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Are ESG Responsible Companies Loss Responsible? - Modelling LGD with ESG Information

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Abstract

Incorporating Environmental, Social, and Governance (ESG) factors into credit risk modelling significantly enhances traditional risk management by providing a holistic view of borrower risk in a dynamic market. Traditional models focus primarily on financial performance, debt characteristics, and macroeconomic conditions. This study highlights the importance of ESG information in the context of Loss Given Default (LGD) modelling, which has remained under-explored. We employ a truncated Gradient Boosting Decision Tree (GBDT) with SHAP for model interpretation, using a unique dataset that merges Moody's Default and Recovery Database with the MSCI:KLD ESG Database. Our findings demonstrate that not only incorporating ESG factors reduces predictive errors compared to models that use only financial and macroeconomic indicators but also the relationship between LGD and ESG factors follows a temporal structure and is uneven for different risk segments. The ESG information tends to work better during adverse macroeconomic environment and for the estimation of naturally riskier samples. Notably, social factors have the greatest impact on LGD estimates among all three pillars of ESG.

1 Introduction

Incorporating Environmental, Social, and Governance (ESG) factors into the modelling of credit risk components represents a significant advancement in the risk management practices. Traditionally, credit risk models have primarily focused on the debtors' financial performances, debt specific characteristics including the debt covenants and collateral values, and the macroeconomic environment. However, integrating ESG considerations provides a more holistic view of borrower risk, particularly in a rapidly evolving global market landscape where sustainability issues increasingly influence financial stability. For example, environmental risks from climate change or regulatory changes for sustainability can affect asset values. Similarly, governance factors, such as corporate management quality and ethical business practices, are attached to a company's repayment ability.

In this study, from a predictive angle, we examine how companies' ESG performances can help financial institutions to more accurately estimate the ultimate loss of the bonds given default with a truncated Gradient Boosting Decision Tree (GBDT) and SHAP for model explanability. We use an unique ESG-LGD dataset obtained by merging Moody's Default and Recovery Database with MSCI:KLD ESG Database, with ESG information presented on the pillar-level (E, S, and G). By comparing the model performances with different groups of features, we find that integrating ESG information can significantly reduce the out-of-time predictive errors. Besides, compared with financial ratios and macroeconomic variables, ESG features presents the best predictive power when each group of features is used alone, and excluding ESG features lead to the most error increase in comparison to the performance of baseline model. Among all three pillars of ESG, social perspective contributes the most to estimating LGD, as it covers multiple aspects from the human right and product externality to community benefit and diversity. This finding is consistent with the existing study (Albuquerque et al. 2019).

In the next part of our empirical study, considering the unobservable heterogeneity of bond seniorities found by Yao et al. (2015), we divide the whole dataset into unsecured part and unsecured part according to the seniority of the debt instruments and examine the ESG factors' predictive power for each subsets. Our result indicates that the model performs significantly better with unsecured subset, and that the ESG factors boost the predictive performances since excluding ESG features leads to a higher error. However, there is a totally different story for the secured subset: ESG factors do not introduce additional predictive power and solely increase model complexity instead. Similarly, then we conduct another segmentation experiment according to the obligors' environmental characteristics, dividing the original dataset into samples with issuers from environment friendly industries and environment unfriendly industries. We find ESG features helps for both segments but more significantly for samples from brown industries. We next analyse the effect of ESG information in multi-stage modelling framework for LGD which is very common in practice. By training classifiers to identify which samples are fully recovered or fully lost, we find ESG features continue showing significant boost on predictive performance in modelling riskier subset. The number of flagged social concerns is a strong feature in identifying those ultimately fully lost debts.

As in our previous experiment, ESG information works well in out-of-time prediction but not in out-of-sample prediction. We infer the relationship between ESG feature group and LGD may change over time in terms of prediction power. In the next part of study we use rolling window regression to analyse how feature importance of ESG variables evolve over time. In this analysis, two important findings are revealed. First, during the financial crisis, the overall predictive error for the ultimate LGD is higher than other time periods. However, ESG information becomes more useful in an adverse macroeconomic condition with a peak of their feature importance ranking especially the social pillar. Second, from the overall trend of feature importance ranking, the predictive power of ESG information is diminishing over time. The ESG mania after the financial crisis let more companies focus on their social responsibility. Some manipulation or over-emphasise on the ESG performance can alter existing relationship between ESG and LGD and make ESG features less helpful in predictions.

Our study contributes to the existing literature in three areas. First, the determinants of LGD/recovery rate. Jankowitsch et al. (2014) found the significant variable groups for recovery rate modelling are financial ratios, macroeconomic variables and debt-specific features. We extend this list with ESG information group, by shedding light on how ESG information can help estimate LGD and how this relationship differs in different segments and evolves over time. Second, the impact of ESG on companies' credit risk profiles. Existing studies such as those conducted by Oikonomou et al. (2014) and Chava (2014) focus on the impact of ESG on cost of debt or credit rating as the indicator of company credit risk. We provide another aspect via LGD and pave the way for revealing the impact channel of ESG on different aspects of company's credit landscape. Third, the predictive modelling of LGD. By incorporating the additional ESG information, the LGD modelling performance of current state-of-the-art techniques can be further improved (Yao et al. 2017, Nazemi et al. 2022).

This study is structured as follows: Section 2 reviews the relevant studies examining the relationship between ESG information and credit risk and highlights those established groups of determinants of LGD. Section 3 describes the sources of data and different groups of variables used in the modelling. Section 4 describes the methodologies for data preprocessing, modelling and model interpretation. Section 5 presents the empirical results of how ESG information can enhance the predictive accuracy for LGD modelling from multiple dimensions. Section 6 concludes the paper.

2 Literature Review

2.1 The Determinants of LGD

According to existing literature, the determinants of Loss Given Default (hereafter LGD) of corporate bonds can be approximately categorised into four types: (1) bond-level information such as the amount of principal, bond term, borrowing purpose and other special arrangements, (2) company-level information including financial indicators, (3) industry-level information and (4) macroeconomic information which jointly depict the external environment of the given debt instrument. Existing literature has demonstrated that LGD of corporate bonds is significantly driven by all four kinds of determinants (Yao et al. 2015).

In his paper *What Do We Know About Loss Given Default?*, Schuermann (2004) discussed the key drivers of differences in LGD of corporate bonds with the data of Moody's Default Risk Service Database. The results revealed that seniority and collateral arrangements could be the most important stratifiers of the corporate bond LGD, because they determined the order of right of claim and whether the corporate bond was secured. If the corporate bond had the highest seniority with collateral arrangement, it was very likely to be recovered during the bankruptcy negotiations. In addition to this, the overall LGD level seemed to follow a certain patter along with the business cycle. Strong evidence was that the LGD during the recession stage was much higher than during the expansion stage. In addition, the study reported that there was an industry impact. By analysing the studies of Altman & Kishore (1996) and Acharya et al. (2003), Schuermann (2004) found that the utilities industry had relatively lower LGD than other industries.

Furthermore, several studies focused on exploring how macroeconomic and industry-level variables influence the differences of LGD. Acharya et al. (2007) then further analysed the impact mechanism of this phenomenon. In a distressed industry, if the non-defaulted firms within the industry were illiquid, creditors would recover less on the defaulted firms in the industry. This situation was likely to become more serious especially when the assets in the industry were special and could not be redeployed easily by firms in other industries and when the defaulted bonds were backed and collateralised by this kind of assets. Qi & Zhao (2013) further studied the determinants of US corporate bond LGD by proposing a new measure of debt seniority and examining how this new variable could explain the variance of LGD. The study showed company-level characteristics could have more explanatory power than industry-level and macroeconomic-level features, and the contribution of the latter two types of the variables depended on the variation of the datasets and modelling techniques. In particular, they found that for companies whose stock price was publicly available, the trailing 12-month stock return played a more important role.

Jankowitsch et al. (2014) thoroughly examined the determinants of recovery rates in the US corporate bond market. They took into consideration a comprehensive set of independent variables including bond-level features, company-level balance sheet ratios, macroeconomic variables and liquidity measures. Their study revealed a series of interesting findings regarding the determinants of US corporate bonds' recovery rates. First of all, all four types of characteristics were found to contribute to the modelling of recovery rates. In particular, they found that the restriction of investment and financing policy attached as the bond covenants were important determinants. This findings should allow creditors to use this effective tool to increase the recovery rate. Secondly, with regards to those company-level financial ratios, the ratios powered by structural credit risk models such as equity ratio and the default barrier had the most significant impact on the recovery rates. Thirdly, by analysing the macroeconomic variables, Jankowitsch et al. (2014) found that higher overall default rate in the market, a systematic risk factor or a higher default rate in certain industry could all lead to a higher LGD. As an important business indicator of the economic cycle and macroeconomy, short-term interest rate showed positive relationship with the recovery rate. Lastly the bonds' liquidity measured by the volume, number of trades and price dispersion measures had positive correlation with the recovery rate. The higher the liquidity, the more creditors can recover given the bond is defaulted (Jankowitsch et al. 2014).

Overall, in terms of the determinants of the LGD of corporate bonds, existing literature is mostly focussed the bond covenants, macroeconomic factors and industry-specific impact. On the other hand, so far, researchers tent to treat company-level characteristics as equal to balance sheet ratios or other pure financial indicators and ignore other perspectives of companies' information such as corporate governance and their commitments to the environment and the society.

2.2 Modelling Credit Risk with ESG Variables

The studies exploring the relationship between ESG and credit risks began to flourish in the 2010s, after the financial crisis. Menz (2010) initiated this trend by examining the relationship between ESG and the valuation of EU corporate bonds, finding that ESG factors were not yet incorporated into the pricing of EU corporate bonds, as the risk premium of socially responsible firms was higher than that of non-socially responsible firms. In the US market, Goss & Roberts (2011) explored the links between ESG and bank debt, revealing that corporates with good social responsibility performance enjoyed 7 to 18 basis points more favourable terms when applying for bank loans. Oikonomou et al. (2014) further investigated the impact of ESG on corporate bond pricing and credit ratings, demonstrating that socially responsible firms were rewarded with lower interest costs and higher credit ratings.

With the development of ESG data infrastructure, various types of ESG information are provided with the investors and the public, allowing researchers examining the effect of ESG on financial risk at a more granular level. Ge & Liu (2015) examined the relationship between ESG and the cost of US corporate bonds, using ex ante credit ratings to represent the cost of corporate bonds. They found that ESG was positively correlated with credit ratings, using ESG data from the RiskMetrics Group KLD STATS database, which divides ESG scores into strengths and concerns. Their study revealed that higher ESG strengths were significantly related to higher credit ratings, and that ESG strengths were negatively correlated with bond yield spread, while ESG concerns were positively correlated. In addition, they found that investors were more tolerant of bonds issued by firms with better ESG performance, establishing fewer covenant restrictions. Dorfleitner et al. (2021) quantified the improvement in credit rating predictions when corporate social performance (CSP) metrics were incorporated into established credit risk models. Their findings demonstrated that CSP is an important predictor of credit ratings, and firms with high CSP are less risky and receive higher credit ratings. Bannier et al. (2022) examined the relationship between different aspects of CSR and corporate credit risk, matching similar conclusions and noting regional variations in the relevance of sustainability elements between the United States and Europe.

Recent findings by Palmieri et al. (2024) suggest that wholesale banks exhibit a negative correlation between improving environmental scores and the probability of default, with regulatory responses to global environmental challenges increasing the risk of default. Retail banks also exhibited a negative correlation, though not significant due to their customer-centred nature. Public awareness of environmental issues and evolving consumer protection regulations can slightly change the risk profile of retail banks. In terms of the social dimension, investment banks initially show a strong positive correlation with social factors, which gradually changes to a negative one over time, while retail banks are particularly sensitive to social factors due to direct consumer interactions. Investment banks show a consistent negative association with governance scores, while wholesale and retail banks display a positive association, benefiting from strong governance.

The relationship between ESG performance and credit risk is also proven significant in emerging markets. Du et al. (2017) analysed data on private firms in China, finding that lenders charged lower interest costs for firms with better environmental performance. Gong et al. (2018) discussed the relationship between ESG disclosure quality and bond financing cost in China, while Li et al. (2022) found that higher ESG ratings reduce default risk for Chinese listed companies, with the mitigating effect increasing with the maturity structure of default risk. Bhattacharya & Sharma (2019) studied the impact of ESG disclosure on credit ratings of Indian companies, showing that overall ESG performance positively impacts credit ratings, while the effect of governance scores is more marginal.

In conclusion, existing studies consistently demonstrate that ESG performance significantly affects credit risk. However, they primarily focus on high-level risk factors such as the cost of debt and credit ratings. Given the strong relationship between ESG performance and credit risk, it is both natural and reasonable to infer that ESG information contains additional information that not captured by other groups of variables and serves as a powerful alternative for modelling specific credit risk components including LGD. This study seeks to move a step forward and address the gap by leveraging ESG data specifically to model LGD to offer a more detailed insight into the impact of ESG factors on credit risk and extend the predictor list of LGD for a better predictive performance.

3 Data and Variables

The recovery data used in this study is derived from Moody's Default and Recovery Database (DRD). Moody's DRD provides the default history of US corporate bonds and has been widely used to analyse recovery rates in the US bond market (Chava et al. 2011, Yao et al. 2015, Qi & Zhao 2011). We construct our basic dataset by merging this recovery database with S&P's Compustat (for financial variables) and U.S, Federal Reserve Economic Database (for macroeconomic variables). It comprises 3,439 samples during 1989-2020, each representing a distinct debt instrument. We further combine this basic dataset with an additional data source of ESG information. We use the MSCI KLD database maintained by Wharton Research Database Services (WRDS), which is one of the ESG metrics that has been used most frequently by academics (Berg et al. 2022) and focuses on assessing the following dimensions: the environment, the community, corporate governance, product quality and safety, diversity, employee relations, human rights, and others (Eccles et al. 2020).[1] We manually matched these datasets based on obligors' names, tickers and CUSIP information. After carefully matching, we construct a unique sample consisting of 1,104 US corporate defaulted debt instruments over the period from 1992 to 2020. The variable list is displayed in Table 1. We will go through each variable group to explain

[1] Kinder, Lydenberg, and Domini (KLD) is the oldest values-driven ESG data vendor founded in 1988. It was acquired by RiskMetrics in 2009 and MSCI bought RiskMetrics in 2010. The data vendor was subsequently renamed to MSCI KLD.

Table 1: Original Variable List and Data Sources

Variable	**Description**	**Data Source**
Target Variable		*Moody's Default and Recovery Database*
LGD	Loss given default	
Debt-level Characteristics		*Moody's Default and Recovery Database*
ORIGINAL_AMNT	Original amount of principal	
EFFECTIVE INTEREST RATE	Effective interest rate	
Type	The type of the debt instrument (indicating senority)	
Maturity	The maturity of the debt instrument	
Industry	The obligor's industry	
Financial Ratios		*S&P Compustat*
Profitability	Profitability ratio	
LTR	Lont-term debt ratio	
DB	Default barrier	
ReveivableR	Receivable ratio	
IntangibleR	Intangible asset ratio	
ESG Information		*MSCI:KLD*
ENV_str_num	Number of ESG strengths in environmental aspect	
ENV_con_num	Number of ESG concerns in environmental aspect	
COM_str_num	Number of ESG strengths in community aspect	
COM_con_num	Number of ESG concerns in community aspect	
PRO_str_num	Number of ESG strengths in product aspect	
PRO_con_num	Number of ESG concerns in product aspect	
CGOV_str_num	Number of ESG strengths in corporate governance aspect	
CGOV_con_num	Number of ESG concerns in corporate governance aspect	
DIV_str_num	Number of ESG strengths in diversity aspect	
DIV_con_num	Number of ESG concerns in diversity aspect	
EMP_str_num	Number of ESG strengths in employment aspect	
EMP_con_num	Number of ESG concerns in employment aspect	
HUM_con_num	Number of ESG strengths in environmental aspect	
Other_con	Number of other ESG concerns	
Macroeconomic Variables		*U.S. St. Louis Federal Reserve*
DFF	Federal interest rate	
CPIAUCSL_PCH	Quarterly CPI percentage change	
UNRATE	Unemployment rate	
logR	Quarterly log return of S&P 500 Index	
GDP_PC1	Quarterly GDP percentage change	

Loss Given Default and Debt-Level Characteristics

Moody's DRD provides three ways to measure debt instruments' LGD: liquidity, settlement or trading price. For every instrument, Moody provides the recommended method for calculating the recovery rate, subject to the availability of the data. Each of them can be calculated in nominal amount or in discounted amount with the effective interest rate of the debt instrument. Here, we select the discounted amount with recommended measurement. We also truncate the part less than 0 to 0 and the part larger than 1 to 1. According to the definition of LGD, it can be calculated with the equation:

$$LGD = 1 - RR$$

Besides, Moody's DRD provides plenty of debt-level characteristics. According to the findings of existing literature, we include the effective interest rate of the instruments, their original borrowing amount, the maturity (measured by the time interval between the expiration date and the issue date), bond seniority (Yao et al. 2015), and obligor's industry (Chava 2014).

Financial Ratios

S&P's Compustat Database provides an enormous number of items on companies' financial statements. Here we import about 150 common items from companies' annual report which are often utilised to calculate financial ratios for evaluating the firms' financial and credit performance, such as total asset, total liability and sales turnover. Out of the consideration of controlling the number of independent variables to get rid of the curse of dimensionality, we follow the feature engineering practices of Jankowitsch et al. (2014) for financial ratios and generate five ratios to depict the obligors' financial condition at the year of default.

$$\textit{LTD Issuance} = \frac{\textit{Long-term Debt}}{\textit{Total Debts}}$$

$$\textit{Profitability} = \frac{\textit{EBITDA}}{\textit{Total Sales}}$$

$$\textit{Intangibility} = \frac{\textit{Intangible Asset}}{\textit{Total Asset}}$$

$$\textit{Receivables} = \frac{\textit{Total Receivables}}{\textit{Total Asset}}$$

$$\textit{Default Barrier} = \frac{\textit{Short-term Debt} + 0.5 * \textit{Long-term Debt}}{\textit{Total Asset}}$$

Macroeconomic Variables

We also incorporate several macroeconomic variables into our LGD models as they could significantly affect the default probability and recovery of debt instruments (Bellotti & Crook 2009, 2012, Yao et al. 2017). Here, we select five aspects to depict the macroeconomic environment when (or right before) the debt instruments were default: gross domestic product (GDP), consumer price index (CPI), unemployment rate, federal interest rate, and US equity index. They are commonly used in existing literature to help depict the macroeconomic environment from multiple dimensions to better predict LGD (Yao et al. 2015, Jankowitsch et al. 2014). Considering that the time span of this dataset is long and the levels of some indicators are not consistent or stationary, we mainly use quarterly percentage change to reflect whether the macroeconomic condition was getting better or worse. Besides, for interest rate and unemployment rate, we keep the original values because they are already informative. We use the macroeconomic data reported a quarter before the time of default, as macroeconomic indicators often have lagged effects on companies' financial conditions. The conditions a quarter prior might directly impact the firm's ability to manage debt and liquidity just before the default occurs. This time frame allows for capturing such lagged effects, providing a more accurate reflection of how macroeconomic changes translate into credit risk.

3.1 ESG Variables

MSCI: KLD is one of the longest continuous ESG database. It provides the relevant annual ESG information from 1991 to present. The specific ESG performance indicators in this dataset can be divided into eight sections: Environment, Community, Human Rights, Employee Relations, Diversity, Product, Governance Performance and Controversial Business Involvement. They jointly depict a company's ESG landscape. The first seven sections have both positive and negative indicators, revealing the advantages and weaknesses of the company in this category. Particularly, the Controversial Business Involvement section has only negative indicators, including whether the company is involved in some controversial business such as alcohol, firearms, gambling, military, nuclear power and tobacco.

MSCI: KLD has different coverage universes, each of which cover different company portfolio such as the components of MSCI USA Index, 1000 largest US companies or non-US companies. Due to data availability, each coverage universe may have different variables. In order to ensure the consistency of the data, we only choose the variables available in all universes with no change of concepts or definitions over time. This database provides yearly updated data of companies' ESG performance. In our study, we choose the ESG information reported in the year of the default for each company to better reflect companies' ESG circumstances.

Noting that the original ESG variables are too granular, we aggregate the raw ESG variables by summing the number of strengths/concerns in each section and output the numbers of strengths/concerns in social, environmental and corporate governance perspectives, according to the definition of ESG. This data aggregation process is consistent with the existing idea of analysing ESG information from its three pillars and avoids the possibility that original feature are too granular to generate meaningful result. Table 2 displays which original ESG variables are included in each engineered variables.

Table 2: Generated ESG Variables

Perspective	**Feature Engineering**
Environmental Concerns	E_con = ENV_con_num
Environmental Strengths	E_str = ENV_str_num
Social Concerns	S_con = COM_con_num + DIV_con_num+ PRO_con_num + HUM_con_num+ EMP_con_num + Other_con
Social Strengths	S_str = COM_str_num + DIV_str_num+ PRO_str_num + EMP_str_num
Company Governance Concerns	G_con = CGOV_con_num
Company Governance Strengths	G_str = CGOV_str_num
ESG Overall	$\sum$ Strengths $-$ $\sum$ Concerns

3.2 Explorative Data Analysis

First of all, we output the descriptive statistics of continuous variables. Table 3 displays the mean value, standard deviation and selected key percentiles of debt-level characteristics. From the the table we understand that the debt samples in this dataset generally have high interest cost (7.49% as the average interest rate) and long maturity (9.65 years as the average maturity). Also, because the debt samples are coming all from large default events in the US, the average principal amount is about 408 million dollars.

Table 3: Descriptive Statistics for Debt Level Characteristics

	Original Amount	**Interest Rate**	**Maturity**	**LGD**
count	1104	1104	1104	1104
mean	408.7369	7.4899	9.6517	0.4525
std	567.4903	2.8190	6.8676	0.3777
min	0.0000	0.0000	0.0000	0.0000
1%	0.0000	1.1645	1.0000	0.0000
5%	2.0000	2.8750	2.7605	0.0000
25%	100.0000	5.6785	5.0300	0.0000
50%	250.0000	7.5000	8.0000	0.4664
75%	500.0000	9.3750	10.0200	0.7935
95%	1377.0865	12.0000	24.9910	0.9956
99%	2297.3360	14.8691	30.1373	1.0000
max	7550.0000	18.0000	60.0300	1.0000

Table 4 displays the descriptive statistics for financial ratios and engineered ESG variables. Different from the sample number in Table 3 (1,104), in this table, the sample number shrinks to 210, because one company can issue multiple bonds at a time with different debt-level characteristics and get them all defaulted. We can find the financial situation of these companies, right before their defaults, looks not promising generally. The profitability ratio has mean of -0.3 and median of 0.005, which means almost half of the companies have serious profitability problem, some of which even had very bad loss. The statistics of two debt-related ratios, *LTR* and *DB*, also tell that the average debt level are relatively high even after adjusting the weight of long-term debt and that more than half of the companies might face liquidity shock, as their LTR is less than 50%. For ESG variables, from the key percentiles of which we can see that most of companies has 0 scores in each specific area of ESG. Because most aspects of ESG strengths/concerns are categorised into social perspective, *S_str* and *S_con* have significantly larger range regarding the values, compared with other four ESG variables.

Table 4: Descriptive Statistics for Financial Ratios and ESG Variables

	Count	**Mean**	**Std**	**Min**	**1%**	**5%**	**25%**	**50%**	**75%**	**95%**	**99%**	**Max**
Profitability	210	-0.3010	1.1291	-7.0731	-6.0216	-2.2680	-0.0950	0.0050	0.0644	0.1692	0.3294	0.4165
LTR	210	0.4355	0.3135	0.0	0.0	0.0	0.1161	0.4940	0.7266	0.8752	0.9107	0.9201
DB	210	0.7070	0.5756	0.0069	0.1803	0.2549	0.4228	0.5766	0.8088	1.6164	2.9162	5.0814
IntangibleR	210	0.1440	0.2064	0.0	0.0	0.0	0.0	0.0496	0.2157	0.6343	0.7639	0.8989
ReceivableR	210	0.1017	0.0921	0.0	0.0	0.0117	0.0381	0.0690	0.1367	0.3129	0.3963	0.4560
S_str	210	0.7476	1.6853	0.0	0.0	0.0	0.0	0.0	1.0	3.0	8.9100	12.0
S_con	210	1.1667	1.3182	0.0	0.0	0.0	0.0	1.0	2.0	3.0	6.0	7.0
E_str	210	0.1429	0.4778	0.0	0.0	0.0	0.0	0.0	0.0	1.0	2.9100	3.0
E_con	210	0.2476	0.6817	0.0	0.0	0.0	0.0	0.0	0.0	2.0	3.0	4.0
G_str	210	0.0905	0.3191	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	2.0
G_con	210	0.3238	0.5446	0.0	0.0	0.0	0.0	0.0	1.0	1.0	2.0	3.0
ESG_Overall	210	-0.7571	2.2098	-7.0	-6.91	-4.0	-2.0	0.0	0.0	2.0	4.0	12.0

Existing literature reveals that the ESG can have significant impact on firms' financial performance, which means these two section of variables may correlated and thus bring downside influence to the model. Therefore, we check the correlations between financial ratios and ESG variables (as well as the correlations within the financial ratios and ESG variables). Figure 1, the heatmap of correlation among variables, shows the maximum value (regarding the magnitude) of correlation is -0.26 between long-term debt ratio and social concerns, which is acceptable for multicollinearity for the modelling. Also, because this paper stays in predictive paradigm, the discussion of endogeneity problem, which is very common in studies examining causal relationships between independent variables and dependent variable, is not included.

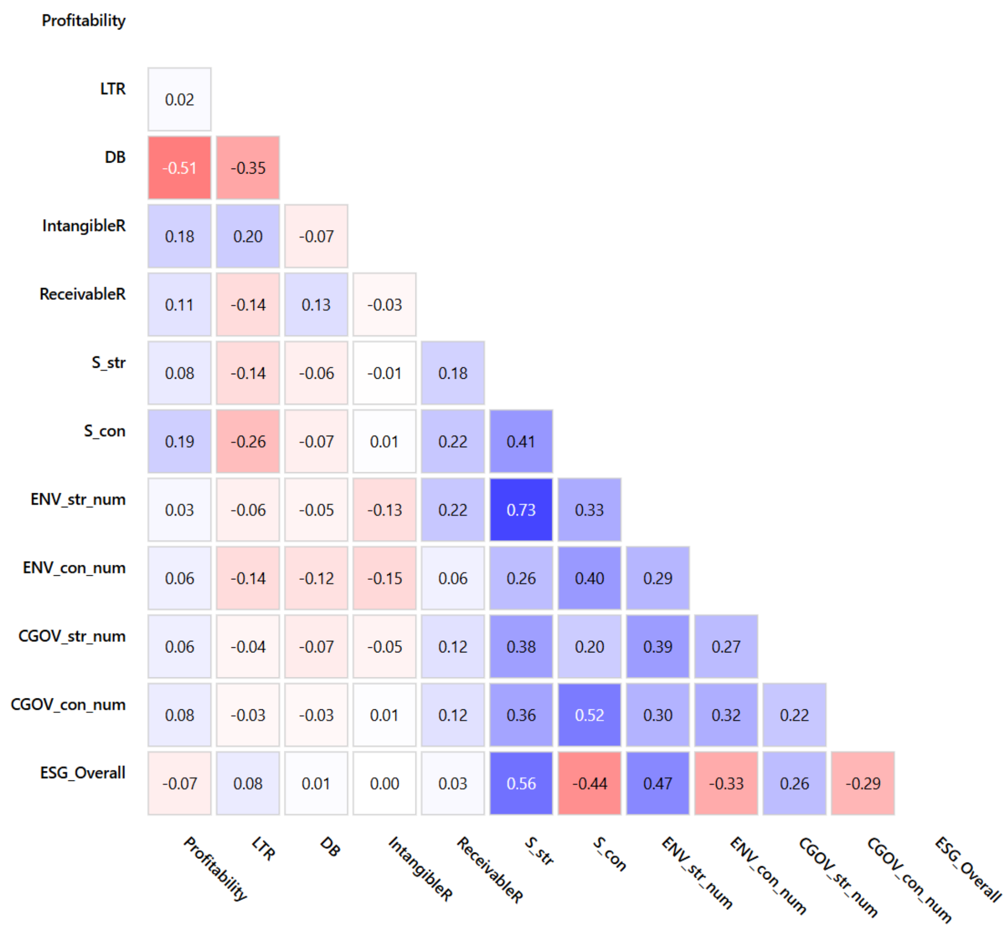


Figure 1: Correlation Heatmap of Financial Ratios and ESG Variables

Also, within the ESG variable group, we find that the pair correlations of perspective variables are all positive, which means a company with higher ESG strength scores tends to have higher ESG concerns as well and vice versa. One possible explanation is that, companies with higher ESG concerns are more motivated to mitigate the negative company ESG profile by practising more positive ESG measures. Admittedly, some mid-level correlation (approximately 0.5) pairs among ESG variables are spotted in the figure, exposing some multicollinearity. However, for our main model truncated GBDT, a rule-based ensemble model focusing on the single feature's predictive power on the target variable instead of the interaction among independent variables, this issue can be ignored. Incorporating the constructed variable *ESG_Overall* is particularly for the sake of feature intepretability. At the end of this section, we offer a correlation heatmap with a correlation value annotated between each ESG features and the target variable LGD respectively, see Figure 2. The result tells 6 out 7 ESG variables are all negative correlated with LGD, except from the number of concerns of corporate governance perspective *CGOV_con_num*.

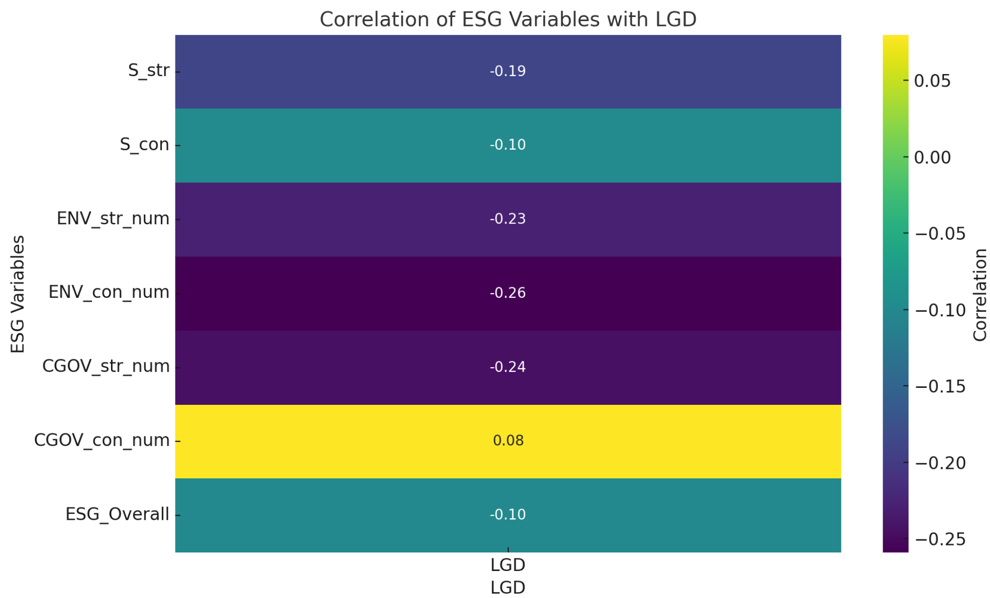


Figure 2: Correlation Heatmap - ESG Variables vs. LGD

4 Experiment Design

In this section, we will go through every aspect of our experiment design, from the data preprocessing, the main model, to the evaluation metrics and the model interpretability method we utilise to help analyse the empirical result.

4.1 AutoEncoder for Feature Extraction

In this study, multiple groups of features are included in the modelling task, in order to reduce the number of features, especially those important but irrelevant to the research questions, we use AutoEncoder to do feature extraction. An AutoEncoder is a neural network model that seeks to learn a compressed representation of an input (Ng et al. 2011). It has two components, an encoder and a decoder. Encoder-Decoder models are a family of models which learn to map data points from an input domain to an output domain via a two-stage network: The encoder, represented by an encoding function $z = f(x)$, compresses the input into a latent-space representation; the decoder, $y = g(z)$, aims to predict the output from the latent space representation (Ng et al. 2011). The AutoEncoder can be leveraged to do feature extraction (Zabalza et al. 2016). Once the AutoEncoder is trained, the decoder is discarded and we only keep the encoder and use it to compress examples of input to vectors output by the bottleneck layer (the last layer in the encoder).

Before feeding the data into the autoEncoder, the data must be scaled between 0 and 1 using MinMaxScaler, because we will use the Sigmoid activation function in the output layer, which outputs a value between 0 and 1. We use a non-symmetrical architecture of AutoEncoder, the specific layer setting is described in the Table 5.

Table 5: The Architecture of the AutoEncoder

	Architecture
Encoder	Dense Layer, 32 neurons, Activation function = ReLu
	Dense Layer, 16 neurons, Activation function = ReLu
	Dense Layer, 8 neurons, Activation function = ReLu
	Dense Layer, 1 neurons, Activation function = ReLu
Decoder	Dense Layer, 16 neurons, Activation function = ReLu
	Dense Layer, 32 neurons, Activation function = ReLu
	Dense Layer, # of features, Activation function = Sigmoid

Particularly, in AutoEncoder, the number of output units must be equal to the number of input units since we are attempting to reconstruct the input data. Also, the number of neurons in bottleneck layers depends on how many feature we would like to have after extraction. In this study, we fix the bottleneck layer with only 1 neuron, because the main purpose of this AutoEncoder model is to provide a single value acting as a score to substitute certain groups of original features. In the experiment, the compressed features are from debt-level characteristics. They are proven the most effective predictors in existing studies. Particularly, for categorical variables, we use one-hot encoding transforming it from classes to a sparse matrix first. Then compress it with other continuous variables.

4.2 Truncated Gradient Boosting Tree Regressor

Gradient boosting decision tree (GBDT) is a very popular and powerful model in different machine learning tasks. It also shows great predictive performances in credit risk modelling context. The mathematical derivation of GBDT is stated below. For dataset $\{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$, and a differentiable loss function $L(y_i, F(\mathbf{x}))$ (squared error for this regression task), the gradient boosting tree regressor initiate its base learner with a constant value, i.e.,

$$F_0(\mathbf{x}) = \underset{\gamma}{\mathrm{argmin}} \sum_{i=1}^{n} L(y_i, \gamma)$$

Then, for $m = 1$ to M, the model compute

$$r_{im} = -[\frac{\partial L(y_i, F(\mathbf{x}_i))}{\partial F(\mathbf{x}_i)}]_{F(\mathbf{x})=F_{m-1}(\mathbf{x})}$$

for $i = 1, ..., n$ and fit a regression tree to the r_{im} values and create terminal regions R_{jm}.

For $j = 1, ..., J_m$, the model computes

$$\gamma_{jm} = \underset{\gamma}{\mathrm{argmin}} \sum_{\mathbf{x}_i \in R_{ij}} L(y_i, F_{m-1}(\mathbf{x}_i) + \gamma)$$

At the end of each iteration for $m = 1$ to M, update

$$F_M(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \beta_m \sum_{j=1}^{J_m} \gamma_{jm} I(\mathbf{x} \in R_{jm})$$

where $beta$ is the weight and the final predictor of gradient boosting tree regressor is $F(\mathbf{x})$. On the top of this gradient boosting tree regressor, we use truncated setting to better estimate LGD. The truncation setting makes the prediction of LGD bounded in $[0, 1]$, i.e.,

$$\hat{y}_T = \min(\max(0, \hat{y}), 1)$$

where $\hat{y}$ is the predicted LGD and $\hat{y}_T$ is the predicted LGD after truncation. This simple method makes the predictions fits the LGD distribution well because the truncation makes the prediction values accumulate at 0 and 1 (Starosta 2021). Also, the gradient boosting tree classifier will be applied to examine the relationship between ESG information and LGD in the context of multi-stage modelling framework. The classifier follows the same methodology as the regressor except from the classifier's loss function is cross-entropy instead of squared error. We use GBDT because it effectively captures non-linear relationships in data, which traditional linear models often fail to do. Additionally, GBDT is robust to outliers due to its iterative boosting framework that minimizes their influence during training. As a rule-based model, GBDT constructs decision trees that split data hierarchically, making it inherently resistant to multicollinearity issues, unlike linear models that may struggle with highly correlated predictors. These features make GBDT a powerful and flexible tool for modelling complex LGD datasets.

4.3 Sample Selection and Dataset Splitting

The selection of samples and their allocation into training and testing sets plays a critical role in ensuring the validity and robustness of the experiment. This study employs both out-of-time split and out-of-sample split approaches to evaluate the predictive performance of models under different conditions and to analyse the significance of various feature groups, particularly ESG information.

Out-of-Time Split

For the out-of-time split, the dataset is arranged chronologically to preserve the temporal sequence of events, reflecting real-world scenarios where past data is used to predict future outcomes. The dataset is divided into a training set and a testing set in a 7:3 ratio. The training set comprises older data, while the testing set contains more recent data. This approach emulates situations where models are required to generalise insights from historical data to new, unseen data. The out-of-time split accounts for the potential structural changes in data over time, such as variations in financial regulations, shifts in macroeconomic conditions, or changes in market dynamics. As the statistical characteristics of the training and testing sets may differ significantly, this divergence presents a realistic challenge that emphasizes the importance of robust models capable of adapting to temporal shifts.

Out-of-Sample Split

In the out-of-sample split, the dataset is randomly partitioned into training and testing sets, also in a 7:3 ratio. By mixing samples from various time periods, this approach ensures that the training and testing sets share similar statistical distributions. Consequently, models can better leverage patterns learned from the training set to achieve higher predictive accuracy on the testing set. While the out-of-sample split improves predictive performance, it may obscure temporal dynamics, such as the evolving influence of ESG variables or financial ratios.

4.4 Evaluation Metrics and Model Intepretability

LGD modelling is a typical regression problem with the dependent variable bounded within [0,1]. Therefore, two standard performance measures for regression, mean squared error (MSE) and mean absolute error (MAE), are applied.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

In this study, SHAP (SHapley Additive exPlanations) is utilised for explaining the prediction results of our gradient boosting tree model (Lundberg & Lee 2017). SHAP has been one of the most popular model for explaining predictions. It is based on the concepts from cooperative game theory and local explanations. Given a set of players, cooperative game theory defines how well and fairly to distribute the payoff amongst all the players that are working in coordination. The analogy here is: players are equivalent to independent features and payoff is the difference between the average prediction of the instance minus the average prediction of all instances. Mathematically, given a predictive model f and an instance x, SHAP values are calculated by considering the contribution of each feature to the difference between the actual prediction and the average prediction over the dataset. The formula for the SHAP value ϕ_i for feature i is defined as follows:

$$\phi_i(f,x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}\left(f_x(S \cup \{i\}) - f_x(S)\right)$$

where F is the set of all features, S is a subset of features excluding i, $|S|$ is the number of features in subset S, $f_x(S)$ is the prediction of the model f when only the features in set S are used, and $f_x(S \cup \{i\})$ is the prediction of the model f when the features in set S and the feature i are used. In particular, SHAP is a model-agnostic technique, which means it is an independent approach for model explanation. It is extremely important and helpful when we use complex non-linear models. In addition, SHAP works very well with tree-based models.

5 Result

5.1 How ESG Information Helps Estimate LGD

In the first experiment, we use only the original features. With debt-level characteristics fixed, we experiment the predictions with different groups of variables.

Table 6: Modelling Performance with Different Variable Groups (***indicating all pairs with this model are significantly different at 99% level)

Out-of-time Split							
	All	**No ESG**	**No Fin**	**No Macro**	**ESG**	**Fin**	**Macro**
MSE	0.1046***	0.1173***	0.0996***	0.1119***	0.1085***	0.1323***	0.1142***
MAE	0.2665***	0.2828***	0.2614***	0.2739***	0.2716***	0.3062***	0.2804***
Out-of-sample Split							
	All	**No ESG**	**No Fin**	**No Macro**	**ESG**	**Fin**	**Macro**
MSE	0.0449***	0.0458***	0.0492	0.0495	0.0693***	0.0498	0.0517***
MAE	0.1369***	0.1387***	0.1489***	0.1500***	0.1896***	0.1520***	0.1547***

From Table 6, we can find that the model without financial variables realised the best performance regarding both MSE and MAE, followed by the model with all types of variables. Since we have not conducted any dimensional reduction method, we can attribute this circumstance to the overfitting caused by overwhelming number of features. Then we exclude ESG variables, financial ratios, and macroeconomic variables one at a time, and only incorporate one of them one at a time to test the marginal effect contributing to the model performance of each feature group. The result reveals that excluding ESG variables can lead to largest performance decline and including ESG variable alone can achieve the best performance. In order to make the result more robust, we trial 1,000 times with different hyperparameter combinations and do the paired T-test to check whether the average modelling performance for each setting are significantly different.

With out-of-sample split approach, the result is highly different from that of with out-of-time split. First, the overall predictive accuracy is higher. Because out-of-sample approach mixes up the samples in different time period well, the data distributions of the training set and of the testing set are tends to be similar without structural change. Therefore the model can better apply what it learns from the training set to the testing set thus harvest a better predictive accuracy. On the contrary, out-of-time approach lets the model learn from the old data and apply it to the new data. The samples in different time periods can be very different regarding their statistical characteristics, which can be triggered by many real-life factors such as the shift of financial regulations and policies, as well as the change of macroeconomic environment. Second, the ESG variable becomes less important according to the marginal contribution to the predictive accuracy. Although with all three groups of variables available the model achieves the best performance. ESG variable group alone performs the worst result among all three groups. And excluding the ESG variables costs the minimum performance sacrifice of the model. Instead, financial ratios show their robustness and effectiveness in LGD modelling,

Next, by examining the feature importance plot of built-in function of gradient boosting tree as well as the SHAP summary plot, we find that every single ESG variable cannot rank at top places, because not only each feature only has limited information, but also the debt-level characteristics such as are very significant to LGD. For example, the effective interest rate can provide an overview of the risk level of the debt instrument, as well as the seniority determines the payback priority of the debt. Therefore, we then use AutoEncoder to extract debt-level information from original features and integrate it to a single value, in this case, debt-level information, as the dominant group of variables, will not shadow the importance of other features. Moreover, the information of categorical variables generated by one-hot encoding can be reserved while getting rid of the problems caused by high dimensional data. From the Table 2 we can notice that, apart from environmental strengths/concerns and corporate governance strengths/concerns themselves, all other features can be categorised into social perspectives, following the definition of ESG (Gillan et al. 2021). Therefore, social perspective is expected to gain higher feature importance than other two perspective within ESG due to the data availability.

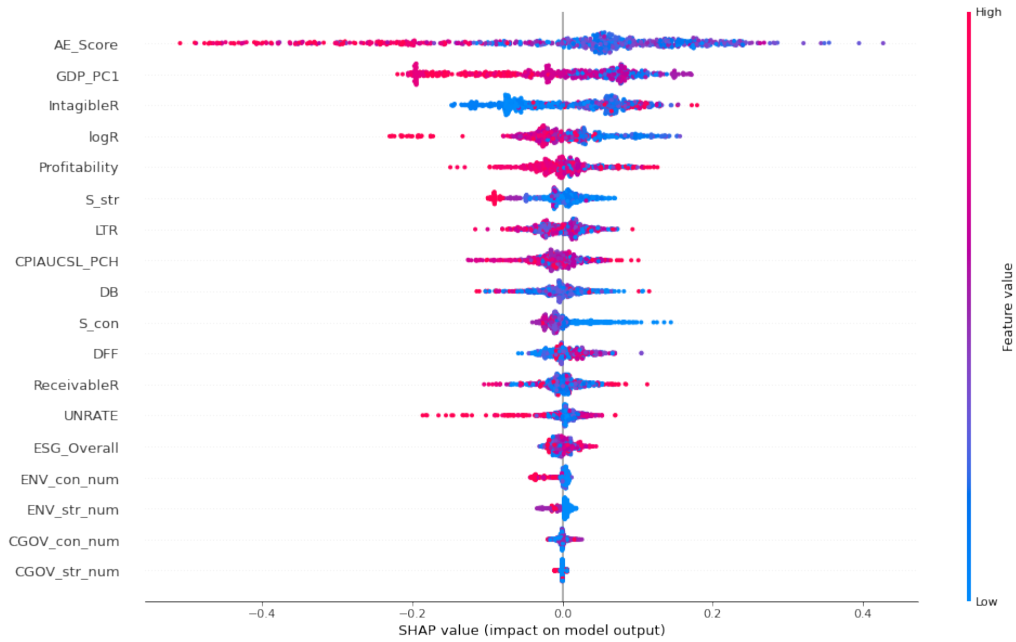


Figure 3: Summary Plot of SHAP for Base Model

The regression result further proves this assumption. With all training samples, social strength plays the most important role among all ESG variables and ranks 6/17 among all variables regarding the SHAP value. And red dots (samples with high feature values) are concentrated on the left hand side of the plot, indicating social strength has negative impact on the LGD – the higher social strength scores the issuer has, the lower LGD the debt instrument can realise. Number of social concerns ranks the second place within the ESG variable and 10/17 among all variables. Other 5 ESG features are at the bottom in the summary plot, including the companies' overall ESG evaluation **ESG_Overall**. Some macroeconomic variables and financial ratios provides strong predictive power but the extracted debt score generated by the AutoEncoder still ranks top. After examining the ESG variables' feature importance in modelling LGD generally, in the next few subsections we will go further to check how their importance are correlated with other variables and how these variables' predictive power fluctuate over time.

5.2 LGD Modelling Segmented by Seniority

In this section, we segment the original dataset into two sub-datasets, according to samples' seniority information, following the idea of Yao et al. (2015) to accommodate unobservable heterogeneity of bond seniorities. Because the seniorities of the bonds are naturally important to estimate the LGD as they decide which bonds are paid back first and which bonds are paid back later once the defaults occur Table 7 shows the mean LGD and the number of samples in each seniority class and reveals the seniority does play an important role in determining the LGD.

Table 7: Mean LGD for Each Seniority Subgroup

TYPE	**Mean LGD**	**Count**
Junior Subordinated Bonds	0.9746	7
Revolver	0.1201	169
Senior Secured Bonds	0.4544	217
Senior Subordinated Bonds	0.7934	43
Senior Unsecured Bonds	0.5763	477
Subordinated Bonds	0.7374	23
Term Loans	0.2846	168

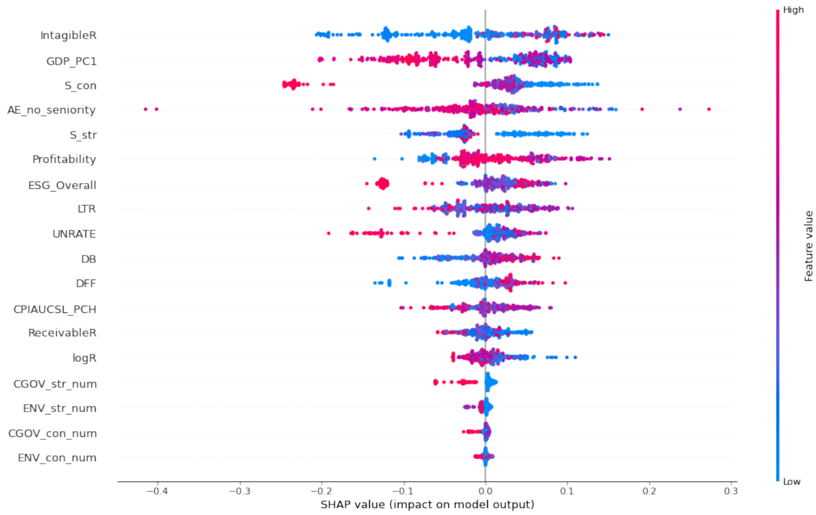
In general, from mean LGD perspective, we can find **Revolver** $<$ **Term Loan** $<$ **Senior Secured** $<$ **Senior Unsecured** $<$ **SubordinatedSenior Sub** $<$ **Junior Sub**, which is consistent with our expectation regarding the relationship between seniority and LGD: debts in the higher priority level tend to be repaid if the company goes out of business and thus have lower LGD on average. Based on this information, we divide the original dataset into two sub-datesets, the SECURED one contains those senior debt types whose mean LGD is less than 0.5 (554 samples), and the other contains those unsecured and junior level debt samples (550 samples), whose average LGD is larger than 0.5.

Table 8: Modelling Performance in Seniority Segmentation

	Secured	**Secured w/o ESG**	**Unsecured**	**Unsecured w/o ESG**
MSE	0.1983	0.1920	0.1076	0.1134
MAE	0.3596	0.3541	0.2685	0.2745

Table 8 reveals that with same setting of predictors, for unsecured segment, the model has significantly better predictive performance. In order to better evaluate the impact of ESG information on the segmentation models, we also experience with models without ESG variables. For secured segmentation, modelling without ESG information can even harvest better prediction accuracy on test set. On the other hand, with ESG information, unsecured segment achieved better predictive accuracy with respect to both MSE and MAE.

Summary plots of SHAP for different segmentations shows significantly different results (see Figure 4). For secured debt instruments. Debt-level characteristics plays an important role in making predictions, followed by several financial ratios and macroeconomic variables. The top ESG related feature only ranks 8/17 (social concerns) and the rest of them are ranked at the bottom. This can explain why ESG variables undermine the overall predictive accuracy for secure segment – ESG information has only small contribution to the regression task, however, the introduction of the variables add the complexity of data and potentially cause the overfitting. While for unsecured debt instruments, social concerns ranks 3/17 among the all features, followed by social strengths (5/17). Not only social perspective, environmental strength and corporate governance strength also move forward from the bottom (compared with secured segment). The discrepancy can be explained from the actual business characteristics of the different bonds. For example, the secured bonds are usually with own collateral or guaranteed by the third party (credit enhancement). Once the default occurs, the ultimate LGD largely depends on the present value of the collateral or the asset from the guarantors. While for the junior bonds with no collateral and guarantors, the ultimate LGD relies more on the obligors' own situation. Figure 4 also shows this point: extracted debt-level information AE_no_seniority ranks at the top in the SECURED section but only 4/17 in UNSECURED section. So the takeaway here is that ESG information works better with the unsecured/junior-level debts regarding both the predictive accuracy and the feature importance.



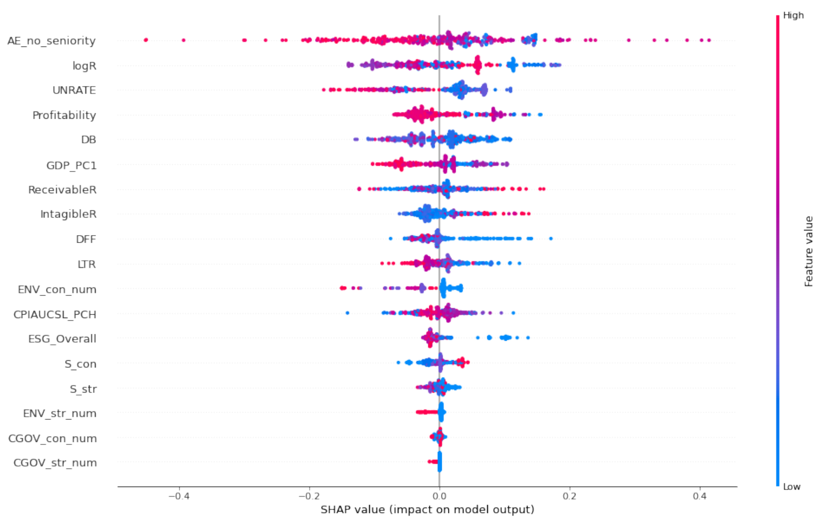


Figure 4: Summary Plots of SHAP, Unsecured (Top) vs Secured (Bottom)

5.3 LGD Modelling Segmented by Industry

Another segmentation modelling attempt is based on another variable, INDUSTRY, which is closely connected with ESG performance. Environmentally responsible performance plays an important role in evaluating a company's ESG performance, and this perspective is relatively easier to be measured because the nature of the business usually has strong correlation with it. Therefore, based on the type of industry the debt issuer are, we divide the whole samples into two groups: Green (potentially light environmental pollution) industry and Brown (potentially heavy environmental pollution) industry. Specific categorisation can be referred to Table 9. For each segment, LGD distribution with class mean LGD is displayed to Figure 5, revealing that there are more fully recovered cases in brown industry and more fully lost samples in green industry.

Table 9: Count for Different Industry Segments

Segmentation	**Industry**	**Count**
	Telecommunications	
	Media	
	Retail	
	Consumer Products	
	Technology	
	Services	
Green	Distribution	436
	Packaging	
	Gaming: Casinos	
	Healthcare	
	Restaurants	
	Retail: Speciality	
	Natural Products	
	Energy	
	Transportation	
	Automotive	
	Manufacturing	
Brown	Chemicals	668
	Metal & Mining	
	Construction	
	Pharmaceuticals	
	Aircraft & Aerospace	

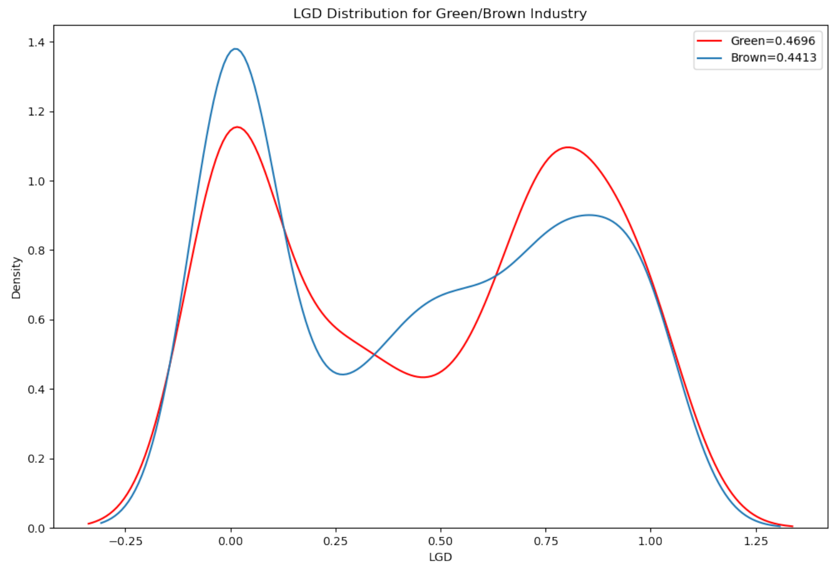


Figure 5: Density Plot for LGD in Green/Brown Industries

The Table 10 below shows the predictive performance for different industry segments. Overall, with the same information, the model is better at estimating samples in heavy industry. Different from the situation of seniority segmentation, here we find ESG information helps for both segments.

Table 10: Modelling Performance in Industry Segmentation

	Brown Industries	**Brown Industries w/o ESG**	**Green Industries**	**Green Industries w/o ESG**
MSE	0.1754	0.1816	0.2165	0.2303
MAE	0.3346	0.3385	0.3692	0.3860

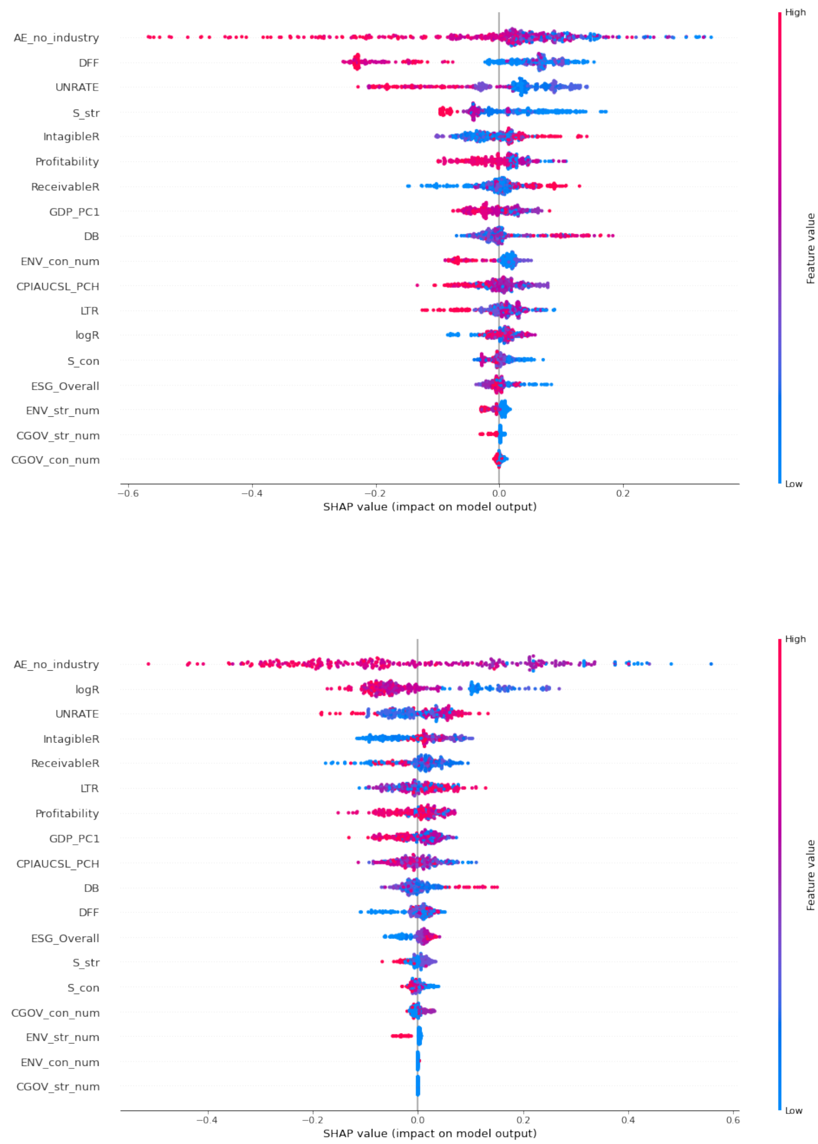


Figure 6: Summary Plots of SHAP, Brown Industries (Top) vs Green Industries (Bottom)

Down to the model interpretation, for brown segment (left in Figure 6 below), social strength still dominate the ESG variables and ranks 4/18 among all variables. It displays clearly negative impact with the target variable LGD. For environmental perspective, which is the main ESG information we focus in this segmentation modelling part, it did not contribute much to the predictive accuracy. Following social strengths, environmental concern is the second important ESG variables in predicting LGD and ranks 10/18 with a slight negative impact on LGD, which is not consistent with our expectation that environment concerns should increase the risk thus results in higher LGD. In order to find the explanation to this situation, we print out the dependence plot of SHAP for the feature environment concerns (see Figure 7). The plot automatically select the variable interacted with the feature environment concerns the most and colours the sample points according to the feature values. Social strengths interacts with the environment concerns the most and it is a more powerful predictor regarding the impact magnitude on LGD, noting that these two variables are positively correlated (see Figure 1). The impact direction of less effective variable is masked by that of stronger one due to their interrelationship. Environmental strength only gets 16/18. Compared with the base model in Section 5.2, the samples within brown industry segment do have more sensitivity to the environmental perspective. For green segment, all six ESG variables ranks at the bottom of all variables, indicating that for modelling the LGD of tertiary sector of the economy, ESG information plays a less pivotal role. The overall ESG score ranks the first place within ESG variable group. But it's revealed as a positive correlation. Following the same strategy, we use the dependence plot of ESG overall score (see Figure 8) and find that long term debt issuance ratio interacts with ESG overall score the most. And LTR has a negative correlation with LGD, which is consistent to the sign of coefficient shown in Jankowitsch et al. (2014). However, social perspective (both concerns and strengths) contribute more to the total predictive accuracy than other ESG perspective. It is in consistent with people's perception that social responsibility issues (e.g. user privacy, employment benefits, and diversity) for these companies have been major concerns. Also, because companies in defined green industry have less business directly interacting with the environment, the contribution of environmental concern is trivial, however, the summary plot also indicates that doing good to the environment relates to lower LGD.

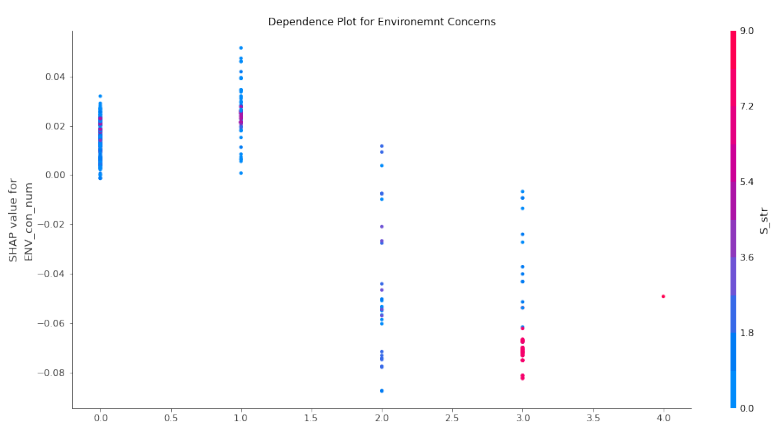


Figure 7: Dependence Plot for Environment Concerns

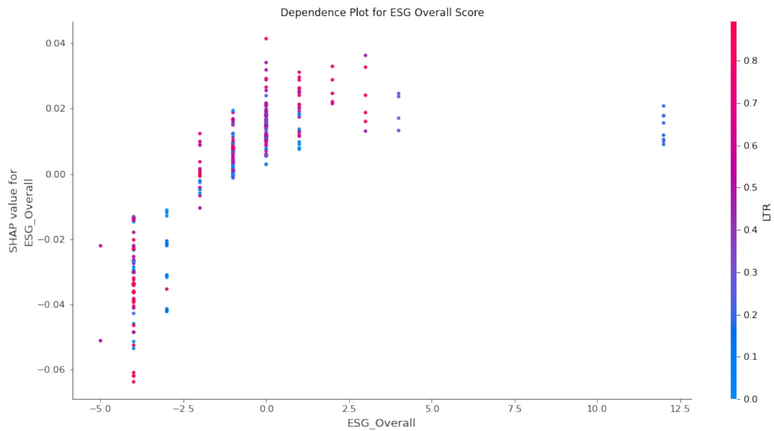


Figure 8: Dependence Plot for ESG Overall Score

5.4 ESG Information in Multi-Stage Modelling Framework of LGD

Considering the characteristics of LGD distribution, which lies in range [0,1] and sometimes has multiple modes, we introduce multi-stage modelling framework. Multi-stage modelling framework for estimating LGD was firstly proposed by Bellotti & Crook (2012). It turns the regression task over a complicated distribution into a series of classification problems followed by a regression task over a relatively simple distribution. There are several studies following this modelling framework of LGD estimation with great modelling performance (Yao et al. 2017). Based on the finding in Data section, we categorised the samples into three class: *Fully Recovered*, *Fully Lost* and *In Between*. Figure 9 shows the T-SNE visualisation of the dataset based on the two most significant components with dots coloured for different classes. The visualisation shows that although the idea of firstly categorising LGD samples into some subgroups could help elevate the predictive accuracy, the real classification task can be very difficult as we can see there are serious overlapping among different classes. Depending on the patterns of the modes in different LGD datasets, the settings of multi-stage modelling vary. One can divide the whole sample sets into fully lost samples and the rest of samples, while the other can divide the whole samples into full recovered samples and the rest of samples.

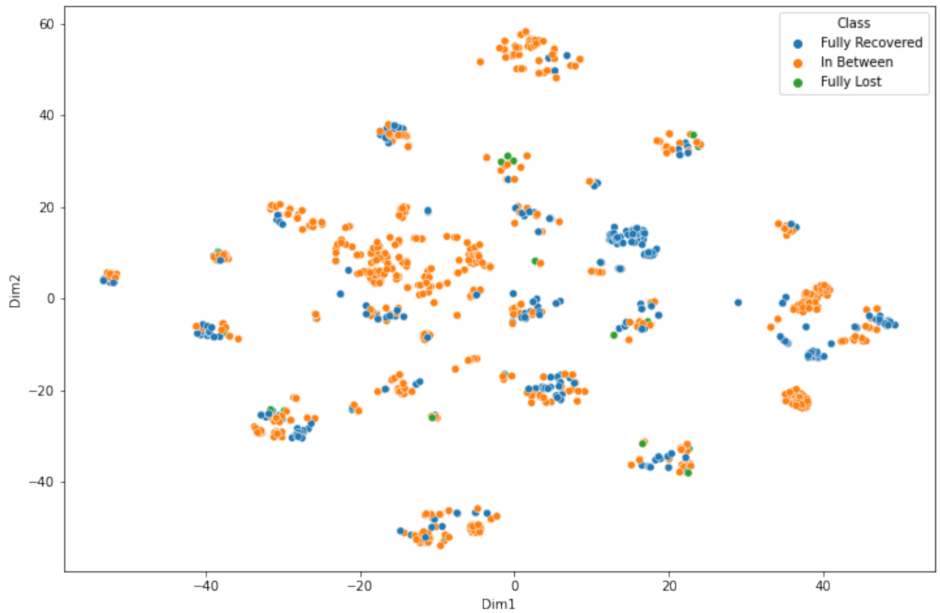


Figure 9: Spatial Visualisation of Three Types of Loss by T-SNE (Fully Recovered: 233, Fully Lost: 28, In Between: 743)

The core of multi-stage modelling of LGD is to simplify complicated distribution by making a classification to remove one of the modes prior to the final regression. In this section, we will explore how ESG variables help classifying these categories one from the others in this early stage tasks. We establish three models: classifying Fully Recovered samples from the others, classifying Full Lost samples from the others, and classifying In Between samples from the others. As for the classification tasks, we use the Area Under Curve (AUC) as the evaluation metric. Because of different imbalance ratios of the three tasks, the classification performances of the three models vary significantly. Table 11 reports the classification performance of three model with and without ESG variables. The result shows that for all classification tasks, incorporating ESG information can boost the predictive performances. All results reported here are the mean value of 1,000 trials and the differences are significant with the pair T-tests.

Table 11: How ESG Information Boosts Classification in Multi-Stage Modelling (AUC)

	Find Fully Lost	**Find Fully Recovered**	**Find In Between**
With ESG Variable	0.6660	0.8680	0.8338
Without ESG Variable	0.5794	0.8395	0.8007
Absolute Improvement	0.0866	0.0285	0.0331
Percentage Improvement	14.94%	3.39%	4.13%

Here we also focus on the relationship between ESG variables and LGD in the modelling so that we plot SHAP summary plots here for analysis (see Figure 10) as well. From the plot we see that corporate governance concerns CGOV_con_num ranks top three in both classifying both Fully Recovered samples and In Between samples. While social concerns is associated with higher importance to distinguish the Fully Lost ones from the others. This result furthers our previous findings that ESG variables becomes more important when predicting riskier samples/subgroups. Giese et al. (2021)'s study about deconstructing ESG into E, S, and G reveals that although the practices of corporate governance perspective can have immediate effect on company's value, social and environmental perspectives contributes to the companies more in the long run, therefore they are associated with higher significance. It supports our finding that more important perspective of ESG works better with riskier samples.

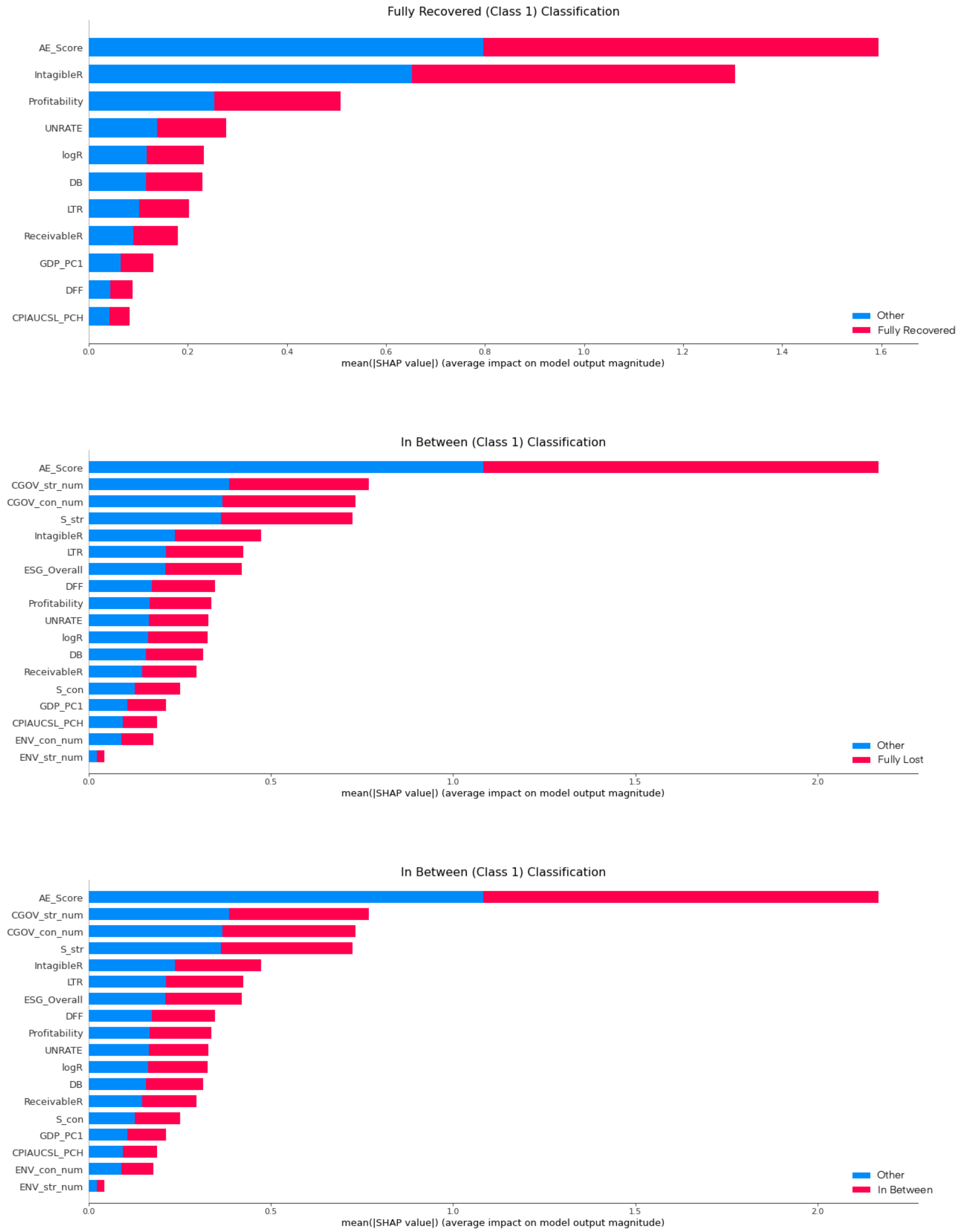


Figure 10: Summary Plots of SHAP for Different Multi-stage Classifier Settings

5.5 Does the Importance of ESG Information Become Higher or Lower in Modelling LGD?

From the section 3.5.2, we observe that the performance of LGD modeling using ESG information fluctuates over time. In order to find out how the relationship between ESG variables and LGD has changed over time. In the last section, we use a rolling window regression method to explore how the relationship changes. We set a rolling window with 300 training samples and 60 testing samples and move the window month by month. First, keep the model settings constant, we record the predictive performance for each window and output how MSE and MAE changes over time in figure 11. We can see that during the 2008-09 financial crisis and immediate post-crisis period, the overall modelling error is higher than other that of other period. The crisis makes the financial risk contagious in the corporate bond markets and results unexpected default and recovery events (Longstaff 2010). Therefore, the predictive power of these variables temporarily decreases.

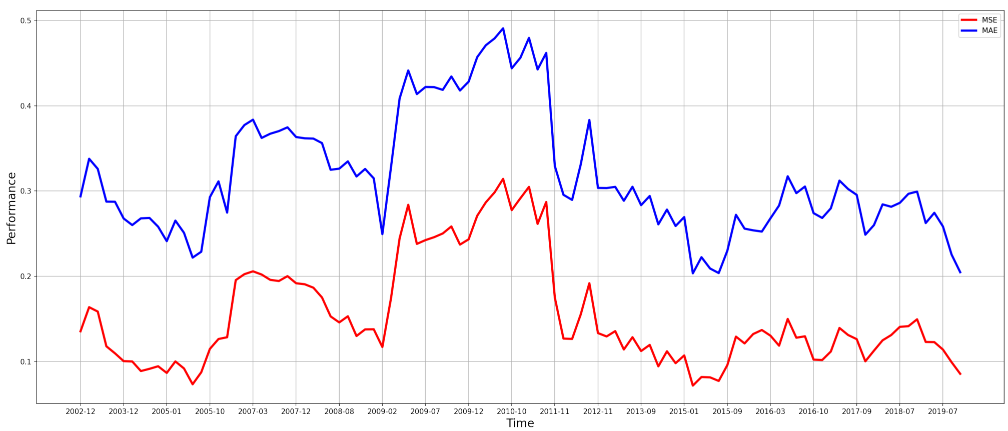


Figure 11: The Change of Predictive Performance of Selected Variables Over Time

Figure 12 depicts how 7 ESG variables' feature importance, which is measured by the ranking of SHAP values, change over time. The higher value means higher importance. The first takeaway from this plot is that, recently, the predictive power of ESG variables has been diminishing, as after 2011-11 lines of ESG variables are concentrated on the lower right corner. Second, by looking at specific lines, we have more findings about each ESG feature. On average, the two most significant features are social strengths (red line) and social concerns (yellow line). In particular, the change of feature importance of social concerns over time have two peak times, one is around 2007-12 and the other is around 2010-10, which are exactly the time periods the model has the lowest predictive performance due to the external macroeconomic shocks. It means during the time that predictors generally become ineffective in modelling LGD, the social perspective information of ESG becomes more reliable and important in estimating LGD. On the other hand, in the several years after the financial crisis, with a new wave of economic growth, the ESG variables becomes less important. Third, environmental strengths (green line), although was quite trivial at the beginning, but within the time span, the feature importance of which has been gradually going up. On the contrary, we notice that environment concerns (blue line) and corporate governance concerns (pink line) play a vital role in modelling LGD at the beginning, but they quickly fall down to the bottom of feature importance ranking later. This situation is different from the conclusion from the previous study of ESG that concerns usually have larger impact than the strengths. We do not exclude the possibility of it caused by the small size of data, and this situation requires further examination. Last but no least, the black line, overall ESG score, has no clear trend of becoming more/less important but it fluctuates much around a low mean feature importance. Combined with the results in previous sections, we find that overall ESG profile alone does not have much predictive power. Because after netting all the perspective, the original information is hidden. For example, there are two companies both with the net number of ESG strengths as 1. One can have only 1 ESG strength and no ESG weakness, while the other can have 5 ESG strengths and 4 ESG weaknesses. The credit performance of the two companies can vary from each other a lot, but with overall scores they have the same results.

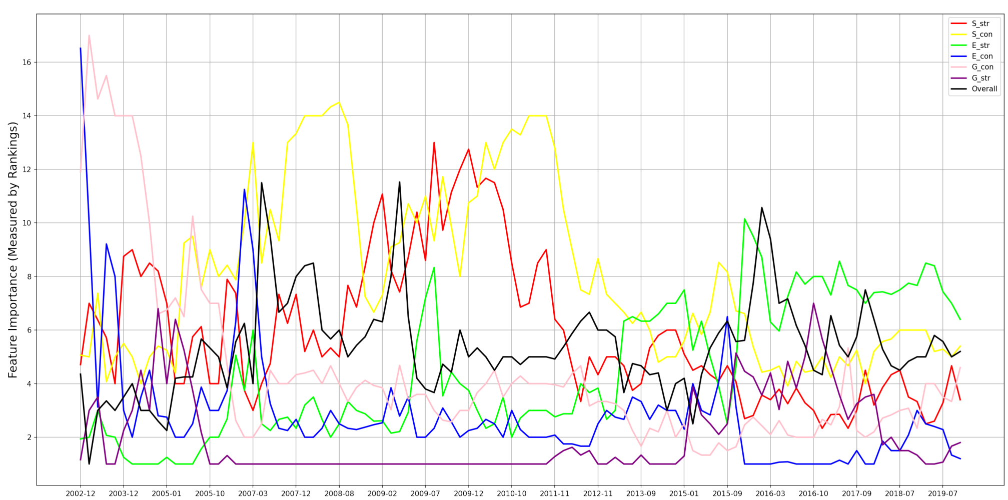


Figure 12: The Change of Feature Importance of ESG Variables Over Time

Figure 13 and Figure 14 display how feature importance of financial ratios and macroeconomic variables change over time, respectively. The positions of lines shows that the feature importance of financial ratios in predicting LGD becomes more stable and does not show any significant trend while the macroeconomic variables are increasingly important.

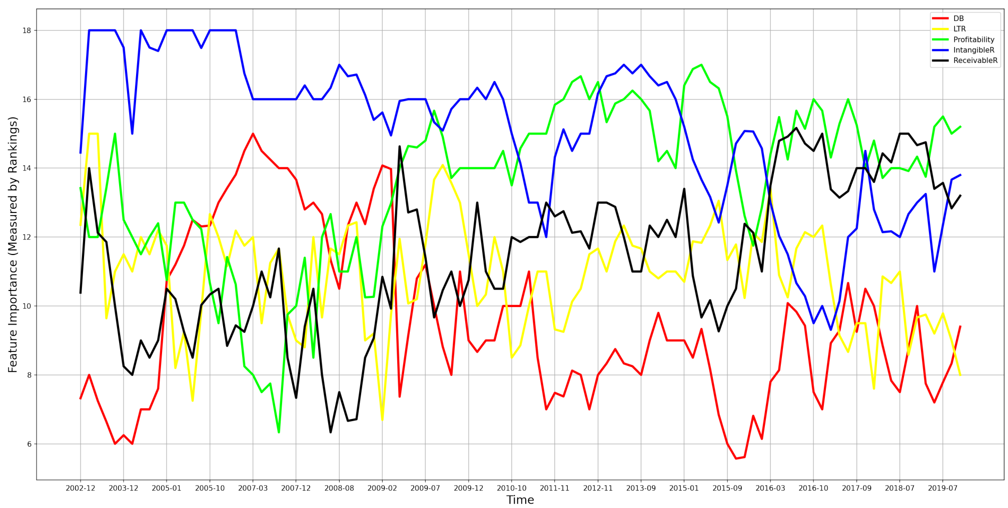


Figure 13: The Change of Feature Importance of Financial Variables Over Time

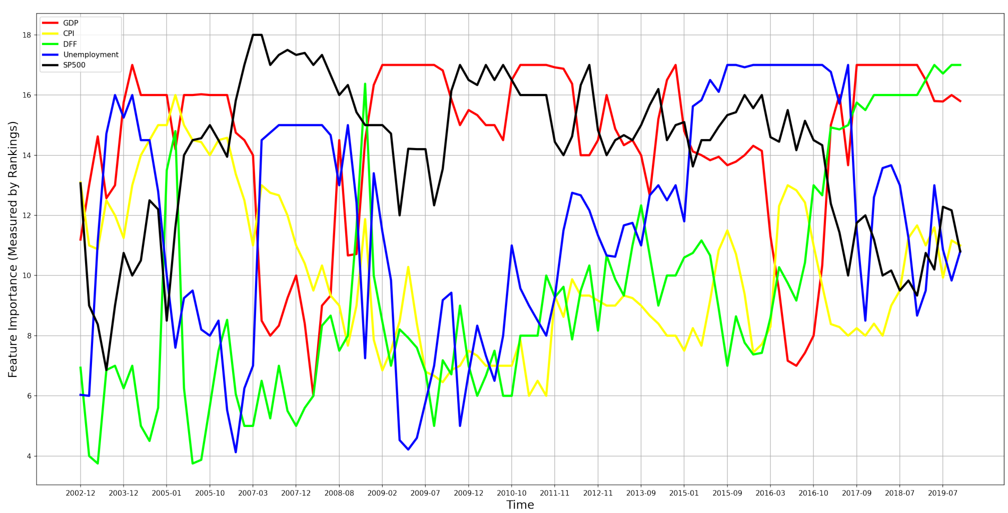


Figure 14: The Change of Feature Importance of Macroeconomic Variables Over Time

6 Conclusion

Exploring the relationship of ESG and firms' credit risk has been a hot topic in recent years. However the current studies stay at the high level risk indicators (e.g. cost of debts and credit ratings) and there is no existing literature going further down to analyse how specific credit risk components interacts with ESG, as far as we know. In this paper, with a customised ESG-LGD dataset, we find ESG information can enhance the predictive accuracy of LGD estimation as the effective supplement to other proven efficient variable groups and this relationship is not static, but change along with the time, especially in different economic cycle stages. Also, from model interpretation perspective, the result shows (1) social perspective play the most significant role in LGD modelling among three pillars of ESG as social perspective includes more information compared with other two dimensions and tends to reflect the risk in the long run and (2) ESG information are more effective when estimating LGD of riskier segments (e.g., junior debts, debts whose issuers are in brown industry and samples in adverse macroeconomic situation). Moreover, with the trending multi-stage modelling framework which reduce the complexity of data distribution when conducting regression by identifying those fully recovered or lost samples at early stage, we examine how ESG variables perform in three classification tasks identifying different focused sample groups, concluding ESG information not only improve the prediction accuracy of regular one-off LGD regression but also work well with multi-stage modelling with classification subtasks. This extended focus helps us better understand the prediction on which samples benefit from this new variance and proves again that ESG information are more helpful in finding out those would ultimately fully lost samples. As the ESG data becomes more available, we suggest incorporate ESG information into the LGD modelling framework for a more accurate estimation. In the future, we will keep focusing on studying the impact of ESG on other credit risk components and exploring their dependent structure under ESG.

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