Quantitative Credit-Rating Models Including ESG Factors

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Summary

We constructed a discriminant function that includes an ESG factor. It has a higher explanatory power in discriminating between industrial companies' good and poor credit qualities than similar models that don't include an ESG factor.

While empirical credit quality research has focused on "classic" credit ratios in the past, we find that adding at least one ESG factor improves quantitative credit-rating models.

1. **Introduction**

For decades, financial analysts have used quantitative methods to assess credit qualities. A milestone in this field was the introduction of discriminant analysis by Altman (Altman 1968). With a few carefully selected, relevant, and material ratios, such models were able to assign credit qualities with the power to predict bankruptcies (Altman 2019). "The development of Altman's Z-Score and other multivariate models has demonstrated that no single financial ratio predicts bankruptcy as accurately as a properly selected combination of ratios." (Fridson and Alvarez 2002). Extended tests of the 1968 Z-score model show "…that the original coefficients are extremely robust across countries and over time" (Altman 2017). Despite the success and usability of multiple discriminant analysis, some critics caution that nonlinear relationships might not be captured well in such a framework. They suggest methodologies such as neural networks, which, on the other hand, could create unwanted problems, such as overfitting and low transparency. (Saunders 1999) Instead, the number of factors in a discriminant function is limited to avoid the problem of fundamental overlaps, which could lead to the problem of multicollinearity. (Gujarati 2003) Therefore, care needs to be taken while including additional factors.

Over the past 20 years, research into sustainability's role in investment managment has increased, leading to the development of tools for measuring and managing investment performance (Ambachtsheer and Pollice 2014). An important step in this growth was the 2000 launch of the UN Global Compact, which seeks to advance responsible corporate citizenship (United Nations Department of Public Information 2004). Over the years, the term ESG (environmental, social, and governance) has evolved as a market standard, thanks to outstanding work by the Principles for Responsible Investment beginning in 2005, as well as by the work of many other organizations (Principles for Responsible Investment 2019; Ahmed 2010; Hesse 2006; Bloomberg 2017; Derwall and Koedijk 2009; Desclèe 2016; Schindler and Schäfer 2017; Papa 2017; Messenger, et al. 2017; Saldern 2017; Strott 2016).

In practice, an increasing number of investment managers and banks are including ESG considerations in their investment and lending procedures, particularly as the models and processes implementing ESG considerations and factors have led to increased risk-adjusted returns, thus justifying the additional workload and costs (Lydenberg 2013; Moret 2015; Mertens 2017; Macquarie 2018; Reznick and Viehs 2017; Schäfer 2014; Inderst and Stewart 2018). Several relevant critical issues are discussed in *The Economist* 2020.

In addition, credit rating agencies are increasingly granulating ESG factors in their credit rating process (Hunter 2015, Kernan 2017, Yanase 2016, Hoerter 2017).

This trend is at least partially driven by investors, standard setters, and regulators such as UN PRI, the EU Commission, ESMA, SASB, CDP, The Bank of England, BaFin, TFCD and DVFA (European Commission, 2018; EU High-Level Expert Group on Sustainable Finance 2018; Nuzzo 2017; ESMA 2018; SASB Industry Standards 2017; SASB Conceptual Framework 2017; Carney 2015; MSCI ESG 2015; Steward 2015; BaFin 2020; TFCD 2017; DVFA and EFFAS 2010; Principles for Responsible Investment 2020).

Since 2015, the introduction of the 17 sustainable development goals by the UN focused the attention of market participants toward the purpose and impact of investments, whereas the implementation of ESG considerations has been considered a more prudent extension of risk management (Hayat and Orsagh 2015; Schäfer 2014).

In December 2015, 195 countries signed a legally binding global climate deal at the Paris climate conference (COP21). This deal aims to limit global warming to below 2°C (UNFCCC 2019).

Academic literature has discussed the specific relationship between ESG and credit quality and provided statistically evident positive relationships. A short overview of meta studies is provided in the footnote, since a description and discussion of the findings would absorb too much space in this paper (Friede 2016; Hoepner and McMillan 2009; Oikonomou 2014; Schröder 2014).

These positive findings form the foundation for this paper as it aims to enhance proven quantitative credit-rating models with relevant and material ESG factors. The central question is: Can the inclusion of ESG factors improve the explanatory power of discrimination functions and enhance the predictive power of bankruptcy forecasting models?

A positive result would lead to the conclusion that ESG aspects should not be ignored in future credit research and could indicate which of the many available ESG factors are most relevant and material for a credit analysis.

2. **Constructing Quantitative Sector Rating Models Including ESG Factors**

This study is designed first to define a corporate universe, second to preselect relevant credit ratios and ESG factors, third to generate and analyze the database, fourth to calculate and discuss the discriminant function, and finally to assess the final model using specific in- and out-of-sample case studies.

2.1. **Defining the Corporate Universe**

For a discriminant analysis that aims to focus on idiosyncratic corporate credit quality, it is important to build a homogeneous group (except for the dimension of corporate credit quality). Therefore, we recommend using data from only one point in time in order to ensure similar macroeconomic or geopolitical influence.[1] Furthermore, the corporates should be based in AAA- or AA-rated countries to focus on their idiosyncratic credit qualities and to avoid being influenced by sovereign credit risks.[2] They should also belong to one industry sector, the more homogeneous the better. Comparing, for example, retailers with industrials is likely to show structural and sectoral differences in leverage or working capital (Altman 2019).

On the other hand, it is essential to use a sizable number of companies to generate significant results for in- and out-of-sample analysis. Therefore, building a discriminant function for automobile producers based in AAA- and AA-rated countries is not feasible, because the number of companies is insufficient.

1. We used corporate data as at 31 December 2017.

2. The selected countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Liechtenstein, Netherlands, New Zealand, Sweden, Switzerland, United Kingdom, and the United States.

In this study we analyzed the **industrial sector**. For this task we had to carefully select different subsectors to form a homogeneous group.[3] The subsectors we selected were consumer products, hardware, industrials, materials, medical equipment and devices manufacturing, and semiconductors.

In this analysis of industrial companies we did not include the subsector of automobile producers because several of them have sizable finance operations that provide leasing arrangements and loans to consumers, which make the balance sheet structurally different from "classic" industrial balance sheets.

We preselected 565 companies by using the criteria mentioned above to screen the entire global Bloomberg LP database.[4]

2.2. Searching for Credit Ratios and ESG Factors

An analysis of the literature indicates that there are several credit ratios that have been successfully included in quantitative credit analysis. These can be grouped by different relevant themes (Caouette 2008).

Leverage: Market capitalization divided by total liabilities, and total debt to totals assets. For the former a higher ratio indicates a better quality, whereas for the latter the opposite is true (De Servigny and Renault 2004; Fridson and Alvarez 2002).

Coverage: Operating cash flow divided by total debt, operating cash flow to total liabilities, free cash flow divided by total debt, free cash flow divided by total liabilities, EBIT to total interest expense. For all those coverage ratios a higher number indicates a better credit quality.[5]

Liquidity: Working capital to total assets, sales to total assets. Higher ratios indicate higher liquidity and better credit quality (Stickney and Brown 1999).

Profitability: EBIT to total assets. A higher profitability means better credit quality.

Retained earnings: Retained earnings divided by total assets. This ratio stands for cumulated historic profitability but also for pay-out policy. High dividend payments or share buybacks would reduce retained earnings. In case of an insolvency, less value would be available to debtholders because payments would have gone to shareholders, although

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3. For this purposed we screened financial data in Bloomberg and exploited research such as that of SASB industry standards 2017.

4. We used Bloomberg LP (EQS and SRCH functions) for screening and preselecting the companies, out of 91.727 active traded companies in the Bloomberg LP universe.

5. Liabilities include lease liabilities and pension liabilities.

in an insolvency, the remaining shareholders would be wiped out. Therefore a higher number indicates a better credit quality (Caouette 2008).

Research: Research and development divided by sales. When research and development investments lead to successful future products and services, they will enhance future competitiveness, profitability, and credit quality (Stickney and Brown 1999).

Steadiness: (Inverse) variation coefficient of operating cash flows. A high stability of operating cash flows is good for bondholders because it increases the predictability of interest payments and reduces the shortfall risk of missed debt payments (Klein 2004). The idea to construct this steadiness factor came from the stability of earnings introduced in the ZETA credit-risk model (Caouette, Altman, and Narayanan 1998). The stability of earnings, as an indicator of business risk, in the ZETA model was calculated as normalized standard error of estimate around a long-term trend of the ratio return on assets (Caouette 2008).

Intangible assets: Intangible assets divided by total assets mainly result from acquired goodwill or capitalized brand names and patents. A higher number could indicate more risk, since in an insolvency such values might evaporate. (Stickney and Brown 1999) On the other hand, intangible assets could represent valuable immaterial assets such as intellectual capital, customer loyalty, or staff satisfaction, which can be understood as human, social, and intellectual capital. (Günther 2106) Unfortunately, such data are rarely reported, since they are costly to establish, and transparency could reduce competitive advantages (Speich 2014).

Size: Total assets and market capitalization. As both are not ratios, the logarithm is often used in quantitative models. Many examples have shown that size is positive for credit quality because it allows better access to capital markets and provides more resilience (Cardoso 2013).

Valuation: Market capitalization divided by total assets and market capitalization divided by book value of equity. Higher numbers are regarded as positive because high equity market valuations are often the result of future growth forecasts and high profitability (De Servingny and Renault 2004).

Altman's Z score: It consists of the following ratios: working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to total liabilities, and sales to total assets (Altman 1968).

Searching for available ESG data, we screened Bloomberg and MSCI ESG databases. Because the academic and practical studies suggested dozens of suitable and relevant ESG factors, we were open to including all of those in our analysis. Unfortunately, the coverage for our preselected 565 companies was rather disappointing. Therefore we had to delete many suggested factors. We kept only those factors that gave us a coverage of at least

80%. The resulting ESG factors are the ESG environmental score, ESG social score, ESG governance score, ESG rating, waste management theme score, carbon emissions greenhouse gas mitigation score,[6] percentage of female directors, percentage of geographic exposure to water high-stress risk, carbon emissions score, and carbon emissions change over five years.[7] (See Table 1 for all selected credit ratios and ESG factors.)

Obviously, the academic literature showing relationships between ESG factors and credit quality is much broader and diverse. (Friede 2016; Hoepner and McMillan 2009; Oikonomou 2014; Schröder 2014; Devalle 2017; Hoepner 2016; Hesse 2015; Eccles 2012; Khan 2016; Ofori 2016; Sahut 2015)

With future growth in quantity and quality of ESG data, more interesting factors could be included in quantitative credit-rating models.

2.3. **Analyzing the Database**

We have been somewhat disappointed by the availability of data for ESG factors. For example the employee turnover is regarded as an important social factor. (McCormick 2017) But the data coverage for our 565 selected industrial companies has been far too low to be considered in further calculations. As mentioned previously, we required a coverage of at least 80% of our 565 preselected industrial companies. For 21 credit ratios and ESG factors we found sufficient data[8] (Table 1). For every ratio we calculated the mean for companies with good credit quality and for the companies with poor credit quality.[9] The means offer a first impression of whether a hypothesis such as "the higher the cash from operation to total debt, the better the credit quality" is correct.

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6. Source: MSCI ESG Research: "The Greenhouse Gas Mitigation Strategy Score (ranging from 0 to 10) is calculated based on the combination of the three mitigation data points: (1) Use of cleaner sources of energy; (2) energy consumption management and operational efficiency enhancements; and (3) CDP disclosure. Companies with strong efforts across all three score highest while those with no initiatives or no disclosure receive the lowest scores."

[1] Use of cleaner sources of energy: This data point indicates our assessment of how aggressively the company has sought to mitigate its carbon emissions through the use of cleaner sources of energy such as solar, wind, geothermal, co-generation, or natural gas in place of oil or coal.

[2] Energy consumption management and operational efficiency enhancements. This data point indicates our assessment of how aggressively the company has sought to mitigate its carbon emissions by managing energy consumption and improving the energy efficiency of its operations.

[3] CDP disclosure: This data point indicates whether the company reports its carbon emissions to the CDP. Possible values: 'Yes' or 'No'.

7. Bloomberg LP, MSCI ESG.

8. As the data source we used Bloomberg LP and MSCI ESG.

9. We classified companies with a rating of BBB and above as good and BBB- and below as poor credit quality.

As a next step we identified outliers for every ratio. If a number was more than three standard deviations from the mean, we labeled it as an *extreme outlier*, and if it was more than two standard deviations, as an *outlier*. We first deleted the extreme outliers and then the outliers to analyze the stability of the means for every ratio. This procedure did not change the direction of the relationships; only the difference between the means deteriorated somewhat.

Table 1: Means Corrected for Different Levels of Outliers

	Including outliers		Excluding extreme outliers (>= 3 Sig)		Excluding outliers (>= 2 Sig)	
	Good credit quality	Poor credit quality	Good c. quality	Poor c. quality	Good c. quality	Poor c. quality
CFO / Total Debt	0.44	0.24	0.39	0.21	0.39	0.20
FCF/TD	0.11	0.07	0.11	0.06	0.10	0.06
FCF/TL	0.29	0.13	0.25	0.11	0.25	0.10
ln(Total Assets)	23.37	21.81	23.41	21.81	23.38	21.71
ln(Market Cap)	23.68	21.56	23.67	21.59	23.65	21.61
Retained Earnings/ Total Assets	0.19	-0.09	0.20	-0.04	0.22	0.00
Market Cap/ Total Liabilities	2.68	1.89	2.56	1.61	2.42	1.54
EBIT/Tot Int Exp:2017	11.59	4.61	10.49	3.64	9.83	3.50
Altman Z-Score	4.44	2.99	4.31	2.83	4.22	2.84
R&D/Net Sales:2017	3.14	2.70	2.56	1.92	2.10	1.56
VACO.CFO.5Y	8.31	3.33	7.83	3.05	7.01	2.83
ESG_SOCIAL_SCORE	4.90	4.56	4.90	4.54	4.86	4.54
ESG_GOVERNANCE_SCORE	5.93	5.70	5.93	5.70	5.96	5.74
ESG_ENVIRONMENTAL_SCORE	5.36	4.02	5.36	3.92	5.18	3.84
ESG RTG Note	14.74	11.24	14.74	11.24	14.92	10.68
WASTE_MGMT_THEME_SCORE	6.15	4.59	6.15	4.59	6.29	4.40
CARBON_EMISSIONS_GHG_MITIGATION_SCORE	6.29	4.33	6.34	4.33	6.76	4.31
FEMALE_DIRECTORS_PCT	24.67	17.07	24.54	16.93	23.63	16.26
WATER_STRESS_HIGH_RISK_GEO_PCT	50.87	60.96	50.87	60.96	50.87	60.96
CARBON_EMISSIONS_SCORE	7.77	5.87	7.80	5.87	8.11	6.07
Carbon Emissions Change 5Y	0.43	1.12	0.08	0.71	0.05	0.64

Source: Bloomberg, MSCI ESG, and author's own calculations.

Generally, all ratios and factors selected in a discriminant function have to show only moderate correlations in order to avoid multi-collinearity problems known from regression analysis (Baetge 1980). In cases of high collinearity, a function with high R^2 and a significant F value can include coefficients that are individually statistically insignificant (Table 2). This can lead to the unwanted effect that the estimated coefficients and their standard errors become sensitive to small changes in the data (Gujarati 2003). Furthermore, multi-collinearity can lead to wrong signs of the coefficients (Baetge 1980). This can make the functions less reliable, and it reduces their forecasting power.

Table 2: Correlations between the Selected Credit Ratios and ESG Factors

Korrelation

	CFO / Total Debt	FCF/TD	FCF/TL	ln(Total Asset	ln(Market Ca	Retained Earn	Intangible Ass	Market Cap/ T	EBIT/Tot Int E	Altman Z-Scor	R&D/Net Sale	VACO.CFO.5Y	WC/TA	MarketCap/T
CFO / Total Debt	1.00	0.45	0.95	0.05	0.14	0.11	-0.07	0.32	0.49	0.26	0.03	0.05	0.04	0.19
FCF/TD		1.00	0.64	0.03	0.20	0.07	0.03	0.82	0.31	0.65	0.29	0.07	0.11	0.40
FCF/TL			1.00	0.06	0.18	0.10	0.00	0.45	0.58	0.39	0.09	0.06	0.07	0.27
ln(Total Assets)				1.00	0.89	0.37	0.10	-0.02	0.10	0.06	0.07	0.34	0.04	0.01
ln(Market Cap)					1.00	0.35	0.15	0.20	0.25	0.33	0.19	0.41	-0.21	0.38
Retained Earnings/ Total Assets						1.00	0.14	0.10	0.11	0.36	-0.07	0.21	0.19	0.11
Intangible Assets/TA							1.00	0.02	0.02	0.18	0.13	0.15	-0.07	0.08
Market Cap/ Total Liabilities								1.00	0.34	0.80	0.36	0.07	0.14	0.59
EBIT/Tot Int Exp:2017									1.00	0.32	0.05	0.12	0.07	0.40
Altman Z-Score										1.00	0.22	0.17	0.20	0.68
R&D/Net Sales:2017											1.00	-0.03	0.21	0.30
VACO.CFO.5Y												1.00	-0.25	0.21
WC/TA													1.00	0.20
MarketCap/Total Assets														1.00
Total Debt/Total Assets														
MarketCap/Book Value														
ESG_SOCIAL_SCORE														
ESG_GOVERNANCE_SCORE														
ESG_ENVIRONMENTAL_SCORE														
ESG RTG Note														
WASTE_MGMT_THEME_SCORE														
CARBON_EMISSIONS_GHG_MITIGATION_SCORE														
FEMALE_DIRECTORS_PCT														
WATER_STRESS_HIGH_RISK_GEO_PCT														
CARBON_EMISSIONS_SCORE														
Carbon Emissions Change 5Y														

	Total Debt/To	Market Cap/B	ESG_SOCIAL_S	ESG_GOVERN	ESG_ENVIRON	ESG RTG Note	WASTE_MGMT	CARBON_EMI	FEMALE_DIRE	WATER_STRES	CARBON_EMI	Carbon Emissi
CFO / Total Debt	-0.26	0.06	0.09	0.15	0.00	0.17	0.01	0.07	0.11	0.04	-0.02	-0.02
FCF/TD	-0.28	0.05	0.03	0.16	0.05	0.10	0.05	0.06	0.02	0.05	0.01	-0.02
FCF/TL	-0.27	0.08	0.07	0.16	0.03	0.18	0.06	0.08	0.10	0.04	0.03	-0.02
ln(Total Assets)	-0.24	0.04	0.05	0.04	0.29	0.31	0.24	0.42	0.32	-0.16	0.34	-0.02
ln(Market Cap)	-0.13	0.12	0.08	0.08	0.36	0.36	0.33	0.47	0.35	-0.14	0.40	-0.03
Retained Earnings/ Total Assets	-0.46	-0.04	0.00	0.10	0.15	0.18	0.11	0.09	0.16	-0.12	0.09	0.00
Intangible Assets/TA	-0.06	-0.03	0.01	0.06	0.16	0.11	0.15	0.05	0.13	-0.02	0.21	0.03
Market Cap/ Total Liabilities	-0.32	0.07	0.08	0.10	0.07	0.11	0.11	0.04	0.01	0.06	0.04	-0.02
EBIT/Tot Int Exp:2017	-0.19	0.08	0.14	0.07	0.08	0.24	0.17	0.16	0.16	-0.05	0.14	-0.03
Altman Z-Score	-0.27	0.11	0.05	0.08	0.15	0.15	0.24	0.07	0.03	0.10	0.19	0.01
R&D/Net Sales:2017	-0.13	0.02	0.06	-0.04	0.13	0.01	0.25	0.01	-0.06	0.00	0.24	-0.01
VACO.CFO.5Y	-0.04	0.07	0.08	0.08	0.26	0.26	0.25	0.25	0.19	-0.13	0.19	-0.06
WC/TA	-0.48	0.01	-0.02	-0.03	-0.11	-0.09	0.00	-0.15	-0.17	0.11	0.00	-0.01
MarketCap/Total Assets	-0.07	0.26	0.04	0.06	0.15	0.10	0.25	0.08	0.05	0.08	0.18	-0.02
Total Debt/Total Assets	1.00	0.10	-0.08	-0.08	0.00	-0.04	0.05	0.04	-0.03	-0.01	0.08	0.00
MarketCap/Book Value		1.00	0.01	0.00	0.12	0.06	0.06	0.03	0.03	0.00	0.06	-0.01
ESG_SOCIAL_SCORE			1.00	0.01	0.08	0.48	0.18	0.12	0.13	-0.04	0.16	-0.06
ESG_GOVERNANCE_SCORE				1.00	0.00	0.37	0.01	0.18	0.18	-0.11	-0.02	-0.03
ESG_ENVIRONMENTAL_SCORE					1.00	0.47	0.57	0.36	0.31	-0.32	0.49	-0.01
ESG RTG Note						1.00	0.44	0.43	0.37	-0.31	0.46	-0.14
WASTE_MGMT_THEME_SCORE							1.00	0.26	0.18	-0.09	0.60	-0.01
CARBON_EMISSIONS_GHG_MITIGATION_SCORE								1.00	0.37	-0.23	0.48	-0.04
FEMALE_DIRECTORS_PCT									1.00	-0.24	0.22	-0.05
WATER_STRESS_HIGH_RISK_GEO_PCT										1.00	-0.20	0.04
CARBON_EMISSIONS_SCORE											1.00	-0.05
Carbon Emissions Change 5Y												1.00

Source: Bloomberg, MSCI ESG, and author's own calculations.

2.4 **Calculating the Discriminant Function**

The discriminant function is optimized by achieving the highest possible hit ratio (lowest misclassification) and by including as few factors as possible to make the function transparent and practicable. All factor coefficients have to show the signs that fit to the fundamental relationships. This process is a “controlled statistical” optimization.

At first, every credit group of the sample is split up so that there are two groups of good and two groups of poor credit quality. One group of good and one group of poor credit quality are then selected (the training set), and the discriminant function is estimated. We used 285 companies for the training set. Subsequently, this function is used to classify the corporations of the two other groups that have not been used for model formation (the test group). This out-of-sample approach controls the reliability of the model.

The discriminant function has the general form (Backhaus 2016):

$$Y = b_0 + b_1 X_1 + b_2 X_2 + ... + b_j X_j$$

Here, the variable Y is the discriminant score and the variables X_1, X_2, .., X_j are the factors used to develop the discriminant function. The constants b_0, b_1, b_2, .., b_j denote the coefficients for corresponding factors. In the analysis, every element (corporation) will be assigned a discriminant score Y, representing its credit quality. The means of the different discriminating factors for every single group are called centroids. These centroids are used to estimate the coefficients b_j.

The key task in this empirical analysis is finding suitable factors to develop the discriminant functions.

To assess credit quality, we use the financial ratios and ESG factors explained above, which condense data and report quantifiable facts. (Fridson and Alvarez 2002) With their help, complicated facts, structures, and procedures of corporations are depicted simply enough to permit a fast and comprehensive overview. To simplify the methodology, the number of financial ratios and ESG factors used should not be too large, and every financial ratio must be plausible. (Saunders 1999) Only ratios with a clear fundamental relationship with credit quality should be included. These should cover the dimensions of the corporations’ net worth, financial position, and results. (Altman 1968) The core of this text is the extension of “classic financial ratios” by relevant ESG factors.

To state the relationships, we generate the following hypothesis: “the higher the ratio the better the credit quality.” With that fundamental knowledge, the direction of the relationship is known ex ante. The coefficient in the discriminant function must show the correct sign as stated in the fundamental hypothesis. For example, when the relationship is "the higher the ratio the better the credit quality" the coefficient for this financial ratio or ESG factor in the function has to be positive. Otherwise, the function cannot be used for scenario analysis or forecasting.

We estimate the discriminant function using multiple discriminant analysis.[10] The coefficients of a discriminant function are estimated in such a way that the resulting means of the scores for solvent and insolvent corporations show a maximum difference. The greater the distance between the means, the more reliable the separation of good credit corporations from those of poor credit quality (Backhaus 2016). Since—even in the case of a successful separation—the distributions of both groups always show overlaps, type I and type II classification errors may occur. A type I error means that solvent corporations are classified as insolvent. A type II error refers to insolvent corporations that are classified as solvent. Since rating methodologies have been developed to serve investors as a means to assess credit risks, it is especially important to minimize the type II error.[11] This can be achieved by setting the critical value for separating corporations of good and poor credit quality not in the center of the overlapping zone, but closer to the mean value of corporations of good credit quality. The cut off value should be adjusted until the type II error has been reduced to an acceptable level.

The optimized discriminant function included four factors in order of importance (Table 3): the logarithm of the market capitalization (size)**,** retained earnings to total assets (cumulative profitability), the carbon emissions GHG mitigation score (ESG factor) and market capitalization to total liabilities (valuation)**.**

Table 3: The Discriminant Function

Retained Earnings/ Total Assets	.390
Market Cap/ Total Liabilities	.228
Carbon Emissions GHG Mitigation Score	.349
ln(Market Cap)	.714

Source: Bloomberg, MSCI ESG, SPSS, own calculations.

The function has the form:

*Y = 0.39 * Retained Earnings / Total Assets + 0.228 * Market Cap / Total Liabilities + 0.349 * Carbon Emissions GHG Mitigation Score + 0,714 * ln (Market Cap).*

Four steps (Table 4) show the construction of the discriminant analysis and the significance of the factors (credit ratios and ESG factor).

10. We performed the discriminant analysis using SPSS.

11. In most cases it is more costly to invest in a corporate that defaults than to miss investing in a bond that increases in credit quality and price.

Table 4: The Discriminant Functions and Their Level of Significance

Step		Tolerance	F to Remove	Wilks' Lambda
1	ln(Market Cap)	1,000	149,663	
2	ln(Market Cap)	1,000	124,285	0,846
	Retained Earnings/ Total Assets	1,000	20,162	0,577
3	ln(Market Cap)	0,947	79,916	0,695
	Retained Earnings/ Total Assets	0,999	19,784	0,547
	Carbon Emissions GHG Mitigation Score	0,947	10,915	0,525
4	ln(Market Cap)	0,921	64,016	0,640
	Retained Earnings/ Total Assets	0,990	16,867	0,526
	Carbon Emissions GHG Mitigation Score	0,932	12,492	0,515
	Market Cap/ Total Liabilities	0,955	5,294	0,498

Source: Bloomberg, MSCI ESG, SPSS, own calculations.

The discriminant criterion relates the variation within the groups to the deviation between the groups. The higher the discriminant criterion, the better the quality of the discriminant function, since high deviations between the groups and low variations within the groups are desired.

Another method used to assess the quality of the discriminant function is Wilk's Lambda. This measure has the advantage of being limited between 0 and 1, allowing easier comparisons between different discriminant functions, whereas the values of the discriminant criterion are unlimited. Wilk's Lambda relates the unexplained variance to the total variance (Backhaus 2016). The lower Wilk's Lambda is, the better the quality of the discriminant function. A third, and more practicable, method for assessing the discriminant function's quality is the hit ratio. Here it is tested whether the function classifies objects correctly into the groups. A completely correct classification by the function results in the ideal hit ratio of 100 percent. (Backhaus 2016). Our discriminant function delivered a hit ratio of 84,6% (Table 5).

In comparison, the best discriminant function using the same data set without the inclusion of ESG factors delivered a lover hit ratio of 84,2%. Therefore the inclusion of an ESG factor improved the hit ratio of the discriminant function by 0.4 percentage points.

Table 5: The Classification Results of the Discriminant Function

			Predicted Group		
		Group	0	1	Total
Original	Count	0	120	19	139
		1	25	121	146
	%	0	86,3	13,7	100
		1	17,1	82,9	100
84,6% are classified correctly					

Source: Bloomberg, MSCI ESG, SPSS, own calculations.

A data set of objects that has not been employed to estimate the discriminant function should be used to analyze reliability as an aspect of the function's quality. This procedure is called "out-of-sample testing." Misclassified objects have to be carefully analyzed to understand fundamental shortcomings of the model. It is especially vital to consider the type of misclassification (type I or type II error as explained before).

Testing the factors of the function is important to the process of selecting factors that support discriminating objects and that are statistically significant. As explained before, the fundamental relationship between factors (financial ratios and ESG factors) and objects (companies with different credit qualities) are stated with hypothesis in the form of: "the higher the ratio the better the credit quality." For this reason the coefficients for the factors have to show the correct sign that fits the fundamental hypothesis. Otherwise the function cannot be used for forecasting purposes.

A user can now also apply the discriminant functions to corporations that had not been included in the estimation of the function. (Baetge 1980) For these objects the ex-ante knowledge of the classification is not required. Therefore the credit quality can be assessed by using this discriminant function and without knowing an external credit rating. This allows credit assessments even for nonrated corporations.

As the classification into "good" and "poor" credit quality is not granulated enough, we examined whether the established discriminant function can provide a more precise assessment. For example, credit rating agencies use different rating classes from AAA to D, which are further subdivided into so-called notches (subclasses), an even finer classification.

To assign finer credit assessments, the discriminant scores were computed for every industrial corporation with the discriminant function selected. These individual credit scores were then compared with the credit rating agency ratings. In order to achieve a minimum difference between model results and agency assessments, the ranges of credit scores were optimised. A minimum difference should refer to the assessments of individual corporations, and the sum of deviations should be minimized over all corporations. Since the correlation between credit quality and score is not linear, the ranges of the individual classes are also not equidistant (Steiner and Heinke 1996). The callibration shows that the notches have different ranges of scores (Table 6).

We assigned the following model credit ratings to the model scores:

Table 6. Transforming Model Scores to Model Credit Ratings

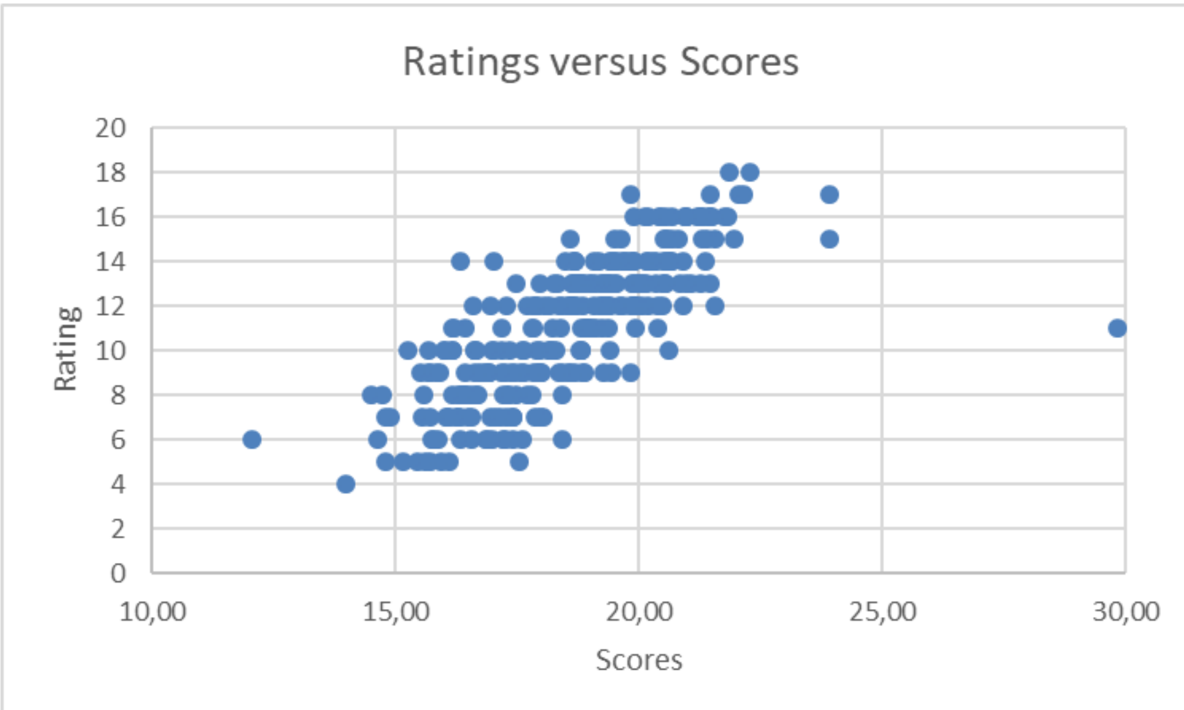
AAA > 24	BBB1 > 19,5	B1 > 16,5	CC > 13
AA1 > 23,5	BBB2 > 19	B2 > 16	C > 12
AA2 > 23	BBB3 > 18,5	B3 > 15	D < 12
AA1 > 22,5	BB1 > 18	CCC1 > 14,5	
A1 > 22	BB2 > 17,5	CCC2 > 14	
A2 > 21	BB3 > 17	CCC3 > 13,5	
A3 > 20			

Source: Author's own calculations.

Overall, the model has a positive bias since the sum of the differences (model scores minus credit rating scores) equals 67.[12]

We plotted the model scores and the credit rating agencies' ratings for the in-sample data set (Figure 1). A value of 18 on the Y-axis corresponds with an AA- credit agency's rating. AA- is the highest credit rating in our data set (Nestle). On the other hand, the by far highest model score is 29,82 (the Australian BBB- rated company Alumina). This score will be analysed later as a case study. Generally, the basic relationship holds: "The higher the model score, the better the credit rating."

Figure 1: Model Scores and Credit Agencies' Ratings



Source: Author's own calculations.

In the optimum case, a straight upward sloping line would be observed. This is obviously not achieved here. There is some similarity, but there are some clear differences and even misclassifications. In theory, we would like to generate a model explaining 100% of the credit rating agencies' ratings delivering a perfect hit ratio, but in practice, it is not necessarily the objective of internal models to exactly mirror the credit rating agencies' ratings, as differences might be the starting point for further research and possible trading strategies to exploit such differences.

12. This bias seems acceptable for 285 companies with an average score of 18,54.

2.5 **Discussing the Function by Using Case Studies**

Despite the previously discussed shortcomings in available ESG data, we managed to demonstrate that a discriminant function for those industrial companies with an ESG factor shows better discriminatory results when compared to models without any ESG factor. The complex ESG factor focusing on greenhouse gas emissions—their dynamics over time and the transparency of the reporting—seems to be a good indicator for the complex and broad ESG risk. This fits with earlier results, like that identified in Van der Velden (2012): "…, just one proxy for ESG risk, CO_2 emissions, shows a far lower level of risk than the index."

Nevertheless, the model result showed some serious misclassifications: The model rating of 12 (out of 285) companies was more than three notches better than their credit agencies' ratings.[13] The model rating of 13 companies was more than three notches worse than their credit agencies' ratings.[14]

Alumina's score is affected by the extremely high Market Capitalization / Total Liabilities ratio of 50,19 (whereas the average has been 2,41). This is due to having a very low debt level.[15]

Now it is important to analyze the out-of-sample results (267 companies). Here we applied the discriminant function to those companies that were not used in building the discriminant function. The cut-off point between companies of good credit quality (BBB and above) and those of poor quality (BBB- and below) is 19.

Out of 120 companies with good credit agencies' ratings, 26 received a model score below 19. Out of 147 companies with poor credit agencies' rating, 13 received a model score of 19 or above. Thus 39 out of 267 companies have been misclassified, which delivers an out-of-sample hit ratio of 84,8%, which is slightly higher than the in-sample hit ratio of 84,6%.

Again, the out-of-sample model results have a small positive bias since the sum of the differences between model scores and credit rating scores equals 77.

More important, again, is the analysis of severe outliers, where model ratings deviate plus or minus more than three notches from the credit rating agencies' ratings. The model

13. The companies are Nvidia, Edwards Life, United Rentals, Becton Dickinson, VAT Group, US Steel, SGL Carbon, First Quantum, Navistar Intl, the above mentioned Alumina LTD, NXP Semiconductors, Brooks Automation
14. These companies are: Port of Tauranga, Timken Co, Element Fleet, Kirby Corp, Universal Corp, Kaman Corp, Stoneridge Inc, Atlas Iron, Aar Corp, Turning Point, Glatfelter, Cai International and Greenbrier Cos.
15. On May 15th 2018, Alumina was upgraded to BBB- (investment grade) by S&P.

rating of 18 companies was more than three notches better than their credit agencies' ratings. The model rating of 12 companies was more than three notches worse than their credit agencies' ratings. The biggest negative deviation (-8) is Fonterra (rated A-) in the packaged food subsector. The main reasons for the poor model score are the very weak ratio Market Capitalization to Total Liabilities of 0,92 (the average in the out-of-sample data set equals 2,13) and the lack of data (equals zero) for the carbon emissions GHG mitigation score. It is a clear message that ESG reporting matters since non-existing data have a negative effect on quantitative model scores.

Because the role of climate change is regarded as critical in the future development of the entire planet, there have been ongoing detailed demands for transparent disclosure of relevant data. "Increasing transparency makes markets more efficient and economies more stable and resilient" (Bloomberg 2017, Nordhaus 2013, Wallace, 2019).

Today, various scenario analyses are available for investors to use in evaluating the cost of climate change (Mercer 2015; 2 degrees Scenario Analysis 2016; Institut Lois Bachelier 2020).

For some assets and industries, the impact of climate change could be severe. They will face risks from dimensions such as regulatory compliance, carbon pricing, reputational issues, and adaption costs, amidst the increasing likelihood of adverse events, depletion, global warming effects, and subsidy losses (Buhr 2016).

Despite increased understanding of the impact future climate change will have, much work has to be done to increase the quality and comparability of data. For example, for carbon data the scope matters: scope 3 includes the emissions that result from using certain products (such as cars). Here the complexities of measurement still lead to inconsistencies (Busch 2018).

3. **Conclusion**

Our results suggest that the inclusion of ESG factors does improve the discriminating power of quantitative rating models. This statistical outcome increases our conviction that ESG is relevant for credit assessments and motivates us to increase our active engagement to improve the ESG quality and reduce the CO_2 emissions of issuers we invest in (Kuhn 2019).

Selecting this dynamic carbon emission factor fits well with the current political and regulatory attention toward climate change. Currently, the EU ESG taxonomy starts with the environmental dimension, particularly by defining contributions to climate change mitigation and adaption (EU Commission 2019, Principles for Responsible Investment 2020). Furthermore, regulators demand climate-related financial disclosures and climate scenario analysis at the portfolio level (Bloomberg 2017).

We will continue working with quantitative credit-rating models—now including a dynamic climate factor in our credit analysis and portfolio management decisions.

Special care will be taken whenever the model rating deviates from that of the credit rating agency. If the model rating is worse, we would most likely not invest in the issuer, but on the other hand, if the model rating is much better than the credit agency's rating we will start a detailed and self-critical analysis, since the model might not have captured crucial information or does not include expectations for important future developments.

Overall, we are looking forward to improving this model further as the quality and quantity of ESG data increase in the future (Eltogby 2019).

Since the 2030 agenda, set in 2015, the introduction of the 17 sustainable development goals by the UN may focus market participants and academics on evaluating the purpose and positive impacts of their investments, whereas, so far, the implementation of ESG considerations has been considered more as prudent risk management (von Weizsäcker and Wijkman 2018).

As the measurement and methodologies for evaluating investments' impact on sustainable development goals continue to evolve, they may generate additional important factors for the development of future discriminant functions (Wendt 2019). Initial ratios to measure SDG impacts have already been developed (Carlsson 2018).

Therefore, the development of this discriminant function is just a small step in a long journey.

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Biography

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Acronyms and Abbreviations

CDP	Carbon Disclosure Project
CFO	Cash from Operations
COP21	UN Climate Summit 2015 in Paris
DVFA	Deutsche Vereinigung für Finanzanalyse und Asset Management
EBIT	Earnings before Interest and Taxes
ESG	ESG Environmental, Social, Governance
ESMA	European Securities and Markets Authority
EU	European Union
GHG	Greenhouse Gas
PRI	Principles for Responsible Investment
SASB	Sustainability Accounting Standards Board
SDG	Sustainable Development Goals
SRI	Socially Responsible Investments
TFCD	Task Force on Climate-Related Financial Disclosures
UN	United Nations

Figure

Tables

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