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# Analysis of the Impact of ESG on Corporate Credit

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## Abstract

This study analyzed the effect of ESG on corporate credit ratings. Currently, interest in ESG at home and abroad is increasing, such as Korea's mandatory disclosure of ESG information in 2025 and the carbon neutrality policy in 2050. At the same time, this study assumed that ESG lists, which are non-financial factors, would have an indirect and partial effect on a company's credit rating, and analyzed it by year and industry. From 2011 to 2021, the importance of variables was measured using ESG division data provided by the Korea Institute of Corporate Governance and Sustainability and KIS-Value's financial statements. Also, Mean Decrease Impurity(MDI) and Recursive Feature Elimination(RFE) were used as variable importance measurement methods.
As a result of the study, the importance of E(Environment), S(Social), and G (Governance) items all increased in 2021, compared to 2011, increasing the effect of ESG on corporate credit ratings. In particular, it was found that the importance of S increased the most. In addition, through analysis by industry, it was confirmed that the degree of impact of ESG lists varies from industry to industry. This is a result that can infer the discriminatory application of ESG by industry.

**Keywords:** ESG, Credit Rating, MDI, RFE, Industry Analysis

**Major Classification Code**: Artificial Intelligence, etc

## 1. Introduction

ESG, an acronym for Environmental Protection, Social Contribution, and Ethical Management (Governance), is recognized as a value that corporations must consider to achieve sustainable development. In December 2021, South Korea announced the K-ESG to reduce confusion among over 600 domestic and international ESG indicators. This initiative outlined 61 core and common items for ESG implementation and evaluation, with plans to establish criteria based on company size. Starting in 2025, companies with assets exceeding 2 trillion KRW will be required to disclose ESG information, with a phased expansion planned from 2030. As ESG-related policies continue to emerge annually and the proportion of ESG management within companies increases, it becomes inevitable that ESG will indirectly affect corporate credit ratings.

Currently, the world is experiencing abnormal weather conditions due to global warming. Since the adoption of the United Nations Framework Convention on Climate Change

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(UNFCCC) by 192 countries in 1992, the international community has been promoting carbon neutrality policies to achieve net-zero carbon emissions by 2050. Following this global trend, advanced capital markets are activating Socially Responsible Investment (SRI), which seeks long-term investment returns by investing in ethical and eco-friendly companies. South Korea also began actively participating in the 2050 carbon neutrality plan by announcing the Green New Deal in 2020 and has significantly increased the scale of socially responsible investments related to non-financial ESG factors, prompting companies to engage in ESG management.

This study is significant because it addresses the growing importance of ESG factors, which have become critical determinants of a company's long-term sustainability and ethical impact. With investors and regulators increasingly prioritizing ESG criteria, understanding their influence on credit ratings is crucial. This research provides timely insights that can inform investment decisions and policy-making by highlighting the effects of ESG factors on financial stability and risk assessment. By elucidating the relationship between ESG performance and credit ratings, the study aids companies in better-managing risks and developing strategic plans to improve their ESG standings, potentially enhancing their creditworthiness and investment appeal. Furthermore, it contributes to the academic literature by filling existing gaps and providing empirical evidence on the quantitative impact of ESG factors, thereby enriching the discourse on sustainable finance and corporate responsibility.

This study aims to analyze the impact of ESG on corporate credit ratings by year and industry amid growing interest in ESG from governments, companies, and investors.

## 2. Literature Review

In the current global landscape, credit rating agencies like Moody's and S&P consider non-financial values such as ESG (Environmental, Social, and Governance) alongside traditional financial values when evaluating corporate credit ratings. Korea Investors Service claims that ESG-related factors are already reflected in the credit rating process, citing changes in profitability due to industry paradigm shifts and environmental regulations (2020). This suggests that while credit rating agencies may not explicitly incorporate ESG factors, these factors are indirectly and partially considered.

The social responsibility activities and eco-friendly management practices of ESG-focused companies may lead to additional costs, potentially deteriorating profitability and negatively affecting credit ratings. Conversely, ESG management can enhance a company's long-term sustainability, thereby reducing credit risk. For instance, companies with superior corporate governance incur lower agency costs due to effective oversight of management, and their social responsibility activities are perceived by investors as reducing management risk. This perception can elevate the company's bond ratings and reduce debt costs. Moreover, companies that engage in sustainable management, or those with high ESG ratings, tend to have higher corporate value.

### 2.1. ESG Impact on Corporate Credit Ratings

Interest in ESG has heightened since the COVID-19 pandemic, and it is analyzed that corporate ESG is somewhat reflected in domestic credit ratings. In particular, the governance factor among ESG elements is known to have a close relationship with credit ratings. Additionally, the European Commission reported in April 2021, through guidelines on non-financial reporting, that a company's creditworthiness is strictly linked not only to its financial status but also to non-financial measures and is related to the level of environmental pollution. This can also be observed in the credit rating agencies' assessment of default risk, where S&P highlighted ESG risks in the building materials, metals and mining, and oil and gas sectors in 2021. Chodnicka-Jaworska (2021) analyzed that the sensitivity to ESG scores varies by sector. The most sensitive sectors are energy, industrial, materials, and utilities, and ESG measures are related to major investment funds' decisions to reduce investments or allocations in securities of companies with high carbon emissions in credit rating assessments. However, for large corporations, even if they are not at the top of the ESG rankings, some have high scores in certain ESG indices, suggesting that ESG figures are not the biggest predictors of ESG risk. Zanin (2022) found that the Environmental score is the dimension of sustainability that most contribute to improving the goodness-of-fit of the credit rating model. It has a significant positive effect on credit ratings in all sectors investigated, with stronger effects for mining and quarrying firms. Firms that manage environmental matters better than their industry peers are perceived as more resilient to long-term risks, and these tend to be rewarded by credit rating agencies. Some mixed evidence between credit rating agencies is found for the social and governance dimensions in terms of statistical significance and estimated marginal effects by sector.

### 2.2. Bond Yields and ESG

Jang et al. (2020) analyzed the relationship between bond yields and ESG scores and found that ESG scores can help reduce funding costs for bond issuers, particularly in companies with high information asymmetry, such as small and medium-sized enterprises (SMEs). They also found that ESG scores complement credit ratings in credit assessments and mitigate credit risk for smaller companies, providing additional safeguards for bond investors. This suggests that ESG can be considered a risk management tool and can be used as an effective strategy for SMEs.

## 2.3. Machine Learning and ESG

Recently, there has been active research using machine learning to predict corporate credit ratings and default risk. However, most predictive analyses performed with single models based on machine learning inherently face bias issues. To address this, stacking ensemble techniques, which use various machine learning models as sub-models, are employed to mitigate the bias inherent in individual models. This approach helps overcome the limitations of oversampling and undersampling that can distort data.

Additionally, ensemble models face multicollinearity issues, meaning if techniques within the model have high correlations, the results from a single model can be more accurate than those from an ensemble model (Dong & Han, 2004; Eom, Kim & Zhang, 2008; Kim & Kang, 2012). Although research is ongoing to improve the bias problem of single models, it is still found that single models can outperform ensemble models. Among single models, the Random Forest model is recommended for its superior performance. Thus, this study analyzes the relationship between ESG and financial variables using a single model rather than an ensemble model.

When applying machine learning models, because they learn from all variables, the presence of less important variables can negatively impact overall performance. This issue can be addressed by using variable selection techniques to eliminate less important variables, thereby removing multicollinearity and improving performance. There are various variable selection techniques. Sermpinis, Tsoukas, and Zhang (2018) predicted U.S. corporate credit ratings using LASSO and ELASTIC NET for variable selection, achieving performance improvements from 48% to 84% and 80%, respectively. Jang et al. (2020) extracted variables through PCA for four industries: finance, energy, healthcare, and consumer goods, and selected key financial variables for each industry using chi-square tests and KMO (Kaiser-Meyer-Olkin) tests. Trivedi (2020) used MDI (Mean Decrease in Impurity), a variable selection method based on chi-square tests and Gini impurity, to predict bankrupt companies, achieving an accuracy of 93%. Kou et al. (2020) also used MDI to select 15 variables, revealing through a variable selection process with NSGA-II that key variables included recent 60-day trading records, industry-specific past default records, and default rates of payment networks. Michalski and Low (2021) analyzed the impact of ESG on credit ratings of U.S. and global companies using MDI, MDA, and TreeSHAP to determine variable importance. Their analysis found that expected carbon emissions, board of directors, and total donations were important for U.S. companies, while female workers, water usage, and carbon emissions were important for global companies, leading to improved predictive performance through variable selection.

Therefore, this study aims to analyze the change in the importance of ESG in determining corporate credit ratings by using MDI to measure the importance ranking among variables and RFE (Recursive Feature Elimination) to progressively remove less important variables and assess the change in the importance of ESG affecting corporate credit ratings.

# 3. Research Methods

## 3.1. Sample and Statistics

In this study, we used corporate bond rating data from domestic credit rating agencies for companies listed on the Korean Stock Exchange and KOSDAQ from 2011 to 2021. For ESG variables, we used mid-category ESG data provided by the Korea ESG Standards Institute. As shown in Table 1, the ESG mid-categories are classified into Environmental Management (E), Social Responsibility Management (S), and Corporate Governance (G).

**Table 1:** ESG Mid-Category Descriptions

| ESG | Variable | Contents |
|---|---|---|
| Environment (E) | Environmental Management (E1) | Environmental leadership, establishment of environmental policies, development of environmental management strategies |
| | Environmental Performance (E2) | Monitoring and measurement of environmental performance, establishment of environmental performance evaluation systems |
| | Stakeholder Engagement (E3) | Identification of stakeholders, participation in domestic and international initiatives, disclosure of environmental information |
| Social (S) | Employees (S1) | Guarantee of basic labor rights, development and support of employee capabilities, support for work-life balance |
| | Partners and Competitors (S2) | Establishment of fair trade order, establishment of co-prosperity foundation |
| | Consumers (S3) | Prevention of consumer rights violations, implementation of ethical marketing, establishment of consumer communication |

| | | |
|---|---|---|
| | | channels |
| | Local Community (S4) | Development of local community engagement strategies, management of local community engagement performance |
| Governance (G) | Protection of Shareholder Rights (G1) | Protection of shareholder rights, stock purchase request system, general meetings of shareholders |
| | Board of Directors (G2) | Establishment and review of corporate goals and strategic direction, ensuring fairness in transactions with conflicts of interest, risk management, board evaluation, outside directors |
| | Disclosure (G3) | Information disclosure, designation of disclosure responsibility |
| | Audit Organization (G4) | Establishment of audit committee, independence of audit committee |

To examine the impact of ESG on different industries, each company's data was classified into a total of 10 industries using the Wise Industry Classification Standard (WICS) provided by FnGuide. Among these, since the Korea ESG Standards Institute has separately evaluated 'Financial Company Governance (FG)' for the financial industry since 2018, this study excluded the financial industry and focused on nine industries.

The financial data for each company was obtained from KIS-Value provided by NICE Credit Rating Information. Missing values in financial statement figures and ESG scores were removed for analysis. In particular, if there were no data on dividend rates and payout ratios in the financial statements, it was interpreted as either no dividends being paid or not being evaluated, and these were converted to zero for use. Total assets, sales, tangible assets, and total liabilities were used after applying the natural logarithm. When the total equity was negative due to reasons such as capital erosion, it was converted to zero using the Box-Cox transformation before use. Corporate credit ratings were quantified to have values between 0 and 100, regardless of + and -, with AAA as 100 and from AA to D as values ranging from 90 to 10.

## 3.2. Methodology

After data preprocessing, the importance of variables for predicting corporate credit ratings was measured using Random Forest. 80% of the entire dataset was divided into training data, and the remaining 20% was used as test data. The variables used for predicting credit ratings included 29 financial variables extracted from financial statements, 3 ESG major-category variables, and 11 ESG mid-category variables. The methods used for measuring variable importance were MDI and RFE.

MDI can be compared to a chef refining a cake recipe by assessing each ingredient's contribution to enhancing flavor. Ingredients that consistently enhance the cake receive higher scores, indicating their importance, while those with minimal impact receive lower scores. This process identifies the crucial ingredients for the recipe.

Conversely, RFE resembles a systematic taste test where all ingredients are initially included. The chef removes the least important ingredients one by one, evaluating the cake's taste at each step. This iterative process continues until the simplest recipe that still delivers optimal flavor is achieved, thereby eliminating unnecessary ingredients and preserving essential ones.

MDI is a method proposed by Breiman (2001) that measures the importance of each variable through the Importance Gain (IG), which is the reduction in Gini impurity when each node splits in a tree-based classifier.

Let us assume that a Random Forest consists of $N$ decision trees, using a dataset $X$ with $p$ independent variables $f_1, \cdots, f_p$ to classify a dependent variable $Y$ composed of $k$ classes. Let the $j$-th decision tree be denoted as $T_j$. In this study, we predicted credit ratings composed of 10 classes: AAA, AA, A, BBB, BB, B, CCC, CC, C, and D, using a total of 41 independent variables, including 27 financial variables, 3 ESG deduction items, and 11 ESG mid-category scores, to generate 200 decision trees. Let $p_t^i$ be the ratio of observations belonging to class $i$ at each node $t$ of a decision tree $T_j$. The Gini impurity $Imp_t$ at node $t$ is defined as follows.

$$Imp_t = \sum_{i=1}^{k} p_t^i\left(1 - p_t^i\right) = 1 - \sum_{i=1}^{k}\left(p_t^i\right)^2$$

for $i = 1, \cdots, k$.

When a node $t$ is split into two child nodes $t_L$ and $t_R$ by a split rule using variable $f_m$, the information gain $IG(t, f_m)$, which represents the degree to which the Gini impurity decreases, can be calculated as follows:

$$IG(t, f_m) = Imp_t - \left(w_L Imp_{t_L} + w_R Imp_{t_R}\right)$$

where $w_L = \frac{n(t_L)}{n(t)}$, $w_R = \frac{n(t_R)}{n(t)}$, $n(t)$ are the numbers of observations in node $t$.

The larger the $IG(t, f_m)$ at node $t$, the more the Gini impurity decreases when the node is split, indicating that the node is important. The method to calculate the MDI variable importance of variable $f_m$ through information gain is as follows:

First, select the variable that maximizes the reduction of Gini impurity at each node:

$$\underset{m}{\operatorname{argmax}}\, IG(t, f_m)$$

where $i = 1, 2, \cdots, p$.

Then, calculate the sum of the information gain $IG(t, f_m)$ at the nodes where the $m$-th predictor variable $f_m$ is used as the split rule in the $j$-th decision tree $T_j$.

$$\sum_{t \in T_j} IG(t, f_m)\, I\left(\underset{m}{\operatorname{argmax}}\, IG(t, f_m) = m\right)$$

By averaging the information gain of the $m$-th predictor variable $f_m$ across all $N$ decision trees, we can express it as equation (1). By repeating the entire process for all predictor variables $f_1, \cdots, f_p$, the MDI variable importance for each variable can be calculated.

$$MDI(f_m) = \sum_{j=1}^{N} \sum_{t \in T_j} IG(t, f_m)\, I\left(\underset{m}{\operatorname{argmax}}\, IG(t, f_m) = m\right) \tag{1}$$

The following describes the algorithm for RFE. RFE is an algorithm that initially includes all variables and iteratively removes the least important variables while performing repeated learning to select the important ones (Guyon et al. 2002). The detailed algorithm can be found in Algorithm 1

**Algorithm 1:** RF-RFE feature ranking method

INPUT :
  $D = \{(X_i, y_i) | X_i \in X,\ y_i \in Y,\ i = 1, \cdots, p\}$ - Training dataset
  $F = \{f_1, \cdots, f_p\}$ - Set of features
  Ranking Method $MDI(f_i)$s
  $S = [1, 2, \cdots, p]$ - Subset of features
OUTPUT :
  Final ordered feature set $R$
BEGIN :
  while $S \neq \emptyset$ do
  Repeat for $i$ in $[1, p]$
    Rank set $F$ using $MDI(f_i)$
    $f^* \leftarrow \underset{f_i \in F}{\operatorname{argmin}}\, MDI(f_i)$
    $R(p - i + 1) \leftarrow f^*$
    $F \leftarrow F - f^*$
  end while
END

In this study, the scikit-learn library in Python was used to measure variable importance through MDI and RFE.

## 4. Results and Discussion

### 4.1. Yearly Analysis

First, we compared 2011, the starting point of ESG data, with the most recent data from 2021 to identify changes in the importance of financial variables and ESG items. The ESG items that showed significant changes in 2021 compared to 2011 are E2 (Environmental Performance), S1 (Employees), G1 (Protection of Shareholder Rights), G3 (Disclosure), and S4 (Local Community). Notably, the rankings of E2, S1, and G1 have significantly risen, indicating that they have greatly influenced the determination of credit ratings.

Regarding S1, the Ministry of Employment and Labor has made continuous efforts, such as the Top 10 Proposals for Work Innovation and the Work-Life Balance Campaign, to improve working culture. In 2018, the Ministry of Culture, Sports and Tourism reported that life satisfaction increases with better work-life balance, reflecting the growing interest in employee protection in South Korea. This likely contributed to the rise in the ranking of S1, which pertains to ensuring basic labor rights.

Additionally, South Korea is currently the only OECD country without legal remedies to protect shareholders' rights. However, through the Corporate Governance Report Improvement Plan in March 2022, it was mandated that when restructuring governance, policies to protect shareholders must be disclosed. Recently (September), measures were announced to protect investors when pursuing physical division, such as granting dissenting shareholders the right to request stock purchases, aiming to prevent damage to minority shareholders. Consequently, the ranking of G1's importance significantly increased in 2021 compared to 2011.

Figure 1 is a graph comparing the changes in rankings of ESG variables between 2011 and 2021. For the ESG major-category analysis, 33 data points were used, including 27 financial variables, 3 ESG deduction items, and 3 major-category items. For the ESG mid-category analysis, 41 data points were used, including financial variables, ESG deductions, and 11 mid-category items. Additionally, Figure 1 uses the average rankings from MDI and RFE, as explained in Chapter 3, to display the graph.

First, in the ESG major-category graph, the importance of E, S, and G all increased in 2021 compared to 2011. This result indicates that with the increased interest in ESG in 2021 compared to 2011, the consideration of non-financial factors like ESG in credit ratings has also increased. Notably, the importance of S increased the most, ranking second in importance. This trend appears due to the rise of consumers engaging in 'value consumption,' where they express their beliefs by purchasing products with social value rather than just necessary goods.

The impact of climate change and environmental pollution often manifests over a long period, but environmental incidents such as wastewater and oil spills can

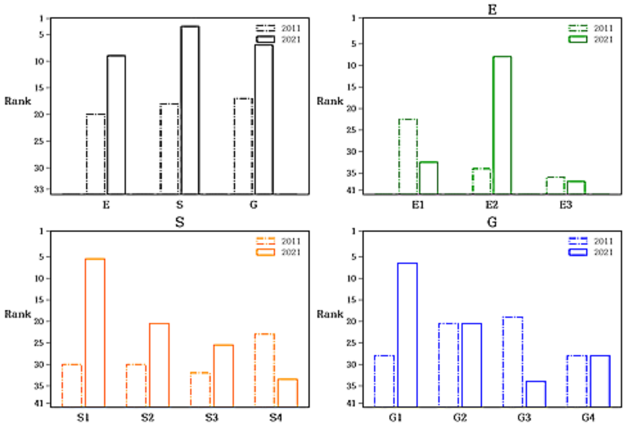

**Figure 1:** Comparison of All Industries in 2011 and 2021

their frequency, based on the scale of damage, leading to directly affect a company's creditworthiness, regardless of the increased importance of E2 (Korea Ratings, 2022). The importance ranking of E2 in Figure 1 reflects this outcome.

In the E mid-category graph of Figure 1, except for E2, the rankings actually decreased in 2021. This seems to result from the contraction of ESG activities among global companies as recession risks grew. In the U.S., there are situations where states dominated by Republicans are attempting to prevent the financial industry from emphasizing ESG factors in business operations to protect traditional industries like oil and coal. Such influences could be expected to affect South Korea as well. Additionally, for small and medium-sized enterprises, issues related to E can act as a burden, making them less accessible. However, South Korea is currently preparing to adopt global ESG disclosures, expanding mandatory scopes based on key indicators. If ESG disclosures become mandatory, ESG management will become an unavoidable task for companies. This is expected to increase the impact of E1 and E3 on credit ratings, thereby improving the situation.

A sharp rise in G1 can be observed in Figure 1. During the stock price decline caused by COVID-19, the Korea Corporate Governance Service (2020) reported that companies with consistently excellent G from 2016 to 2018 experienced an average of 4.13 percentage points less decline in stock prices than those without, indicating a stock price defense effect from corporate governance. In particular, companies with excellent G1 experienced about 5.25 percentage points less decline in stock prices, asserting that efforts to improve ownership governance structures, such as stock buybacks and effective dividend policies, helped defend the stock prices of companies focusing on G1, supporting the sharp rise in G1's importance.

In the S and G mid-category graphs, the sharp rise in importance of S1 and G1 aligns with the aforementioned content. However, the importance of both S4 (Local Community) and G3 (Disclosure) decreased, likely due to the growing global recession risks and the increasing opinions among domestic companies that continuing ESG activities, which require significant time and capital, is burdensome.

## 4.2. Industry Analysis

In considering the varying importance of ESG factors across nine industries, we examined the impact of ESG items on each industry. Figure 2 illustrates the ranking of the importance of ESG items from 2011 to 2021, the entire data range, with the importance rankings in each figure representing the average of the MDI and RFE rankings, as explained in Chapter 3, similar to Figure 1.
When considering all years and industries, S2 and S1 hold the highest importance, followed by the G category, which mostly occupies the mid-range of importance.

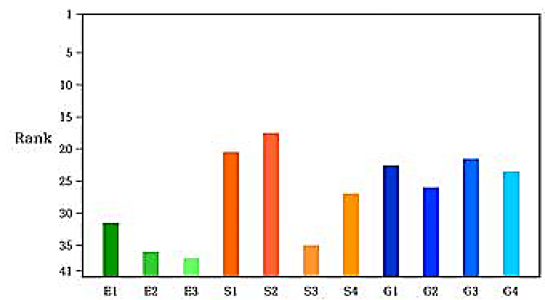


**Figure 2:** Overall Year ESG Mid-Category Rankings

Figure 3 to Figure 6 show the ESG importance rankings for the industrials, consumer staples, utilities, and communication services sectors, respectively. Unlike the overall data, E1 ranks higher in industries other than communication services.

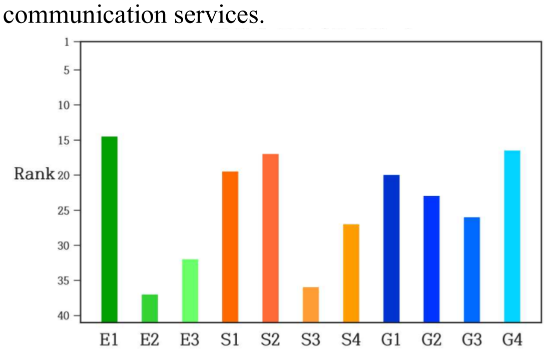

**Figure 3:** Industrial Rankings

Contrary to the yearly analysis results in Figure 1, E2 ranks lower in Figures 2, 3, 4, and 6, excluding the utility sector, and in the industry-specific importance rankings for all years shown in Table 2.

In 2021, South Korea declared '2050 Carbon Neutrality,' and the EU announced the 'Green Deal' in 2020, introducing legislative proposals for the Carbon Border Adjustment Mechanism in 2021, increasing international focus on

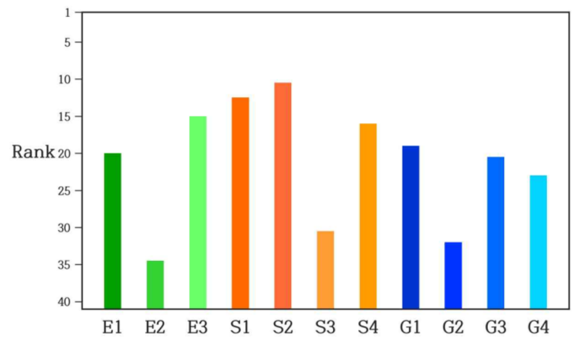


**Figure 4:** Consumer Staples Rankings

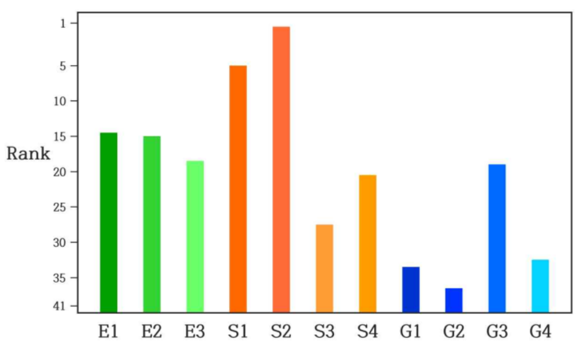


**Figure 5:** Utility Rankings

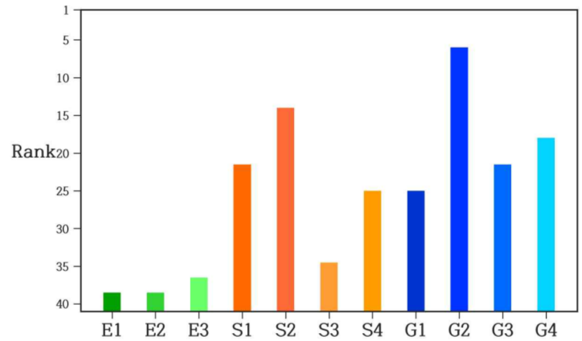


**Figure 6:** Communication Services Rankings

environmental concerns, particularly E2. Furthermore, the World Economic Forum (WEF) in 2022 reported that environmental issues such as climate response failure and extreme weather accounted for half of the biggest risks over the next decade, underscoring the importance of E2. Thus, it can be interpreted that, unlike in the past, the closer we get to 2021, the more E2 influences credit rating decisions.

As evidenced by social issues with SPC, S is significant for consumer staples related to food. Figure 4 shows high rankings for S2, S1, and S4 in consumer staples, reflecting this. According to Samjong KPMG's Future Strategy for Retail and Consumer Goods Companies (2022), major ESG issues in the consumer staples sector include E1-related investments for food upcycling and co-prosperity management through partner support related to S2. It claims that consumer staples companies engage in E-focused activities, with many companies in the restaurant franchise sector engaging in S and G-related activities.

**Table 2:** Overall Year Industry-Specific ESG Mid-Category Rankings

| Mid-Category | Industry | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Overall | Industrials | Consumer Discretionary | Materials | IT | Consumer Staples | Healthcare | Communication Services | Utilities | Energy |
| E1 | 32.5 | 15.5 | 24 | 24 | 21 | 21 | 37 | 39.5 | 16.5 | 17 |
| E2 | 37 | 38 | 38 | 28.5 | 38 | 35.5 | 39.5 | 39.5 | 13 | 34.5 |
| E3 | 38 | 33 | 37 | 27.5 | 34.5 | 16 | 37.5 | 37.5 | 20.5 | 29 |
| S1 | 21.5 | 20.5 | 23 | 16 | 18 | 13.5 | 29.5 | 22.5 | 7 | 18 |
| S2 | 18.5 | 18 | 17 | 16.5 | 14 | 11.5 | 35 | 15 | 1.5 | 25 |
| S3 | 36 | 37 | 32.5 | 38 | 36.5 | 31.5 | 31.5 | 33.5 | 29.5 | 28.5 |
| S4 | 28 | 28 | 27 | 34.5 | 24.5 | 17 | 25 | 26 | 22.5 | 12.5 |
| G1 | 23.5 | 21 | 30 | 21 | 33.5 | 20 | 21.5 | 26 | 35.5 | 11.5 |
| G2 | 27 | 24 | 19.5 | 30 | 29.5 | 33 | 33 | 7 | 38.5 | 27 |
| G3 | 22.5 | 27 | 17.5 | 24.5 | 34.5 | 21.5 | 23.5 | 22.5 | 21 | 21.5 |
| G4 | 24.5 | 17.5 | 22.5 | 19.5 | 28.5 | 39.5 | 19 | 19 | 39 | 21.5 |

For consumer staples, Table 2, which shows industry-specific importance rankings for all years, indicates that S2 ranks 11.5th (MDI 10th, RFE 13th), followed by S1 at 13.5th (MDI 12th, RFE 15th) and E3 at 16th (MDI 15th, RFE 17th). Notably, S2 and E3 maintain high importance in the 2021 industry-specific ESG mid-category rankings at 9.5th (MDI 10th, RFE 9th) and 2.5th (MDI 3rd, RFE 2nd), respectively. In Figure 3, the utility sector shows S2 ranking 1.5th (MDI 1st, RFE 2nd) and S1 ranking 7th (MDI 3rd, RFE 11th), achieving the highest rankings in overall importance. According to WICS, companies in the utility sector include electric or mixed public utility companies, such as the Korea District Heating Corporation and Korea Gas Corporation. A representative example is Korea Electric Power Corporation, which is promoting strategies such as co-prosperity and shared growth (S2) and a safe and happy workplace (S1) under the ESG slogan 'People-Centered Clean and Warm Energy,' as reflected in from Figure 3 to Figure 6 and Table 2. Additionally, the utility sector is experiencing increased importance of E1 and E2, as the IMF in 2021 advocated for implementing a carbon price floor, predicting a surge in energy prices like coal, natural gas, gasoline, and electricity (Korea Chamber of Commerce and Industry). In the 2021 industry-specific ESG importance rankings, E2 ranks 3.5th (MDI 4th, RFE 3rd), supporting this. In most industries, S2 (Partners and Competitors) ranks the Directors) ranks 7th (MDI 5th, RFE 9th), the highest among all ranks. Communication services include telecommunications, media, and entertainment industries, where board importance is inevitably high. For example, in 2021, Kakao faced a stock price crash as it was revealed that executives sold large amounts of stock, negatively impacting the company. This supports the high importance of G2, as shown in Figure 4 and Table 2, and explains why the E mid-category ranks remained between 38th and 40th in the 2021 industry-specific ESG importance rankings, as these companies lack physical presence and environmental relevance.

## 5. Conclusions

This study analyzes the impact of ESG on credit ratings in a context where the importance of ESG is increasingly emphasized, and interest in ESG from governments, corporations, and investors is growing. As the proportion of ESG management in companies increases, the study was conducted on the assumption that ESG, a non-financial factor, indirectly affects credit rating decisions. The mid-category data from the Korea ESG Standards Institute was used for ESG data, and KIS-Value was used for financial variable data. For industry classification, the WICS industry classification standard was used, classifying into a total of 9 industries excluding the financial sector.

The analysis results are as follows. First, in the yearly analysis, the importance of all ESG major-category items increased significantly from 2011 to 2021, indicating that the indirect impact of ESG data on corporate credit rating decisions has increased overall. Specifically, in the mid-category items, E2, S1, and G1 showed a sharp rise in importance rankings, significantly increasing their impact on credit ratings in 2021.

When analyzing the entire dataset without considering the years from 2011 to 2021, S2 was found to have the greatest indirect impact on credit ratings. When analyzed by industry, only those industries that showed a different pattern from the overall results were examined, and the findings are as follows:

In the industrial sector, E1 had the highest importance at 15.5th place, while in consumer staples, S2 had the highest importance at 11.5th place. In utilities, E1 and S1 were in the upper-middle range of importance, but notably, S2 was almost at the top, indicating that S2 had the greatest impact on credit ratings, surpassing other financial variables. In communication services, S2 was also in the upper-middle range of importance, but unlike other industries, G2 ranked 7th, confirming that the impact of ESG items on credit ratings varies by industry.

This paper is distinguished by analyzing the impact of ESG management on corporate credit ratings by year, confirming that the importance of ESG increased in 2021 compared to 2011, indicating that the impact of ESG on credit ratings is rising. Additionally, during the analysis process, it was confirmed that ESG items, as non-financial factors, indirectly affect credit ratings and that the extent of their impact varies by industry.

However, there were difficulties in analyzing yearly trends due to the limited ESG item data, which consisted of only 10 data points from 2011 to 2021. Particularly, although not detailed in the results of this paper, after analyzing by industry and checking by year, there were movements that were difficult to explain, which are expected to be analyzable with future accumulated yearly data. The analysis began in 2011, utilizing data up to 2021, as this period marked significant changes and increased attention to the importance of ESG. We believe that examining the period after 2021 would yield similar results, although a thorough investigation in future studies is necessary.

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