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ESG Ratings: The Road Ahead

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EXECUTIVE SUMMARY

Environmental, social, and governance (ESG) issues have become particularly important in recent years for investors, spurring companies to increase their efforts at being socially responsible. Many leading publicly traded firms are releasing more information about their ESG efforts. This trend is particularly true for social issues, which have become more prominent amid widespread concerns about race relations, law enforcement, and the pandemic.

In the absence of a structured framework to report and monitor firms' ESG efforts, the burden lies on companies to communicate on their initiatives and on investors to research them. New technologies, such as big data analysis or AI, can help process a larger set of information from different sources such as firms' communication strategies or other alternative sources. However, there is a need to define a core set of variables that would capture these efforts as part of a long-term strategy. ESG rating agencies could then process this information and provide their assessment of the firms.

In this report, we show that a standard set of variables would partially resolve inconsistencies and lack of uniform standards among rating providers, which often confuses investors. Furthermore, we dissociate the impact of the rating agencies' different focus on E, S, or G from that of using non-standardized data. While the former, if properly disclosed, can be useful as it allows investors to choose what rating will align more with their preferences, the latter necessarily requires harmonization of the data.

Using publicly available information, we illustrate how difficult it is to understand or predict some of the existing ratings. Yet we are also able to identify some commonalities. All ratings agree on the worst performers. They also reach some consensus when measuring risks arising from governance factors, especially for

Corporate Social Responsibility Strategy and Management. Corporate Social Responsibility Strategy includes variables that reflect a company's practices to communicate that it integrates economic (financial), social, and environmental dimensions into its daily decisions. Management includes variables that measure a company's commitment and effectiveness towards following best practice corporate governance principles.

Overall, our study has two main implications in assessing how well-equipped firms are to address ESG risks. First, there is a need for data standardization, starting with establishing common disclosure standards for ESG worldwide. The coordination of data collection would reduce the reporting burden for firms, leading to improved information quality. The goal is not to add to the existing efforts but to consolidate and standardize the data collection efforts. This would increase firms' participation while improving the rating agencies' credibility with investors.

The second implication of our study is the importance of transparency in the methodologies used to calculate the rating. In other words, are E, S, and G factors equally important? Or does the rating focus mostly on one of them? Each method uses a different set of weights to aggregate data, which leads to a different rating, even when using the same data. Rating agencies' different emphases can be informative as long as the agencies are clear about which ESG issues they prioritize and to what degree. Such transparency will allow investors, firms, and other users to decide which rating aligns best with their priorities.

INTRODUCTION

Asset owners and managers are increasingly incorporating Environmental, Social, and Governance (ESG) factors into their financial analysis and decisions. According to the Global Sustainable Investment Alliance (GSIA), an international agency that collects information across Europe, the United States, Canada, Japan, Australia, and New Zealand, the value of assets under management with an explicit ESG mandate reached US $30.7 trillion at the beginning of 2018, an impressive 34 percent increase relative to 2016. Investment strategies that explicitly incorporate ESG criteria now command a significant fraction of all professionally managed assets across all these regions, ranging from about 18 percent in Japan to more than 50 percent in Canada, Australia, and New Zealand (see Figure 1.b).[1]

However, ESG-focused funds remain a low percentage of total assets under management at the world's largest asset managers (see Table 1). The lack of offerings may be one of the explanations (see Figure 2 and Appendix 1).

The increasing focus on ESG investing has spurred an increase in the number and influence of ESG rating agencies. By providing clear, cost-effective, and consistent information about companies' ESG performance, these agencies can play a crucial role in helping funds and other investment groups pinpoint firms that meet their ESG philosophies and standards. Moreover, an independent assessment of a company's ESG performance can also present companies with an opportunity to differentiate themselves, potentially influencing them to adopt better practices to avert downgrades or improve their scores.[2]

Some market participants remain skeptical of the value of ESG rating agencies' information. A recent survey conducted by Sustainalytics, a major provider of ESG research and ratings, found that many investors regularly rely on ratings to inform their decisions. Yet, they find them difficult to use and sometimes are frustrated by them.[3] Inconsistencies in the information used and lack of comparability across ratings have particularly confused investors and become a barrier to greater adoption of ESG investing.[4] These discrepancies across ESG ratings affect company managers, who may face less urgency to improve their ESG performance and identify appropriate strategies to do so.

1 The volume of assets under management with an ESG focus can vary a lot depending on what is included. The numbers in the GSIA report should be considered as broad estimates, as they include multiple investment strategies.

2 For an analysis of this "monitoring effect" in a corporate governance context, see Grimminger and Di Benedetta (2013).

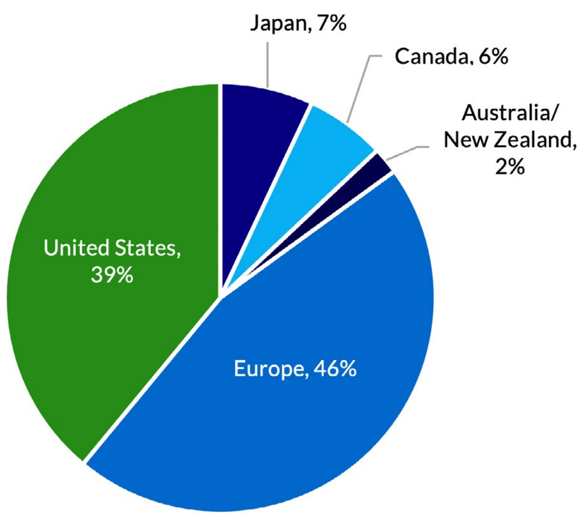
3 Wong and Petroy (2020).

4 BNP Paribas (2019).

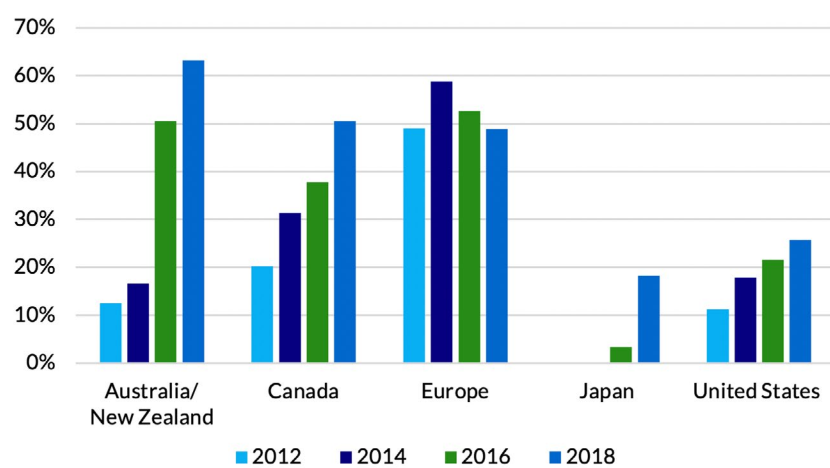
Differences across ESG scores can naturally emerge if rating providers adopt different definitions of ESG performance. Some agencies, for example, may equate ESG performance with a company's compliance with specific ethical standards. In contrast, others may emphasize a company's ability to manage financially material risks and opportunities arising from ESG factors. To a certain extent, the availability of ratings with different definitions is natural, given the subjective nature of ESG criteria. But more importantly, it might be required to satisfy investors and asset managers with different needs and motivations. Agencies do not have to agree on a single definition but they should focus on standardizing data, labeling ratings more clearly, and ensuring they are transparent about their objectives. Such priorities would allow market participants to differentiate products better and to determine whether a particular definition aligns with their goals.

Figure 1: Professionally Managed Assets with an ESG Mandate

a) Fraction of Global ESG Investing by Region (as of 2018)



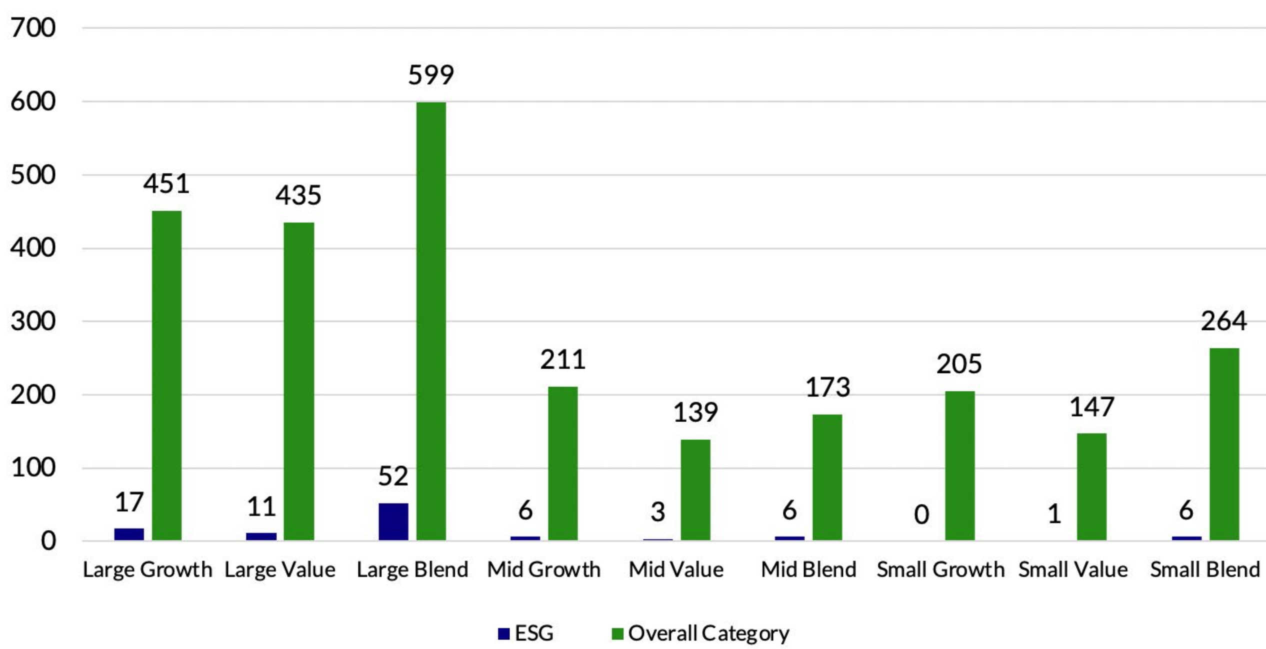
b) ESG Investing as a Fraction of Total Assets under Management, 2012-2018



Source: GSIA (2019)

Inconsistencies across ESG rating agencies are not only an issue of definitions. At least two other reasons can lead rating providers to score the same company differently. First, rating providers may disagree on how to measure the same ESG factor. Despite efforts by multiple standard-setting organizations, there is no universally accepted approach to measuring non-financial indicators. Rating agencies employ hundreds of ESG-related variables. Some come from company reports and regulatory filings and, therefore, should be consistent across agencies. Yet many others come through interviews or questionnaires and third-party independent reports with potentially conflicting approaches. Second, even if agencies agree on how to measure different ESG-related factors, each ESG agency has developed its own methodology to decide what ESG-related indicators to consider and how to aggregate them into an overall score.

Figure 2. Funds Satisfying Basic Investment Screen: ESG-Focused Funds versus Overall Category



Note: Out of 288 ESG-focused funds identified by Morningstar in the US, only 104 would pass a simple investment screen commonly employed by fund-of-fund managers: at least three years of historical returns and a fund size over US$50 million (Lauricella, 2020).

Source: Morningstar Direct (2020)

Besides documenting the extent of the disagreement among ESG scores, we provide insights into the drivers behind the inconsistencies. We contrast the impact of the data and of the methodologies. We agree that the lack of data standardization is an issue for both investors and assessed firms, and it should be resolved by harmonizing the data collected and streamlining the process. However, differing methodologies are not necessarily a negative thing if they reflect each rating agency's prioritization

Table 1. Assets under Management (AUM) in ESG-Focused Funds

Company	AUM ($US Billions)	ESG Investment ($US Billions)	ESG AUM Percentage
BlackRock	$6,470.00	$17.58	0.27%
Vanguard	$6,200.00	$9.54	0.15%
UBS	$3,260.00	$0.29	0.01%
Fidelity	$2,900.00	$0.67	0.02%
State Street	$2,690.00	$0.17	0.01%
Allianz	$2,490.00	$0.21	0.01%
Capital Group	$2,060.00	$0.00	0.00%
JP Morgan Asset Management	$1,900.00	$0.08	0.00%
Goldman Sachs	$1,859.00	$0.13	0.01%
Bank of New York Mellon	$1,800.00	$0.36	0.02%
PIMCO	$1,780.00	$1.96	0.11%
Amundi	$1,653.00	$0.32	0.02%
Prudential Financial	$1,481.00	$0.00	0.00%
AXA Group	$879.00	$0.00	0.00%
Morgan Stanley	$552.00	$6.72	1.22%

Note: Funds classified as ESG explicitly stated in their mandates that the investments were chosen primarily for their ESG-risk mitigating characteristics. Keywords in the primary investment mandate also include impact investing, gender/ethnic diversification, and environmental sustainability.

Source: Morningstar Direct (2020)

or specialization in a particular dimension (E, S, or G). However, agencies must be transparent about what they are offering users and regarding how they arrived at the assessment. Overall, we hope to inform market participants on how to contextualize and critically evaluate discrepancies in ESG scores and offer useful information on how to address them.

Our analysis focuses on rating agencies that employ the same definition of ESG performance: a company's ability to manage financially material risks and opportunities arising from ESG factors. This allows us to concentrate on differences in how agencies measure ESG factors and their methodologies for aggregating them into a single score.

We shed light on the sources of disagreement among ESG ratings using an indirect approach. Our indirect method relies on machine learning techniques to identify and estimate the relationship between the ESG ratings and publicly available explanatory variables, which do not (necessarily) coincide with the ones used by the rating agencies. We then compare the relationships among the rating of three agencies using various methods. Finally, we assess the ability of our estimated ratings to replicate the disagreement among the agencies' ratings.

While all the agencies in our study use the same definition of ESG performance, their ratings strongly coincide only for the worst performers, which represent a relatively small number of firms. Overall, the substantial discrepancies among rating providers cannot be easily explained based on information readily available to investors.

Our findings underscore the importance of data standardization and the necessity for agencies to be transparent regarding the method they used and the information they prioritize in their ESG assessment. Addressing these two issues will enable companies and investors to make more sense of the ratings and use the information about ESG factors to make better decisions.

The remainder of this report is organized as follows. To establish common terminology, we begin with a discussion of the definition of ESG investing. We then document the extent of disagreement over ESG scores among the three major rating agencies at different levels of data aggregation. Next, we use machine learning techniques to understand better how the various rating agencies assess a company's ESG performance based on a set of publicly available explanatory variables. Finally, we offer some conclusions drawn from our analysis.

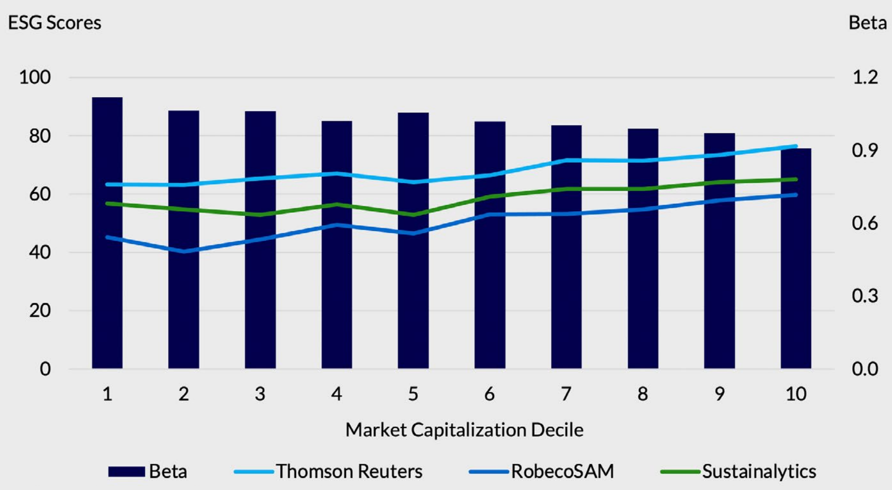
BOX 1

ESG SCORE LEVELS AND FINANCIAL VARIABLES

This box illustrates the relationship between ESG score levels and some widely used financial variables for the studied group of companies.

After sorting the firms from the largest (10th decile) to the smallest (1st decile) based on their market capitalization, Figure 3 plots the average Beta (a measure of a particular asset's volatility relative to the risk of general systemic market movement) and the average ESG scores for the three rating agencies. All three rating agencies award higher average scores to larger companies. These same firms show more resiliency (lower Beta) to risks, including ESG ones.

Figure 3. ESG Scores and Beta by Market Capitalization Decile



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

WHAT IS ESG INVESTING?

Although there is no universally accepted definition, ESG investing is widely understood as an investment approach that looks beyond traditional financial indicators by considering environmental, social, and governance (ESG) factors in the selection and management of an investment portfolio. In various ways, many investors have already been incorporating ESG issues into their investment frameworks for some time. The modern reference to ESG investing, however, denotes a more explicit, systematic integration of ESG factors into the investment process, as opposed to a more informal, less structured approach.

INVESTORS CAN HAVE MULTIPLE MOTIVATIONS

Investors integrate ESG factors into their financial decisions for various (not mutually exclusive) reasons. (See Box 2 for a list of factors commonly referred to as ESG).

- Some investors may consider that ESG data can help paint a broader picture of a company's operating environment. Accordingly, they rely on ESG investing to identify and manage risks and opportunities that they cannot easily detect through standard financial analysis—that is, as a source of financial value. According to Dan Hanson, former managing director at BlackRock, "ESG is a proxy for risk that is not priced in, and companies that better manage these risks can deliver returns with greater certainty …"[5] Reducing exposure to polluters or companies with poor waste management policies, for example, can help mitigate regulatory risk, whereas screening for good social practices (such as workplace culture, human rights protection, or corporate community engagement) can reduce exposure to scandals that could damage a company's reputation.[6]

- Other investors rely on ESG investing to meet their values (e.g., ethical, religious, political, or cultural) or to promote specific environmental, social, or governance outcomes they deem desirable. Investors, for instance, may integrate ESG factors into their financial decisions to identify and exclude companies engaging in practices they find morally questionable, including low labor standards or human rights violations. These investors might seek to advance their non-financial objectives without hampering financial objectives. In some cases, they might

[5] Cited in Koehler and Hespenheide (2013).

[6] For studies on the relationship between ESG performance and profitability, see Friede et al. (2015) and, more recently, Verheyden et al. (2016).

even be willing to sacrifice financial returns to achieve their non-financial goals. A recent survey conducted by UBS among asset owners across 46 countries found that "doing good for society and the environment" is among the top four drivers behind ESG investing.[7]

- And still others, such as institutional investors or financial advisors acting on behalf of a third party, may rely on ESG criteria to satisfy specific legal requirements. One of the world's largest investment funds, for example, the Norwegian Government Pension Fund Global, is mandated to avoid companies that contribute to or are responsible for "serious or systematic human rights violations, … serious violations of the rights of individuals in situations of war or conflict, severe environmental damage, … gross corruption, [or] other particularly serious violations of fundamental ethical norms."[8]

MULTIPLE LABELS FOR SIMILAR ISSUES

Despite its growing popularity, there are substantial terminological and conceptual inconsistencies surrounding ESG investing. Phrases such as sustainable, responsible, or socially responsible investing are sometimes conflated or used interchangeably with the term ESG investing. The broad array of terms that describe various ESG approaches and a lack of consistency in their use have confused investors. A recent survey conducted by State Street Global Advisors found that over half of those investors already implementing some type of ESG strategy within their portfolio were struggling with a lack of clarity around ESG terminology in their organizations.[9]

To reduce confusion among investors, and because the common theme underlying all the different labels is an emphasis on ESG issues, we believe that the more neutral term, ESG investing, is appropriate. Accordingly, we see ESG investing as an umbrella term for an investment approach that involves some type of environmental, social, or governance consideration that can have various motivations and that, depending on the investor's goals, resources, and circumstances, may involve different strategies.[10]

[7] See, for example, Fritsch (2019).

[8] Norway's Ministry of Finance (2019).

[9] State Street Global Advisors (2018).

[10] For a detailed discussion on how to incorporate ESG factors into the investment process, see Grim and Berkowitz (2018).

BOX 2

ESG Factors

Broadly defined, environmental factors focus on a company's environmental impact, social factors examine how it manages relationships with different stakeholders (such as customers, employees, suppliers, and the communities within which it operates), and governance factors deal with a company's leadership, internal controls, and shareholder rights.

ESG factors cover a wide range of topics. The relevant issues are likely to depend on the company being analyzed, its industry, and, ultimately, on the investor's preferences and objectives. For these reasons, it should not be surprising that a definitive list of ESG factors does not exist.

Table 2. Examples of Well-Known ESG factors

Environmental	Social	Governance
Climate change policies, plans, and disclosure practices	Community engagement	Management structure
Air and water pollution	Human rights	Executive compensation
Deforestation	Labor practices	Board composition
Biodiversity impact	Product safety	Business integrity
Water stress	Data security and customer privacy	Transparency
Waste and hazardous materials management	Diversity and inclusion	Bribery and corruption
Usage of renewable energy	Customer relations	Lobbying
	Ethical supply chain sourcing	Whistleblower schemes
		Shareholder relations

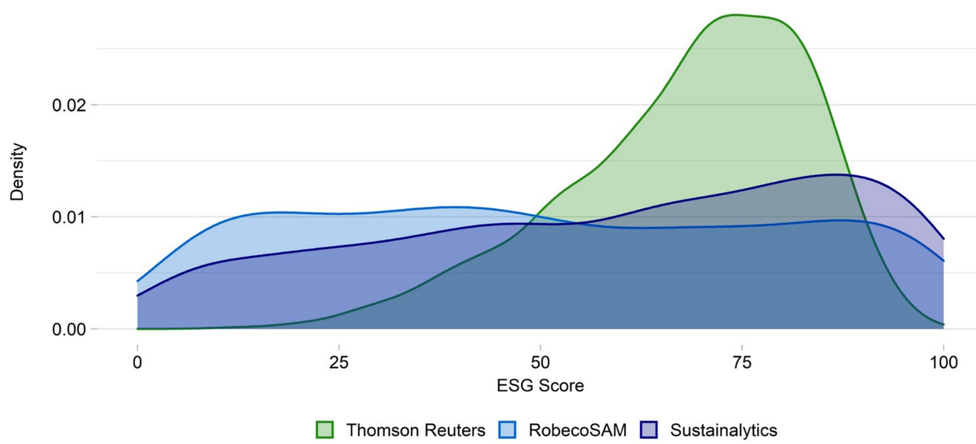
Source: Milken Institute (2020)

DISAGREEMENT AMONG ESG RATINGS

Our analysis considers three major rating agencies that emphasize the financial impact of ESG factors when measuring a company's ESG performance: RobecoSAM, Sustainalytics, and Thomson Reuters.[11] Considering only ratings that agree on a definition of ESG performance allows us to concentrate on the different ways agencies measure ESG factors and the methodologies they use to aggregate them into a single score. Our sample contains annual information on 943 firms for the year 2018, the latest for which all three ESG scores were available.[12] The data were collected from Bloomberg and Refinitiv Eikon.

A simple glance at the distributions of ESG ratings (see Figure 4) confirms that the agencies' assessments of the firms are different: Most of Thomson Reuters scores are concentrated around high values, between 50 and 80, while RobecoSAM and Sustainalytics spread them mostly evenly between 10 and 90.

Figure 4: ESG Score Distributions



Bloomberg and Refinitiv Eikon (2020)

11 According to Gaffuri (2017), RobecoSAM's methodology seeks to identify "… any [ESG] factor which might have a present or future impact on companies' value drivers, competitive position, and thus on long-term shareholder value creation." According to Sustainalytics (2019), its rating "measure[s] the degree to which a company's economic value is at risk driven by ESG factors." And according to Thomson Reuters (2018), its rating helps to "easily identify companies with … exposure to ESG risks."

12 To construct our sample of firms, we started with the 2,000 largest companies by market capitalization. We then excluded companies for which we were unable to procure information on all three different ESG scores, as well as companies for which a substantial fraction of the explanatory variables used in the following section was missing. For multiannual scores, we consider the last available for 2018.

The pairwise correlations, reported in Table 3, confirm that RobecoSAM and Sustainalytics tend to agree the most in their assessment with a correlation of 0.72. This level of agreement is significantly lower than the one usually encountered among credit ratings, with an average correlation of 0.986.[13]

Table 3: Correlations between ESG Ratings

Pair of Scores	Correlation
RobecoSAM vs. Sustainalytics	0.72
RobecoSAM vs. Thomson Reuters	0.65
Sustainalytics vs. Thomson Reuters	0.65

Note: The correlations are the Pearson product-moment correlation coefficients.

Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

DISAGREEMENT BY ECONOMIC SECTOR

A look at the economic sectors (with Figure 5 for correlations and Table 4 for a short description of the sectors including their unique regulatory and financial characteristics) allows us to derive more granular insights into the differences:[14]

- The overall level of agreement among ratings (i.e., the average pairwise correlation between ESG scores) varies substantially across sectors, ranging from 0.50 in Energy to 0.77 in Technology.

- The highest within-sector heterogeneity in the level of agreement among ratings occurs in the sector with the lowest correlation, Energy.[15] The companies in this sector may be harder to evaluate, as they are highly regulated or because significant investments in infrastructure make it harder to identify the relevant ESG risks and the appropriate strategies to deal with those risks.

13 For other studies reporting correlations among ESG rating agencies, see Berg et al. (2020), Gibson et al. (2019), and State Street Global Advisors (2019).

14 We use the Thomson Reuters Business Classification to assign each company into one of ten different economic sectors.

15 The higher heterogeneity in the Energy sector should be taken carefully, for it is also one of the sectors with the lowest number of observations (48).

- Sectors with a higher level of agreement among ratings, such as Financials, Technology, and Cyclical Consumer Goods & Services, seem to place less emphasis on environmental factors, particularly the first two. This insight could indicate, for example, more consistency across rating agencies on the appropriate way to measure financially material risks arising from social and governance factors.

Overall, the three rating agencies give very different ESG scores, with a correlation below 0.5, to more than 60 percent of the firms. In contrast, they have a very similar assessment, with a correlation of 0.95 or more, for only 10 percent of the firms, the worst-performing ones. (See Appendices 3 and 4 for an analysis of disagreement by market capitalization decile and at the firm level).

Substantial discrepancies in ESG scores across rating agencies is a problem for both investors and companies. Investors may have difficulties in integrating ESG factors into their portfolios in a manner that reflects their preferences. Companies could be discouraged from improving their ESG performance, as they may not be able to identify an appropriate strategy, or they may find the outcome too uncertain and not worth the investment.

Figure 5: Correlations between ESG Ratings

	Energy	Basic Materials	Industrials	Cyclical Consumer G&S	Non-Cyclical Consumer G&S	Financials	Health Care	Technology	Telecom Services	Utilities
Thomson Reuters vs. RobecoSAM	0.48	0.57	0.64	0.72	0.50	0.71	0.74	0.72	0.62	0.56
Thomson Reuters vs. Sustainalytics	0.32	0.64	0.58	0.70	0.48	0.71	0.65	0.79	0.79	0.62
RobecoSAM vs. Sustainalytics	0.70	0.64	0.72	0.80	0.58	0.79	0.72	0.79	0.66	0.62
Mean	0.50	0.62	0.65	0.74	0.52	0.74	0.70	0.77	0.69	0.60
Median	0.48	0.64	0.64	0.72	0.50	0.71	0.72	0.79	0.66	0.62

Sector

Bloomberg and Refinitiv Eikon (2020)

Table 4. Economic Sectors: Description and Unique Features

Sector	Description	Unique Financial and Regulatory Characteristics
Basic Material (68)	Companies involved in the discovery, development, and processing of raw materials, including mining and metal refining, chemicals, and packaging (e.g., Ecolab, Dupont, Dow).	Companies in this sector supply most of the materials used in construction. Thus, they are sensitive to changes in the business cycle and tend to thrive when the economy is strong, exhibiting a rather high Beta of 1.13 on average.
Consumer Cyclical (120)	Companies that produce elastic or non-essential goods and services purchased by individuals and households such as automobiles (e.g., Ford, GM), specialty retailers (e.g., Amazon), hotels and entertainment (e.g., Marriott International), and media-publishing (e.g., ViacomCBS).	Compared to the Consumer Non-Cyclical sector, the Consumer Cyclical sector has higher profit margins, but its demand is more sensitive to the business cycle. The sector has a reactive Beta to the market, at 1.17. Consumer Non-Cyclical companies trade at the lowest sector average of 2.1x sales.
Consumer Non-Cyclical (82)	Companies that produce inelastic or essential goods and services purchased by individuals and households. Industries within the sector include food and drug retailers (e.g., Walmart), food and tobacco producers (e.g., General Mills), beverage producers (e.g., Coca-Cola), and personal and household products/services (e.g., Procter & Gamble).	Within the Consumer Non-Cyclical sector, businesses provide goods/services that have a relatively inelastic demand. Due to this inelasticity, Consumer Non-Cyclical companies can employ larger debt levels relative to other sectors, utilizing leverage to increase return on equity (ROE). Consumer Non-Cyclicals exhibit a comparatively smaller average Beta at just 0.65.
Energy (48)	The Energy sector includes companies involved in the exploration and development of oil or gas reserves, oil and gas drilling, and refining (e.g., Exxon Mobil, Chevron, Occidental Petroleum, Schlumberger).	Companies in the Energy sector incur large capital expenditure costs to create and maintain core business activity infrastructure. Energy providers are extremely susceptible to output pricing and supply and demand shocks, leading to the highest average Beta across sectors (at 1.36). The industry also pays the largest dividend yield to investors, averaging 7.06 percent on an annual basis.

Table 4. Economic Sectors: Description and Unique Features (continued)

Sector	Description	Unique Financial and Regulatory Characteristics
Financials (226)	The largest represented sector in the S&P 500 by number of firms. It includes large banking institutions (e.g., JPMorgan Chase & Co., Bank of America), payment services (e.g., American Express), as well as insurance and asset management institutions (e.g., BlackRock and MetLife).	The Financials sector treats debt fundamentally different from all other economic sectors, utilizing it as a revenue-generating asset from a lender/investor perspective. This feature creates the widest discrepancy between enterprise value and market capitalization at a 2.09:1 ratio among the economic sectors. Financials are more volatile than the overall market, with an average Beta of 1.08. ROE for the sector was 12.01 percent, below the sector-agnostic average of 27 percent. The Financials sector is also highly regulated and therefore affected by governmental decisions.
Health Care (83)	The Health Care sector consists of companies that provide medical services (e.g., UnitedHealth Group, Cigna), health-care equipment and devices (e.g., Johnson & Johnson, Thermo Fisher Scientific), and pharmaceuticals/biotechnology (e.g., Gilead, Pfizer, Merck).	Because of the necessity of its products, the Health Care sector has a Beta (.98) that most closely mirrors the S&P 500, while generating the second-highest average ROE at 31 percent. Influenced by outliers within the highly volatile biotechnology industry, the Health Care sector has by far the largest average EV/EBIT valuation multiple at 111x, ranging from 7x to 7,152x. The sector also exhibits the second-highest average price-to-earnings ratio at 38, partly due to the highly regulated Food and Drug Administration approval process (with successful drug patents allowing for monopolies on certain drug/treatment advancements that possess pricing power to recoup R&D costs).
Industrials (132)	Enterprises that produce machinery (e.g., Boeing, Caterpillar), passenger and material transportation (e.g., Delta, UPS), and aerospace and defense (e.g., Lockheed Martin, Raytheon) all fall under the Industrials umbrella.	The most diverse sector in terms of products or services, Industrials exhibits the largest range of ROE in the S&P 500, returning anywhere between -225 percent and +766 percent. Industrials also exhibit comparatively lower valuation multiples on average: 14x EV/EBITDA, 16x EV/EBIT, 2.8x EV/Sales, and 21 P/E.

Table 4. Economic Sectors: Description and Unique Features (continued)

Sector	Description	Unique Financial and Regulatory Characteristics
Technology (96)	The Technology sector offers a wide range of products and services for both customers and other businesses. Industries within the Technology sector include software and IT (e.g., Microsoft), communications and networking (e.g., Facebook), computers, phones, household electronics (e.g., Apple), and office equipment (e.g., Cisco).	The Technology sector is unique in many ways. Contrary to other sectors, profit takes a back seat to growth, and operating metrics are not as pertinent to the valuation discussion. Because of this growth focus, operators in this sector tend to shy away from debt financing, exhibiting a comparatively low 82 percent debt-to-equity ratio on average for 2018. The propensity for equity financing provides for larger cash-on-hand in the balance sheet, making it the only sector in the S&P 500 whose average market capitalization is greater than the enterprise value of the firm. Strong cash infusions through equity offerings allow tech companies to possess the largest average current and quick ratios on the balance sheet, at 2.35 and 2.14, respectively. The Technology sector is characterized by high average valuation multiples, trading at 22x EBITDA, 5.5x sales, and 52x earnings, the highest of any sector.
Telecom (29)	The Telecommunications sector consists of companies that transmit data in words, voice, audio, or video globally (e.g., AT&T, Verizon, T-Mobile, CenturyLink).	While the sector remains concentrated, it is moving toward a more decentralized system with less regulation and barriers to entry. Beta is much lower than average at .62. Because firms often operate on a subscription and revenue recognition model, dividend yields are larger than in most other economic sectors at an average of 5.52 percent yield per year, second only to Energy.
Utilities (59)	The Utilities sector includes companies that provide basic amenities, such as water, sewage services, electricity, dams, and natural gas (e.g., Nextera Energy, Duke Energy, Edison International, Sempra).	Utilities are part of the public service landscape and, therefore, heavily regulated. It typically offers stable and consistent dividends (4.47 percent), coupled with less price volatility relative to equity markets, possessing the smallest average Beta at .61. Because of the inelastic nature of the products and services provided, Utilities companies do not need the same type of balance sheet cash cushion required in other economic sectors, allowing them to possess the lowest average quick and current ratios of any sector at .85 and .93, respectively.

Note: The number in parenthesis below the sector name indicates the number of companies in our sample.

Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

WHAT IS DRIVING THE DISCREPANCIES IN ESG SCORES?

Understanding what drives these discrepancies is essential to make sense of them. Not having access to the raw data or the detailed methodologies employed by the different ESG rating agencies, our analysis of their disagreement relies on an indirect approach that uses publicly available information. It consists of three steps:

1. **Collection of publicly available ESG and other indicators for the firms studied.** A total of 207 ESG indicators (58 related to environmental factors, 70 to social factors, and 79 to corporate governance factors), as well as 35 financial variables and information on both headquarters location and economic sector.[16]

2. **Estimation of the relation between the ESG ratings and the explanatory variables.** Standard econometric techniques cannot easily handle a large number of variables, and they usually require specifying a particular structure on the relationships among variables. As an alternative, we use a machine learning technique called random forest. Random forest models can accommodate complex, non-linear patterns and can handle different types of variables efficiently.[17]

3. **Comparison of the estimation results across ratings.** Estimation results look at three distinct and complementary angles: (i) the variables' ability to predict the ESG scores, (ii) their contribution to the ratings predicted by our estimation, and (iii) the importance of the variables' interaction when predicting the ESG scores. Exercises (i) and (ii) tell us how informative individual variables are regarding the content of the ratings. On the other hand, (iii) tells us something about how that information is aggregated into a single score (not how agencies actually do it, but how it is done in terms of the estimated relations between ratings and explanatory variables). Finally, we compare the disagreement among the predicted ESG ratings with the one observed among the agencies' ratings.

[16] The data were collected from Refinitiv-Eikon, a major provider of financial news and information. A detailed list of all the explanatory variables is available upon request.

[17] In contrast to other algorithms, random forest models also generate an internal measure of the model's ability to predict previously unseen observations, thereby eliminating the need to use a separate dataset to evaluate their performance.

BOX
3

RANDOM FOREST MODELS: A PRIMER

A random forest is a machine learning algorithm. It combines the outcomes of a large number of individual decision trees to generate a single prediction, either by calculating the average (when the prediction variable is continuous) or by implementing a "majority vote" (when the prediction variable is categorical). Unsurprisingly, the model is called a forest because it relies on a multiplicity of decision trees. But what exactly is a decision tree? Why do we need many of them? And in what sense is the forest random?

A decision tree is a predictive algorithm that, as its name implies, uses a tree-like structure to predict the value of a target variable using a set of explanatory variables. A decision tree starts with a single node, which then branches into possible outcomes based on the value of one of the explanatory variables. Each of those outcomes leads to additional nodes, which once again branch off into other possibilities based on another explanatory variable, giving it a tree-like shape. This process continues until a terminal node is reached, which leads to no additional sub-nodes and contains our prediction for the variable of interest. Decisions regarding what explanatory variables to use at each node, and how to use them to split the tree, are taken sequentially (from top to bottom) and are based on the gain in precision induced by the split.

Although decision trees provide a very intuitive modeling approach, they tend to perform poorly when predicting previously unseen observations (i.e., observations that were not used to estimate the model). This poor performance occurs because decision trees suffer from a problem called "high variance." Since decision tree models are incredibly flexible, they tend to overfit the data used to estimate them. As a result, decision trees tend to capture not only the actual relationship between predictors and outcome but also the noise contained in the sample (which results in poor predictive performance).

Various techniques (such as pruning, minimum node size, and maximum number of terminal nodes) can mitigate overfitting, but estimating a random forest is one of the most common approaches. The basic idea is simple: By combining many "imperfect" decision trees, we can "average out" their individual mistakes and dramatically improve the accuracy of our predictions. This approach, however, requires that each decision tree in the forest be different so that it provides new information. It is here where the "random" part of the model becomes relevant. Ideally, we would like to estimate each decision tree using a different sample from the population of interest; this is rarely feasible. Instead, we can achieve something similar by injecting randomness into the tree-growing process by doing the following: 1) estimating each tree using a different random sample with replacement drawn from the original dataset, and 2) deciding how to split a node and limiting the search to a randomly selected subset of explanatory variables.

IS IT ABOUT THE DATA?

We use data publicly available on the firms to identify what information the ESG ratings are capturing. Although these variables do not necessarily coincide with those employed by the rating agencies, we can expect them to be related to the various ESG ratings—and, therefore, to be representative of their content. Furthermore, using the same variables across the ratings allows us to indirectly assess the impact of standardizing the information.

Variables' Predictive Power[18]

One way to do that is by assessing the ability of the explanatory variables, individually or grouped, to predict the rating agencies' ESG scores.

First, focusing on the top 10 variables with the highest predictive power for each of the ESG scores, Table 5 shows that:[19]

- **The factors have different predictive power across the ratings.** Although environmental factors seem to be important predictors for all three ESG scores, they are disproportionally so for Thomson Reuters. By contrast, RobecoSAM and Sustainalytics appear to offer a more balanced picture across environmental, social, and governance indicators.

- **Very few factors overlap across the three ratings.** Of the top ten predictors, only two are common among all rating providers: *Target Emissions* and *Corporate Social Responsibility Reporting*.[20] However, RobecoSAM and Sustainalytics share eight common top predictors.

Second, we extend the analysis to all variables. To do so, we aggregate them in categories when assessing how well they predict the different ratings. Figure 6 reports the outcome when considering five broad categories: environmental, social, governance, financial, and others. Figure 7 expands the analysis to 18 subcategories: three environmental, four social, three governance, six financial, and two related to other factors.

18 Our analysis is based on two of the most widely used measures, Mean Decrease in Impurity and Perturbation Importance, using Li et al. (2019) and Breiman (2001), respectively.

19 The top predictors were chosen by ranking all explanatory variables in ascending order according to each of our two measures and selecting the first 10 variables to appear in both rankings.

20 *Target Emissions* measures whether a company has set and achieved short-term and long-term targets to reduce emissions to land, air, or water from business operations. *Corporate Social Responsibility Reporting* measures a company's efforts to publish a report on Corporate Social Responsibility, Health and Safety, or Sustainability issues.

- **The overall environmental and governance factors have the highest predictive power for all three ESG scores.** Social and financial considerations—in no particular order—follow, and then other factors.

- **Emissions and Resource Use have the most predictive power for environmental factors.** Emissions refers to variables that measure a company's commitment and effectiveness in reducing environmental emissions in production and operational processes. Resource Use refers to variables that reflect a company's performance and capacity to reduce the use of materials, energy, or water, and to find more eco-efficient solutions by improving supply chain management. The subcategory Innovation, which includes variables that reflect a company's capacity to reduce its environmental impact through new environmental technologies and processes, shows little power.

Table 5. Top 10 Predictors for ESG Scores

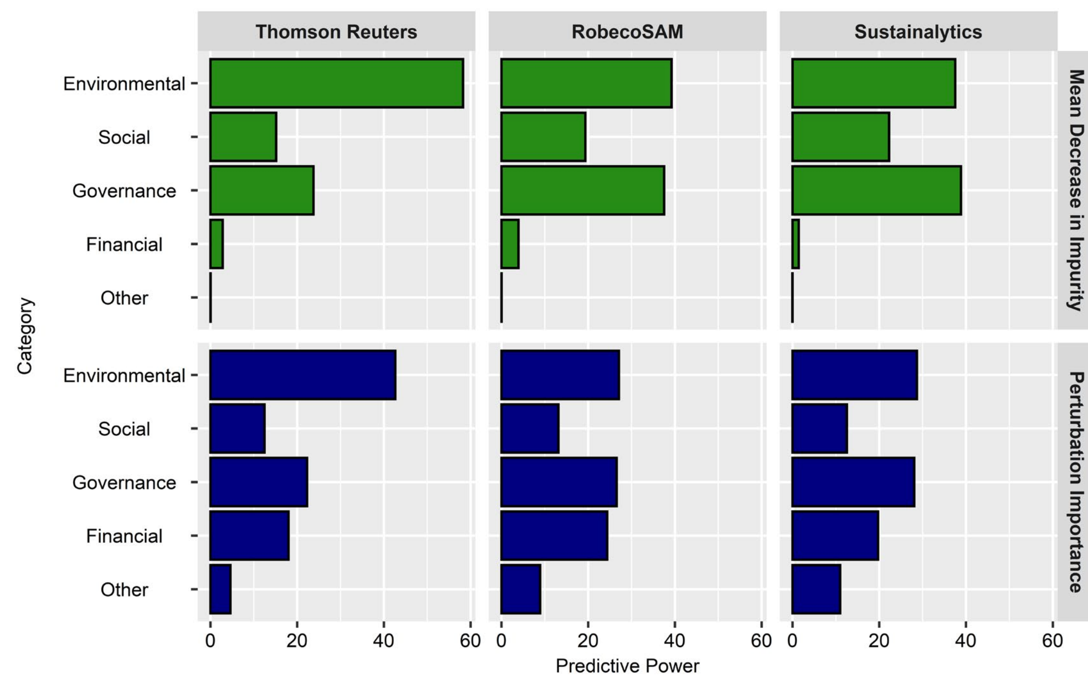
Thomson Reuters	RobecoSAM	Sustainalytics
Environmental Variables		
Target Emissions	Target Emissions	Target Emissions
Resource Reduction Policy	Renewable Energy Use	Renewable Energy Use
Emissions Policy	Resource Reduction Targets	Environmental Supply Chain Management
Environmental Supply Chain Management		Policy Environmental Supply Chain
Environmental Supply Chain Policy		Resource Reduction Targets
Environment Management Training		
Energy Efficiency Policy		
Social Variables		
Flexible Working Hours	Fundamental Human Rights	Fundamental Human Rights
	Human Rights Contractor	Human Rights Contractor
	Human Rights Policy	
Governance Variables		
Corporate Social Responsibility Reporting	Corporate Social Responsibility Reporting	Corporate Social Responsibility Reporting
Independent Board Members	Stakeholder Engagement	Stakeholder Engagement
	Global Compact Signatory	Global Compact Signatory
	Board Gender Diversity	

Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

- **CSR Strategy and Management capture most of the predictive power of governance factors across the ratings.**[21] Yet Management is significantly more relevant than CSR Strategy in predicting Sustainalytics' ESG scores. The results also confirm our previous finding that the relative importance of environmental variables is significantly higher for Thomson Reuters than for the other two rating agencies.

- **Among social variables, Human Rights and Workforce have the highest predictive power across all agencies.** Product Responsibility has the lowest.[22] However, while Workforce is the most critical social subcategory for Thomson Reuters, Human Rights is the top predictor for RobecoSAM and Sustainalytics.

Figure 6: Predictive Power by Category



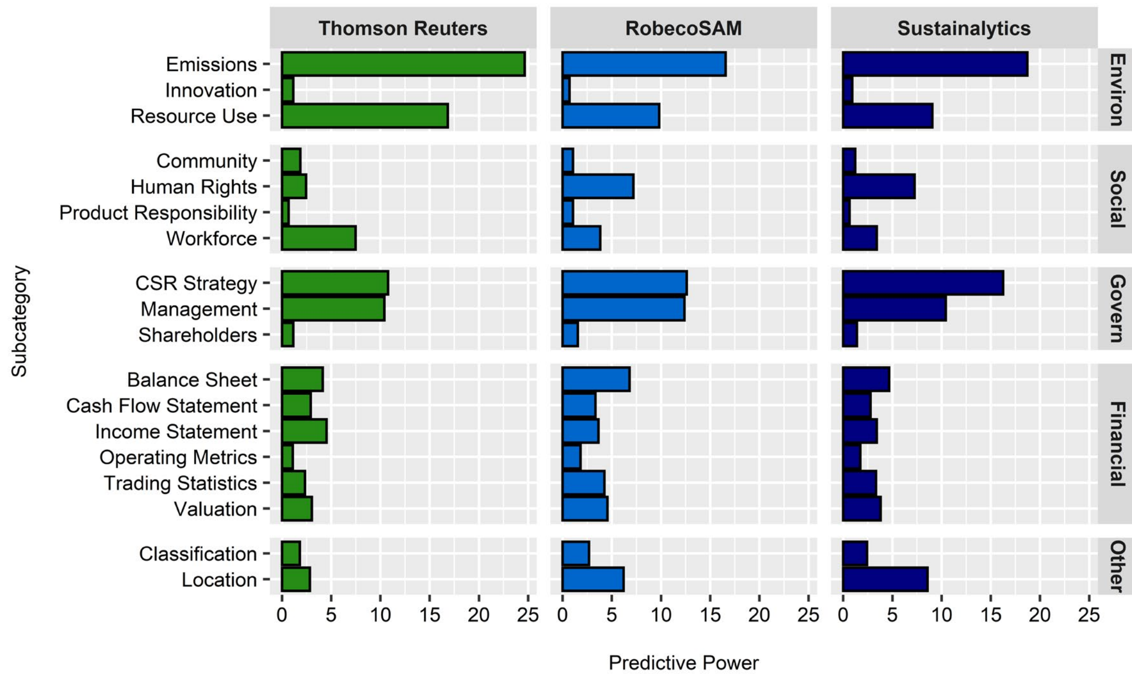
Source: Bloomberg and Refinitiv Eikon (2020)

21 *CSR Strategy* includes variables that reflect a company's practices to communicate that it integrates the economic (financial), social, and environmental dimensions into its daily decision-making processes. On the other hand, *Management* includes variables that measure a company's commitment toward and effectiveness in following best practice corporate governance principles.

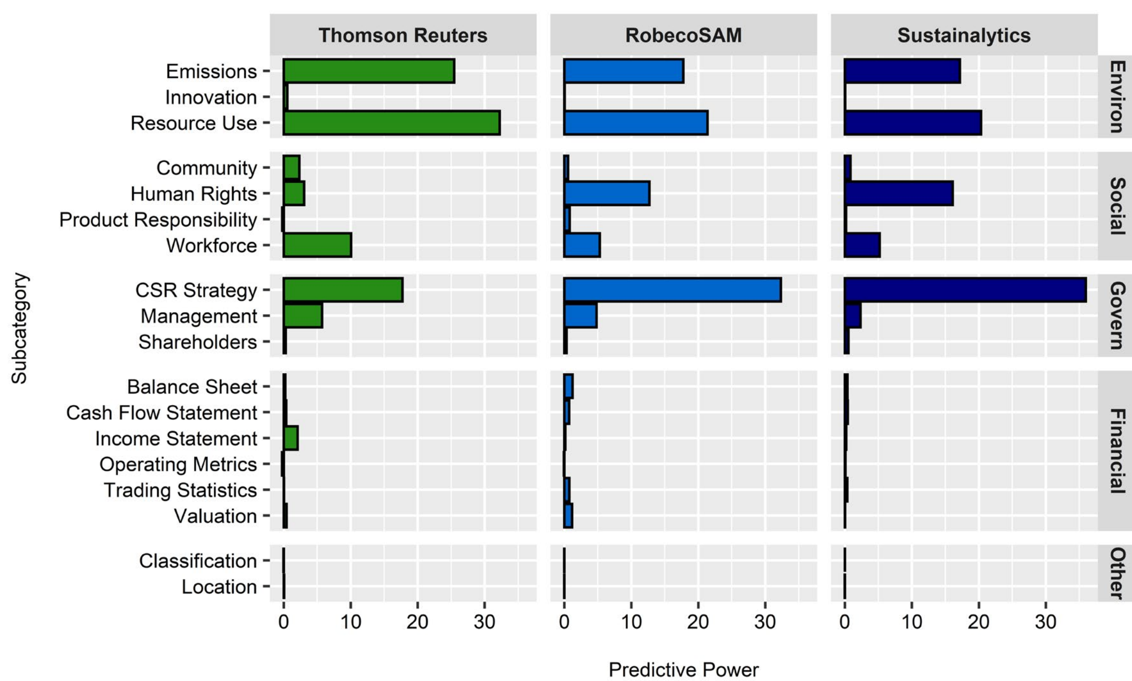
22 *Human Rights* include variables that measure a company's effectiveness towards respecting the fundamental human rights conventions. *Workforce* refers to variables that reflect a company's effectiveness towards job satisfaction, a healthy and safe workplace, maintaining diversity and equal opportunities, and development opportunities for its workforce. *Product Responsibility* includes variables that reflect a company's capacity to produce quality goods and services integrating the customer's health and safety, integrity, and data privacy.

Figure 7: Predictive Power by Subcategory

a) Measure 1: Mean Decrease in Impurity



b) Measure 2: Perturbation Impurity



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Variable Contributions

The other way to identify what information the ESG ratings are capturing is to evaluate how much each variable contributes to the predicted ESG rating. To do so, we use the predictive power of the variables to generate new ESG ratings. We then estimate the actual contribution of each group of variables to these predicted ESG ratings. Figure 8 reports the results for the categories and Figure 9 for the subcategories.[23] Ultimately, this allows us to identify how much the different factors matter when calculating the various ratings, based on the information derived from the machine learning analysis:

- **Governance and financial variables are the top two contributors for all three ratings.** Governance is the category whose importance is robust across the two analyses: prediction power of a category and contribution to the predicted score. Yet, its magnitude varies significantly across rating providers.

- ***Management* and *CSR Strategy* drive the contribution of governance, in line with the previous analysis.** Yet, CSR Strategy contributes negatively to the predicted Sustainalytics score.

- ***Balance Sheet* and *Cash Flow Statement* drive the contribution of financial variables.** And both are negatively related to the predicted Sustainalytics score.

- **Environmental variables are still important for the predicted Thomson Reuters score, especially *Emissions* and *Resources Use*.**

- ***Workforce* remains an important sub-category for social variables, in line with the previous analysis.**

IS IT ABOUT THE METHODS?

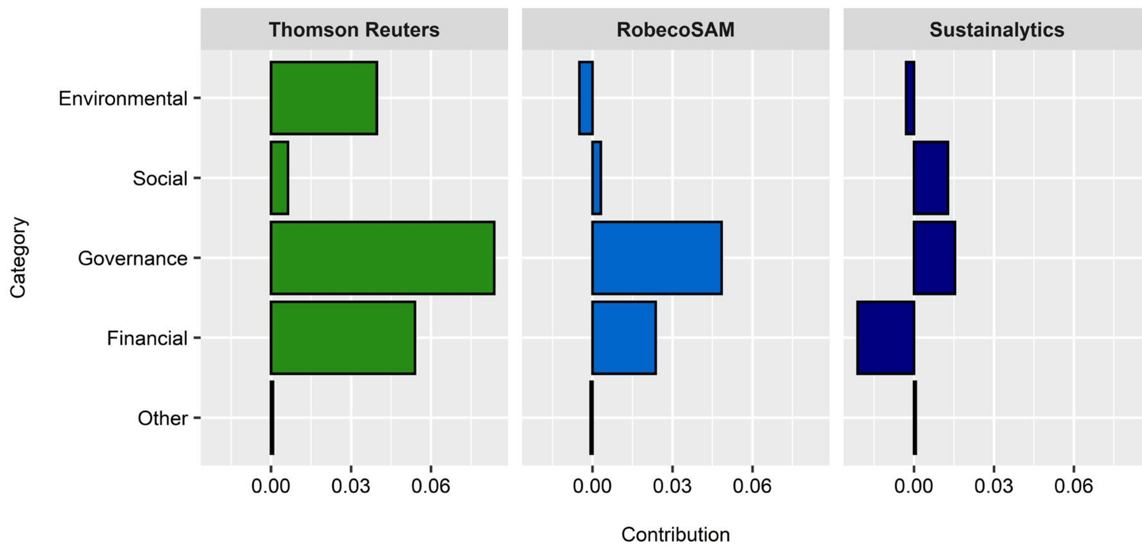
Beyond the variables, the methods for aggregating the information differ from one rating to another. We illustrate this point by looking at how the variables interact. Finally, we show how challenging it is for investors to understand and rationalize the discrepancies across ESG scores by comparing the rating we have generated with the one provided by the agencies.

Variable Interactions

Looking at the interaction among variables or groups of variables helps explain how the ways agencies aggregate information impacts ratings. We use the estimated random forests to determine whether—and to what extent—the different explanatory

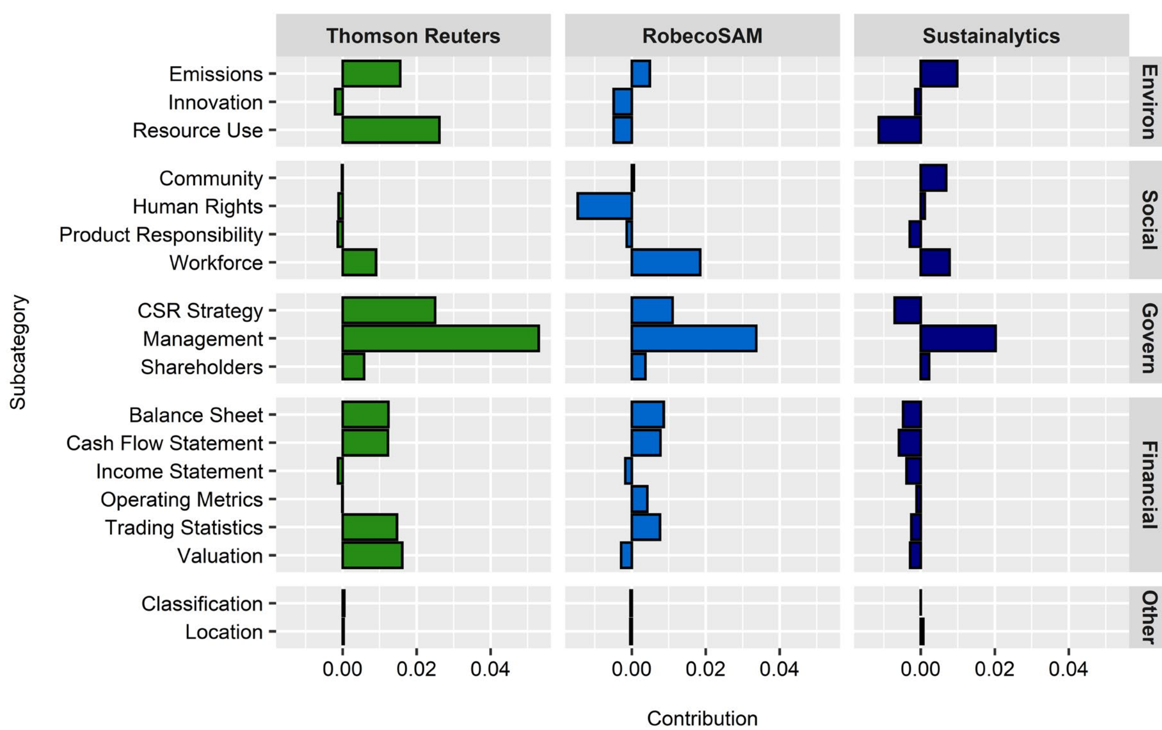
[23] See Appendix 7 for more details on how variable contributions are calculated.

Figure 8. Contribution to Predicted ESG Scores by Category



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Figure 9. Contribution to Predicted ESG Scores by Subcategory



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

variables interact with each other when predicting the ESG scores. The overall interaction (see Figures 10 and 11) is different across the ratings, especially at the subcategory level. For example, while the overall interaction effects of environmental variables are concentrated on the subcategory *Resource Use* for the predicted Thomson Reuters and RobecoSAM ratings, they appear to be (roughly) evenly divided between *Emissions* and *Resource Use* for Sustainalytics. Similarly, although the overall interaction effects associated with governance variables seem to be concentrated on the subcategory *Management* for the predicted Sustainalytics rating, they are more evenly distributed between *Management* and *Shareholders* for RobecoSAM and (to a lesser extent) for Thomson Reuters.

Figures 12 and 13 focus on the pairwise interaction by category and subcategories.[24] These pairwise effects measure the extent to which variables belonging to one group interact with variables in another group. As expected, the results show significant differences across rating agencies. For the predicted Thomson Reuters rating, for example, most pairwise interaction effects are relatively weak and evenly distributed across categories and subcategories.

By contrast, pairwise interaction effects appear to be relatively larger and more concentrated for the other two predicted ratings. In the case of RobecoSAM, the most substantial pairwise interaction effects are between financial and governance variables (especially between *Valuation* and *Management*), within financial variables (driven by the interaction between *Balance Sheet* and *Operating Metrics*), between environmental and social variables (mostly driven by the interaction between *Emissions* and *Product Responsibility*), and between financial variables and other (*Valuation* and *Location*).

Similarly, for the predicted Sustainalytics rating, there are significant interaction effects between governance and environment (*Management* and *Resource Use*), governance and finance (*Human Rights* and *Balance Sheet*), and within governance (variables in the *Management* subcategory).

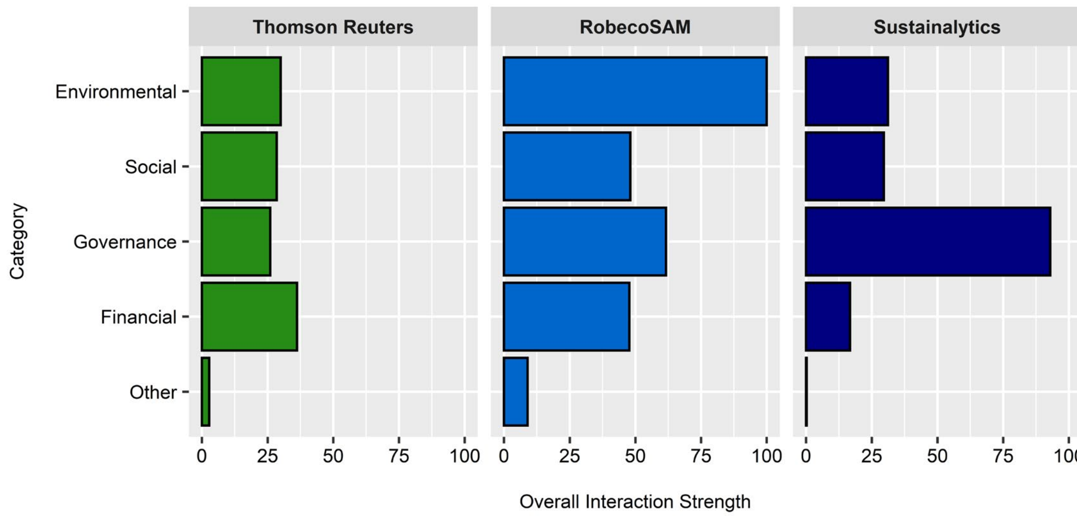
Perhaps surprisingly, the interaction between *Classification* (which includes a company's economic sector) and all the environmental, social, and governance subcategories appears to be very weak. This result is at odds with the use of sector-specific methodologies, a claim made by all three rating agencies in our sample.[25]

Our analysis uses standardized data to show how information processing matters for the ratings. Yet harmonization of the methods is not necessarily the solution.

[24] Following Friedman and Popescu (2008), we estimate variable interaction effects by decomposing the prediction function into main and interaction effects and measuring how much the variance in the model's predictions depends on the latter.

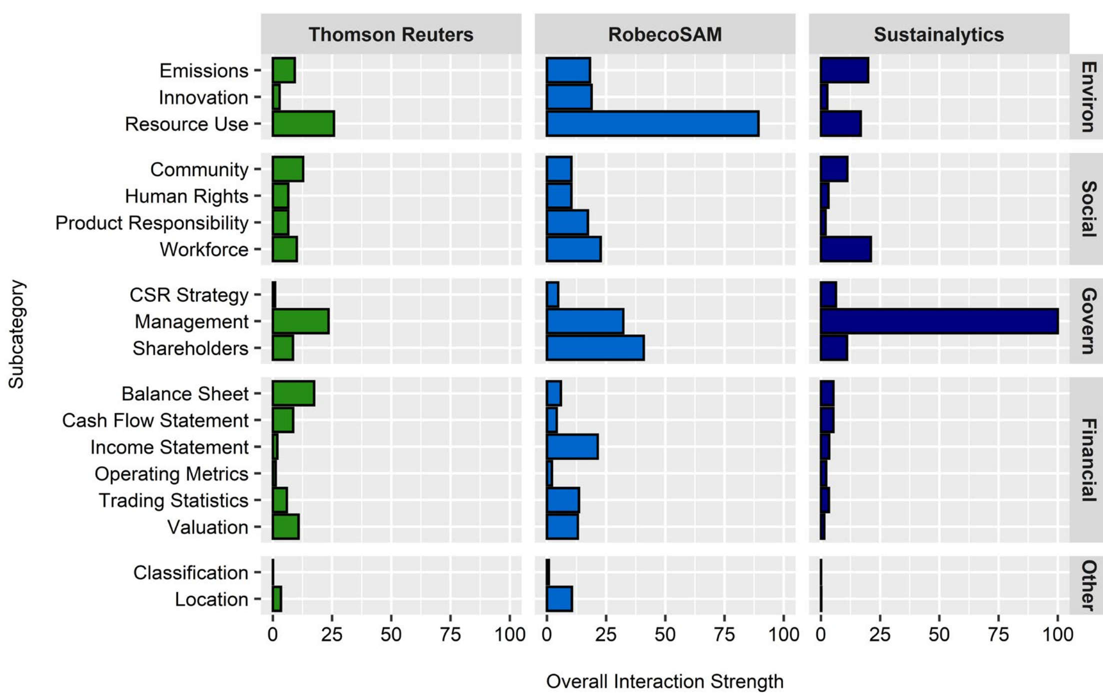
[25] See Gaffuri (2017, p. 11), Sutainalytics (2019, p. 5-6), and Thomson Reuters (2018, p. 6).

Figure 10. Overall Interaction Strength by Category



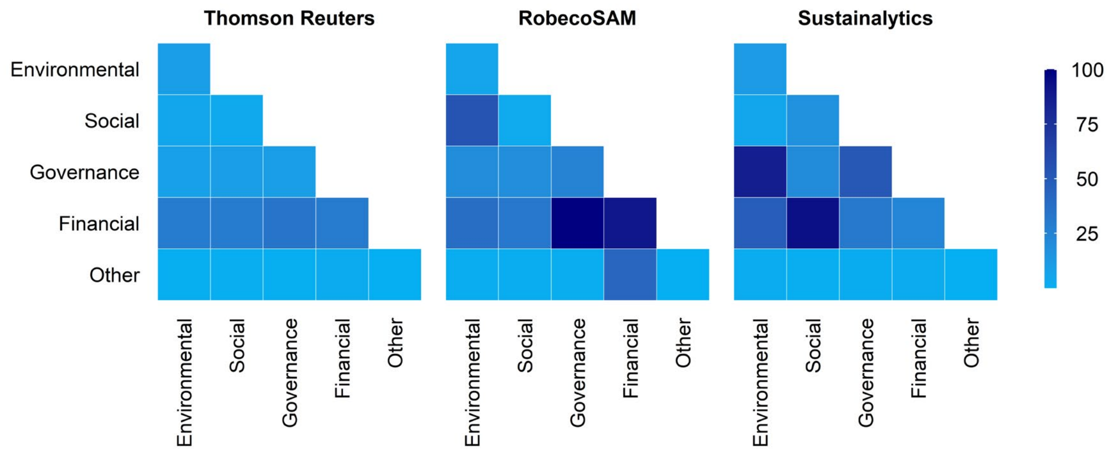
Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Figure 11. Overall Interaction Strength by Subcategory



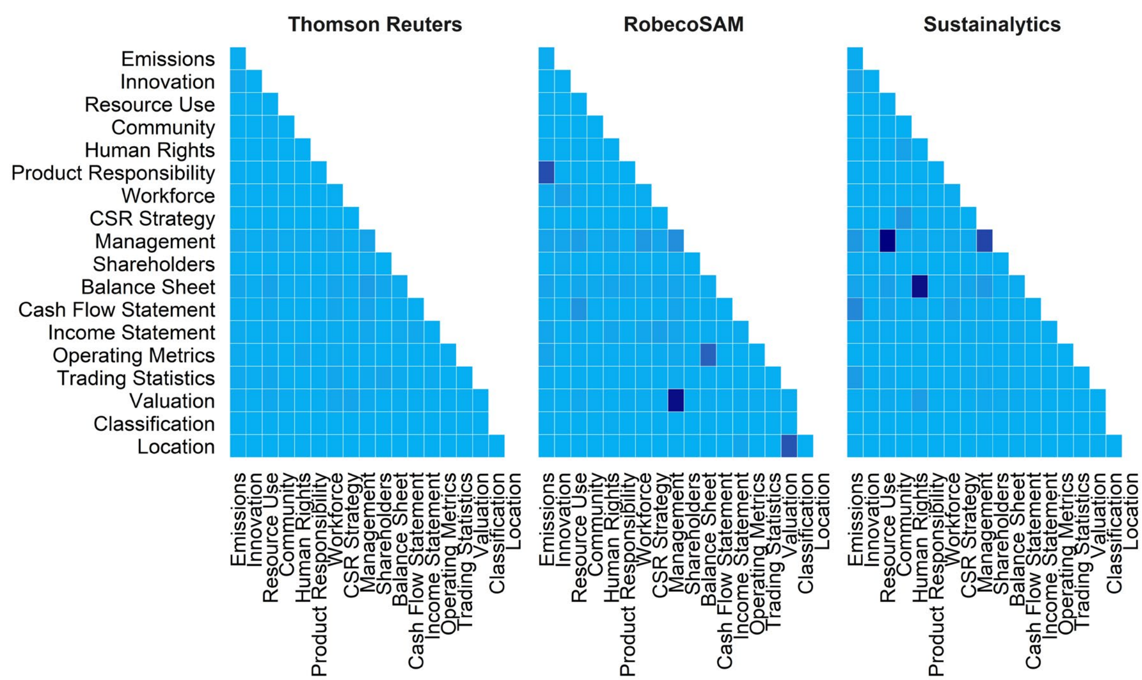
Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Figure 12. Pairwise Interaction Strength by Category



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Figure 13. Pairwise Interaction Strength by Subcategory



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Not being able to reconcile the ratings due to their different data treatment is not an issue as long as the differences reflect the rating agencies' priorities, emphasizing the ESG issues they deem most important. If that is the case, these choices must be shared with the rating users, investors, or firms, which will decide which rating is more aligned with their priorities.

RATINGS: OBSERVED VERSUS GENERATED

To conclude our analysis, we check the ability of the generated ratings to replicate the level of disagreement between the actual ESG rating of the agencies. Comparing predicted and observed levels of disagreement offers valuable information to investors: It captures the difficulty in predicting and understanding the discrepancies across ESG scores based on information readily available to market participants.

Table 6 reports correlation coefficients for each possible pair of ESG scores as predicted by the estimated random forests and as observed in the data. For all three pairs, the correlations between predicted scores are greater than those observed in the agencies' ESG ratings. Using similar data while allowing for different methods to process it strengthens the convergence across the ratings, confirming that using standardized data will lead to more comparable ratings.[26]

Table 6. Correlations between ESG Ratings: Observed and Predicted

	Observed ESG Scores	Predicted ESG Scores
RobecoSAM vs. Sustainalytics	0.72	0.87
RobecoSAM vs. Thomson Reuters	0.65	0.82
Sustainalytics vs. Thomson Reuters	0.65	0.79

Note: The correlations are the Pearson product-moment correlation coefficients.

Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

[26] Novick (2020).

CONCLUSION

Rating providers' inconsistencies and the inability to compare their findings often confuse investors. While differences across ESG scores can naturally emerge if rating providers adopt different definitions of ESG performance, our analysis shows that differences arise even when the rating agencies use similar definitions. Thus, the focus when it comes to ESG ratings should not be on agreeing on a single definition but on standardizing the data, achieving greater clarity in labeling ratings, and making their objectives more transparent.

Our analysis illustrates how difficult it is to understand or predict the ratings. It shows that most discrepancies among rating providers cannot be easily explained by information readily available to investors or other users of these ratings. Yet two clear outcomes emerge:

- The three ratings strongly agree on who are the worst performers, with a correlation higher than 0.95.
- The three ratings reach some consensus when measuring risks arising from governance factors, especially for *Corporate Social Responsibility Strategy* and *Management*. The first subcategory of governance includes variables that reflect a company's practices to communicate that it integrates economic (financial), social, and environmental concerns into its daily decision-making. The second one includes variables that measure a company's commitment toward and effectiveness in following best practice and corporate governance principles.

Overall, our study has two main implications in assessing how well-equipped firms are to deal with ESG risks. First, there is a need for data standardization. The use of standardized data will help to reconcile the ratings, at least partially. The first step will be to agree on common disclosure standards and to align the different existing ESG disclosure standards worldwide. The resulting harmonization of the data would reduce the reporting burden on the firms and increase the quality of the information collected. This will increase the firms' participation while improving the rating agencies' credibility with investors.

Creating consistent, high-quality data is only part of the solution. The second implication of our study is the importance of transparency regarding the methodologies to calculate the rating or the focus of the rating. Are E, S, and G factors equally important? Or is the rating focusing mostly on one of them? Our study highlights the importance of rating agencies' different methodologies for aggregating data and their impact on the ratings. Rating agencies' different emphases can be informative by reflecting the ESG issues that agencies deem most important. But the agencies must be transparent about their methods with investors, firms, and other users who can then decide which rating most aligns with their priorities.

APPENDIX 1.

Number of ESG-Focused Funds

Table A.1. Number of ESG-Focused Funds in Largest Asset Management Firms

Company	# of Funds (All Share Classes)	# of ESG Funds	Percentage ESG
BlackRock	1,038	18	1.73%
Prudential Financial	322	0	0.00%
Fidelity	318	5	1.57%
Morgan Stanley	262	7	2.67%
Vanguard	207	6	2.90%
Bank of New York Mellon	205	8	3.90%
JP Morgan Asset Management	197	2	1.02%
PIMCO	146	14	9.59%
State Street	140	2	1.43%
Amundi	136	5	3.68%
Goldman Sachs	104	2	1.92%
Capital Group	62	0	0.00%
Allianz	51	3	5.88%
UBS	26	4	15.38%
AXA Group	10	0	0.00%

Note: Funds classified as ESG explicitly stated in their mandates that investments were chosen primarily for their ESG-risk mitigating characteristics. Keywords in the primary investment mandate also included impact investing, gender/ethnic diversification, and environmental sustainability.

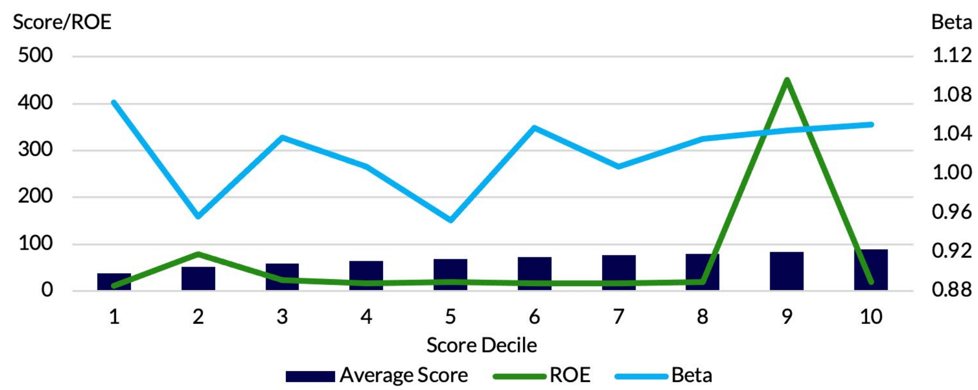
Source: Morningstar Direct (2020)

APPENDIX 2.

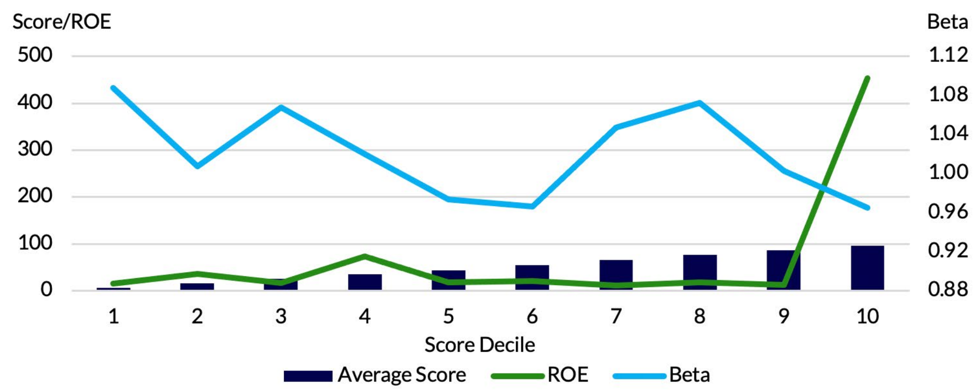
ROE and Beta by ESG Score Decile

Figure A.1.

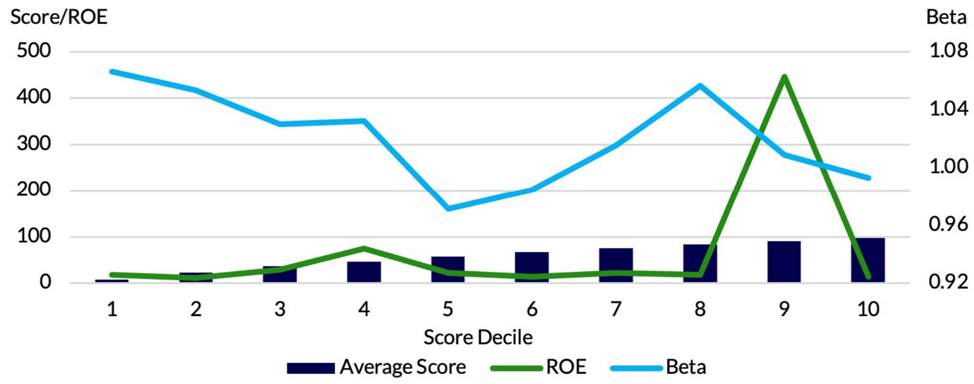
a) Thomson Reuters' ROE and Beta by ESG Score Decile



b) RobecoSAM's ROE and Beta by ESG Score Decile



c) Sustainalytics' ROE and Beta by ESG Score Decile



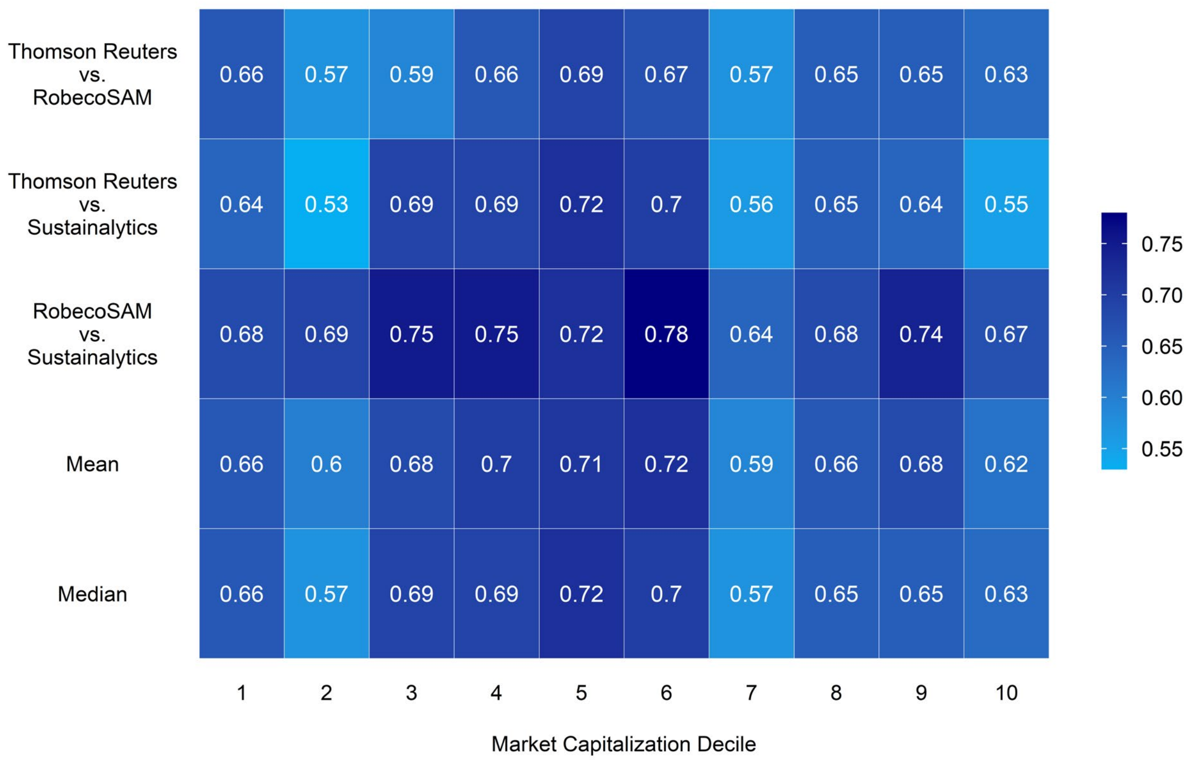
Source: Bloomberg and Refinitiv Eikon data (2020)

APPENDIX 3.

Disagreement among Ratings and Market Capitalization

The analysis in the main text indicates that the extent of disagreement among ESG ratings varies substantially. To better understand what is driving this heterogeneity, this appendix shows correlations for each pair of ESG scores after dividing companies into deciles based on their market capitalization. Figure A.2 below shows the results of the exercise.

Figure A.2. Correlations between ESG Scores by Market Capitalization Decile



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

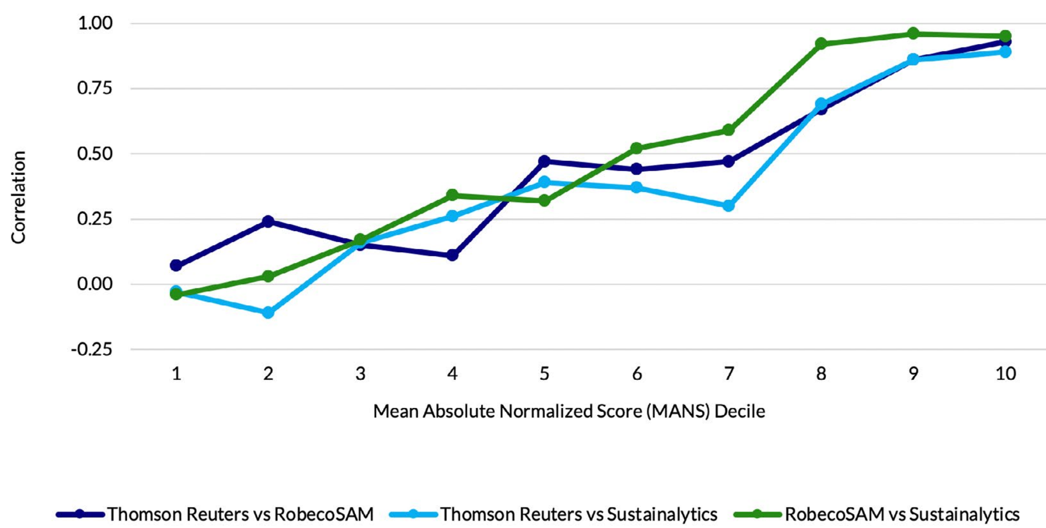
First, consistent with our previous findings (both when we pool all firms and when we divide them by economic sector), RobecoSAM and Sustainalytics exhibit the highest pairwise correlation across market capitalization deciles. Second, all pairwise correlations follow a relatively similar pattern as we move from companies with low market capitalization to companies with high market capitalization. Third, the relationship between the (average) level of agreement among ratings and the level of market capitalization is not monotonic. The level of agreement among rating agencies appears to be slightly higher for companies with intermediate levels of market capitalizations (i.e., deciles 4, 5, and 6) than for companies with low or high levels (especially those in deciles 2, 7, and 10). The results suggest no clear relationship between the level of market capitalization and the degree of agreement among rating agencies in our sample.

APPENDIX 4.

Disagreement among Ratings at the Firm Level

Figure A.3 explores how disagreement varies across individual firms. It shows correlations between ESG scores after grouping companies based on an individual measure of "disagreement among rating agencies."[27] Surprisingly, the results reveal that the extent of the inconsistencies among rating providers varies substantially across firms. Indeed, if disagreement among agencies were roughly constant across all companies, the curve in Figure A.3 would be relatively flat. Instead, the average correlation between ESG scores increases from a value of about 0 (for companies in the first decile) to a value slightly above 0.9 (for companies in the top decile).

Figure A.3. Correlations between ESG Scores by Decile (Based on Firm-Specific Measure of Disagreement)

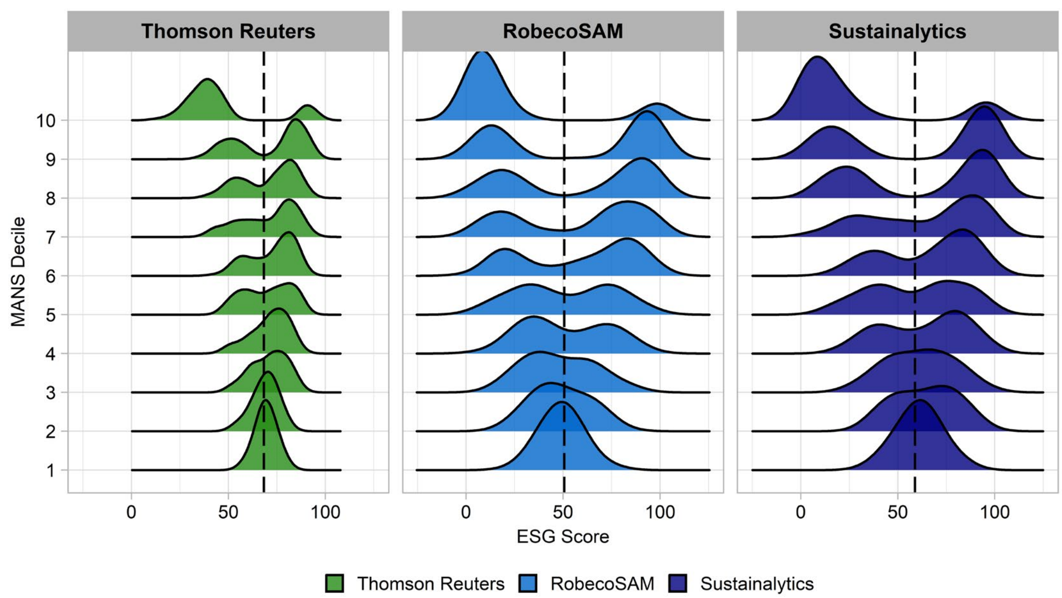


Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

[27] To calculate our firm-level measure of disagreement, we first normalize all ESG scores by subtracting their respective means and dividing them by their respective standard deviations. For each company in our sample, we then calculate the mean of the absolute value of the normalized scores across all three rating agencies. The resulting number is our firm-level measure of disagreement. For a similar exercise, see Berg et al. (2019).

As discussed in section four, economic sectors explain part of the variation in disagreement across firms. Figure A.4, which plots the distributions of ESG scores after grouping companies based on our firm-specific measure of disagreement, offers two additional insights. First, as the firm-level measure of inconsistencies increases, ESG scores move away from their respective means (i.e., the vertical dotted lines). Thus, the level of agreement among ratings appears to be higher for companies whose scores are away from the mean (i.e., "relatively good" and "relatively bad" firms) than it is for companies whose scores are close to the average. Second, for all three rating agencies, most companies in the top decile of our firm-specific measure of disagreement have extremely low ESG scores, indicating that the strongest agreement among rating providers occurs across the worst performers.

Figure A.4. ESG Score Distributions by Decile (Based on Firm-Specific Measure of Disagreement)



Note: The vertical dotted line represents the overall average score for each of the rating agencies.

Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

APPENDIX 5.

Top Individual Predictors for ESG Scores

Table A.2. Variables and Definitions

	Variable	Definition
Environmental	Environment Management Training	Does the company train its employees on environmental issues?
	Environmental Supply Chain Management	Does the company use environmental criteria (ISO 14000, energy consumption, etc.) in the selection process of its suppliers or sourcing partners?
	Emissions Policy	Does the company have a policy to improve emission reduction?
	Energy Efficiency Policy	Does the company have a policy to improve its energy efficiency?
	Environmental Supply Chain Policy	Does the company have a policy to include its supply chain in its efforts to lessen its overall environmental impact?
	Renewable Energy Use	Does the company make use of renewable energy?
	Resource Reduction Policy	Does the company have a policy for reducing the use of natural resources or to lessen the environmental impact of its supply chain?
	Resource Reduction Targets	Does the company set specific objectives to be achieved on resource efficiency?
	Target Emissions	Has the company set targets or objectives for emission reduction?

	Variable	Definition
Social	Flexible Working Hours	Does the company claim to provide flexible working hours or working hours that promote a work-life balance?
	Fundamental Human Rights	Does the company claim to comply with the fundamental human rights convention of the ILO or support the UN declaration of human rights?
	Human Rights Contractor	Does the company report or show to use human rights criteria in the selection or monitoring process of its suppliers or sourcing partners?
	Human Rights Policy	Does the company have a policy to ensure the respect of human rights in general?
Governance	Board Gender Diversity	What is the percentage of females on the board?
	Corporate Social Responsibility Reporting	Does the company publish a separate corporate social responsibility/health and safety/sustainability report or a section in its annual report on these issues?
	Global Compact Signatory	Has the company signed the UN Global Compact? The UN GC is a non-binding United Nations pact to encourage businesses worldwide to adopt sustainable and socially responsible policies and to report on their implementation.
	Independent Board Members	What is the percentage of independent board members as reported by the company?
	Stakeholder Engagement	Does the company explain how it engages with its stakeholders? How does it involve the stakeholders in its decision-making process?

APPENDIX 6.

Variable Subcategories

Table A.3. Definition of Variable Subcategories

Category	Subcategory	Subcategory Definition
Environmental	Emissions	Variables that measure a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes.
Environmental	Innovation	Variables that reflect a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.
Environmental	Resource Use	Variables that reflect a company's performance and capacity to reduce the use of materials, energy, or water, and to find more eco-efficient solutions by improving supply chain management.
Social	Community	Variables that reflect a company's commitment to being a good citizen, protecting public health, and respecting business ethics.
Social	Human Rights	Variables that reflect a company's effectiveness in respecting fundamental human rights conventions.
Social	Product Responsibility	Variables that reflect a company's capacity to produce quality goods and services, integrating the customer's health and safety, integrity, and data privacy.
Social	Workforce	Variables that measure a company's effectiveness in providing job satisfaction, providing a healthy and safe workplace, maintaining diversity and equal opportunities, and developing opportunities for its workforce.

Category	Subcategory	Subcategory Definition
Governance	CSR Strategy	Variables that reflect a company's practices to communicate that it integrates economic (financial), social, and environmental dimensions into its daily decision-making processes.
Governance	Management	Variables that measure a company's commitment and effectiveness towards following best practice corporate governance principles.
Governance	Shareholders	Variables that measure a company's effectiveness towards equal treatment of shareholders and the use of anti-takeover devices.
Financial	Balance Sheet	Variables that reflect a company's assets, liabilities, and shareholders' equity.
Financial	Cash Flow Statement	Variables that summarize the amount of cash and cash equivalents entering and leaving a company.
Financial	Income Statement	Variables that measure a company's revenues and expenses during a period. Variables also indicating how the revenues are transformed into the net income or net profit.
Financial	Operating Metrics	Variables that illustrate a company's overall performance, such as return on equity, return on assets, and EBITDA.
Financial	Trading Statistics	Variables that reflect the trading of a company's stock, such as monthly Sharpe Ratio, volatility, institutional ownership, 200-day price PCT change, and liquidity measures.
Financial	Valuation Metrics	Variables that reflect and are related to a company's valuation, such as market capitalization, enterprise value, P/E ratio, P/EG ratio, Beta, and dividend yield.
Others	Classification	Economic sector, according to the Thomson Reuters Business Classification.
Others	Location	Country of headquarters, also known as Country of Domicile.

APPENDIX 7.

Calculating Variable Contributions

To understand how variable contributions are calculated in a random forest model, notice that given a set of independent variables or predictors, we can estimate how the value of the prediction changes after every split in each decision tree. Since each split is associated with a variable, and since the split either adds or subtracts to the predicted value given in the previous node, the final prediction can be boiled down to the sum of the variable contributions plus the "bias" (i.e., the model's prediction at the beginning of the decision tree). After averaging all the individual decision trees in the random forest model, the final prediction can be represented by the following formula:

prediction(x) = bias + contribution(1, x) + … + contribution(n, x)

where

- x is a set of predictors,
- *bias* is the model's prediction before using any predictor (usually the mean of the variable we want to predict in the original dataset),
- *contribution (j, x)* is the contribution of variable j to the final prediction, and
- *n* is the number of predictors.

Although the previous expression is superficially similar to a linear regression, the coefficients of a linear regression are fixed, with a single constant for every variable. For the random forest model, by contrast, each variable's contribution is a complex function, one that also depends on all other variables that together determine the decision path that generates the prediction, and thus, the contributions that are passed along the way.[28]

[28] For a detailed discussion of the methodology, see https://blog.datadive.net/interpreting-random-forests/.

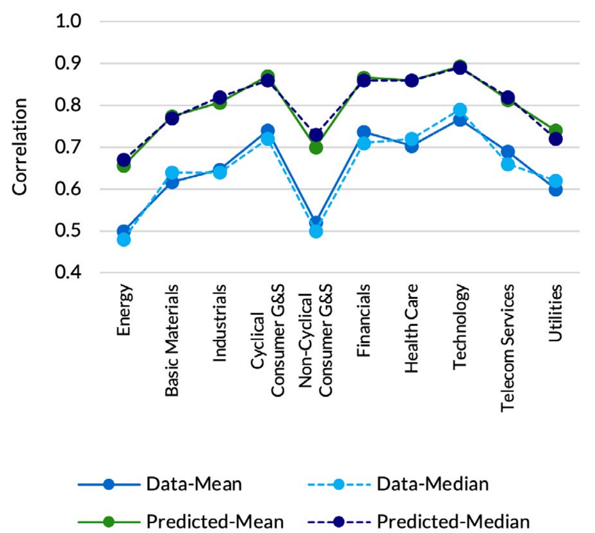
APPENDIX 8.

Observed versus Generated Ratings and Firms’ Characteristics

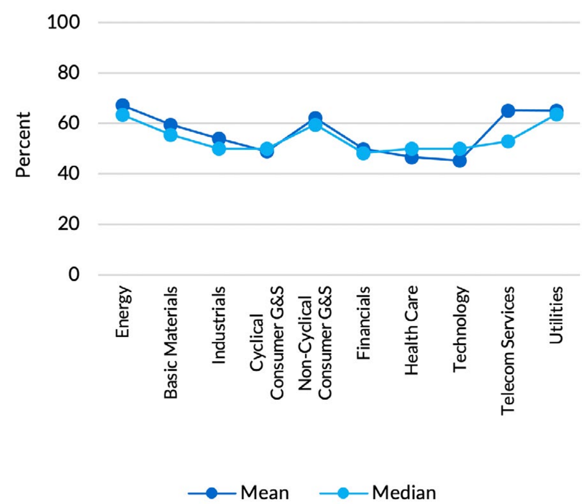
In this appendix, we explore whether our model’s ability to account for the disagreement among ESG rating agencies varies with some of the firms’ characteristics. To this end, we divide companies by economic sector and market capitalization decile and then compare the mean and median correlations between the ESG scores observed in the actual data with those predicted by the random forest models. Figures A.5(a) and A.6(a) show the results of the exercise. The results suggest that the random forests do a reasonably good job at capturing variations in the level of disagreement among ratings across sectors and market capitalization deciles but that they tend to underpredict the level itself. Thus, the figures indicate that the importance of factors not captured by the random forests in explaining the disagreement among ratings remains significant across all economic sectors and market capitalization deciles. This last point is confirmed by Figures A.5(b) and A.6(b), which display the fraction of disagreement explained by the random forest models for each economics sector and market capitalization decile. The figures show that the ability of the random forests to account for the disagreement among agencies ranges from 45.2 percent to 67.3 percent across economic sectors and from 46.6 percent to 59.5 percent across market capitalization. Although the specific numbers may vary, the overall picture seems to confirm that the models can account for around half the observed disagreement among rating agencies.

Figure A.5. Explanatory Power of Random Forest Models by Economic Sector

a) Predicted versus Observed Correlations between ESG Scores



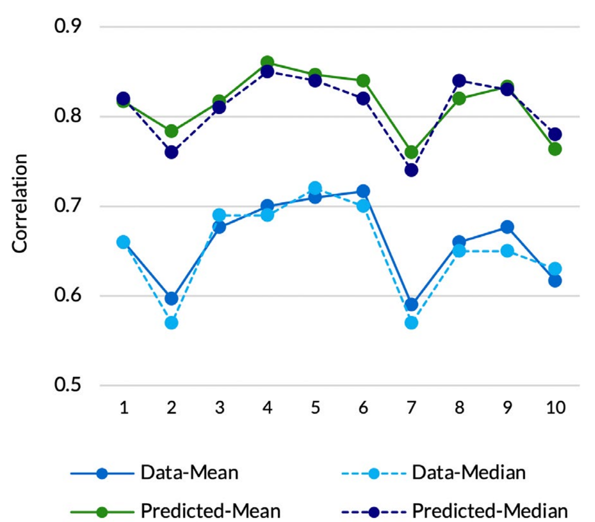
b) Percent of Disagreement Explained by Random Forest Models



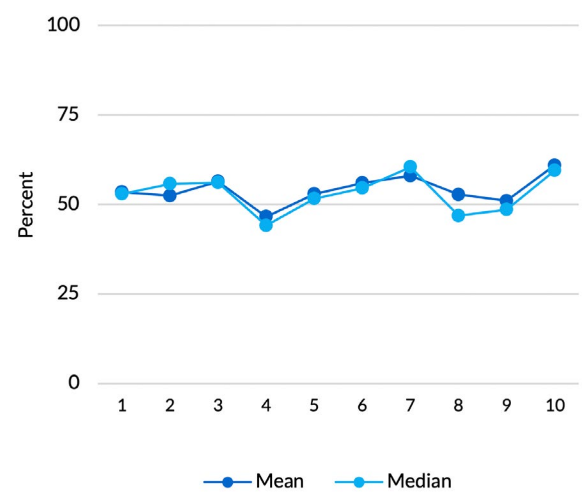
Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

Figure A.6. Explanatory Power of Random Forest Models by Market Capitalization Decile

a) Predicted versus Observed Correlations between ESG Scores



b) Percent of Disagreement Explained by Random Forest Models



Source: Authors' calculations using Bloomberg and Refinitiv Eikon data (2020)

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