Universität Stuttgart
Fakultät Wirtschafts-
und Sozialwissenschaften
Betriebswirtschaftliches Institut
Abteilung III (Finanzwirtschaft)
Prof. Dr. Henry Schäfer

University of Stuttgart
Faculty of Business
and Social Science
Institute of Business Administration
Department III (Corporate Finance)
Prof. Dr. Henry Schäfer

Quantitative Credit Rating Models including ESG factors

Christoph Klein, CFA, CEFA, Dipl. Kaufm.

Research Report

No. 01/2019

ISSN 1864-0125

Stuttgart, September 2019

University of Stuttgart

Faculty of Business and Social Science
Institute of Business Administration
Department III (Corporate Finance)

Keplerstraße 17
70174 Stuttgart
Germany

T: +49 (0)711-685-86000
F: +49 (0)711-685-86009
E: h.schaefer@bwi.uni-stuttgart.de

Christoph Klein, CFA, CEFA, ESG Portfolio Management GmbH, likes to thank Prof. Dr. Edward I. Altman, Dr. Robert Buhr, Vladislav Krivenkov, Prof. Dr. Hellmuth Milde, Dr. Carmen Nuzzo and Prof. Dr. Henry Schäfer for their inspiration and support.

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Abbreviations

CDP	Carbon Disclosure Project
CFO	Casf From Operations
COP21	UN Climate Summit 2015 in Paris
DVFA	Deutsche Vereiningung für Finanzanalyse und Asset Management
EBIT	Earnings before Interest and Taxes
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
U.N.	United Nations

Summary

We construct a discriminant function including an ESG factor that has a higher explanatory power in discriminating industrial companies between good and poor credit qualities than similar models without 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

Credit qualities have been assessed using quantitative methods for decades. A milestone has been the introduction of discriminant analysis by Altman in this field.[1] With few, carefully selected, relevant and material ratios such models assign credit qualities with predictive power regarding bankruptcies.[2] “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.”[3] Extended tests of the 1968 Z-score model show “…that the original coefficients are extremely robust across countries and over time”[4]. Despite the success and usability of multiple discriminant analysis, some critizise that non-linear relationships might not be catpured well in such a framework and suggest methodologies like neural networks which on the other hand could create unwanted problems such as overfitting and low transparency.[5] The number of factors in a discriminant function is rather limited to avoid the problem of fundamental overlaps, which could lead to the problem of multicollinearity.[6] Therefore, care needs to be taken while including further factors.

Over the last twenty years there have been increasing developments and research regarding sustainability in investment management.[7] An important step has been the launch of the U.N. Global Compact in 2000 which seeks to advance responsible corporate citizenship.[8] Over the years, the term ESG (environmental, social and

1 Altman, E. I., 1968, pp. 589-609.
2 Altman, E. I., et al., 2019, pp. 203.
3 Fridson, M., Alvarez, F., 2002, p. 175.
4 Altman, E. I., et al., 2017, p.127.
5 Saunders, A., 1999, pp. 16.
6 Gujarati, D. N., p. 354.
7 Ambachtsheer, J., and Pollice, R., 2014, pp. 391.
8 United Nations Department of Public Information, 2004, p. viii.

governance) has evolved as a market standard, thanks to outstanding work by the Principles of Responsible Investment since 2005 and many more.[9]

In practice, an increasing number of investment managers and banks are including ESG considerations in their investment and lending process, as models and processes implementing ESG considerations and factors have led to increased risk adjusted returns, justifying the additional work load and costs.[10] In addition, credit rating agencies are increasingly granulating ESG factors in their credit rating process.[11] This trend is at least partially driven by investors, standard setters and regulators like UN PRI, the EU Commission, ESMA, SASB, CDP, The Bank of England, TFCD and DVFA.[12]

Since 2015, the introduction of the the 17 sustainable development goals by the United Nations focused the attention of market participants towards purpose and impact of investments, whereas the implementation of ESG considerations has been considered as a more prudent extension of risk management.[13] In December 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.[14]

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. A decription and discussion of the findings would absorb too much space in this paper.[15] 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

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9 See for example: Principles for Responsible Investment, uploaded 2019, Ahmed, P., et al., 2010, Hesse, A., 2006, Bloomberg, M. et al., 2017, Derwall, J. and Koedijk, K., 2009, pp. 210, Desclèe, A., et al, 2016, Schindler, A. and Schäfer, 2017, Papa, V. et al, 2018, Saldern, v. N.,2017, Strott, E., et al., 2016.

10 See for example: Lydenberg, S., 2013, pp. 44, Moret, L., et al. 2015, Mertens, H., 2017, Macquarie, 2018, Reznick, M. and Viehs, M., 2017, Schäfer, H., 2014. Inderst, G., Stewart F., 2018, p 18. A rare counter argumentation is provided by Bajic, S., 2015.

11 See for example: Hunter, W., et al, 2015, Kernan, P., et al, 2017, Yanase, M., et al., 2016, Hoerter, S.,2017, p. 7.

12 See for example: European Commission, Action Plan: Financing Sustainable Growth, 2018, EU High-Level Expert Group On Sustainable Finance, 2018, Nuzzo, C., 2017, ESMA, 2018, SASB Industry Standards, 2017, pp. 12, SASB Conceptual Framework, 2017, Carney, M, 2015, MSCI ESG 2015, pp. 7, Steward, L., 2015, p. 58, TFCD, 2017, DVFA/EFFAS, 2010, pp. 7.

13 Hayat, U. and Orsagh, M., 2015, p. 11, Schäfer, H., 2014, pp. 6.

14 UNFCCC, 2019.

15 See for example Friede, G. et al., 2016, Hoepner, A. and McMillan, D., 2009, Oikonomou, I., et al., 2014, Schröder, M., 2014, p. 342.

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 deliver an indication 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

The design of this study is first to define a corporate universe, second to preselect relevant credit ratios and ESG factors, third to generate and analyse the database, fourth to calculate and discuss the discrimant 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 credit quality, it is important to build a homogeneous group (except for the dimension of corporate credit quality). Therefore it is recommended, to use one point of time data only, to have similar macroeconomic or geopolitical influence.[16] 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.[17] Also, the corporates should 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.[18]

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 disciminant function for automobile producers based in AAA and AA rated countries is not feasible, as the number of companies is insufficient.

In this study we analyse the **industrial sector**. For this task we had to carefully select different subsectors to form a homogeneous group.[19] The selected subsectors

[16] We used corporate data as at 31 December 2017.
[17] The selected countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Liechtenstein, Netherlands, New Zealand, Sweden, Switzerland, United Kindom and the United States.
[18] Altman, E. I., et al., 2019, pp. 203.
[19] For this purposed we screened financial data in Bloomberg and exploited research like: SASB industry standards A field guide, 2017, pp. 14,

are: consumer products, hardware, industrials, materials, medical equipment and devices manufacturing and semiconductors.

We did not include the subsector automobile producers in this analysis for industrial companies as several of these issuers have sizeable finance operations providing leasing and loans for consumers, which makes the balance sheet structurally different to “classic” industrial balance sheets.

Screening the company universe using the entire global Bloomberg LP database by the criteria mentioned above we preselected 565 companies.[20]

2.2 Searching for credit ratios and ESG factors

An analysis of the literature indicates that there are several credit ratios which have been successfully included in quantitative credit analysis. These can be grouped by different relevant themes:[21]

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.[22]

Coverage: Operating cash flow divided by total debt, operating cash flow to total liabilities, free cash flow divided by total debt, free cash flow by total liabilities, EBIT to total interest expense. For all those coverage ratios a higher number indicates a better credit quality.[23]

Liquidity: Working capital to total assets, sales to total assets. Higher ratios indicate higher liquidity and better credit quality.[24]

Profitability: EBIT to total assets. A higher profitability means better credit quality.[25]

Retained earnings: Retained earnings 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 able for debtholders as it has been already paid to shareholders, although

[20] 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.
[21] Caouette, J. B., et. al., 2008, pp. 108.
[22] De Servigny, A. and Renault, O., 2004, p. 320, Fridson, M. and Alvarez, F., 2002, pp. 268.
[23] Liabilities include lease liabilities and pension liabilities.
[24] Stickney, C. P. and Brown, P. R., 1999, pp. 640.
[25] Ebenda, pp. 125.

in an insolvency remaining shareholders would be wiped out. Therefore a higher number indicates a better credit quality.[26]

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.[27]

Steadiness: (Inverse) variation coefficient of operating cash flows. A high stability of operating cash flows is good for bondholders as it increases the predictability of interest payments, and reduces the shortfall risk of missed debt payments.[28] The idea to construct this steadiness factor came fromthe stability of earnings introduced in the ZETA credit risk model.[29] 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.[30]

Intangible assets: Intangible assets by total assets mainly result from acquired goodwill or capitalized brand names and patents. A higher number could indicate more risk as in an insolvency such values might evaporate.[31] On the other hand intangible assets could represent valuable immaterial assets such as intellectual capital, customer loyality or staff satisfaction which can be understood as human, social and intellectual capital.[32]Unfortunately, such data is rarely reported, as it is costly to establish and transparency could reduce competitive advantages.[33]

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 as it allows better access to capital markets and provides more resilience.[34]

Valuation: Market capitalization divided by total assets and market capitalization divided by book value of equity. Higher numbers are regarded as positive as high

[26] Caouette, J. B., et al., 2008, p. 144.
[27] Stickney, C. P. and Brown, P. R., 1999, pp. 321.
[28] Klein, C., 2004, p. 879.
[29] Altman, E. I., et al., 1998, pp. 123.
[30] Caouette, J. B., et al., 2008, p. 152.
[31] Stickney, C. P. and Brown, P. R., 1999, p. 320.
[32] Günther, E., et al., 2016, pp. 40.
[33] Speich, I., 2014, pp. 216.
[34] Cardoso, V. S., et al., 2013, pp. 53.

equity market valuations are often the result of future growth forecasts and high profitability.[35]

Altman's Z score: It consists of the 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.[36]

Searching for available ESG data we screened Bloomberg and MSCI ESG databases. As the academic and practical studies suggested dozens of suitable and relevant ESG factors, we have been open to include all of those in our analysis. Unfortunately, the coverage for our preselected 565 companies was rather disapponting. Therefore we had to delete many suggested factors. We kept only those factors where we got at least a coverage of 80%. The resulting ESG factors are: the ESG environmental score, ESG social score, ESG governance score, the ESG rating, the waste management theme score, the carbon emissions greenhouse gas mitigation score[37], female directors in percentage, percentage of geographic exposure to water high stress risk, the carbon emissions score and the carbon emissions change over five years.[38]

All selected credit ratios and ESG factors are presented in table 1.

Obviously, the academic literature showing relationships between ESG factors and credit quality is much broader and diverse.[39] With future growth in quantity and quality of ESG data, more interesting factors could be included in quantitative credit rating models.

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[35] De Servigny, A. and Renault, O., 2004, p. 39.

[36] Altman, E. I., 1968, pp. 589-609.

[37] 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 4) 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'.

[38] Bloomberg LP, MSCI ESG.

[39] For overviews see: Friede, G. et al., 2016, Hoepner, A. and McMillan, D., 2009, Oikonomou, I., et al., 2014, Schröder, M., 2014, p. 342, Devalle, A. et al., 2017, pp. 53., Hoepner, A., et al., 2016, pp. 158, Hesse, A., 2015, Eccles, R., et al., 2012, pp. 65, Khan, M., et al., 2016, pp. 1697-1724, Ofori, E., 2016, pp. 59-65, Sahut, J-M..

2.3 Analysing 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.[40] But the data coverage for our 565 selected industrial companies has been far too low to be considered in further calculations. As mentioned above, 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.[41] For every ratio we calculated the mean for companies with good credit quality and for the companies with poor credit quality.[42] The means offer a first impression whether a hypothesis like “the higher the cash from operation to total debt the better the credit quality” is correct.

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 extreme outlier and for more than two standard deviations as an outlier. We deleted firstly the extreme outliers and then the outliers to analyse 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

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

40 McCormick, C., 2017, p. 1.
41 As data source we used Bloomberg LP and MSCI ESG
42 We classified companies with a rating of BBB and above as good and BBB- and below as poor credit quality.

regression analysis.[43] In cases of high collinearity a function with high R^2 and a significant F value can include coefficients which are individually statistically insignificant. This can lead to the unwanted effect that the estimated coefficients and their standard errors become sensitive to small changes in the data.[44] Furthermore, multi collinearity can lead to wrong signs of the coefficients.[45] This can make the functions less reliable and reduces their forecasting power.

43 Baetge, J., 1980, pp. 651.
44 Gujarati, D. N., 2003, p. 354.
45 Baetge, J. 1980, p. 657.

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 Earr	Intangible As	Market Cap/T	EBIT/Tot Int E	Altman Z-Scor	R&D/Net Sale	VACO.CFO.5Y	WC/TA	MarketCap/T	Total Debt/To	Market Cap/B	ESG SOCIAL S	ESG GOVERN	ESG ENVIRON	ESG RTG Note	WASTE MGM	CARBON EMI	FEMALE DIRE	WATER STRES	CARBON EMI	Carbon Emissi
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	-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		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	-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			1.00	0.06	0.18	0.10	0.00	0.45	0.58	0.39	0.09	0.06	0.07	0.27	-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)				1.00	0.89	0.37	0.10	-0.02	0.10	0.06	0.07	0.34	0.04	0.01	-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)					1.00	0.35	0.15	0.20	0.25	0.33	0.19	0.41	-0.21	0.38	-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						1.00	0.14	0.10	0.11	0.36	-0.07	0.21	0.19	0.11	-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							1.00	0.02	0.02	0.18	0.13	0.15	-0.07	0.08	-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								1.00	0.34	0.80	0.36	0.07	0.14	0.59	-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									1.00	0.32	0.05	0.12	0.07	0.40	-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										1.00	0.22	0.17	0.20	0.68	-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											1.00	-0.03	0.21	0.30	-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												1.00	-0.25	0.21	-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													1.00	0.20	-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														1.00	-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

2.4 Calculating the discriminant function

The discriminant function is optimized by achieving the highest possible hit ratio (lowest misclassification) and to include as few factors as possible in order 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 corporations of good and one group of corporations of poor credit quality are selected (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 (test group). This out-of-sample approach controls the reliability of the model.

The discriminant function has the general form:[46]

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

Here, Y is the discriminant score and X_j are the different discriminant factors. The b_j denote the coefficients for factors j. b_0 is a constant. In the analysis every element (corporation) will be assigned a discriminant score Y representing its credit quality. The means of the different discriminant 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.[47] With their help complicated facts, structures and procedures of corporations are depicted in a simple way 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.[48] Only ratios with a clear fundamental relationship with credit quality should be included. These should cover the dimensions of the corporations’

[46] Backhaus, K., et al., 2016, p. 221.
[47] Fridson, M. and Alvarez, F., 2002, p.232.
[48] Saunders, A., 1999, pp. 17.

net worth, financial position and results.[49] 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 has to 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. 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 is the separation of corporations of good from poor credit quality.[50] 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 which 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.[51] 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: 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).

[49] Altman, E. I., 1968, pp. 589.
[50] Backhaus, K., et al., 2016, pp. 223.
[51] In most cases it is more costly to invest in a corporate which defaults than to miss investing in a bond which increases in credit quality and price.

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

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).*

The following table shows the stepwise construction of the discriminant analysis and the significance of the factors (credit ratios and ESG factor).

Table 4: The discriminant function 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

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 as 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.[52] The lower Wilk’s Lambda, the better is 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

[52] Backhaus, K., et al., 2016, pp. 240.

function results in the ideal hit ratio of 100 percent.[53] Our discriminant function delivered a hit ratio of 84.6%.

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 per cent. 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					

To analyse the reliability as an aspect of the function's quality a data set of objects should be used which has not been employed to estimate the discriminant function. This procedure is called out-of-sample testing. Misclassified objects have to be carefully analysed to understand fundamental shortcomings of the model. Especially the type of misclassification (type I or type II error as explained before) has to be considered.

Testing the factors of the function is important to select factors which support discriminating objects and which 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.[54] For these objects the ex-ante knowledge of the classification is not required. Therefore the credit quality can be assessed using this discriminant function without knowing an external credit rating. This allows credit assessments even for nonrated corporations.

53 Backhaus, K., et al., 2016, pp. 238.
54 Baetge, J. 1980, pp. 651.

As the classification into “good” and “poor” credit quality is not granulated enough, it is 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 are computed for every industrial corporation with the discriminant function selected. **These individual credit scores are 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 not only refer to the assessments of individual corporations, but also the sum of deviations should be minimised over all corporations. Since the correlation between credit quality and score is not linear, the ranges of the individual classes are also not equidistant.[55] The following callibration table shows that the notches have different ranges of scores.

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			

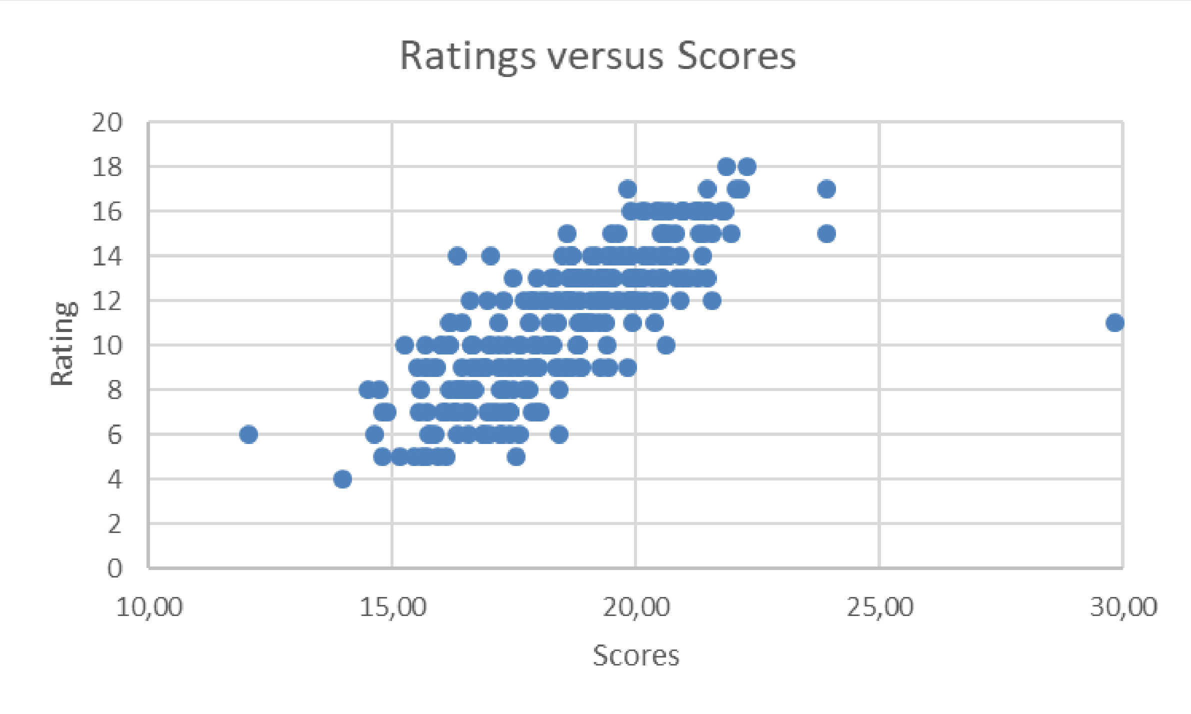
Overall, the model has a positive bias as the sum of the differences (model scores minus credit rating scores) equals 67.[56]

The following figure depicts the plots of the model scores and the credit rating agencies’ ratings for the in sample data set. 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.

55 Steiner, M. and Heinke, V. G., 1996. pp. 579.
56 This bias seems acceptable for 285 companies with an average score of 18.54.

Generally, the basic relationship holds: "The higher the model score, the better the credit rating".

Figure 1: Model scores and credit agencies' ratings



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 hatio, 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.

2.5 Discussing the function using case studies

Despite the shortcomings in available ESG data as discussed before, we managed to show that a discriminant function for industrial companies including an ESG factor shows better discriminatory results compared to models without any ESG factor. The complex ESG factor focussing on green house gas emissions – their dynamics over time and transparency of the repoting seems to be a good indicator for the complex and broad ESG risk. This fits to earlier results like: "…, just one proxy for ESG risk, CO2, emissions, shows a far lower level of risk than the index."[57]

[57] Van der Velden, A. and van Buul, O., 2012, p. 54.

Nevertheless, the model result showed some serious misclassifications: Twelve (out of 285) companies got a model rating more than three notches better than their credit agencies' ratings.[58] Thirteen companies got a model rating more than three notches worse than their credit agencies' rating.[59]

Alumina's score gets affected by the extremely high ratio Market Capitalization / Total Liabilities of 50,19, (whereas the average has been 2.41). This is due to a very low debt level.[60]

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

Out of 120 companies with good credit agencies rating 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 percent, which is slightly higher than the in sample hit ratio of 84,6%.

The out of sample model results have again a small positive bias as the sum of the differences between model scores and credit rating scores equals 77.

More important is again the analysis of severe outliers, where model ratings deviate plus or minus more than three notches from the credit rating agencies' ratings. Eighteen companies got a model rating more than three notches better than their credit agencies' ratings. Twelve companies got a model rating more than three notches worse than their credit agencies' rating. 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 Liablities 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

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58 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

59 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.

60 On May 15th 2018, Alumina was upgraded to BBB- (investment grade) by S&P.

reporting matters as non-existing data has a negative effect on quantitative model scores.

As climate change is regarded as critical for 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.”[61]

Today, there are several scenario analysis attempts available for investors to evaluate the cost of climate change.[62] For several assets and industries the impact of climate change could be severe, as risks from dimensions like regulatory compliance, carbon pricing, reputational issues, and adaption costs, increasing likelihood of adverse events, depletion, global warming effects and subsidy losses are expected to increase.[63]

Despite increasing understanding of the significance of future climate change impact, much work has to be done to increase the quality and comparability of data. For example for carbon data the scope matters as scope 3 includes the emissions which result from using the products (such as cars). Here the complexities of measurement still lead to inconsistencies.[64]

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 CO2 emissions of issuers we invest in.[65]

Selecting this dynamic carbon emission factor fits well to the current political and regulatory attention towards climate change. Currently, the EU ESG taxonomy starts with the environmental dimension, especially defining contribution to climate change

61 Bloomberg, M. R., 2017, p. II.
62 See for example: Mercer, 2015 or the 2 degrees Scenario Analysis, 2016.
63 Buhr, B., 2016, pp. 3.
64 Busch, T., et al., 2018, p. 31.
65 Kuhn, Wolfgang, 2019, p. 3.

mitigation and adaption.[66] Furthermore, regulators demand climate related financial disclosures and portfolio climate scenario analysis.[67]

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 the credit rating agency's rating. 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 very detailed and self critical analysis as the model might not have captured crucial information or does not include expectations for important future developments.

Overall, we are looking forward to improve this model further as the quality and quantity of ESG data will increase in the future.[68]

Since the 2030 agenda, set in 2015, the introduction of the the 17 sustainable development goals by the United Nations may open the focus of market participants and academics towards purpose and positive impact of investments, whereas the implementation of ESG considerations has been considered so far more as prudent risk management.[69]

With the evolution of measurement and methodologies for investments' impact towards the sustainable development goals, further important factors for future discriminant functions may be generated.[70] Initial ratios to measure SDG impacts have already been developed.[71]

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

66 European Commission, 2019, pp. 1.
67 Bloomberg, M. R., et al., 2017, pp. 1.
68 Eltogby, M., et al., 2019, p. 20.
69 Weizsäcker, v., E.U. and Wijkman, A., 2018, pp. 38.
70 Wendt, K., 2019, pp. 48.
71 Carlsson, M., 2018, pp. 9.

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