ESG Factors and Firms' Credit Risk

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Long Abstract

In this paper, we study the link between the risk of default and Environmental, Social and Governance (ESG) factors using Supervised Machine Learning (SML) techniques on a cross-section of European listed companies.

Recent studies have shown the existence of a relationship between ESG scores and firms' performance (see Friede et al. (2015) for a review). For instance, Albuquerque et al. (2020) find that companies with higher ES ratings exhibited higher returns, lower volatility, and higher trading volumes than other stocks during the recent Covid-19 pandemic. Cornett et al. (2016) find that banks' financial performance is positively and significantly related to CSR (Corporate Social Responsibility) scores. At the same time, some recent contributions have reported how ESG scores can be misleading, as the criteria underlying their formation change over time and lead to different classifications of companies (Berg et al. (2019) and Berg et al. (2020)). For this reason, we focus on ESG *factors* as opposed to *scores*, i.e. we take into account only the "raw" information used by rating companies for the construction of ESG scores. The advantage of this procedure is twofold: on the one hand, our results are independent from the ESG rating providers, hence from different rating schemes or weights as well as from potential changes they might exhibit over time; on the other hand, our results can be applied to non-rated corporations and used by lenders in their screening process, reducing adverse selection concerns and the probability of credit rationing equilibria (Stiglitz and Weiss, 1981).

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In our study, we proxy credit risk by using the z-score originally proposed by Altman (1968), that is a linear combination of accounting ratios used to classify companies in different categories according to their risk of default (distressed/uncertain/safe). Balance sheet information for the construction of the z-score are taken from Factset and Orbis; ESG raw information instead is derived from MSCI ESG Manager and it includes about seven hundred ESG variables, ranging from carbon emissions to worker fatalities per company as well as governance information (for instance, board diversity and composition). We also include individual company's characteristics such as age and export status as potential explanatory variables for the z-score. The resulting sample is a cross-section of 1251 European firms in the year 2019 and it includes 590 candidate variables to explain the z-score.

Due to the huge number of variables involved, we employ techniques of supervised machine learning, in particular the Least Absolute Shrinkage and Selection Operator (LASSO) firstly proposed by Tibshirani (1994), to select the best model. Since our objective is to predict the sign of the selected variables on the risk of default, we use LASSO for inference methods. Our preliminary results show that a selection of ESG factors in addition to the usual accounting ratios helps explaining a firm's probability of default as approximated by the z-score. We also develop a model based on Holmstrom and Tirole (1997) to explain short-term credit rationing augmented for ESG factors to interpret our results.

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The research question

Is there a relationship between the **risk of default** and Environmental, Social Responsibility and Governance (**ESG**) *factors*?

Our aim is constructing a credit risk model including ESG dimensions.

We use Supervised Machine Learning techniques on a cross-section of European listed companies to understand what factors could play a role.

Roadmap:

1. data presentation
2. empirical strategy
3. preliminary results
4. next steps

Motivation

- ESG disclosure on part of firms is required by recent EU regulations such as the Non-Financial Reporting Directive (NFRD) and the Sustainable Finance Disclosure Regulation (SDFR)
- Empirical studies show that ESG performance -measured by ESG scores- is linked to corporate performance (Cornett et al., 2016, Albuquerque et al., 2020 and Friede et al, 2015)
- ESG characteristics are also linked to a firm's credit risk (Weber et al, 2008). Over 170 investors and 26 credit rating agencies recently agreed that *"ESG factors can affect borrowers' cash flows and the likelihood that they will default on their debt obligations"*
- Despite this evidence, the existing literature lacks a credit risk model that explicitly includes ESG dimensions among the determinants of the risk of default

Our contribution

- Our aim is to develop a credit risk model that includes ESG dimensions. We start by looking for the ESG characteristics that are associated with the risk of default
- We focus on ESG **factors** as opposed to *scores*
  - to avoid relying on undisclosed models used for the construction of the ESG ratings
  - to develop a model that lenders can use in their screening of non-rated companies

What are ESG factors?

ESG *scores* are built following a pyramid scheme, with different levels of aggregation.

We call *ESG factors* the base of the pyramid, i.e the “raw” information that ESG rating companies ultimately use for constructing their scores.

Our contribution (continued)

- We use the Least Absolute Shrinkage and Selection Operator (LASSO), a Supervised Machine Learning (SML) technique
- We explore different routes for post-selection inference with LASSO
- We adapt the model by Holmstrom and Tirole (1997) to interpret our findings

ESG factors

The dataset we constructed employs information available via MSCI ESG Manager and used by MSCI to provide ESG ratings to company.

The original dataset is huge and it contains very diverse info. Here are some examples:

- **Environmental**: CO_2 emissions (scope 1, 2, 3), other pollutants emissions, water intensity, renewable energy sources used, impact on biodiversity...
- **Social Responsibility**: percentage of revenues from products that typically contain substances of chemical safety concerns, existence of formal business ethics policies, investment in community development projects, workers fatalities, workers complaints...
- **Governance**: board diversity, base salary of CEO, age of board members, percentage of shares held by controlling shareholder...

How to measure credit risk

Credit risk is usually measured using

- credit ratings from agencies such as Moody's, S&P, Fitch
- CDS prices (they can be used to compute the implied probability of default)
- Altman z-score, constructed using accounting ratios

While credit ratings and CDS are only available for listed companies, the Altman z-score can be computed for non-listed firms as well.

In this paper, we use the Altman z-score, taking balance sheet information from **Factset** and **Orbis**.

The Altman z-score

We exploit Altman's (1968) measure of default risk which classifies firms in groups (distressed/grey/safe) according to a score computed as a linear combination of accounting ratios.

The weights are obtained using MDA (Multiple Discriminant Analysis) on a sample of firms that already filed for bankruptcy.

For non US companies, the formula turns out to be the following:

$$Z = 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4 + 3.25$$

where

X_1 = Working Capital / Total Assets
X_2 = Retained Earnings / Total Assets
X_3 = Earnings Before Interest and Taxes / Total Assets
X_4 = Book Value of Equity / Book Value of Total Liabilities

Our final dataset

We construct a cross-section dated 2019 of 1251 European firms, for which we could construct the Altman z-score and for which we have ESG info.

Potential explanatory variables:

580 E-S-G-X factors

531 ESG variables[1], many of which manually cleaned and transformed (i.e. de-stringed, encoded, scaled if needed. . .)

49 X variables (company's age, export status, number of employees, balance sheet info)

Summary statistics

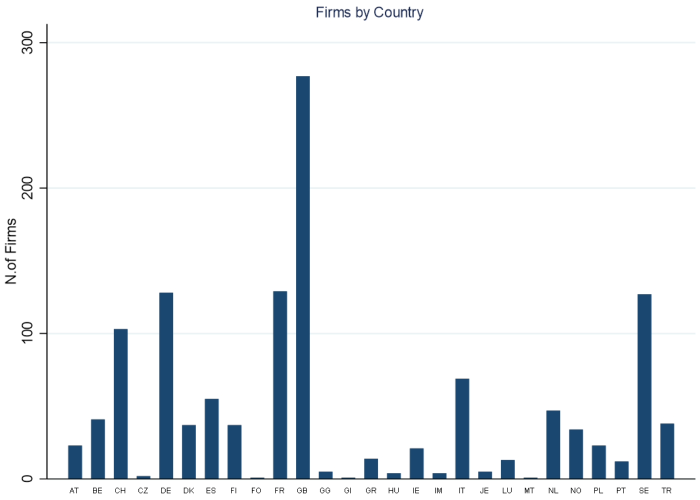
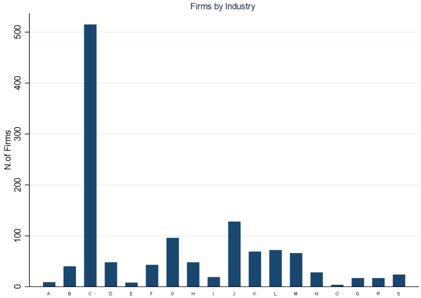


Table: Sector list

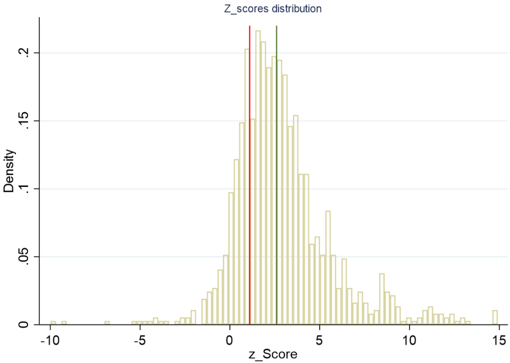
Code	Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and AC supply
E	Water supply; sewerage, waste management and remediation act
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcy
H	Transportation and storage
I	Accommodation and food service act.
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities



Altman z-score

Table: Z score

Firm classification	Frequency	Percent
Distressed	290	23%
Grey	357	29%
Safe	604	48%
Total	1251	100%



Number of variables per subcategory

ENVIRONMENTAL	
Biodiversity & Land Use	9
Carbon Emissions	39
Electronic Waste	6
Energy Efficiency	3
Financing Environmental Impact	4
Opportunities in Clean Tech	3
Opportunities in Green Building	6
Opportunities in Renewable Energy	7
Packaging Material & Waste	9
Product Carbon Footprint	3
Raw Material Sourcing	3
Toxic Emissions and Waste	32
Water Stress	23
Total	**148**

SOCIAL	
Access to Communications	3
Access to Finance	6
Access to Healthcare	6
Chemical Safety	9
Community Relations	21
Consumer Financial Protection	6
Controversial Sourcing	3
Health & Safety	28
Human Capital Development	6
Insuring Health & Demographic Risk	6
Labor Management	15
Opportunities in Nutrition and Health	9
Privacy & Data Security	19
Product Safety and Quality	6
Responsible Investment	6
Supply Chain Labor Standards	12
Total	**161**

GOVERNANCE	
Corporate Behaviour:	
Business Ethics	22
Legacy Data	33
Tax Transparency	6
Corporate Governance:	
Accounting	6
Board	28
Director Data:	
- Board Committees	1
- Board Seats	26
- Director Election Vote Results	19
- Individual Data	6
- Pay	9
Management and Shareholders Proposals	24
Ownership and Control	29
Pay	13
Total	**222**

Empirical Strategy

- Our cross-section includes many potential explanatory variables relatively to the number of companies observed
- For this reason, we employ LASSO, firstly proposed by Tibshirani (1994), for *selecting* the variables to be included in the model
- Since LASSO includes a penalty depending on the absolute value of the coefficients, some coefficients are shrunk to zero and hence eliminated from the model

Very preliminary results

List of the variables selected by LASSO:

Factor	Categ	Description
CARBON EMISSIONS ENERGY MGMT EFFIC.	E	Mitigation of carbon emissions by managing energy consumption.
CARBON EMISSIONS - LOW RISK	E	Revenues from lines of business with a low level of carbon intensity.
GREEN BUILDING - HIGH	E	Buildings with high energy requirements & subject to green building regulations.
PRODUCT CARBON FOOTPRINT - MEDIUM	E	Revenues from products that are of moderate carbon-intensity.
CHEMICAL SAFETY - HIGH	S	Revenues from products with substances of high concern.
HEALTH SAFETY - LOW	S	Revenues from lines of business that typically have low worker injury rates.
HUMAN CAPITAL DEVELOPMENT - HIGH	S	Revenue from lines of business very much reliant on highly-skilled workers.
RESPONSIBLE INVESTMENT - HIGH RISK	S	Revenues from activities involving management of investment assets.
ROA	X	Returns on Assets
Current Ratio	X	Current Assets - Current Liabilities
Solvency Ratio	X	After tax net income + depreciation divided by liabilities
EBIT	X	Earning Before Interest and Taxes margin
Age	X	Company's age
Standardised Legal Form	X	A company's legal form

Moving forward

- LASSO is a **selection** method. Ultimately, we are interested in the *statistical significance*, *sign* and *magnitude* of the ESG variables on the Altman Z-score.

  To have robust and interpretable coefficients, we are exploring alternative methods:

  - Bootstrapping
  - Exact post-selection inference applied to LASSO (Lee et al., 2016 and Taylor and Tibshirani, 2016)

- We apply a model adapted from Holmstrom and Tirole (1997) to understand how each ESG factor affects the credit strenght of individual companies in our sample

Thank you!