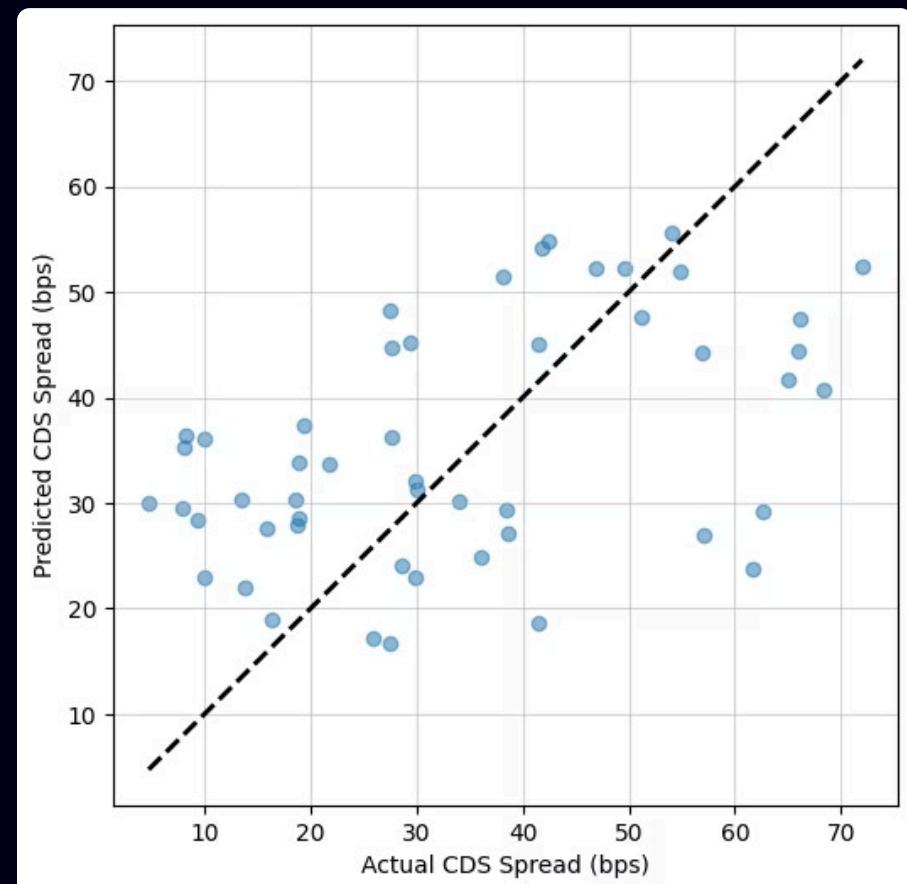


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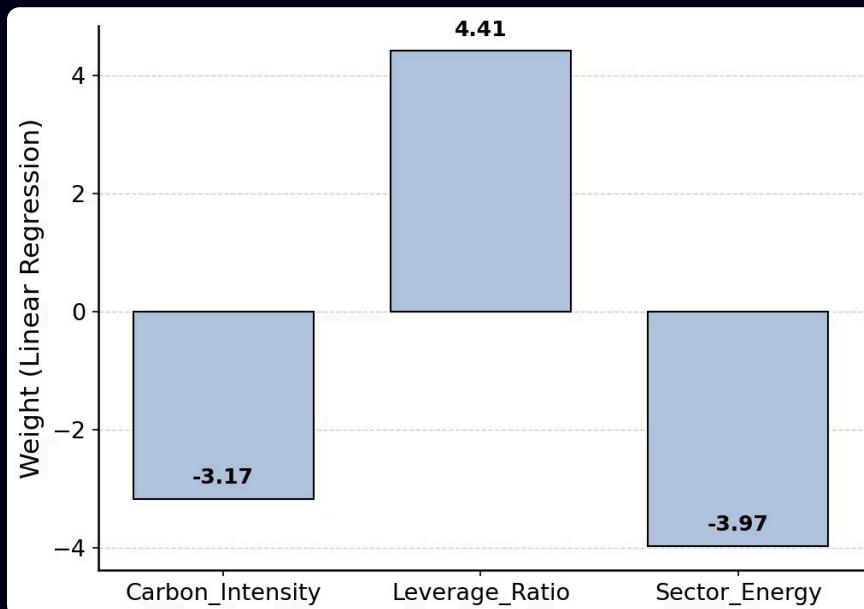


**Features Selected:** EBITDA Margin, Leverage\_Ratio, Sector Energy

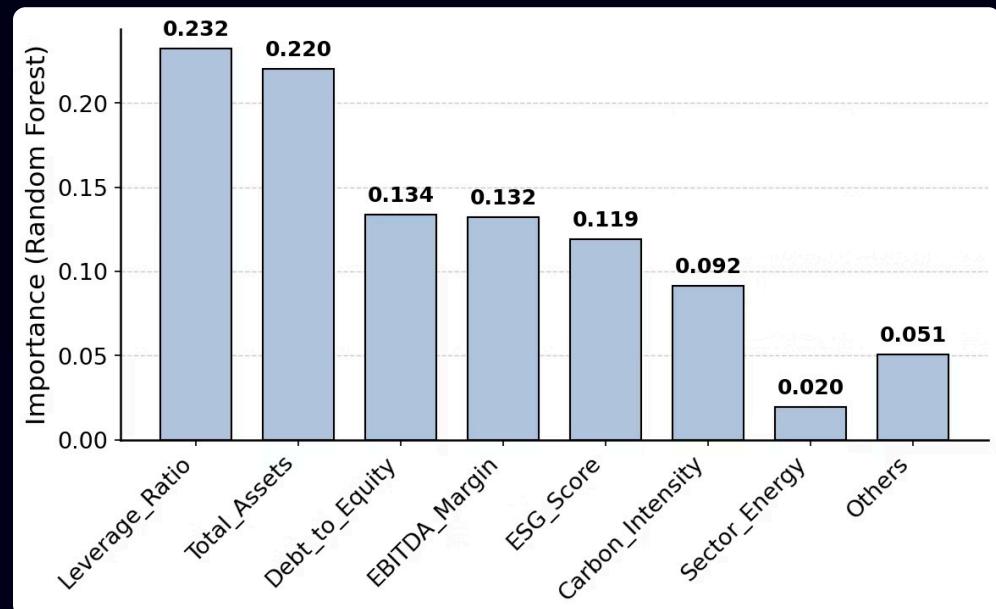
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# Interpretability

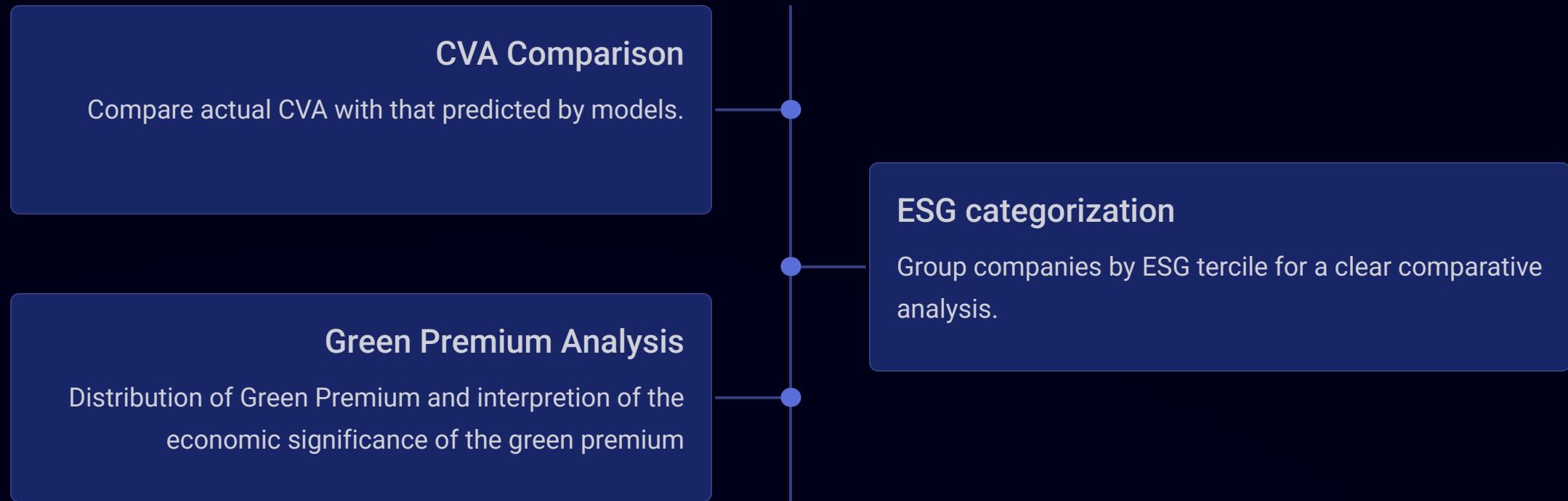
Linear Regression



Random Forest



# Insights and Quantification of the "Green Premium"



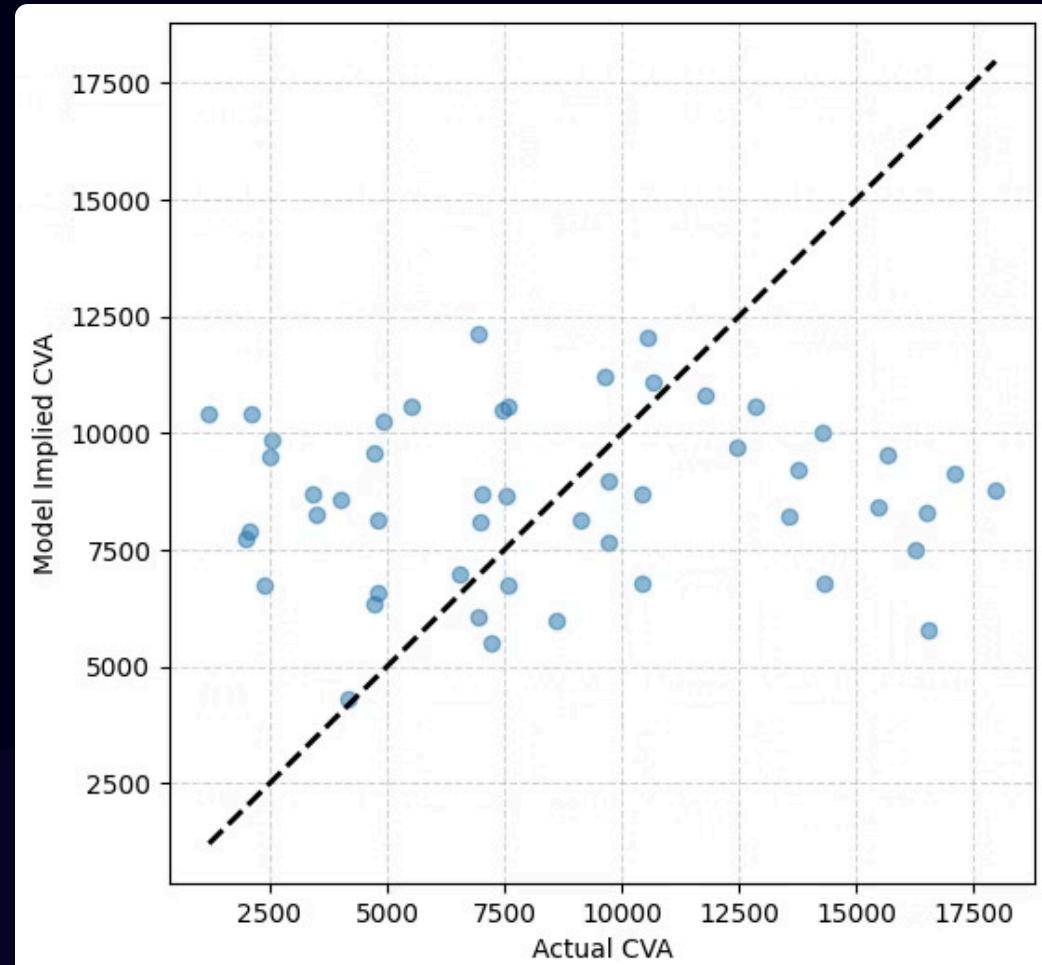
# CVA Calculation

- **CDS Spread to Hazard Rate Conversion:** Transform CDS spreads, both market and model-predicted, into default rates (hazard rates).
- **CVA Formula Application:** Use the unilateral CVA formula, applying it to the provided Expected Exposure (EE) profile. The assumption of a fixed Loss-Given-Default (LGD) of 0.6 is a key parameter in this calculation.

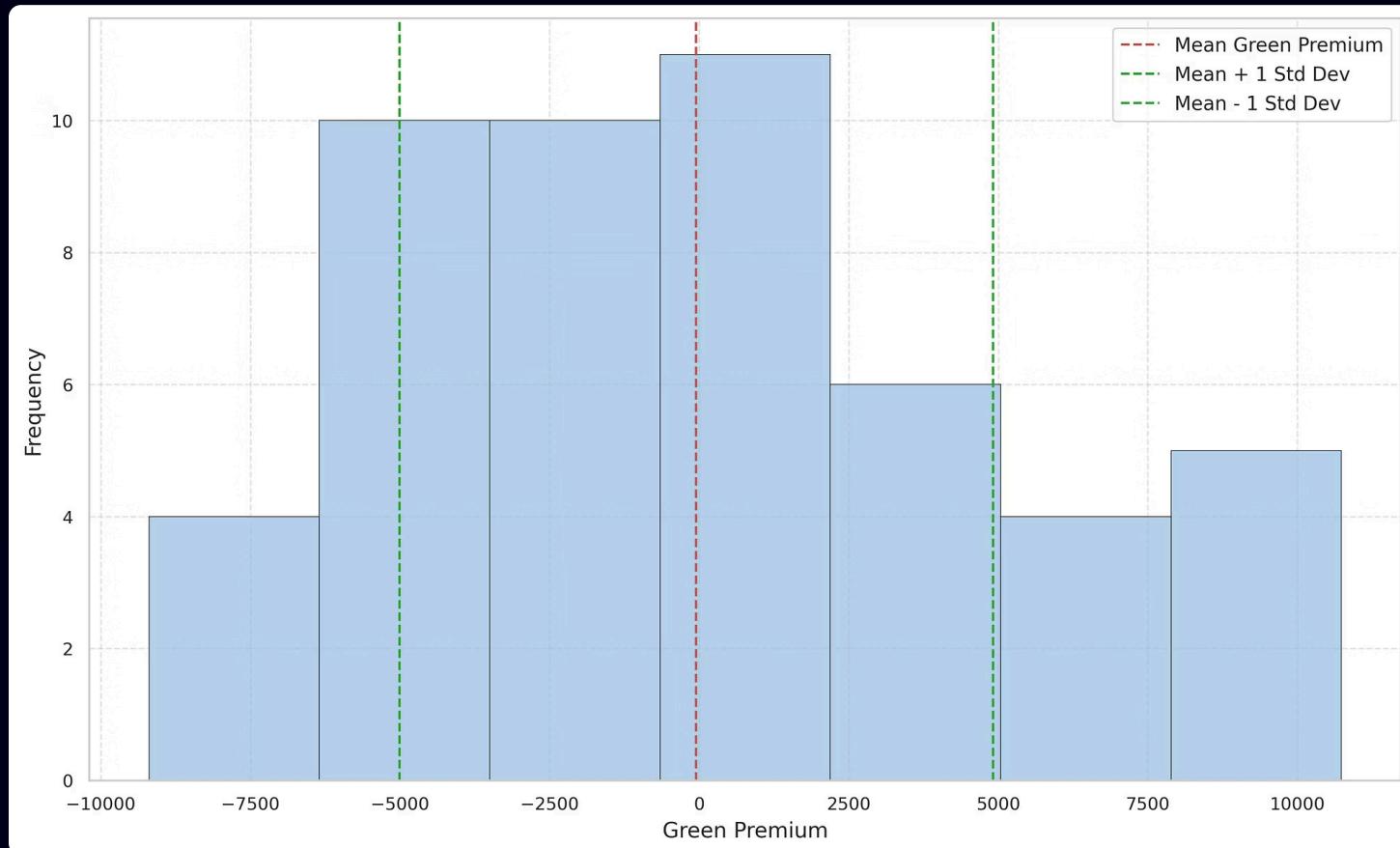
$$CVA \approx LGD \cdot \sum_{i=1}^N EE_i \cdot DF_i \cdot (S_{i-1} - S_i)$$

$$\bullet S_i = \exp(-\lambda \cdot t_i)$$

$$\bullet \lambda = \frac{CDS_{Spread}}{1-R}$$



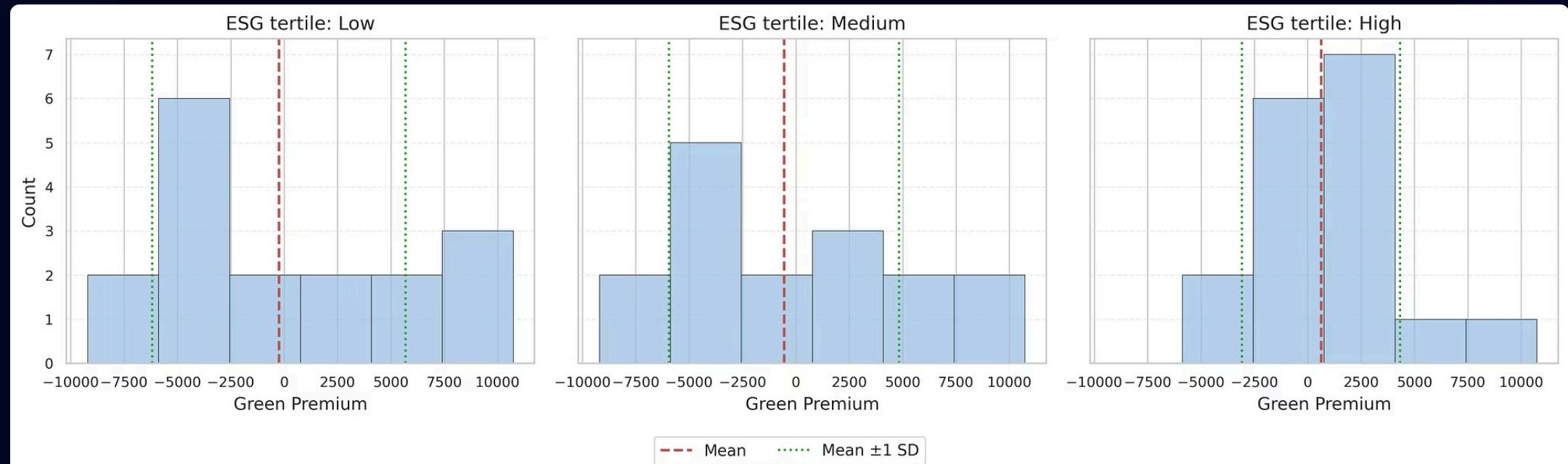
# Green Premium Analysis



$$\text{Green Premium} = \text{CVA}_{\text{actual}} - \text{CVA}_{\text{predicted}}$$

# Green Premium Analysis

Green premium bucket firms by ESG tertile



# Conclusions

- **Objective**

Test whether ESG factors contribute to explaining CDS spreads, asses whether this implies greener firms benefit from a “green premium” in terms of lower CVA charges.

- **What the model does**

Our modeling framework can highlight whether ESG factors have statistical relevance for CDS spreads.

Any claim beyond this would require a broader empirical strategy

- **What the model does not**

The difference between actual and model-predicted CDS (and CVA) is simply the model error.

This means that the gap we label as a “green premium” is not in itself evidence of a true pricing differential in credit markets.

# Limitations & Future Developments

- **Scarcity of data**

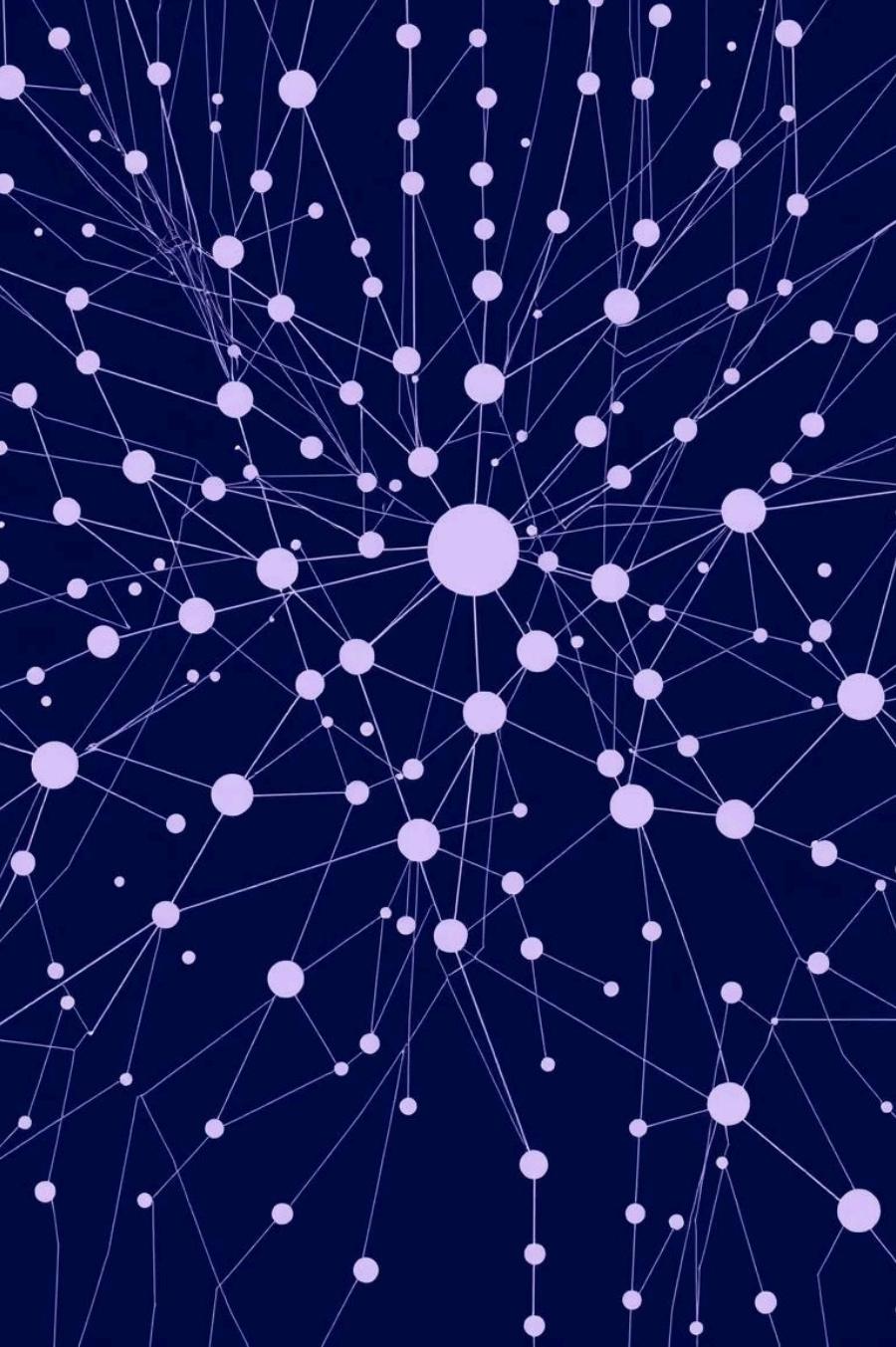
- Only ~ 50 observations available
- Same dataset used for tuning & testing → reliability issues
- CV helps but is not a substitute for a true test set or nested CV

- **Synthetic data generation**

- Small sample size makes synthetic data generation unreliable
- Artificial patterns could distort results more than help

- **Stress testing**

- No stress tests performed on the zero rate curve
- Important next step to assess CVA sensitivity under different scenarios



# Thank you for your attention!

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