The Convergence of Sovereign Environmental, Social and Governance Ratings

Eric Bouyé Diane Menville



Treasury Asset Management & Advisory Department March 2021

Abstract

This paper studies sovereign environmental, social, and governance (ESG) ratings from the qualitative and quantitative angles. First, it introduces the landscape for sovereign ESG ratings. Second, it provides a comparison with the history of credit ratings, factoring in that ESG ratings are in an early development stage. Third, the paper reviews different actors, key issues, including taxonomy, models and data from different providers. The paper provides a qualitative assessment of the convergence of ratings among providers by introducing a factor attribution method, that maps all providers' ratings into a common taxonomy defined by the United Nations-supported Principles for Responsible Investment (UNPRI). Then, a quantitative analysis of the convergence is performed by regressing the scores on variables from the World Bank sovereign ESG database. A noticeable contribution to the literature is a high level of explanatory power of these variables across all rating methodologies, with a R2 ranging between 0.78 and 0.98. An analysis of the importance of variables using a lasso regression exhibits the preponderance of the governance factor and the limited role of demographic shifts for all providers.

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The Convergence of Sovereign Environmental, Social and Governance Ratings

Eric Bouyé^a

Diane Menville^b

Keywords: ESG, sovereign bonds, ratings. **JEL classification:** M14, G23, G24.

*For their comments and the data, we thank Sarah Gabler, Manna Neghassi and Wayne Seaton (Sustainalytics), Wendy Fernandez (MSCI), Shirley Zhang (FTSE Russell), Coziana Ciurea and Agnes Terestchenko (Vigeo-Eiris). This manuscript solely reflects the views of the authors, not necessarily the one of their employer. Diane Menville participated to the paper while working at the World Bank. We remain sole responsible for any mistake or error.

^aWorld Bank. 1818 H Street, NW Washington, DC 20433, USA. e-mail: ebouye@worldbank.org. ^b Scope SE & Co. KGaA. 23, Boulevard des Capucines, 75002 Paris. e-mail: d.menville@scopegroup.com.

1 Introduction

Environmental, social and governance (ESG) indicators are becoming more integrated into assessments of the risk exposure for sovereign and corporate entities, as a complement to standard financial indicators. The number of data providers has increased over the last decade, and each of them has been developing a proprietary methodology to provide ESG ratings to investors¹. The standardization of data and methodologies has been an ongoing discussion among practitioners, either as a source of diversity or confusion (Berg, Kölbel and Rigobon, 2019).

Financial markets and investors have been accustomed to the use of credit ratings that conveniently summarize the impact of all financial information (and governance to some extent) in one score reflecting the probability of default. However, ESG factors have an impact at both macroeconomic (Nordhaus, 1977) and microeconomic levels, especially during times of crisis (Lins and Servaes, 2017; Dietz, Gollier and Kessler, 2018). In response to the growing appetite of the financial sector for sovereign ESG ratings, the data source, the taxonomy and models have been evolving, as demonstrated by the recent change in their sovereign models by leading ESG data providers (e.g. MSCI from 2016 to 2019, and Sustainalytics in 2019). Whether these changes have led to a larger consensus among ratings is still an open question. The level of correlations between ESG scores for corporates has been demonstrated to be low, probably between 0.4 and 0.6 (Bender *et al*, 2018; Berg, Kölbel and Rigobon, 2019), however should we expect higher correlation for sovereign ESG scores due to closer methodologies among providers? Moreover, due to the specific nature of governments, it is reasonable to assess the link between credit ratings (probability of default) and ESG ratings.

The development of credit rating agencies and scores during the last century provides an interesting comparison. The convergence of credit ratings has been supported by regulation, industry investments in applied research and the development of standardized data. The recent acquisition of ESG specialized firms by major rating agencies has sent a strong signal from the financial industry in terms of willingness to invest resources and capital – e.g. Beyond Ratings by London Stock Exchange Group (LSEG) in 2019, and Vigeo Eiris by Moody's in

 $^{^{1}}$ At the same time, there has been a growing interest in 'ESG' and 'ESG rating' as indicated by Google trends (see Appendix A.2).

2019. One can legitimately ask if the ESG rating industry will follow a similar path as the credit rating one and if ESG rating scores will become mainstream. Regulation may play a similar role as it did for credit, noting that initiatives from supervising entities have started but without legal enforcement at this stage (NGFS, 2019; BIS, 2020).

The next section provides a comparison with the history of credit ratings, factoring in that ESG ratings are in an early development stage. The third section reviews sovereign ESG rating characteristics from different providers (MSCI, Sustainalytics, Beyond Ratings, RepRisk), and identifies the possible sources of discrepancies between ratings. Specifically, scores could diverge because of differences in scope, taxonomy, peer groups, or indicators. Then, we study the quantitative convergence using the World Bank sovereign ESG database. The understanding of discrepancies and bias is key for investors to ensure that the chosen ratings are aligned with their 'ethical' utility function. The fourth section concludes.

2 Credit versus ESG rating: An historical perspective

Credit rating agencies play an important economic role: they support the debt market in providing reliable information about the risks of default of an issuer or a type of debt. The perceived risk determines the yield of the financial instrument, and the ratings participate in this pricing mechanism. Do ESG ratings play a similar role? Calling them 'ratings' may imply that ESG scores could be complementary in assessing both financial and non-financial risks. Interestingly, ESG ratings may be combined with credit ratings to measure sovereign risk exposure and viability of the debt.

In this context, a review of the characteristics of credit rating activity could be useful to define a path for responsible investing scoring. The history of credit agencies started in the early 1900s and went through many steps before becoming mainstream and central for financial markets. As of today, the global credit rating industry is highly concentrated, with three agencies – S&P Global Ratings, Moody's Investor Service and Fitch Ratings – controlling nearly the entire market. For example, the European Securities and Markets Authority (ESMA) indicates that the three largest credit rating agencies (CRA) account for 92.1% of the European Union (EU)

market (ESMA, Market Share Calculation 2019).

The beginning of the century has been characterized by an increase of the regulatory pressure e.g. EU directives, such as the Capital Requirements Directive of 2006, Credit Rating Agency Reform Act of 2006, and the 2008 global financial crisis. However, even before regulatory changes that have been impacting CRA, their business practices and their disclosure requirements, they were already largely used by the financial markets. In a similar way, ESG rating agencies could take a central role in financial markets even before significant regulatory changes.

Four dimensions can be used to compare credit and ESG indicators: (i) the level of discrepancy between scores or ratings, (ii) the methodology and associated bias, (iii) the facility to replicate indicators and their sensitivity to business cycles, and (iv) the existence of an asset pricing factor e.g. credit or ESG factors. The literature on these topics has been extensive for credit ratings (Powell, 2013).

Firstly, one of the most common critics regarding ESG ratings is their lack of convergence. However, the earlier stages of development of CRA exhibit differences. For example, while the correlation is quite high between sovereign ratings, the top three credit agencies were in disagreement about 50% of the time for a 10-year historical analysis (Powell and Martinez, 2008), even if the difference is usually limited to one notch. Moreover, convergence has been evolving through time. We analyzed cross-sectional and time-series correlation between the top three CRA using annual data from 1949 to 2019 for 163 countries (Table 1). The average crosssectional correlations are higher than the average time-series correlations over the full period. The average cross-countries correlation of Fitch with Moody's and S&P are significantly higher than the one between Moody's and S&P. Given that Fitch data are only available since 1994, it would tend to support that the correlation was lower at the beginning of the sample and higher after 1994 (Figure 1). A closer look at the correlation between Moody's and S&P before 1994 exhibits a structural break in 1983, that could reflect both a significant discrepancy and the impact of having a small number of countries rated (Figure 2). Moreover, time-series correlation over the full period is high (about 80%) but does not demonstrate a full convergence. We obtain similar results if we look at the ratings of the first six countries rated by two agencies

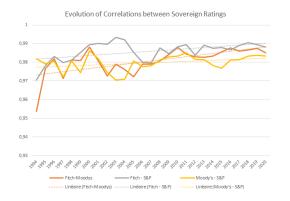


Figure 1: Cross-sectional (countries) correlations between CRA for sovereign ratings for the period 1994-2019. Source: tradingeconomics.com.



Figure 2: Cross-sectional (countries) correlations between CRA for sovereign ratings for the period 1978-1993. Source: tradingeconomics.com.

(Appendix A.2).

Table 1: Average cross-sectional and time-series correlations for sovereign ratings between the top three CRA. Annual data, end of year, from 1949 to 2020 for 163 countries. Source: tradingeco-nomics.com.

Correlations	Cross-sectional	Time-series
Fitch-Moody's	98.1%	79.0%
Fitch-S&P	98.6%	80.4%
S&P-Moody's	81.9%	83.8%

From history, we observe a convergence between credit ratings that took time and regulation has not been the main driver. Reducing the differences between ESG rating providers may not be an objective *per se* as they may have complementary approaches depending on their respective modelling choices.

Secondly, credit rating agencies have different models to come up with a sovereign rating. For example, Moody's has a scorecard model, while Fitch developed a proprietary sovereign model with a qualitative overlay. However, their calibration leads to similar results because they all measure credit risk either through probability of default, loss given default or both. On the contrary, ESG ratings may have different objectives: some measure long-term sustainability impact, but some others assess short-term risks. These objectives lead to different definitions of materiality and to different models, including the weights chosen to aggregate the E, S, and G sub-scores and the overall ESG score. For example, the degree of development of a country, its regulations and other economic factors may influence the weighting scheme. Moreover, ESG ratings could also suffer from scoring bias, by taking into account ratings from other providers, or from the previous years leading to a momentum or stickiness effect.

Thirdly, can ESG ratings be easily replicated with a limited number of factors and are they sensitive to business cycles? Credit ratings are explained by a limited number of factors including per capita income, GDP growth, inflation, external debt, level of economic development, and default history (Cantor and Packer, 1996; Powell and Martinez, 2008). A direct implication is the sensitivity of credit ratings to business cycles. Then, the same question applies to ESG ratings, as social risks, for example, are correlated to economic cycles. ESG ratings have to integrate different factors across three distinct characteristics and time horizons into one overall score. Even if some variables can be objectively measured such as carbon emissions, the choice of other ESG factors is more subjective. The definition of social and governance risks, and environmental to some extent, is large and can be difficult to summarize in a small number of indicators. Also ESG data have still not reached the level of standardization of financial data. For example, 46% of institutional investors found the social part to be the most difficult to analyse and embed in their strategies (BNP Paribas Securities Services, 2019).

Fourthly, what is the impact of ESG factors on asset returns and the perceived risk by investors? This has been a topic of debate for the last decade with an extensive literature and opposite conclusions. Some authors find that carbon emissions change may have a positive and significant effect on firms' stock returns (e.g. Bolton and Kacperczyk, 2019), while some others indicate that strategies that lowered carbon emissions more aggressively performed better (e.g. Cheema-Fox *et al*, 2019). However, the robustness of results related to pricing factors in general is a challenging and still open topic (Hou, Xue and Zhang, 2019). Finally, to bridge the gap between credit and ESG, few recent studies analyze the relationship between credit default swaps (CDS) and ESG sovereign ratings and the results are mixed. For emerging and frontier markets, Renaissance Capital find a zero correlation between CDS and their internal per capita adjusted ESG score (Robertson and Lopez, 2018). Hermes Investment Management and Beyond Ratings develop a joint study for 59 countries between 2009 and 2018 concluding that countries with the best ESG scores tend to have the lowest CDS spreads and vice versa (Reznick *et al*, 2019). Interestingly, companies with the highest number of controversies in some sectors (Information Technology, Industrials, Materials) show a positive relationship between their CDS spread and ESG ratings (Landry, Castillo-Lazaro and Lee, 2017). Additionally, although the authors find no relationship between ESG scores and the severity of the controversy, higher E, S, and G scores are negatively correlated with the frequency of E, S, and G controversies. Our paper provides new insights by examining the relationship between CDS spread and ratings across four leading ESG score providers.

3 Discrepancies and convergence of ESG data

The number of ESG ratings providers has been increasing. Some actors seem to have taken the lead, new comers have an increasing popularity, while some acquisitions have also impacted the trend. We observe three groups:

- The big players: all major rating agencies have either acquired or launched an ESG data activity and many major financial players have positioned themselves on ESG e.g. S&Ps, Moody's, Bloomberg, FTSE Russell, MSCI, Thomson Reuters, Morningstar.
- The ESG specialists: data providers focusing solely on ESG research, ratings, and analysis e.g. RepRisk, Arabesque, Covalence, CSRHub, Ethos, Inrate, RobecoSAM, Oekom research, Vigeo Eiris, Sustainalytics.
- The ESG specialists with focus: data providers that focus on one or more aspects of ESG, but not all three e.g. Carbon Disclosure Project (CDP) for climate change and water, Trucost for environmental risks, ISS for governance.

All providers acquire a large quantity of data to cover the several dimensions of an ESG rating. The core data for sovereigns are usually sourced from both public and private databases, including international institutions e.g. the World Bank², the International Monetary Fund,

 $^{^{2}}$ The World Bank launched a Sovereign ESG Data Portal in October 2019: a free, open and easy to use online platform that provides users with sovereign-level environmental, social and governance (ESG) data http://datatopics.worldbank.org/esg/.

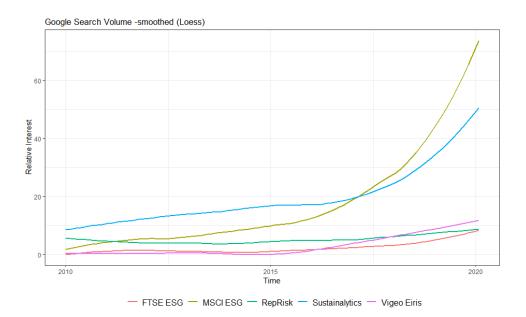


Figure 3: Popularity of the 5 ESG rating providers used for the analysis: MSCI, Sustainalytics, FTSE/Beyond Ratings, Vigeo-Eiris and RepRisk.

the World Health Organization, the Food and Agriculture Organization, etc. Sovereign data generally come from more robust and standardized sources than corporates. Most providers have leveraged on big data and machine learning tools.

3.1 Data set and taxonomy

Our qualitative analysis includes MSCI, Sustainalytics, FTSE/Beyond Ratings, Vigeo-Eiris and RepRisk³. Using Google trends on a set of five ESG rating providers, we could observe changes in popularity (Figure 3). The characteristics of our dataset are summarized in Table 2.

 $^{^{3}}$ RobecoSAM was not able to participate since S&P Global was finalizing the acquisition of the SAM ESG Ratings and ESG Benchmarking Business at the time of the analysis.

	MSCI	Sustainalytics	Beyond	RepRisk	Vigeo-Eiris	RobecoSAM
			Ratings			
Name of prod-	ESG Gov-	Country	Sovereign	RepRisk	Sovereign	Country
uct	ernment	Risk Rating	Risk Moni-	Index	Sustainabil-	Sustain-
	Rating		tors	(RRI)	ity Rating	ability
						Score
Included in our	Yes	Yes	Yes	Yes	No	No
analysis						
Number of	243	170	145	243	180	65
countries						
and/or Local						
Authorities						
Datapoints	4000+	8000+	$11,400^{*}$	80,000	172	
				sources		
Available	27	32 (and 10	34	$1~{\rm score}~(28$	17 subdo-	17
granularity -		events)		issues)	mains (56	
themes pro-					criteria)	
vided for our						
analysis						
Existence of E,	6 Manage-	yes and	yes and 4	yes (not	yes	yes
S and G scores	ment and	country	financial	included		
	Exposure	wealth scores	ones	in the		
	subscores			analysis)		
E, S and G	25%-25%-	15%- $35%$ -	30%-30%-	na	33%-33%-	15%- $25%$ -
scores weights	50%	50%	40%		33%	60%
Output scale	AAA	100 (lowest)	0 (lowest)	0 (lowest)	0 (lowest) to	1 (low-
	(highest)	to 0	to 100	to 100	100 (highest)	est) to 10
	to CCC		(highest)	(highest)		(highest)
	(lowest)					

Table 2: Characteristics of ESG rating providers.

 * (78 indicators x 146 countries x 80 quarters)

For the qualitative assessment of the five ESG rating providers, we used both public and private data, and contacted them to confirm our understanding using a questionnaire listing six characteristics identified during the process of comparison: the source of data (questionnaire or public data), the type of analysis (quantitative or qualitative), the objective of the rating (risk exposure or impact), the aggregation methodology (equally weighted, materiality based e.g. SASB⁴, model based), the inclusion of controversies, and the type of output (absolute or relative) – see Appendix A.4. The results are summarized^{5,6} in Table 3.

The intersection of the four providers used for the quantitative analysis contains 139 countries for 2017. Figure 4 represents the set of rated countries or local authorities for each provider.

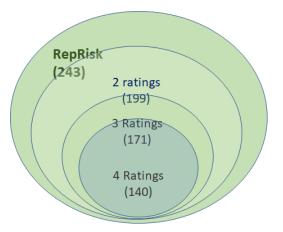


Figure 4: Number of ratings available by countries or local authorities (2017 data).

⁴The Sustainability Accounting Standards Board (SASB) has developed a set of 77 industry standards that were published in November 2018.

 $^{{}^{5}}$ Vigeo-Eiris provided some feedback for the qualitative review but due to time constraints, we were not able to use their ratings.

⁶The financial data were not included in our questionnaire, added afterwards.

		MSCI	Sustainalytics	Vigeo-Eiris	RepRisk	F'I'SE - BR
Product Name		ESG	Country	Sovereign	RepRisk	Sovereign
		Govern-	Risk Rating	Sustain-	Index	Risk
		ment		ability		Monitor
		Rating		Rating		
Data	Questionnaires			x		
Source	Public Data	Х	х		x	x(+private)
Type of	Quantitative				x	x
analysis	Qualitative	х	Х	Х		
Obiootivo	Risk	x	Х		x	x
OnJective	Impact			x (perf.)		
Aggregation	Fixed/Equally	x				
of	Weighted					
indicators	Materiality stan-		Х			
	dard					
	Model Weights			х	х	x
Continuenting	included		х		x	
COLLINATION	not included	Х		х		х
Financial	included	x	Х			x
Data	not included			х	х	
Outwit	Absolute Rating		х	X	x	x
Output	Relative Rating	х		х		

Table 3: Characteristics of 5 ESG ratings Providers

The cross-sectional correlations have been estimated between the four selected providers (Table 4). The correlations have been computed using normalized data ('z-scored'). The first key difference with corporate ratings is the high level of correlation, ranging from 0.72 between RepRisk and MSCI to 0.95 between Beyond Ratings and Sustainalytics. RepRisk has the lowest correlation with other providers, probably due to its specific approach. A first conclusion is that sovereigns exhibit significantly higher correlated ESG ratings than corporates.

()	/			*
Cross-sectional (coun-	MSCI	Sustainalyti	csBeyond	RepRisk
tries) correlations			Ratings	
MSCI	1			
Sustainalytics	0.93	1		
Beyond Ratings	0.93	0.95	1	
RepRisk	0.72	0.78	0.86	1

Table 4: Cross-sectional (countries) correlations between the selected ESG providers.

3.2 Qualitative convergence using the UNPRI taxonomy

The objective of this section is to compare the exposures of different providers using a common taxonomy. In September 2019, UNPRI issued a 'PRI Practical Guide to ESG Integration in Sovereign Debt' to help investors integrate ESG factors into the research and analysis of sovereign issuers (UNPRI, 2019). Among other efforts to standardize the process of ESG integration, UNPRI provided a list of sub-indicators in the section 'Identifying ESG factors'. They cover the three pillars with six governance factors, four social factors and four environmental factors. MSCI data includes 14 sub-indicators for the management of ESG risks, 13 for the exposure and the respective aggregated scores. MSCI has a published methodology to aggregate and calculate the ESG total score. Sustainalytics provides 20 events data and 32 sub-indices for E, S and G. Sustainalytics does not introduce environmental, social and governmental pillars *per se* but three close categories: Natural and Produced Capital (NCPC), Human Capital (HC) and Institutional Capital (IC). Additionally, Sustainalytics provides the Country-Risk score which equally weights a wealth score and an overall ESG score (calculated using the performance of the sub-indices and events pillars). FTSE/Beyond Ratings data consists of an aggregated score, seven pillars including four financial and economic scores and three (E, S, G) scores that are divided into 18 sub-indicators.

For each provider, only the ESG sub-indices were used when relevant, then normalized ('zscored') and mapped towards UNPRI factors. A comparable exercise has already been performed for corporate ratings (Berg, Kölbel and Rigobon, 2019). Our approach is different as we use a target taxonomy that is independent and not the result of the union of the source taxonomies of the existing providers – however the authors indicate they have also tested the SASB taxonomy for corporates that lead to similar conclusions. A mapping introduces a qualitative bias but only very few situations occur where the mapping from the source to the target taxonomy is ambiguous. The goal of this analysis is to illustrate the exposure to the UNPRI factors for different providers, for a chosen mapping that has by construction a subjective component we think to be limited. In order to assess the robustness of our results, we have tested alternative mappings for few debatable cases and obtain comparable results.

Ordinary least squares (OLS) regressions are performed where the endogenous variable is the global score for each provider and the explanatory variables are the UNPRI sub-indices built by mapping the sub-indices of the original data. The results are reported in Table 5. All the coefficients are positive with their sum close or equal to one.

Table 5: Implied weights obtained using an OLS regression. The endogenous variable is the global score for each provider. The explanatory variables are the UNPRI sub-indices build by mapping the original data sub-indices.

UNPRI Indicators	BR-ESG	MSCI	Sustainalytics
			- ESG factors
Natural resources	7%	14%	7%
Physical risks	11%	4%	-
Energy transition Risk	7%	4%	-
Energy security	2%	-	4%
Demographic change	3%	-	17%
Education and human capi-	10%	8%	3%
tal			
Living standards and income	8%	28%	4%
inequality			
Social cohesion	8%	-	15%
Institutional strength	4%	12%	-
Political stability	12%	8%	10%
Government effectiveness	10%	-	14%
Regulatory effectiveness	3%	-	18%
Rule of law	9%	8%	-
Corruption	6%	14%	9%
\mathbb{R}^2	0.99	0.92	0.98
Provider disclosed weight			
Environmental	30%	25%	15%
Social	30%	25%	35%
Governance	40%	50%	50%

A stepwise regression method is implemented and can lead to some of the UNPRI factors not being selected. It could reflect either that a specific UNPRI indicator is not represented by a given provider, or some collinearity between the explanatory variables. The obtained R^2 for Beyond Ratings and Sustainalytics are respectively 0.99 and 0.98. MSCI has the lowest R^2 at 0.92, probably due to the non-linear aggregation method. For comparison, we also retrieved SDG sovereign scores (available at https://www.sdgindex.org/) and mapped their 75 indicators into UNPRI factors. The \mathbb{R}^2 reached 'only' 62%. Our approach can be interpreted as a linear projection of the global scores to the UNPRI indicators. Indeed, for some of them, the aggregation and the weighting rules are not fully known. The results (Table 5) indicate that the exposures of BR-ESG scores are balanced across sub-indicators with the highest coefficients for Political stability and Physical risks. MSCI and Sustainalytics ratings are more concentrated with respective higher exposures for Living standards and income inequality (28%) and Regulatory effectiveness (18%).

3.3 Quantitative convergence using the World Bank sovereign ESG database

One of the drawbacks of the qualitative approach to assess ratings convergence is that the results are dependent of the chosen mapping which is inevitably subjective. In this section, we propose to use a set of independent data to measure the degree of convergence: the World Bank Sovereign ESG Data. The dataset provides information on 17 key sustainability themes spanning environmental, social, and governance components:

- Environment: Emissions & pollution, Natural capital endowment & management, Energy use & security, Environment/climate risk & resilience, Food security;
- Social: Education & skills, Employment, Demography, Poverty & inequality, Health & nutrition, Access to services;
- Governance: Human rights, Government effectiveness, Stability & rule of law, Economic environment, Gender, Innovation.

The initial set of data has 67 indicators (See the list in Appendix A.6). When an indicator is not available for at least 50 countries, it is excluded. That reduces the explanatory data set to 32 indicators: 9 for Environment, 10 for Social and 13 for Governance. Table 6 summarizes the decrease in number of variables for each sustainability theme. The environment pillar is characterized by the highest reduction in the universe of explanatory variables, especially for the energy use & security and environment/climate risk & resilience themes. For the social pillar, the poverty & inequality theme is not represented due to a lack of sufficient data. The database provides annual data from 1960 to 2019, 2017 are used for the analysis. If for a given variable, the data for 2017 are not available, the most recent year is used, but not earlier than 2014.

Sustainability Theme		
Emissions & pollution	5	1
Natural capital endowment and management	6	4
Energy use & security	7	0
Environment/climate risk & resilience	6	1
Food Security	3	3
Environment Pillar	27	9
Education & skills	3	2
Employment	3	2
Demography	3	3
Poverty & Inequality	4	0
Health & Nutrition	5	3
Access to Services	4	2
Social Pillar	22	10
Human Rights	2	2
Government Effectiveness	2	2
Stability & Rule of Law	4	4
Economic Environment	3	2
Gender	4	2
Innovation	3	1
Governance Pillar	13	13
# of variables	67	32

Table 6: Number of explanatory variables from the World Bank sovereign ESG database used for the regression of ESG ratings.

Five types of regressions are performed: stepwise, principal component, ridge, lasso and elasticnet regressions, see Hastie, Tibshirani and Friedman (2016) for an introduction to these regression models.

The stepwise regression is performed using OLS and AIC as criterion for variable selection. The ridge regression penalizes the residual sum of squares as follows;

$$\beta_{ridge} = \underset{\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{K} x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^{K} \beta_j^2 \right\}$$

with y_i the ESG rating for country i, x_{ij} the j^{th} explanatory variable for country i, β_0 the

constant, β_j the loading for the j^{th} explanatory variable, N the number of observations, K the number of explanatory variables and λ the parameter that controls the degree of shrinkage. Alternatively the lasso parameters are obtained through a different penalization method (L_1 for lasso versus L_2 for ridge):

$$\beta_{lasso} = \arg\min_{\beta} \left\{ \frac{1}{2} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{K} x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^{K} |\beta_j| \right\}.$$

Finally, another penalty function called elastic-net offers a mix between ridge and lasso methods:

$$\beta_{lasso} = \underset{\beta}{\operatorname{arg\,min}} \left\{ \frac{1}{2} \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{K} x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^{K} \left(\alpha \beta_j^2 + (1-\alpha) \left| \beta_j \right| \right) \right\}.$$

with α controlling the weight between the L_1 and L_2 penalty functions. The principal component regression (pcr) consists in regressing the ys on the orthogonal factors obtained through principal component analysis.

Table 7 reports the \mathbb{R}^2 values of the test data for the five models: stepwise, principal components, ridge, lasso and elastic-net regressions. The \mathbb{R}^2 are impressively high, ranging between 0.78 and 0.98. The explanatory power is the highest for the score from Beyond Ratings, followed by Sustainalytics and MSCI. Reprisk exhibits the lowest explanatory power. Table 8 details the estimated hyperparameters for the four models: principal components, ridge, lasso and elastic-net regressions. The parameter λ is the regularization penalty and was selected using a 10-fold cross validation. Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample. In k-fold cross-validation, the original sample is randomly partitioned into k subsamples of equal size. A single subsample is retained as the validation data for testing the model, while the k - 1 remaining subsamples constitute the training data. The cross-validation process is then repeated k times with each of the k subsamples used exactly once as the validation data. A value of λ close to 0 indicates that model is very close to OLS, while a large value corresponds to a higher penalization of coefficients' size. It is interesting to note that the λ s of the lasso regression are close to 0 which confirms a proximity to the linear regression and, in particular for Sustainalytics and Beyond Ratings.

Table 7: \mathbb{R}^2 values of the	test data for the five models:	stepwise, principal	components, ridge, lasso
and elastic-net regressions.	The training/test data split f	for is $80/20$.	

\mathbf{R}^2 test	MSCI	Sustain.	BR	Reprisk
Stepwise	0.87	0.93	0.96	0.80
PCR	0.89	0.91	0.97	0.78
Ridge	0.90	0.93	0.98	0.78
Lasso	0.88	0.93	0.97	0.79
ElasticNet	0.88	0.93	0.98	0.79
# countries	138	125	106	140

Table 8: Estimated hyperparameters for the five models: stepwise, principal components, ridge, lasso and elastic-net regressions. The training/test data split for is 80/20.

Hyperparameters	MSCI	Sustain.	BR	Reprisk
PCR factors	9.00	10.00	10.00	5.00
$\mathbf{Ridge} \ \hat{\lambda}$	0.08	0.10	0.08	0.13
Lasso $\hat{\lambda}$	0.06	0.00	0.00	0.01
ElasticNet $\hat{\alpha}$ $\hat{\lambda}$	1 0.057	1 0.00210	$0.1 \ 0.1597$	0.9 0.0106

Table 9 reports the coefficients of the lasso regression of the ESG scores versus the 32 selected explanatory variables from the World Bank sovereign ESG database. Given that the results of the different models are all roughly equally robust, we have chosen to detail the parameters of the lasso model which has the virtue of limiting the number of explanatory parameters, especially when it does not converge to OLS, and simplifying the reading of the results. Let us detail some interesting results. **Table 9:** Coefficients of the lasso regression of the ESG scores versus the 32 selected explanatory variables from the World Bank sovereign ESG database (9 for Environment, 10 for Social and 13 for Governance).

	Lassu			
Variable	MSCI	Sust.	BR	$\operatorname{RepRisk}$
Constant	0.006	(0.034)	(0.167)	0.005
PM2.5 air pollution, mean annual exposure (micrograms per cubic meter)		(0.040)	(0.039)	
Adjusted savings: natural resources depletion (% of GNI)	ı	0.065	ı	I
Adjusted savings: net forest depletion ($\%$ of GNI)	T	(0.059)	I	ı
Forest area (% of land area)	0.070	0.018	ı	
Terrestrial and marine protected areas ($\%$ of total territorial area)	0.015	0.042	0.020	(0.026)
Population density (people per sq. km of land area)	I	(0.034)	(0.038)	ı
Agricultural land (% of land area)	ı	(0.033)	ı	0.070
Agriculture, value added ($\%$ of GDP)	I	(0.085)	(0.039)	ı
Food production index $(2004-2006 = 100)$		0.031	0.016	(0.109)
Labor force participation rate, total ($\%$ of total population ages 15-64) (modeled ILO estimate)	0.039			
Unemployment, total ($\%$ of total labor force) (modeled ILO estimate)	ı	(0.060)	(0.037)	ı
Fertility rate, total (births per woman)	ı	ı	ı	ı
Life expectancy at birth, total (years)		0.147	0.033	
Population ages 65 and above ($\%$ of total population)	0.016	0.021	0.052	ı
Cause of death, by communicable diseases and maternal, prenatal and nutrition conditions (% of total)		ı	(0.017)	
Mortality rate, under-5 (per 1,000 live births)		0.101	ı	(0.022)
Prevalence of overweight ($\%$ of adults)	0.083	0.027	0.024	0.039
Access to clean fuels and technologies for cooking (% of population)	0.021	0.118	0.166	ı
Access to electricity ($\%$ of population)	ı	0.055	0.032	ı
Strength of legal rights index $(0=\text{weak to } 12=\text{strong})$	0.020	ı	ı	0.001
Voice and Accountability: Estimate	0.132	0.059	0.122	0.101
Government Effectiveness: Estimate	0.178	0.087	0.205	ı
Regulatory Quality: Estimate	0.266	ı	0.072	
Control of Corruption: Estimate	0.092	0.048	0.130	0.451
Net migration	ı	(0.008)	ı	ı
Political Stability and Absence of Violence/Terrorism: Estimate	0.059	0.099	0.031	0.231
Rule of Law: Estimate	ı	0.278	0.154	0.074
GDP growth (annual $\%$)	ı	(0.082)	0.014	ı
Individuals using the Internet $(\%$ of population)	0.122	0.118	0.075	
Proportion of seats held by women in national parliaments ($\%$)	0.024	ī	0.014	(0.046)
Ratio of female to male labor force participation rate ($\%$) (modeled ILO estimate)	0.016	0.091	0.062	

Importance of a pillar. Since all variables have been normalized, we can interpret the coefficients of the lasso regression as the elasticity of our rating with respect to the explanatory variable. A negative coefficient suggests that as the independent variable increases, the dependent variable tends to decrease. The coefficient value indicates how much the mean of the dependent variable changes given a one-unit shift in the independent variable while holding other variables in the model constant. These elasticities can be positive or negative and to assess their weight we use their absolute value, which we will call the importance of the variable. The importance of a pillar P is defined as $I_P = \sum_{n_P}^{m_P} |\beta_i| / \sum_{1}^{32} |\beta_i|$ where i is the index of the coefficients of the regression and n_P and m_P the ranks of the initial and last coefficients related to pillar P (that can take the values Environment, Social or Governance). The analysis of this importance (Table 10) shows the preponderance of the governance factor for all providers. While it reaches 49% for Sustainalytics, it represents 79% for MSCI. The environment is the least represented pillar: from 7% for MSCI to 22% for Sustainalytics.

Table 10: Importance of each pillar in the methodology of four providers. The importance of a pillar P is defined as $I_P = \sum_{n_P}^{m_P} |\beta_i| / \sum_{1}^{32} |\beta_i|$ where i is the index of the coefficients of the regression and n_P and m_P the ranks of the initial and last coefficients related to pillar P. The numbers are reported for the lasso regression.

	MSCI	Sust.	\mathbf{BR}	${\operatorname{RepRisk}}$
Environment Pillar	7%	22%	11%	18%
Social Pillar	14%	29%	26%	5%
Governance Pillar	79%	49%	63%	77%

The specific case of Reprisk. There is a convergence in the sign (positive or negative) of the coefficients among all providers except for Reprisk. Reprisk has a negative coefficient for indicators like terrestrial and marine protected area or food production index and even mortality rate or the number of seats held by women in the parliament. This highlights the specificity of the Reprisk score. As explained on their website "the purpose of RepRisk's dataset is not to provide ESG ratings, but to systematically identify and assess material ESG risks." It is a tool focusing on controversies which gives Reprisk an unique position in this environment. The most important data explaining the model for Reprisk are: Control of Corruption, Political Stability and Absence of Violence/Terrorism. Both are positively correlated with the rating.

The selected explanatory variables. The score from Sustainalytics exhibits the highest number of variables, reaching 26 indicators. Beyond Ratings rating can be predicted using 23 indicators, 15 for MSCI and 11 for RepRisk. For the reasons explained above, we will compare all ESG data providers except Reprisk. When an explanatory variable is selected by the model to explain ratings, it always has the same sign among providers, with only one exception. That strongly confirms of a common understanding of positive and negative effects of the factors on ESG risks. The exception is for GDP growth, with a negative coefficient for Sustainalytics while a positive one for Beyond Ratings. It could be explained by the higher weight given to the Environment pillar in the model replicating Sustainalytics. Indeed, when GDP is high, the intensity of environmental externalities may impact negatively the overall score. However, the GDP growth coefficient is low for both models, that limits the influence on the overall score. Looking at the average importance of indicators among the three data providers, the most important variables all belong to the Governance pillar and are the following (by decreasing order): Government effectiveness, Rule of Law, Regulatory Quality, Individuals using the Internet (% of population), and Voice and Accountability. For thr Environment pillar, the most important variables are Agriculture, value added (% of GDP), which is negatively correlated to the rating, followed by Forest area (% of land area), positively correlated. For the Social pillar, the most important indicators are Access to clean fuels and technologies for cooking (% of population) and Life expectancy at birth, total (years) which are positively correlated to the rating. The relative importance of the Worldwide Governance Indicators (Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption) is high, being 63%, 31%, 46% and 73%, respectively for MSCI, Sustainalytics, BeyondRatings and Reprisk.

The non-selected explanatory variables. Some of the variables are neither used or barely significant when looking at the results. It may be the result of collinearity with other factors or

may highlight that they are not included at that stage in the ESG ratings: Fertility rate, total (births per woman), Net migration, Cause of death, by communicable diseases and maternal, prenatal and nutrition conditions (% of total). The demographic shifts may be underestimated in the existing models, unless captured by other data.

4 Conclusion

The rapid growth of ESG integration requires to understand taxonomy and scores provided by the ESG data industry for sovereigns. The contribution of the paper to the literature is twofold. Firstly, a qualitative review of the various approaches show some clear discrepancies that can be measured using a common taxonomy (UNPRI) and OLS regressions. The obtained implied weights exhibit different choices of ESG factors and weights (with more or less concentration) across methodologies. Secondly, we show that the scores of selected providers can be explained by the publicly available World Bank sovereign ESG database. An analysis of the importance of variables indicates that governance is the most dominant pillar while demographic shifts do not play a significant role for all providers.

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A Appendix

A.1 ESG ratings and CDS spreads

This section explores the relationship between ESG ratings and the 5-year sovereign CDS spread for the four providers at the end of 2017. The 5-year spread was computed as the average of the monthly observations for the last quarter, obtained from Bloomberg (CMAN NY). The República Bolivariana de Venezuela was excluded from the dataset due to the level of CDS at the end of 2017 reaching an average of 8000 bps. The 5-year CDS spreads were initially available for 68 countries, but reduces down to 64 when put in common with ratings. Figure 5 clearly shows a negative relationship: the higher the ESG score, the lower the spread. A spline interpolation may suggest a non-linear relationship for at least two providers.

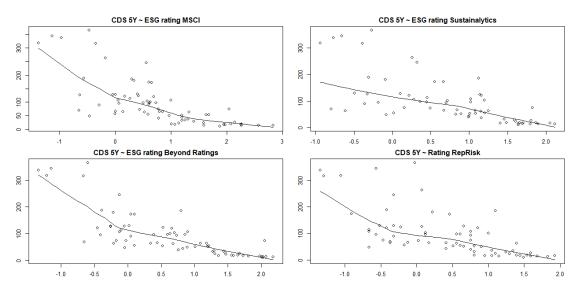


Figure 5: 5-year CDS spread and ESG score for the four analyzed providers (MSCI, Sustainalytics, Beyond Ratings, RepRisk).

We performed linear regressions to test the explanatory power of ESG ratings both as the unique explanatory variable and as an additional variable to the credit rating. The latter is measured by averaging the credit ratings from the top three providers. We alternatively test the relationship with the logarithm of the 5-year CDS spread to take into account the possible non-linearity. Tables 5 and 6 report the estimates for the estimated intercept and coefficients

with their respective t-values, and the R-squared for the overall regression. The score used for Beyond Ratings is the ESG-augmented financial credit risk score. The model includes 2 profiles: an economic and financial profile with 4 sub-pillars and a sustainability profile, which is broken down into 3 sub-pillars covering E, S G. We report two sets of regressions: one with the full score and one with the sustainability component only.

The R-squared for the simple regression with the ESG rating as a unique explanatory variable lies between 0.45 and 0.60 (RepRisk < Sustainalytics < MSCI < BR-ESG < BR). The use of the logarithm for the spread significantly increases the R-squared, ranging between 0.59 and 0.74, while keeping the hierarchy between data providers. The introduction of the average credit rating improves the explanatory power with very close R-squared for all providers (0.84-0.86). Beyond Ratings logically exhibits the highest explanatory power for its score including the credit profile. All coefficients are significant at 99% level and very close between ESG data providers.

uci.			
Estimate	\mathbb{R}^2	$\Pr(> t)$	
145.4	0.52	< 2e-16	***
-67.1		8.2e-12	***
151.1	0.49	< 2e-16	***
-74.4		8.4e-11	***
141.8	0.60	< 2e-16	***
-74.4		3.1e-14	***
144.5	0.56	< 2e-16	***
-75.31		6.6e-13	***
124.71	0.45	< 2e-16	***
-71.17		8.8e-10	***
Estimate	\mathbb{R}^2	$\Pr(> t)$	
4.77	0.66	< 2e-16	***
-0.81		1.3e-16	***
4.84	0.61	< 2e-16	***
-0.89		1.3e-14	***
4.72	0.74	< 2e-16	***
-0.89		< 2e-16	***
4.75	0.67	< 2e-16	***
0.00		< 2e-16	***
-0.89		< 20 10	
-0.89 4.53	0.59	< 2e-16	***
	Estimate 145.4 -67.1 151.1 -74.4 141.8 -74.4 144.5 -75.31 124.71 -71.17 Estimate 4.77 -0.81 4.84 -0.89 4.72 -0.89 4.75	Estimate \mathbb{R}^2 145.40.52-67.10.49-74.40.60-74.40.60-74.40.56-75.310.45124.710.45-71.170.45Estimate \mathbb{R}^2 4.770.66-0.810.614.720.74-0.890.67	Estimate \mathbb{R}^2 $\Pr(> t)$ 145.40.52< 2e-16

Table 11: Results of the linear regressions for the 5-year CDS spread (CDS5Y), and its logarithm $(\log(CDS5Y))$ for each ESG data provider.

Table 12: Results of the linear regressions for the logarithm of the 5-year CDS spread $(\log(\text{CDS5Y}))$ including the credit rating as an explanatory variable for each ESG data provider.

Model with ESG rat-	Estimate	\mathbf{R}^2	$\Pr(> t)$	
ings and CRA credit				
rating for logCDS5Y				
(Intercept)	4.83	0.85	< 2e-16	***
Average Credit Rating	-0.8		3.6e-13	***
MSCI	-0.25		1.9e-3	***
(Intercept)	4.83	0.84	< 2e-16	***
Average Credit Rating	-0.89		1.1e-13	***
Sustainalytics	-0.17		8.2e-2	***
(Intercept)	4.8	0.86	< 2e-16	***
Average Credit Rating	-0.73		6.3e-10	***
Beyond Ratings	-0.33		6.9e-4	***
(Intercept)	4.83	0.86	< 2e-16	***
Average Credit Rating	-0.78		3.6e-13	***
BR - ESG	-0.3		5.1e-4	***
(Intercept)	4.78	0.86	< 2e-16	***
Average Credit Rating	-0.82		9.6-17	***
RepRisk	-0.3		1.7e-4	***

While the results do not exclude a country income effect, we observe a similarity in explaining CDS spreads among scores from different providers. Moreover, ESG scores provide additional information on top of the credit rating. A possible extension would be to test the relationship for the subsequent years.

A.2 ESG rating and Google Trends

This section reports the popularity of 'ESG' searches on Google since 2010 (Figure 6). A rapid increase is observed after 2017, that is consistent with the perceived interest in ESG integration both from risk and opportunity perspectives. Google trends information was extracted at a more granular level, looking for 'ESG data', 'ESG scoring', 'ESG integration' and 'ESG rating' searches. The latter seems to be the most popular together with 'ESG data' (Figure 8).

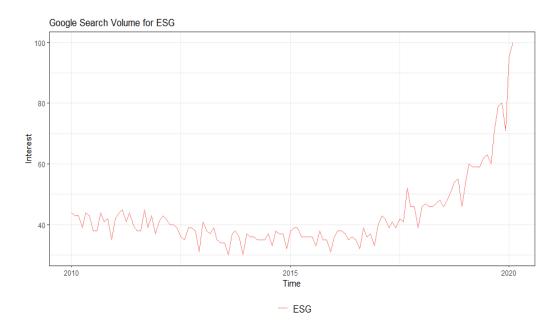


Figure 6: Evolution of the popularity of the term 'ESG' in Google searches since 2010.

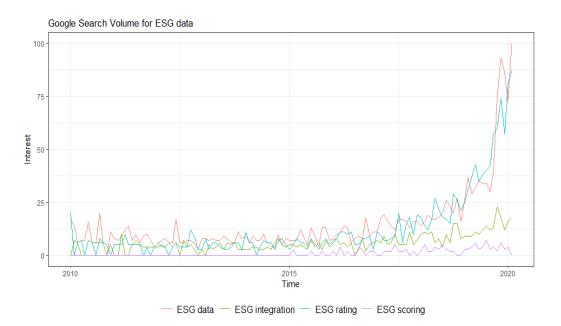


Figure 7: Comparison of several ESG related searches ('ESG data', 'ESG integration', 'ESG rating', 'ESG scoring') on Google since 2010.

A.3 Credit ratings

This appendix provides the difference in rating (number of notches) for the first countries rated by S&P and Moody's: Australia (1962), New-Zealand (1965), Canada (1968), Finland (1977), Norway (1978), and Denmark (1981). The United States and Austria are excluded as they have obtained the same AAA rating. Interestingly, these six countries are among the best quality issuers and have experienced discrepancies despite being supposedly less volatile.

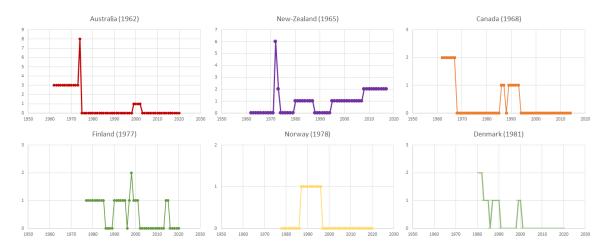


Figure 8: Difference in rating (number of notches) by S&P and Moody's for Australia (1962), New-Zealand (1965), Canada (1968), Finland (1977), Norway (1978), and Denmark (1981).

A.4 Questionnaire sent to ESG rating providers

- **Data sourcing**. Use of questionnaire or only public data? Do you send questionnaires to the issuer?
- Methodology. Is your scoring the result of a model only (quantitative approach) or is there a qualitative/analyst correction included as well?
- Risk exposure or impact. Risk exposure or efforts on SDG integrated?
- Absolute or relative scoring. Do you have geographic or economic peer comparisons? Are those peer groups standardized to be relatively comparable?
- Controversies. Are they included in the ESG score? If yes, how frequently updated?
- Weighting of E, S and G in ESG score. Are they fixed by peer group? Is the weight determined quantitatively or qualitatively?
- Weighting of indicators in each category (E, S or G). Same question as above.

Environment	Natural resources	the availability and quality of biodiversity, water, air and soil; and land use (urban, agricultural and forests).
	Physical risks	the physical effects of climate change (such as weather volatility, sea-level rise) and natural disaster risks (volcanic eruptions and earthquakes).
	Energy transition risk	regulatory factors and technological developments associated with the global energy transition to a less carbon-intensive global economy
	Energy security	the availability and management of (non)-renewable energy resources; and resource depletion.
Social	Demographic change	population trends; age distribution; and rates of immigration
	Education and human capital	availability of and access to education; quality of educational attainment; and employment rights.
		respect for human rights (including the right to life, the right to freedom of association and the right to health);
	Living standards and income inequality	measures of poverty and income inequality; gender inequality; unemployment rates; public sector wages;
		availability of and access to healthcare, personal safety and housing; food security and obesity
	Social cohosion	political freedom and representation; levels of trust in institutions and politicians; social inclusion and mobility;

prevalence of civic organisations; degree of social order; and capacity of political institutions to respond to societal priorities. strength of institutional and regulatory frameworks; independence of institutions; quality and availability of public data;

prevalence of corruption; rule of law; ease of doing business; and business climate.

quality of bureaucracy and administration; policy planning and implementation capabilities;

and independence of the civil service from political interference efficiency of regulatory systems and policy implementation;

freedom of expression; press freedom; and freedom of information and speech.

political rights and civil liberties; political upheaval and violence in society;

property rights; institutional and regulatory framework; and independence of the judiciary accountability and transparency of institutions; money laundering/illicit financial flows

predictability of policy making; ease of doing business; and business climate.

Debt
ereign
or Sover
my for
Taxonomy
UNPRI
A.5

Source: UNPRI (2019)

Government effectiveness

Institutional Strength

Governance

Social cohesion

Political stability

Regulatory effectiveness

Rule of law Corruption

A.6 World Bank Sovereign ESG Data

- Environment Pillar
 - Emissions & pollution
 - * CO2 emissions (metric tons per capita)
 - * GHG net emissions/removals by LUCF (Mt of CO2 equivalent)
 - * Methane emissions (metric tons of CO2 equivalent per capita)
 - * Nitrous oxide emissions (metric tons of CO2 equivalent per capita)
 - * PM2.5 air pollution, mean annual exposure (micrograms per cubic meter)
 - Natural capital endowment and management
 - * Adjusted savings: natural resources depletion (% of GNI)
 - * Adjusted savings: net forest depletion (% of GNI)
 - * Annual freshwater withdrawals, total (% of internal resources)
 - * Forest area (% of land area)
 - * Mammal species, threatened
 - * Terrestrial and marine protected areas (% of total territorial area)
 - Energy use & security
 - * Electricity production from coal sources (% of total)
 - * Energy imports, net (% of energy use)
 - * Energy intensity level of primary energy (MJ/\$2011 PPP GDP)
 - * Energy use (kg of oil equivalent per capita)
 - * Fossil fuel energy consumption (% of total)
 - * Renewable electricity output (% of total electricity output)
 - * Renewable energy consumption (% of total final energy consumption)
 - Environment/climate risk & resilience
 - * Cooling Degree Days (projected change in number of degree Celsius)

- * Droughts, floods, extreme temperatures (% of population, average 1990-2009)
- * Heat Index 35 (projected change in days)
- * Maximum 5-day Rainfall, 25-year Return Level (projected change in mm)
- * Mean Drought Index (projected change, unitless)
- * Population density (people per sq. km of land area)
- Food Security
 - * Agricultural land (% of land area)
 - * Agriculture, value added (% of GDP)
 - * Food production index (2004-2006 = 100)
- Social Pillar
 - Education & skills
 - * Government expenditure on education, total (% of government expenditure)
 - * Literacy rate, adult total (% of people ages 15 and above)
 - * School enrollment, primary (% gross)
 - Employment
 - * Children in employment, total (% of children ages 7-14)
 - * Labor force participation rate, total (% of total population ages 15-64) (modeled ILO estimate)
 - * Unemployment, total (% of total labor force) (modeled ILO estimate)
 - Demography
 - * Fertility rate, total (births per woman)
 - * Life expectancy at birth, total (years)
 - * Population ages 65 and above (% of total population)
 - Poverty & Inequality
 - * Annualized average growth rate in per capita real survey mean consumption or income, total population (%)

- * GINI index (World Bank estimate)
- * Income share held by lowest 20%
- * Poverty headcount ratio at national poverty lines (% of population)
- Health & Nutrition
 - * Cause of death, by communicable diseases and maternal, prenatal and nutrition conditions (% of total)
 - * Hospital beds (per 1,000 people)
 - * Mortality rate, under-5 (per 1,000 live births)
 - * Prevalence of overweight (% of adults)
 - * Prevalence of undernourishment (% of population)
- Access to Services
 - * Access to clean fuels and technologies for cooking (% of population)
 - * Access to electricity (% of population)
 - * People using safely managed drinking water services (% of population)
 - * People using safely managed sanitation services (% of population)
- Governance Pillar
 - Human Rights
 - * Strength of legal rights index (0=weak to 12=strong)
 - * Voice and Accountability: Estimate
 - Government Effectiveness
 - * Government Effectiveness: Estimate
 - * Regulatory Quality: Estimate
 - Stability & Rule of Law
 - * Control of Corruption: Estimate
 - * Net migration

- * Political Stability and Absence of Violence/Terrorism: Estimate
- * Rule of Law: Estimate
- Economic Environment
 - * Ease of doing business index (1=most business-friendly regulations)
 - * GDP growth (annual %)
 - * Individuals using the Internet (% of population)
- Gender
 - * Proportion of seats held by women in national parliaments (%)
 - * Ratio of female to male labor force participation rate (%) (modeled ILO estimate)
 - * School enrollment, primary and secondary (gross), gender parity index (GPI)
 - * Unmet need for contraception (% of married women ages 15-49)
- Innovation
 - * Patent applications, residents
 - * Research and development expenditure (% of GDP)
 - * Scientific and technical journal articles.

A.7 Normalized sovereign ESG Ratings



Figure 9: Normalized ESG Ratings for sovereigns (2017 data).