THE PREDICTIVE ROLE OF COUNTRY–LEVEL ESG INDICATORS IN FINANCIAL DECISION–MAKING

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ABSTRACT

Environmental, social and governance aspects, collectively known as ESG factors, have gained significant importance in finance recently. This paper focuses on uncovering the importance of the predictive power of country-level ESG indicators in estimating risk premiums. We use the Worldwide Governance Indicators and the database of global ESG indicators provided by the World Bank, while we apply the neural networks methodology. A constant relationship between ESG factors and risk premiums would result in obvious implications for policymakers, as well as for investors. We seek empirical evidence to leverage ESG considerations in investment decisions and policymaking to ensure sustainable economic development.

Keywords: ESG investments, neural networks, risk premium, sustainability

JEL codes: G11, Q01, Q56

1   INTRODUCTION

The outbreak and spread of the coronavirus pandemic showed us how a regional risk can accelerate into a global crisis with severe humanitarian, economic, financial and political consequences. The coronavirus also drew attention to today's closely connected world, and showed how an in-depth analysis of Environmental (E), Social (S) and Governance (G) factors is imperative for a comprehensive assessment of a country's underlying vulnerability and resilience (RobecoSAM, 2020).

ESG indicators have thus become the focus of attention. There are tremendous research articles by both academics and financial professionals that have analyzed

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the link between environmental, social and corporate governance-related (ESG) indicators and financial risk and performance, primarily in the case of companies (*Friede* et al., 2015). However, ESG indicators and ratings are applied to countries as well, similarly to credit ratings which are nowadays becoming more important. These ESG indicators provide investors with insights when assessing a country's long-term credit risk and evaluating sovereign bonds, sub-sovereign bonds, and government-related enterprises. With these new insights, investors and researchers can gain a better understanding of inherent long-term risks both from a values-based and an economic perspective (*Comble* et al., 2019), as opposed to dividend-based thinking (*Kerti–Keresztúri*, 2017).

In this paper, we focused on uncovering the predictive power of country-level ESG indicators in estimating risk premiums. We examined whether country-level ESG indicators are good predictors of risk premiums, and we analyzed the structure of the index in more depth with neural networks. We tested according to two hypotheses: if the importance of each indicator remains constant over years, and if the importance of each indicator remains constant in the case of different income groups.

With this research, we contribute to the literature in three ways. First, we apply the lending risk premium as a measure of credit risk. Second, we use the ESG rating methodology of RobecoSAM, including ESG indicators along with Environmental risk, Environmental status, Ageing, Social unrest, Corruption, Institutions, and Political risk (RobecoSAM, 2020). We measure not only the predictive power of each determinant, but also the importance of each factor along time horizon and income level. Third, we used the neural networks method to analyze the importance of each factor.

Using machine learning methods for analyzing the determinative power of variables is one of the most commonly used techniques today. It has many definitions in the literature. *Gu* et al. (2020) define machine learning methods as "a diverse collection of high-dimensional models for statistical prediction, combined with so-called 'regularization' methods for model selection and mitigation of overfit, and efficient algorithms for searching among a vast number of potential model specifications." This method could also prove more optimal than other methodologies in this case for the following reasons. First of all, machine learning methods are flexible. Moreover, these methods emphasize stable out-of-sample performance to explicitly guard against overfitting. These methodologies could be optimal for prediction problems by reducing degrees of freedom and condensing redundant variation among predictors. Finally, they can handle nonlinear relationships and interactions (Gu et al., 2020).

The remainder of this paper is organized as follows. First, we discuss the literature and relevant research background, followed by the proposed theoretical frame-

work. Next, we present an overview of empirical studies, followed by the details and results of each study. The paper concludes with a summary of the theoretical and managerial implications, as well as limitations and avenues for future research.

2   LITERATURE REVIEW

This study ties into multiple areas of the specialised literature, country-level ESG factors being a widely researched topic. In the research of *Crifo* et al. (2017), econometric analysis of the relationship between ESG performance and government bond spreads was applied for 23 OECD countries over the period 2007–2012. Their results showed that high ESG ratings are associated with low borrowing costs and the impact of ESG ratings on the cost of sovereign borrowing is more pronounced in bonds of shorter maturities.

Capelle-Blancard et al. (2016, 2019) examined the extent to which ESG performance can affect sovereign bond spreads. They observed that countries with good ESG performance tend to have less default risk and thus lower bond spreads. Also, they found that the economic impact is stronger in the long run, suggesting that ESG performance is a long-lasting phenomenon. They also examined the financial impact of separate ESG dimensions: here, the results suggested that the environmental dimension appears to have no financial impact, whereas governance weighs more than social factors. In their work, they used a standard panel model to create an ESG index using Principal Component Analysis.

Tarmuji et al. (2016) examined the impact of ESG practices on economic performance. In their research, they examined non-financial data from two countries (Malaysia and Singapore) between 2010 and 2014. The results of their work showed that social and governance practices significantly influence economic performance. In their study, they used descriptive statistics, correlation analysis and linear regression to analyze data.

There are several approaches in the literature to define the determinants of the risk premium and its measurement. Usually, they apply financial indicators as predictors, such as public debt/GDP, GDP growth or inflation rate.

Gu et al. (2018) performed a comparative analysis of machine learning methods for the canonical problem of empirical asset pricing: measuring asset risk premiums. They applied trees and neural networks in their research. Their results suggested that both methods agree on the same set of dominant predictive signals, a set that includes variations on momentum, liquidity and volatility. *Mpapalika–Malikane* (2019) examined the determinants of the sovereign risk premium in African countries. They applied the time-series Generalized Method of Mo-

ments (GMM). Their findings indicate that public debt/GDP, GDP growth, inflation rate, foreign exchange reserves, market sentiment and commodity prices are highly significant in influencing the sovereign risk premium in all periods.

Gibson et al. (2019) studied the impact of ESG rating disagreement on stock returns. They used explanatory statistics and regression in their analysis and the results suggested that in extreme bull market conditions, the risk-based hypothesis prevails irrespective of the rating pillar considered and irrespective of the legal origin of the ESG rating providers.

Dunn et al. (2018) discussed the risk and return implications of incorporating ESG considerations into an investment strategy. They focused on the finding that ESG exposures may be informative about the risks of individual firms. As a result, they found that stocks with the worst ESG exposures have total and stock-specific volatility that is up to 10-15% higher, and betas up to 3% higher, than stocks with the best ESG exposures. Their findings suggest that ESG may have a role in investment portfolios that extends beyond ethical considerations, particularly for investors interested in tilting toward safer stocks.

In his study, *Hübel* (2020) analyzed the role of countries' ESG performance in sovereign credit default swap (CDS) markets. He analyzed 60 countries between 2007 and 2017, and found that countries with superior ESG performance not only show lower CDS spreads, but also exhibit flatter CDS implied credit curves. He applied linear regression and bivariate statistics in his study, while he also used RobecoSAM ESG ratings to measure country sustainability.

The study of *De Franco* et al. (2020) applied a machine learning algorithm that identifies patterns between ESG profiles and financial performance for companies in a large investment universe. By linking the ESG features with financial performance in a non-linear way, their machine learning algorithm-based strategy turns out to be an efficient stock picking tool, which outperforms classic strategies that screen stocks according to their ESG ratings as the popular best-in-class approach. In our research, we would also link ESG indicators with financial performance, but on a country level.

De Lucia et al. (2020) aimed to predict the accuracy of main financial indicators such as expected Return on Equity (ROE) and Return on Assets (ROA) of public enterprises in Europe based on ESG indicators and other economic metrics, and to identify whether ESG initiatives affect the financial performance of public European enterprises. They applied machine learning techniques and an inferential model, and found in their analysis that machine learning methods accurately predict ROA and ROE and indicate, through the ordered logistic regression model, the existence of a positive relationship between ESG practices and financial indicators.

In our research, the calculation method of ESG ratings plays an important role as well. The expertise of ESG rating agencies has turned them into a key reference point in the case of ESG assessments of a firm or country.

Escrig-Olmedo et al. (2019) made a comparative study of the different methodologies for calculation of ESG ratings by different companies. In their study, they found that ESG rating agencies focus on analyzing environmental, social and governance criteria, whereas the economic dimension is less studied. Moreover, they observed that ESG rating agencies do not fully integrate sustainability principles into the corporate sustainability assessment process. Escrig-Olmedo et al. (2019) carried out an in-depth analysis of how environmental criteria have changed, comparing 2008 to 2018 at ESG rating agencies in the case of firms. "Specifically, in 2008, the most widely used analysis criteria were environmental policy/management (100%), emissions (62.5%), and climate change (50%), while in 2018 the main criteria analyzed were environmental policy/management (87.5%), water use and management (87.5%), and protection of biodiversity (87.5%). In addition, the aspects that have been incorporated into the assessment process of ESG rating agencies in 2018 were climate change (75%), emissions (75%), and waste management/reduction (75%). The results show a greater interest in environmental concerns than 10 years ago." In the case of social criteria, the study added, "the aspects that have been mainly considered in the assessment process of ESG rating agencies analyzed in 2008 were human capital development and training (100%), human rights (87.5%), and community relations (87.5%). On the contrary, the aspects incorporated into the assessment process of all ESG rating agencies in 2018 were labor management, human rights, and quality working conditions, health and safety." Finally, regarding the governance pillar, they found that "corporate governance functions and committees (100%), board structure (75%), and remuneration/compensation policy (62.5%) were the most valuable criteria. These criteria, generally included in the corporate governance codes, were regarded as important in 2018. However, the increase in the prevention of corruption and bribery issues and in the transparency issues stresses a significant difference between 2008 and 2018, since they are now the second most analyzed aspects in the assessment process (87.5%) (Escrig-Olmedo et al., 2019:10–12).

To sum up, there is a significant amount of literature dealing with the ESG determinants of risk premiums, and these typically analyze firm-level, not country-level indicators. Using machine learning methods to analyze relationships is rare in the literature. However, Hübel (2020), De Franco et al. (2020) and Capelle-Blancard et al. (2016, 2019) were able to provide a framework to our research in which we analyzed the predictive relationship between country-level ESG indicators and risk premiums.

3   DATA AND METHODOLOGY

In our research, we used the database of global ESG indicators provided by the World Bank (World Bank, 2020a). The original database of the World Bank consists of 68 ESG indicators for 239 countries and country groups. For analysis, we selected seven variables from the ESG indicators, based on the indicators used by RobecoSAM (2020) and relevant literature of country-level ESG factors (Capelle-Blancard et al., 2016, 2019). RobecoSAM calculates a country's ESG score based on 40 different indicators measuring environmental, social and governance factors. The factors are weighted across the three ESG dimensions as follows: 20% to environmental, 30% to social, and 50% to governance factors (RobecoSAM, 2020).

In our research, we included the following variables:

Environmental factor – 20%
- Environmental risk: Forest area (% of land area)
- Environmental status: PM2.5 air pollution, mean annual exposure (micrograms per cubic metre)

Social factor – 30%
- Ageing: Life expectancy at birth, total (years), population aged 65 and above (% of total population)
- Social unrest: Unemployment (%)

Governance factor – 50%
- Corruption: Control of Corruption: Estimate
- Institutions: Government Effectiveness: Estimate, Rule of Law: Estimate
- Political risk: Political Stability and Absence of Violence/Terrorism: Estimate, Voice and Accountability: Estimate

Our research covers 127 countries for the single years of 2016 and 2010. For the hypothesis testing, we used further data from the World Bank database, and as a risk premium we used the lending risk premium (%) (World Bank, 2020b).

The applied methodology was the neural networks application in SPSSS, the Multilayer Perceptron (MLP) method, designed to reveal the importance of each variable in connection with a risk premium. The Multilayer Perceptron procedure produces a predictive model for one or more dependent (target) variables based on the values of the predictor variables (IBM, 2020). It is one type of neural network, consisting of at least three layers of nodes: an input layer, a hidden layer, and an output layer.
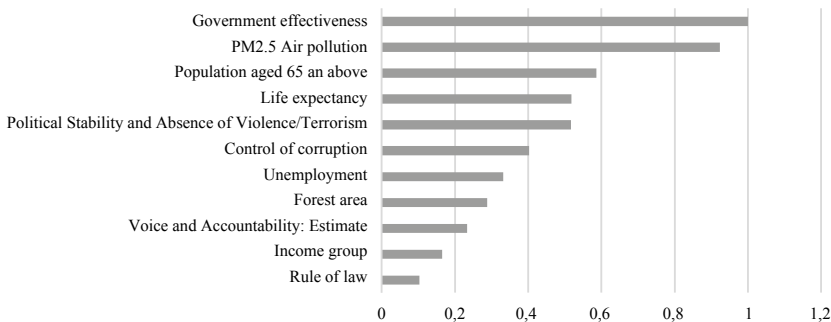
4   RESULTS

We analyzed ESG indicators provided by the World Bank to find out how these indicators determine the lending risk premium, where the importance of each factor depends on the income group or change over time. We tested two hypotheses to analyze the research question.

4.1   Hypothesis 1

H1: **The importance of ESG indicators in determining the lending risk premium remains constant over years.**

Firstly, we tested if the importance of the selected ESG indicators remains constant over a period of years. We applied neural networks methodology in SPSSS, the Multilayer Perceptron model. We used data for 2010 and 2016 and the results are as follows.

Figure 1
Normalized importance of ESG determinants in 2016

Source: World Bank (2020a, 2020b)

The results suggest that the most important determinative factor in the calculation is government effectiveness, the air pollution and the population 65 and above. The results show us that the overpresented governance factors do not have more importance with respect to the lending risk premium than social or environmental factors. The less important factors are rule of law and voice and accountability.

Figure 2
Normalized importance of ESG determinants in 2010
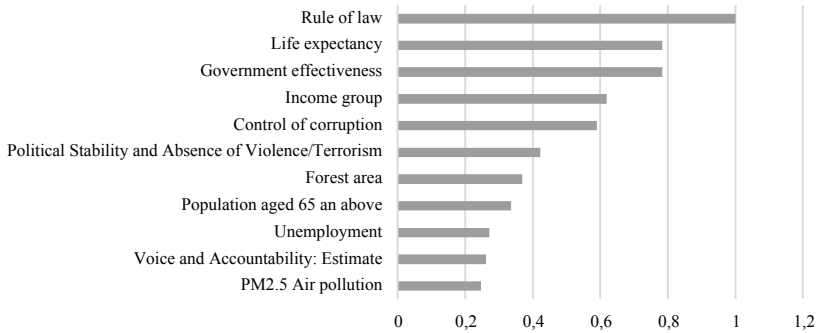
Source: World Bank (2020a, 2020b)

In the case of 2010, we can see that the rule of law and life expectancy are the most important factors for determining the lending risk premium, while voice and accountability and air pollution are the least important.

To sum up, we can see that the importance of ESG indicators in determining the lending risk premium does not remain constant when comparing 2010 and 2016, so we rejected the H1 hypothesis.

4.2   Hypothesis 2

*H2: **The importance of ESG indicators in determining the lending risk premium remains the same irrespective of income groups.***

In this case we examined four different income group categories in 2016. The income group categories depended on yearly GNI per capita: low-income economies are defined as those with a GNI per capita, calculated using the World Bank Atlas method, of $1,035 or less; lower-middle-income economies are those with a GNI per capita between $1,036 and $4,045; upper-middle-income economies are those with a GNI per capita between $4,046 and $12,535; and high-income economies are those with a GNI per capita of $12,536 or more (World Bank, 2020c).

Firstly, we tested the high-income group countries, and in *Figure 3* we can see the results.

Figure 3
Normalized importance of ESG determinants in 2016
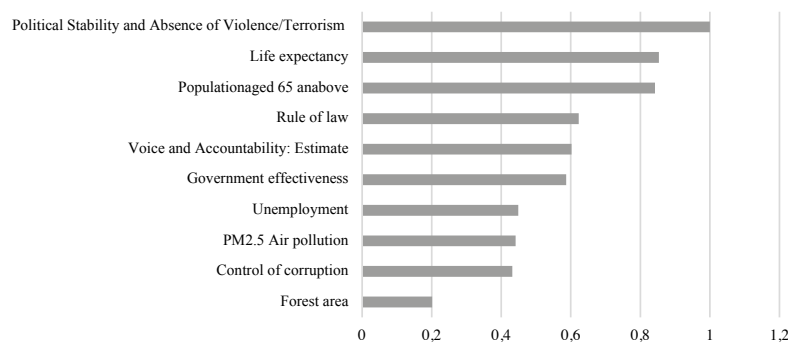**in case of high-income countries**
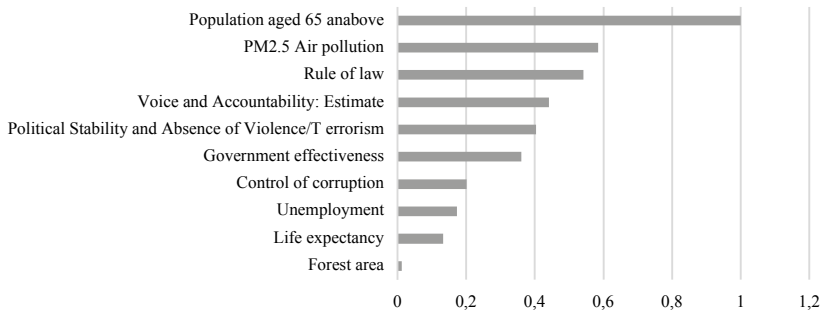
Source: World Bank (2020a, 2020b, 2020c)

We can see on the graph that the most important factors are population aged 65, air pollution and rule of law, while the least important are life expectancy and forest area. This is slightly in line with the worldwide results in Figure 1, as the population aged 65 and air pollution are in the top.

The results of the upper-middle-income countries are shown in *Figure 4*.

Figure 4
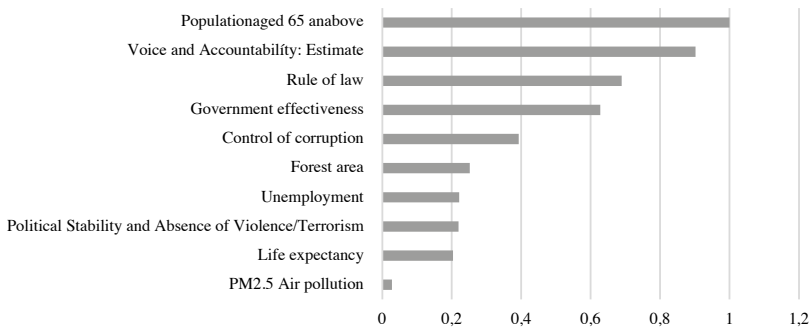**Normalized importance of ESG determinants (%)**

Source: World Bank (2020a, 2020b, 2020c)

The graph suggests that in the case of upper-middle-income countries political stability has the most important role in determining the lending risk premium, which in the case of the high-income group and worldwide results is among the

least important factors. Life expectancy is also at the top, along with Population above 65 years, which means that in this income group social factors have more important predictive power in determining the lending risk premium than with other income groups.

Figure 5
Normalized importance of ESG determinants in 2016
in case of lower-middle-income countries

Source: World Bank (2020a, 2020b, 2020c)

Figure 5 shows the results of the lower-middle-income countries. In this case, population above 65 is the most important factor, while the life expectancy and air pollution are the less important factors. An interesting fact is that the governmental factors are all in the top in this case.

Figure 6
Normalized importance of ESG determinants in 2016
in case of low-income countries
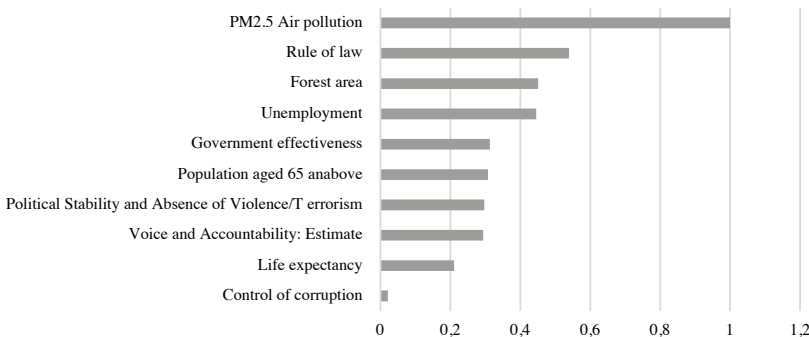
Source: World Bank (2020a, 2020b, 2020c)

In the case of the low-income group, air pollution is the most important determinant factor and rule of law is second, while governance factors are less or only moderately important in determining the lending risk premium in the case of this country group.

Summarizing the results in the case of *H2*, we rejected the hypothesis that the importance of ESG indicators in determining the lending risk premium remains the same irrespective of income groups.

5   SUMMARY

In this study we examined whether the importance of the chosen ESG determinant factors remains constant over a period of years and in the case of different country groups. We utilized country-level ESG indicators and lending risk premium data provided by the World Bank for this analysis. We applied the neural networks method, the Multilayer Perceptron, on the selected countries and indicators to analyze this question through two hypotheses. Firstly, we tested the temporal constancy, then the consistency between different income categories. We rejected both hypotheses, finding that the importance of the chosen ESG determinant factors does not remain constant over years and in the case of different country groups.

The findings are partly in line with RobecoSAM's ESG rating calculation that governance and social indicators are becoming more important, and these are accordingly assigned weightings of 50% and 30% in their calculation method. The results do not match with the studies of Capelle-Blancard et al. (2016, 2019) and Tarmuji et al. (2016), as they highlighted that the environmental dimension appears to have no financial impact. However, the findings match with Escrig-Olmedo et al. (2019), who found that there is a greater interest in environmental concerns in 2018 than in 2008.

The results of our research have several practical benefits. Based on these results, investors can integrate ESG factors into their portfolios smoothly. They can optimize risk budgeting and make better-informed investment decisions. Moreover, the coronavirus pandemic shows us that there is a need for comprehensive ESG analysis to more fully understand a country's true status. We think a recent study could be the beginning of a complex study. The crisis drew attention to the fact that beyond healthy living standards, good governance plays an important role in a country's capacity to protect public health, reduce economic fallout and mitigate socio-political disturbances (RobecoSAM, 2020b).

This research has limitations. Firstly, robustness checks are required to further enhance the reliability of the results. Moreover, the results are valid only for selected data for 2016 and 2010, so that no general conclusions can be drawn from this analysis.

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