Quantifying the Returns of ESG Investing: An Empirical Analysis with Six ESG Metrics*

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Abstract

We quantify the financial performance of environmental, social, and governance (ESG) portfolios in the U.S., Europe, and Japan, based on data from six major ESG rating agencies. We document statistically significant excess returns in ESG portfolios from 2014 to 2020 in the U.S. and Japan. We propose several statistical and voting-based methods to aggregate individual ESG ratings. We find that aggregate ESG ratings improves portfolio performance.

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In addition, we find that a portfolio based on Treynor-Black weights further improves the performance of ESG portfolios. Overall, these results suggest there is a significant signal in ESG rating scores that can be used for portfolio construction despite their noisy nature.

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Contents

Introduction

In recent years, environmental, social and governance (ESG) concerns have gained considerable attention from investors. The market for ESG investing is currently estimated at $9 trillion in the U.S.,[1] while the number of organizations that are signatories of the United Nations Principles for Responsible Investment (UN-PRI) has increased from 450 in 2016 to 4935 in 2022, representing over $100 trillion of assets under management.

Investors who want to implement ESG factors in their portfolios typically rely on ESG scores provided by third-party rating agencies that specialize in measuring ESG performance. There is a rapidly growing number of such rating agencies, and in our sample, we rely on ratings from some of the largest agencies, such as MSCI Inc, S&P Global, ISS, Moody's ESG Solutions, Reprisk, and TruValue Labs.Each rating agency has a proprietary methodology for the calculation of their ratings. This process typically involves gathering data from a variety of sources, including yearly regulatory filings, media reports, and self-disclosed data from firms and international organizations. The choice of different data methodologies and sources can lead to a substantial divergence between rating providers (Berg, Kölbel, and Rigobon, 2022).[2] ESG ratings, and sustainable investing in general, have received a number of high-profile critiques. For example, the *Economist* dedicated a recent cover story to ESG investing, concluding that ESG ratings are too complex and contain too much measurement error to be useful. This raises the question whether ESG ratings are in fact useful for portfolio construction, and if so, how to optimally exploit the signal in ESG ratings, despite their noisy nature.

One of the most important critiques of ESG ratings raised by regulators concerns the fiduciary responsibility of financial institutions. Portfolios constructed using the ESG scores are constrained, and therefore, if such a constraint reduces portfolio returns, it could be considered an illegal act — especially if the financial institution fails to clearly inform the

[1] `https://www.rockpa.org/guide/impact-investing-introduction/`

[2] Furthermore, Berg et al. (2021) show that these ratings contain a considerable amount of measurement error.

investor of such a possibility. In general, most of the regulatory commentary is based on the intuition that restricted portfolios are by necessity less profitable than unrestricted ones. However, this intuition is correct only if a constraint is orthogonal to returns. That is not the case if the selection mechanism is associated with the fundamental characteristics of the stocks. Consequently, understanding if ESG scores are associated with excess returns is of crucial importance to investors, regulators, financial institutions, and ultimately, to those that care about ESG impact to society in general.

In our empirical analysis, we construct ESG portfolios for the U.S., European, and Japanese stock markets, using ESG scores from six major rating agencies. We quantify the excess returns of these portfolios with respect to standard asset pricing models, including the capital asset pricing model (CAPM) and several Fama-French factor models. Our sample ranges from 2014 to 2020. We find a wide range of excess returns in portfolios constructed using different ESG scores. For example, the MSCI-based portfolio that goes long the top quartile of stocks with the highest ESG ratings and short the bottom quartile achieves a statistically significant annual alpha of 3.8% in excess of the Fama-French five-factor model in the U.S., while the same portfolio using other ESG ratings shows much lower (and usually neutral) excess returns. In addition, the same rating agency may have very different excess returns across regions. This instability in coefficients should have been expected, considering the sizeable noise in ESG scores.

To address the problem of noise, we propose several different ways to aggregate ESG scores across vendors. We construct a single measure of ESG by combining individual ESG scores from six different vendors using various statistical and voting aggregation techniques, including simple averages, the Mahalanobis distance, principal component analysis, average voting, and singular transferable voting. Our goal is to retain the ESG signal in the aggregated rating while attenuating the noise. Different aggregation methods will necessarily weight the ESG scores from rating agencies differently. For example, the simple average attributes equal weights to scores from all vendors, while the Mahalanobis distance aggregates ratings based on their variance-covariance, and principal component analysis weights the rating agencies in such a way to retain the direction of their maximum observed variance.

We find that aggregating individual ESG ratings improves portfolio performance significantly. We construct sorted ESG portfolios (from high to low scores) and analyze their risk-adjusted returns, excess returns, and exposures to fundamental factors. In particular, we find that portfolios in the U.S. based on the Mahalanobis distance achieve the highest annualized alpha, over 6%, while portfolios based on singular transferable voting achieve the highest annualized alpha, over 6% in Europe and 9% in Japan.

The empirical evidence on excess returns of ESG investing has been mixed in the existing literature. Some document a positive relationship between ESG scores and excess returns (see, for example, Edmans (2011), Khan, Serafeim, and Yoon (2016), Lins, Servaes, and Tamayo (2017), and Albuquerque, Koskinen, and Zhang (2019)), while others find a negative relationship (see, for example, Chava (2014), El Ghoul et al. (2011), and Bolton and Kacperczyk (2020)). Berg et al. (2021) describe a theoretical model explaining both relationships. They explain the positive realized returns by unexpected inflows into stocks with high ESG performance. As these inflows level out, the expected returns become lower. Put differently, high ESG firms benefit from a lower cost of capital due to higher market capitalization. Another possible explanation is found in omitted variable bias, in particular the omission of management quality. If good ESG performance is correlated to high management quality, the link between ESG performance and returns would no longer be causal. In our sample from 2014 to 2020, we found a positive relationship in the U.S. and Japan most likely due to inflows of funds from new ESG investors into high ESG stocks. For example, Berg, Heeb, and Kölbel (2022) find that MSCI rating changes drive changes in ESG mutual fund holdings in the U.S. market, albeit with a very slow integration of up to 18 months. They also show that this correlates temporally with returns.

We find that the portfolio construction methodology proposed by Lo and Zhang (2021) further improves the performance of ESG portfolios. Lo and Zhang's (2021) methodology begins by quantifying the excess returns for individual assets using a small number of parameters,[3] then applies Treynor-Black weights to optimize the Sharpe ratio of an ESG portfolio, in which the weights are proportional to the rank of the ESG score of each firm.[4] Using this framework, we achieve improved excess returns in ESG portfolios, especially for portfolios with a large number of assets. This is valid in particular for portfolios constructed to go long the top 4 deciles of stocks with the highest ESG ratings and short the bottom 4 deciles of stocks with the lowest ratings, so that weights based on the rank of each firm's ESG score have a meaningful impact.

Some investors may prefer to rely on E, S, or G scores individually in the creation of their portfolios. Consequently, we also investigate the aggregation of individual E, S, and G scores across vendors, and analyze the excess returns of top-bottom sorted portfolios. We find the highest excess returns for portfolios based on E scores in the U.S. and Japan. In portfolios based on S and G scores, we find positive excess returns only for some portfolios and aggregation methods.

Our paper is related to several strands in the literature. The first strand is about disagreement between ESG providers. Our work is based on the growing literature that highlights the divergence between ESG ratings (see, for example, Dorfleitner, Halbritter, and Nguyen (2015), Semenova and Hassel (2015), Berg, Kölbel, and Rigobon (2022), and Gibson Brandon, Krueger, and Schmidt (2021)).

Second, our work is also closely related to literature that explores the relationship between ESG and stock returns. Some research shows higher returns (Edmans, 2011; Khan, Serafeim, and Yoon, 2016; Lins, Servaes, and Tamayo, 2017), while other work shows a negative relationship both empirically (Bolton and Kacperczyk, 2020) and theoretically (Ľuboš Pástor, Stambaugh, and Taylor, 2021). Pástor, Stambaugh, and Taylor (2022) show that the high returns for green assets in recent years reflect unexpectedly strong increases in en-

[3]Specifically, it uses the cross-sectional correlation between ESG scores and excess returns of each stock.

[4]We compare the excess returns of ESG portfolios using the model of Lo and Zhang (2021) to their forward-looking realized excess returns and find a high degree of consistency between the two, thereby validating the model.

vironmental concerns, not high expected returns. Our work differs in our acknowledgement of the noisiness of ESG ratings and our proposal of different aggregation methods.

Third, our research is related to the nascent literature in dealing with measurement noise in ESG ratings and its impact on returns. Berg et al. (2021) use instrumented variable regressions to remove the noise in one version of the ESG score using others. In our work, we improve the signal using aggregation methods that combine multiple sources of data, and we leverage the optimal portfolios of Lo and Zhang (2021) to further improve the performance of these ESG portfolios.

In the remainder of this article, Section 1 discusses the methodology used to quantify excess returns, construct portfolios, and aggregate individual ESG scores. We then discuss the data and present summary statistics in Section 2. Section 3 presents our extensive empirical analysis using different ESG scores and portfolio construction methodologies. Finally, we conclude in Section 5.

1 Methodology

In this section, we describe the methodology used to construct portfolios based on ESG scores. We discuss our strategy to quantify excess returns for individual stocks, the portfolio construction methodologies, and several methods to aggregate multiple ESG scores.

1.1 Quantifying Excess Returns

We start with describing a methodology first proposed by Lo and Zhang (2021), which we adapt to ESG portfolios. We quantify the excess returns (alphas) of individual stocks ranked by their ESG scores. This allows us to optimize the weights used in ESG portfolios and to quantify their portfolio returns.

We consider a universe of N stocks with returns R_{it} that satisfy the following linear multi-factor model (e.g., the Fama-French factor model):

$$R_{it} - R_{ft} \;=\; \alpha_i \;+\; \beta_{i1}\,(\Lambda_{1t} - R_{ft}) \;+\; \cdots \;+\; \beta_{iK}\,(\Lambda_{Kt} - R_{ft}) \;+\; \epsilon_{it} \tag{1}$$

$$\text{such that} \;\; \mathbb{E}[\epsilon_{it}|\Lambda_{kt}] = 0 \;\;,\;\; k = 1, \ldots, K \tag{2}$$

where Λ_{kt} is the k-th factor return, $k = 1, \ldots, K$, R_{ft} is the risk-free rate, α_i and β_{ik} are the excess return and factor betas, respectively, and ϵ_{it} is the idiosyncratic return component.

ESG investors typically rank stocks according to their ESG scores, which we denote by ESG_i, and we use $\alpha_{[i:N]}$ to represent the alpha of the i-th ranked stock.[5] Lo and Zhang (2021) show that the expected values, variances, and covariances of these ranked alphas are given by

$$\mathbb{E}(\alpha_{[i:N]}) = \sigma_\alpha \cdot \rho \cdot \mathbb{E}(Y_{i:N}), \tag{3}$$

$$\mathrm{Var}(\alpha_{[i:N]}) = \sigma_\alpha^2 \cdot (1 - \rho^2 + \rho^2 \cdot \mathrm{Var}(Y_{i:N})), \tag{4}$$

$$\mathrm{Cov}(\alpha_{[i:N]}, \alpha_{[j:N]}) = \sigma_\alpha^2 \cdot \rho^2 \cdot \mathrm{Cov}(Y_{i:N}, Y_{j:N}), \tag{5}$$

for $i, j = 1, 2, \ldots, N$, and $i \neq j$. Here, ρ is the cross-sectional correlation between α_i and ESG_i,[6] σ_α is the standard deviation of α_i, and $Y_{1:N} < Y_{2:N} < \cdots < Y_{N:N}$ are the order statistics of N independent and identically distributed standard Gaussian random variables.

To estimate Equations (3)–(5) in practice, for each year, we first perform a time series regression[7] using daily returns to obtain an estimate of α_i for each stock. We then compute

[5]In the statistics literature, these indirectly ranked variables are termed *induced order statistics* (Bhattacharya, 1974), because they are ranked not by their own values (α_i in our case) but by the values of another variable (ESG_i in our case). As such, α_i's are modeled as random variables to reflect the fact that they may be correlated with the ESG scores. This specification was used in Lo and MacKinlay (1990) to represent the cross-sectional estimation errors of intercepts derived from CAPM regressions. In the current context, we interpret the randomness in α_i as a measure of uncertainty regarding the degree of mispricings of stocks, which is similar to the treatment in Pástor and Stambaugh (1999).

[6]Lo and Zhang (2021) assume that they are jointly normally distributed, and Lo et al. (2022) generalize the framework to arbitrary marginal distributions.

[7]The factors in the time series regression are decided on the basis of the Capital Asset Pricing Model or

ρ and σ_α based on ESG_i and the estimated α_i. Finally, we calculate the moments related to $Y_{i:N}$ based on a simulation of N standard normal random variables.

The results in Equations (3)–(5) are useful for two reasons. First, they allow us to construct optimal Treynor-Black portfolios that maximize the Sharpe ratio of the ESG portfolios. In particular, the expected excess returns in Equation (3) are crucial in determining the weights of those portfolios. The advantage of using this specific framework lies in its robustness, because only two parameters, ρ and σ_α, need to be estimated, compared to traditional Markowitz portfolios, which are known to produce unstable weights (Brodie et al., 2009; Tu and Zhou, 2011).

Second, the results in Equation (3) allow us to quantify the excess return of any ESG portfolio, α_p, with weights ω_i, $i = 1, \ldots, N$:

$$\mathbb{E}\left(\alpha_p\right) = \sum_{i=1}^{N} \omega_i \mathbb{E}(\alpha_{[i:N]}) = \rho\sigma_\alpha \sum_{i=1}^{N} \omega_i \mathbb{E}\left[Y_{i:N}\right]. \tag{6}$$

This provides an estimate of the alpha for ESG portfolios, which we refer to as the *model-implied alpha* henceforth. We validate the model-implied alpha empirically against a forward-looking estimate of alpha in Section 3. In particular, the realized alpha for any portfolio can be computed by performing a time-series regression based on a multi-factor model, such as the CAPM, the Fama-French three-factor model (FF3), or the Fama-French five-factor model (FF5). At time t, the forward-looking realized one-year alpha is computed using returns $r_{t+1}, r_{t+2}, r_{t+3}, \ldots, r_{t+252}$ for a portfolio p. The realized alpha is represented by α_p^f, where f may be CAPM, FF3 or FF5.

1.2 Portfolio Creation

Given a set of ESG scores for all firms, we construct ESG portfolios and estimate their performances. At time t, we sort the stocks based on ESG scores and construct three

selected Fama-French factor models.

long/short portfolios. The first, $pf_{(\pm 10)}$, represents a portfolio that goes long the top decile of stocks with equal weights (denoted by $pf_{(+10)}$) and short the bottom decile of stocks with equal weights (denoted by $pf_{(-10)}$). The second, $pf_{(\pm 25)}$, represents a portfolio that goes long the top quartile of stocks with equal weights (denoted by $pf_{(+25)}$) and short the bottom quartile of stocks with equal weights (denoted by $pf_{(-25)}$). The third, $pf_{(\pm 40)}$, represents a portfolio that goes long the top 4 deciles of stocks with equal weights (denoted by $pf_{(+40)}$) and short the bottom 4 deciles of stocks with equal weights (denoted by $pf_{(-40)}$). The total weights of individual stocks on the long and short sides are both set to one to give all portfolios the same amount of leverage. We refer to these three portfolios as the ± 40, ± 25 and ± 10 portfolios henceforth. These portfolios are rebalanced once a year because ESG scores are updated by vendors once a year (with the exception of Reprisk). We observed very high cross-sectional autocorrelations between scores, as shown in Table A.1 in the supplementary material.

In addition to these equal-weighted portfolios, we build optimized Treynor-Black portfolios using the model-implied alphas for individual stocks in Equations (3)–(5), which use the rank of stocks in the ESG sorted portfolio. For example, in $pf_{(+10)}$ for equal-weighted portfolios, all stocks in the 10th decile (percentiles 90 to 100) are given equal weights. However, in Treynor-Black weighting, higher-ranked stocks are given larger weights than lower-ranked stocks, if the correlation ρ between the ESG score and stock alpha is positive. Specifically, Lo and Zhang (2021) show that the weight of the ith ranked stock in a universe of N stocks can be approximated by the following equation:[8]

$$\omega_i \propto \Phi^{-1}(\zeta_i) \tag{7}$$

where $\zeta_i = i/N$ and Φ^{-1} is the inverse of the cumulative standard normal distribution.

Once these ESG portfolios are constructed, we can combine them further with any other

[8]The approximation holds when the number of stocks is large and stocks have identical idiosyncratic volatilities.

portfolio. The most natural application is to combine the active (ESG) portfolio with a passive index, such as the market portfolio. The returns of the combined portfolio are given by:

$$r_{active+passive} = \omega_A * r_{active} + (1 - \omega_A) * r_{passive} \tag{8}$$

where r_{active} can be any return of a top-bottom equal-weighted or Treynor-Black weighted portfolio, $r_{passive}$ is the return of the passive portfolio (e.g., the market index), and ω is the weight of the active portfolio. In our analysis, we have fixed ω_A at 0.5 as an illustrative example.

In Section 3, we evaluate the performance of all equal-weighted, Treynor-Black, and active-plus-passive portfolios.

1.3 ESG Rating Aggregation

Berg et al. (2021) show that ESG ratings are certainly noisy but nevertheless contain a signal. The measurement error inherent to ESG ratings makes it difficult to find significant risk premia. To solve this problem, we propose several different ways of aggregating ESG scores. Let $ESG_{i,t,j}$ be the ESG score of company i rated by vendor j at time t. We then compute $ESG_{i,t,m}$, where m is the aggregation method. We describe each aggregation method in the following paragraphs, and analyze the performance of portfolios based on these aggregated ESG scores in Section 3.

Equal Weighted Average

The first and simplest aggregation method under consideration is the equal-weighted cross-sectional average of all ESG ratings. The average is a widely used method for noise attenuation, and we intuitively expect the ESG signal to be stronger here than in the case of a single rating. We use AVG to indicate the equal-weighted average rating.

$$ESG_{i,t,avg} = \sum_{j \in \{\text{MSCI,S\&PGlobal,...,TVL}\}} ESG_{i,t,j} \tag{9}$$

PCA

Principal Component Analysis (PCA) is a widely used dimensionality reduction method. In some cases, it can also be used as a tool for noise reduction. The PCA performs a change of basis transformation and projects the data in the direction of the maximum variance. If errors are similarly distributed between ratings, it will minimize the information loss. We treat the ESG scores from the six vendors in our sample as high-dimensional data and obtain its lower dimensional (1-d) representation as the aggregate score.

$$ESG_{i,t,PCA} = PCA(ESG_{i,t,MSCI}, ESG_{i,t,S\&PGlobal}...ESG_{i,t,TVL}) \tag{10}$$

We use PCA to indicate the aggregate score obtained by principal component analysis.

Mahalanobis Distance

The Mahalanobis distance is the distance between two points after accounting for variances and covariances across dimensions. In brief, highly correlated ESG scores will not be given excess weight in the calculation of the aggregate score. Let the ESG scores of firm i be the vector x and y be the vector with minimum ESG scores. We then calculate the Mahalanobis distance as follows:

$$\begin{aligned}
x_{i,t} &= (ESG_{i,t,MSCI}, ESG_{i,t,S\&PGlobal}...ESG_{i,t,TVL}) \\
y_t &= (min_i(ESG_{i,t,MSCI}), min_i(ESG_{i,t,S\&PGlobal})...min_i(ESG_{i,t,TVL})) \\
ESG_{i,t,Maha} &= \sqrt{(x_{i,t} - y_t)^T S_t^{-1} (x_{i,t} - y_t)}
\end{aligned} \tag{11}$$

where S_t is the variance-covariance matrix for the ESG ratings at time t. We refer to the aggregate score obtained by the computation of the Mahalanobis distance as $MAHA$.

Voting Average

The voting average is based on the theory of social choice, that is, the aggregation or combination of individual preferences in collective decisions. In voting aggregation methods, the ESG scores from a rating agency are considered as a ranked list of choices and the different agencies are considered as voters. In the voting average process, each rank is averaged to compute an aggregate rank of each firm. It is represented by AVG_{vote} in our subsequent analysis.

Voting STV

The Singular Transferable Vote (STV) method is another way of aggregating the ESG ratings. In this aggregation method, the least preferred candidate is eliminated and the vote is transferred to the next preferred candidate. The process is repeated until all the candidates are eliminated, one by one. The eliminated candidates are ranked in the order of elimination to form a ranked list of the candidates. The aggregated ESG score using this method is represented by STV_{vote} in our subsequent analysis.

Optimized ESG Score

The optimized ESG score is a linear combination of ESG scores from all rating agencies. The weights are derived from an optimization that maximizes the cross-sectional correlation between ESG scores and the one-year future excess returns of the stocks.

$$\begin{gathered} ESG_{i,t,opt} = \sum_{r \in MSCI, S\&PGlobal...} w_r * ESG_{i,t,r} \\ w_r : max(avg_t(corr_i(ESG_{i,t,opt}, \alpha_{i,t}))) \end{gathered} \tag{12}$$

Since the optimization involves the use of out-of-sample excess returns, the excess returns obtained using $ESG_{i,t,opt}$ cannot be realized. However, the ESG scores optimized in this way have the maximum correlation with excess returns that can be achieved by a linear aggregation of ESG scores from different rating agencies. The aggregate scores obtained using optimization are referred to as OPT in our analysis.

2 Data and Summary Statistics

2.1 Data

We obtained data from six leading ESG rating providers, including MSCI, S&P Global, ISS, Moody's ESG Solutions, Reprisk and TruValueLabs.[9] We observe non-overlapping coverage in our dataset across rating agencies. Hence, for a fair comparison across different providers, we only include those firms with observations from all six rating agencies. We also have E, S and G ratings in our dataset for all agencies, except for TruValueLabs, which does not offer such scores.

For our analysis, we classify firms into three different regions: the U.S., Europe, and Japan. The total number of firms in each region are 633 in the U.S, 547 in Europe, and 274 in Japan. Our sample spans from March 2014 to 2020. The relatively short time series is explained by the fact that sustainable investing is a fairly recent phenomenon. Since ESG ratings from different providers have different scales, we renormalize them to have zero mean and unit variance in the cross-section.

The daily returns were queried from the Refinitiv workspace[10]. For the calculation of excess returns, we obtained our data from the Fama-French data library[11]. We retrieved the

[9] We also have data from Sustainlytics and Refinitiv. However, Refinitiv and Sustainalytics have changed their methodologies over time, and their ESG scores were backfilled using these new methodologies (Berg, Fabisik, and Sautner, 2020). Adding these two providers to our analysis would introduce a forward-looking bias to our analysis.

[10] https://www.refinitiv.com/en/products/refinitiv-workspace

[11] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

daily MSCI index returns for U.S., Europe and Japan from MSCI Index Solutions[12].

2.2 Summary Statistics: Excess Returns and ESG

	ISS: ESG	MSCI: ESG	Reprisk: ESG	SP-Global: ESG	TVL: ESG	Moody's: ESG	AVG: ESG	PCA: ESG	MAHA: ESG	AVG_{vote}: ESG	STV_{vote}: ESG
ISS: ESG	1.00	0.40	-0.24	0.59	0.12	0.62	0.73	0.80	0.48	0.75	0.59
MSCI: ESG	0.40	1.00	-0.02	0.34	0.18	0.38	0.67	0.57	0.45	0.68	0.33
Reprisk: ESG	-0.24	-0.02	1.00	-0.41	0.14	-0.33	0.03	-0.43	0.43	0.00	-0.14
SP-Global: ESG	0.59	0.34	-0.41	1.00	0.06	0.69	0.67	0.84	0.46	0.69	0.60
TVL: ESG	0.12	0.18	0.14	0.06	1.00	0.10	0.46	0.18	0.45	0.45	0.56
Moody's: ESG	0.62	0.38	-0.33	0.69	0.10	1.00	0.73	0.85	0.46	0.74	0.50
AVG: ESG	0.73	0.67	0.03	0.67	0.46	0.73	1.00	0.84	0.84	0.99	0.73
PCA: ESG	0.80	0.57	-0.43	0.84	0.18	0.85	0.84	1.00	0.50	0.86	0.66
MAHA: ESG	0.48	0.45	0.43	0.46	0.45	0.46	0.84	0.50	1.00	0.80	0.62
AVG_{vote}: ESG	0.75	0.68	0.00	0.69	0.45	0.74	0.99	0.86	0.80	1.00	0.72
STV_{vote}: ESG	0.59	0.33	-0.14	0.60	0.56	0.50	0.73	0.66	0.62	0.72	1.00

Table 1: The cross-sectional rank correlation between ESG scores (individual and aggregate) averaged over time.

[12] https://www.msci.com/our-solutions/indexes

We averaged the cross-sectional rank[13] correlations between different individual and aggregated ESG scores over time, and present them in Table 1. We show that the correlation between different ESG ratings vary over time. Some scores are highly correlated with each other, like ISS, MSCI, SPGlobal and Moody's. Rather surprisingly, Reprisk has a negative correlation with the other ratings. Among the aggregate scores, AVG, PCA and AVG_{vote} exhibit relatively high correlations (>80%). However, the aggregate scores based on STV voting are significantly different from other aggregate scores, given their smaller correlation coefficients (60-70%). We find relatively similar correlations (in the range of 40-50%) between individual ESG scores and scores computed using the Mahalanobis distance (MAHA). This is due to the variance-covariance normalization property of the Mahalanobis distance.

Region	FF5		FF3		CAPM	
	Mean	Std	Mean	Std	Mean	Std
USA	1.02	19.76	1.13	19.98	-0.55	22.93
Europe	6.55	21.46	6.14	21.60	3.86	23.35
Japan	4.27	18.64	3.29	19.13	0.14	20.72

Table 2: Alpha Statistics. The cross-sectional mean and standard deviation of excess returns (alpha) of the sampled companies, computed using different factor models (FF5, FF3 and CAPM) averaged over time.

In Table 2, we present the cross-sectional mean and standard deviation of excess returns (alphas $\alpha_{i,t}$: the one-year future alpha of the stock i at time t) computed as follows: $mean_\alpha = avg_t(avg_i(\alpha_{i,t}))$, $std_\alpha = avg_t(std_i(\alpha_{i,t}))$, where i is the company and t is the time. We find that the cross-sectional standard deviation of excess returns varies between 18 and 25%, while the cross-sectional mean of excess returns varies widely between regions. These parameters are necessary to quantify the excess returns of portfolios constructed as described in Section 1.1.

[13] In the construction of a long-short ESG portfolio, the rank of a company matters more than its score value.

3 Performance of ESG Portfolios

In this section, we begin our study of the performance of ESG portfolios by first measuring the cross-sectional correlation between ESG scores and excess returns of individual stocks. We then summarize the empirical properties of both the raw returns and the returns in excess of Fama-French factor models for portfolios based on their individual and aggregated ESG scores. We then look at ESG portfolios constructed using Treynor-Black weights, and ESG portfolios combined with passive index portfolios.

3.1 Correlations between ESG ratings and Excess Returns

	USA			Europe			Japan		
ESG	FF5	FF3	CAPM	FF5	FF3	CAPM	FF5	FF3	CAPM
ISS: ESG	2.88	3.40	7.75	5.66	7.03	4.23	6.07	6.86	8.43
MSCI: ESG	4.46	4.77	6.70	3.74	5.13	5.38	5.41	5.09	6.23
Reprisk: ESG	2.75	2.36	2.71	-3.22	-1.37	6.11	2.40	1.88	4.45
SPGlobal: ESG	1.72	1.90	2.58	3.63	2.83	-3.66	6.41	5.51	6.01
TVL: ESG	2.17	2.92	3.43	2.42	4.43	5.62	3.63	3.47	2.24
Moody: ESG	2.81	2.82	4.38	3.22	3.12	-2.60	5.66	5.33	5.02
AVG: ESG	4.91	5.32	8.09	4.70	6.41	4.61	8.74	8.32	9.57
PCA: ESG	2.79	3.20	5.55	5.33	5.51	-0.36	6.73	6.57	6.93
MAHA: ESG	5.42	5.52	7.88	1.78	3.62	4.96	9.02	8.26	9.91
AVG_{vote}: ESG	4.90	5.40	7.67	5.11	6.69	4.62	8.85	8.66	9.89
STV_{vote}: ESG	3.59	4.18	5.45	4.31	4.86	0.86	8.25	7.85	7.74
OPT: ESG	6.06	6.14	9.32	6.56	7.99	5.32	9.13	8.47	10.37

Table 3: Average cross-sectional correlation between ESG scores and alpha (excess returns).

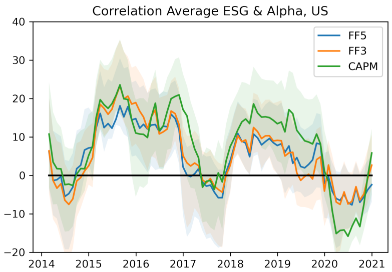
Given the ESG scores of individual stocks and their excess returns, we compute the cross-sectional correlations, $corr_t = corr_i(ESG_{i,t}, \alpha_{i,t})$, on date t for different ESG scoring methods, where $\alpha_{i,t}$ is the one-year forward-looking alpha of stock i at date t. The average values of $corr_t$ are presented in Table 3 for both individual and aggregated ESG scores. The last row shows that the maximum possible correlation (OPT: ESG) from linear combinations of individual ESG scores is in the range of 6 to 10% for all alphas and regions. Although the correlations for other aggregate ESG scores are inevitably lower, they are not much lower compared to the optimized ESG score. Different regions have different scores with the highest correlations. For example, in the U.S., MAHA: ESG and AVG: ESG achieve the highest correlations, while ISS: ESG has the highest correlations in Europe.

In Figure 1, we show the time series correlation values for AVG: ESG scores. We observe that correlations are typically in the range from 30 to 40% in the U.S. and Japan. However, there are some instances of negative correlation as well. A negative correlation implies that a high-low portfolio has negative excess returns. We find positive correlations in our sample on average because from 2014 to 2020, the ESG portfolio potentially had positive excess returns.

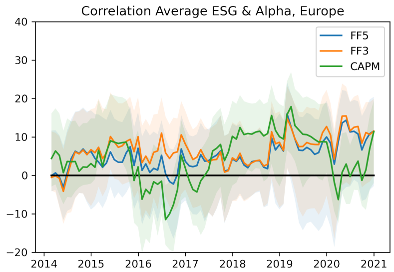
The different statistics described in Tables 2–3 can be used to obtain the average excess returns as described in Section 1.1. For example, the average alpha for the top decile/bottom decile ESG portfolio with a cross-sectional α deviation 20% and correlation value of 5% will be $2 * 0.20 * 5 * 1.64 = 3.28\%$. We discuss the excess returns of different ESG portfolios in Section 3.3 in more detail.

3.2 Returns and Factor Exposure

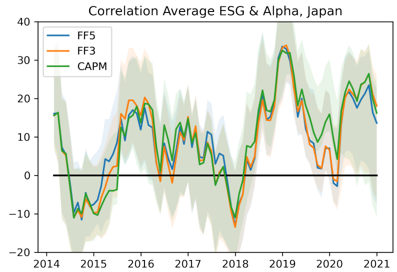
Following Section 1.2, we construct multiple ESG top-bottom portfolios (± 40, ± 25, and ± 10) and compute their properties, such as their returns, risk-adjusted returns (Sharpe ratios), excess returns (alphas) and exposure to different factors. In addition to portfolios based on the ESG scores from individual vendors, we also construct portfolios using the aggregate scores computed with the methods described in Section 1.3. We also include a portfolio which is simply the average portfolio constructed using individual ESG scores (represented



(a)



(b)



(c)

Figure 1: The correlation between average ESG score & stock performance (alpha) (y-axis) versus time (x-axis). We find that the correlation between α and the average ESG score can be as high as 20% to 30% (in the U.S. and Japan, respectively); however, it clearly varies over time.

by INDI-AVG: ESG).[14].

Table 4 presents the mean returns and annualized Sharpe ratios for ESG portfolios computed using individual vendor and aggregated ESG scores. The ESG portfolios achieve annualized returns as high as 6% in the U.S. and Japan, and 3% in Europe. Similarly, the highest Sharpe ratios are around 1 in the U.S. and Japan, and 0.7 in Europe. We find that portfolios based on ESG scores from individual vendors have nonuniform returns and Sharpe ratios. ESG scores from ISS, MSCI, and Reprisk have consistently positive returns across different regions, while portfolios based on scores from SPGlobal, TVL, and Moody's have negative returns in some regions. However, the portfolios using aggregated scores have positive returns, and are generally higher than returns of those based on constituent vendors.

Given the time series of portfolio returns, we follow Equation 1 and perform a time-series regression to compute the excess returns and fundamental factor exposure of these ESG portfolios. The response variable of the regression is the portfolio return, and the factors are chosen to be the Fama-French five factors.

We find that the ESG portfolios have varying exposures to multiple fundamental factors.

[14]This portfolio differs from the AVG: ESG portfolio because in AVG: ESG, we first compute the average ESG scores and then construct portfolios based on the average. However, in INDI-AVG: ESG, the first step is to construct portfolios based on individual ESG scores, and the second step is to average the returns of individual ESG portfolios.

	USA			Europe			Japan		
Portfolio	±40%	±25%	±10%	±40%	±25%	±10%	±40%	±25%	±10%
Mean Returns									
ISS: ESG	4.89	4.57	5.51	2.37	1.66	1.10	4.68	5.76	6.98
MSCI: ESG	3.25	4.72	5.48	3.89	4.13	3.76	3.48	5.24	1.53
Reprisk: ESG	2.07	2.05	4.17	1.21	3.29	6.30	1.14	2.31	4.29
SPGlobal: ESG	-0.08	-0.48	1.46	-1.14	-0.70	2.02	2.62	3.63	7.78
TVL: ESG	2.39	2.49	-0.46	2.00	3.05	1.14	-0.52	-0.24	1.11
Moody: ESG	1.58	2.19	3.91	-0.93	-0.29	-1.89	2.35	1.86	6.39
INDI-AVG: ESG	2.35	2.59	3.34	1.23	1.85	2.18	2.29	3.09	4.68
AVG: ESG	3.32	6.48	6.39	2.60	3.21	4.30	5.26	5.38	4.83
PCA: ESG	2.26	3.69	2.94	0.28	0.68	1.54	3.04	3.81	4.20
MAHA: ESG	4.18	6.03	7.50	2.15	3.46	3.47	4.43	5.46	5.52
AVG_{vote}: ESG	3.18	5.56	6.85	2.29	3.49	4.46	4.99	6.13	5.29
STV_{vote}: ESG	2.59	2.07	1.30	-0.25	1.34	5.75	2.97	4.32	8.00
OPT: ESG	4.77	6.54	8.36	1.64	2.09	5.76	4.97	5.99	5.24
Sharpe Ratio									
ISS: ESG	1.04	0.83	0.81	0.57	0.33	0.15	1.07	1.05	0.84
MSCI: ESG	1.07	1.23	0.94	1.00	0.86	0.53	0.93	1.05	0.19
Reprisk: ESG	0.53	0.45	0.67	0.27	0.57	0.73	0.25	0.39	0.51
SPGlobal: ESG	-0.03	-0.12	0.26	-0.28	-0.13	0.28	0.53	0.53	0.82
TVL: ESG	0.60	0.50	-0.07	0.58	0.75	0.21	-0.13	-0.05	0.17
Moody: ESG	0.45	0.45	0.55	-0.24	-0.06	-0.28	0.42	0.26	0.68
INDI-AVG: ESG	1.03	0.92	0.92	0.63	0.75	0.58	0.82	0.87	1.06
AVG: ESG	0.81	1.18	0.85	0.70	0.71	0.62	1.12	0.93	0.58
PCA: ESG	0.59	0.73	0.42	0.07	0.13	0.21	0.59	0.57	0.49
MAHA: ESG	0.99	1.09	1.04	0.61	0.79	0.51	1.17	1.08	0.73
AVG_{vote}: ESG	0.83	1.03	0.97	0.61	0.75	0.66	0.99	1.00	0.61
STV_{vote}: ESG	0.62	0.41	0.20	-0.07	0.31	0.96	0.67	0.70	1.03
OPT: ESG	1.14	1.25	1.22	0.43	0.43	0.79	1.15	1.07	0.67

Table 4: Mean returns and Sharpe ratios for the top $y\%$ minus bottom $y\%$ ESG portfolios (individual and aggregate scores) for the U.S., Europe and Japan, where $y = 40, 25, 10$.

We present the exposures in Table 5. We have a total of 33 portfolios (11 different ESG scores multiplied by 3 top-bottom portfolios). Table 5 presents the number of positive and negative significant betas (defined by a p-value $< 5\%$) out of 33 ESG portfolios. In the U.S. and Europe, ESG portfolios tend to have a negative exposure to the market and size factors, while having a positive exposure to the profitability factor. However, in Japan, ESG portfolios tend to have negative exposure to the profitability and the investment factors.

A varying exposure to different risk factors implies that the returns of the portfolios are not purely due to ESG risk premia. They may be due to exposure to different fundamental factors, as shown by the statistically significant coefficients in Table 5. Therefore, we next analyze the excess returns of the ESG portfolios.

		Market		Size		BM		Profitability		Investment	
		+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve
11*3 Portfolios	USA	0	8	3	22	4	13	4	0	1	2
	Europe	0	22	3	25	14	3	25	0	0	3
	Japan	5	0	0	2	4	9	0	17	0	18

Table 5: Number of significant positive (+ve) and negative (-ve) betas (defined by a p-value $< 5\%$) for all 33 top-bottom ESG portfolios (11 ESG scores by 3 portfolios).

3.3 Estimating Excess Returns

In this section, we evaluate the returns of ESG portfolios in excess of their Fama-French factors using two methods. The first method estimates the portfolio alphas based on Equation 6 in Section 1.1. Here, we use the theory first proposed by Lo and Zhang (2021) to quantify the excess returns based on the correlation ρ between ESG scores and alphas of individual stocks. The second method estimates a forward-looking time-series regression of raw returns on Fama-French factors. We refer to the former as the model-implied alpha and the latter as the realized alpha. We compute the alphas of yearly top-bottom quantile portfolios using both methods, and show that the model-implied alphas match realized alphas very well.

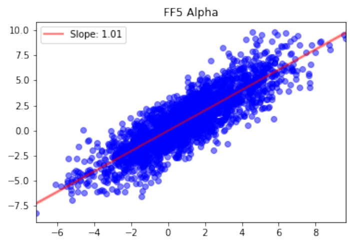
We construct top-bottom quantile ESG portfolios in which stocks are sorted by individual ESG score. The stocks in each quantile portfolio are given equal weights. Therefore, for each score, we will have four portfolios at time t, denoted by Q1, Q2, Q3, and Q4. Figure 2 presents the scatter plot of model-implied and realized alphas. At time t, both the model-implied and realized alphas are computed for a one-year forward-looking window. The number of data points in the scatter plot is 6 (the number of ESG vendor scores) $\times 4$ (the number of quantile portfolios) $\times 108$ months in our sample $= 2592$. To robustly validate the proposed model, we compute the FF5, FF3 and CAPM alphas.

Figure 2 demonstrates that the realized and model-implied alphas of Lo and Zhang (2021) match each other reasonably well, all data points falling around the line $y = x$. The slope of a simple linear regression of realized alphas against model-implied alphas is very close to 1 (p-value $< 1\%$) for all combinations of regions and factor models. Consequently, we only report the realized alphas using forward-looking time-series regressions henceforth.[15]

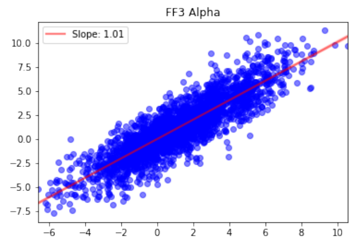
Next, we evaluate the annualized excess returns of the top-bottom ESG portfolios (± 40, ± 25 and ± 25), as described in Section 1.2. In Table 6, we present the excess returns (alphas) from the time series regression (Equation 1) using the Fama-French five-factor model and the Capital Asset Pricing Model. From Table 6, we find that the excess returns are positive and significant in the U.S. and Japan, but not in Europe. The CAPM alphas are generally higher than the FF5 alphas, implying that the Fama-French factors partially explain the positive returns beyond the market factor of the CAPM.

The excess returns of the OPT portfolios are comparable to the highest returns from those constructed using other aggregation methods or by individual scores. The excess returns from the ESG portfolios using OPT cannot be realized, however, but the other aggregate and individual ESG score alphas can. Hence, the highest realizable alpha is close to the maximum possible alpha that can be obtained using a linear combination of different

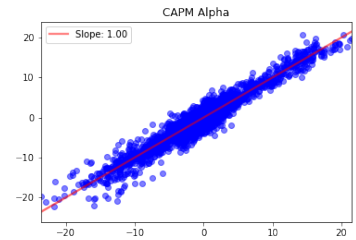
[15] The results using model-implied alphas are of course similar.



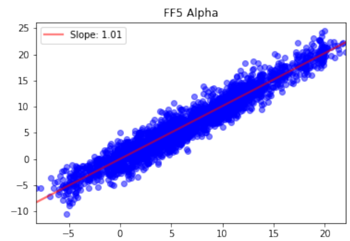
(a) **USA**, Alpha: **FF5**



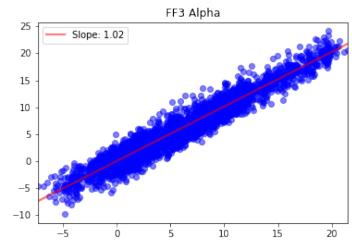
(b) **USA**, Alpha: **FF3**



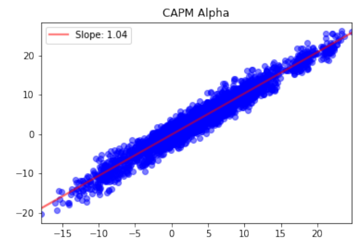
(c) **USA**, Alpha: **CAPM**



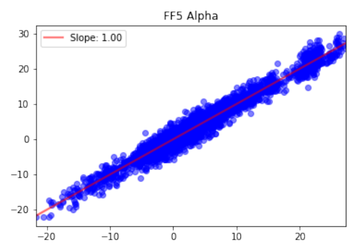
(d) **Europe**, Alpha: **FF5**



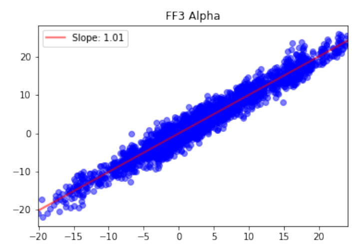
(e) **Europe**, **FF3**



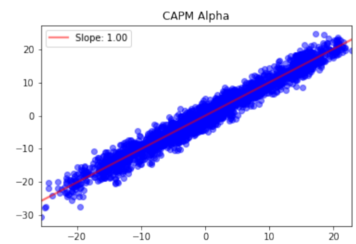
(f) **Europe**, **CAPM**



(g) **Japan**, **FF5**



(h) **Japan**, **FF3**



(i) **Japan**, **CAPM**

Figure 2: Realized alphas for portfolios created using ESG scores (y-axis) versus implied alphas (x-axis) for the same portfolios using the methods described in Section 1.1.

	USA			Europe			Japan		
Portfolio	±40%	±25%	±10%	±40%	±25%	±10%	±40%	±25%	±10%
FF5 Alpha									
ISS: ESG	3.30***	2.34*	3.01*	1.95	1.82	0.27	4.27**	5.96***	7.71***
MSCI: ESG	2.47**	3.80***	4.81**	2.90**	2.89**	1.49**	3.93**	5.84***	3.59***
Reprisk: ESG	0.95	0.86	2.75	-1.46	-0.40	0.80	0.09	1.27	2.88**
SPGlobal: ESG	0.72	0.31	1.92	0.43	1.22	3.26*	3.99***	5.11***	9.09***
TVL: ESG	2.37	1.79	-1.04	0.11	0.83	-1.28	-0.41	0.12	0.77
Moody: ESG	1.59*	2.73*	4.40**	0.58	1.29	-0.48	2.71*	1.94*	7.04**
INDI-AVG: ESG	1.90**	1.98**	2.64**	0.76	1.28	0.78	2.43**	3.37**	5.19***
AVG: ESG	2.69**	5.40***	4.50**	1.82*	2.32*	2.12*	5.58***	5.52**	5.92**
PCA: ESG	1.91*	3.23**	3.36*	1.70	1.93	2.51	3.92***	4.81**	5.17**
MAHA: ESG	3.44***	4.34**	6.09***	0.34	0.95	-0.49	4.14**	5.79***	7.25*
AVG_{vote}: ESG	2.58**	4.36***	5.44**	1.60	2.82*	2.85*	5.31***	6.33***	7.00**
STV_{vote}: ESG	2.96**	2.44**	0.88**	-0.49	1.39	6.06***	3.69**	5.36**	9.56***
OPT: ESG	3.87***	4.70***	5.73**	1.24	1.52	5.20**	5.32***	6.12***	6.47**
CAPM Alpha									
ISS: ESG	5.94***	5.39***	6.27***	2.46**	1.72**	1.31**	4.18**	5.22***	6.49**
MSCI: ESG	3.51***	5.00***	6.58***	4.11***	4.42**	4.21*	3.14**	4.79**	1.22**
Reprisk: ESG	1.86**	1.48**	2.89**	1.28	3.44*	6.57**	1.27	2.32	4.35***
SPGlobal: ESG	0.16	-0.26	2.26	-1.15	-0.75	1.96	2.09	2.87	6.56*
TVL: ESG	3.30**	3.02**	-0.30**	1.97	3.07*	1.14*	-1.20	-1.15	0.66
Moody's: ESG	2.14*	3.11**	5.10***	-0.92	-0.29	-1.96	1.32	0.41	4.82
INDI-AVG: ESG	2.82***	2.96**	3.80***	1.30**	1.94**	2.32*	1.79	2.40*	4.01**
AVG: ESG	4.23**	7.72***	7.41***	2.72**	3.34**	4.60**	4.58***	4.46**	3.71**
PCA: ESG	2.96**	4.76***	5.12**	0.32	0.75	1.73	2.35	2.88	3.17
MAHA: ESG	5.16***	6.89***	8.60***	2.29*	3.66**	3.80**	3.98**	4.76**	4.75**
AVG_{vote}: ESG	3.91***	6.55***	7.25***	2.41*	3.63**	4.76**	4.23**	5.03**	3.93**
STV_{vote}: ESG	3.75**	3.11**	1.34**	-0.21	1.37	5.80***	2.46	3.56	7.07**
OPT: ESG	5.76***	7.49***	8.78***	1.69	2.17	5.99***	4.58***	5.17**	4.11**

Table 6: FF5 and CAPM alphas for top-bottom ESG portfolios (±40%, ±25%, ±10%). The alphas are computed using time series regression. The standard errors are computed using heteroskedastic and autocorrelation consistent standard error estimators, with statistical significance highlighted at the 1% (***), 5% (**), and 10% (*) levels.

ESG scores.

Among the individual scores, MSCI score portfolios consistently have the highest FF5 alphas across all regions, while ISS score portfolios have significant alphas in the U.S. and Japan. The aggregate ESG scores generally have higher alphas than most individual scores. These portfolios behave differently across regions and quantiles. For example, the STV_{vote} voting aggregate score generally has high ± 10 portfolio alphas in Europe and Japan. Broadly speaking, the alphas of different aggregation methods are similar to each other, due to high correlation between their scores.

From Table 6, we find there are significant excess returns of 4.8%, 2.9% and 9% using individual ESG scores in the U.S., Europe, and Japan, respectively, while there are excess returns of 6%, 6% and 9.6% using aggregate ESG scores. The alpha of portfolios based on Reprisk, TVL, Moody's scores are not statistically significant (possibly due to the noise in the scores). However, the alphas for the aggregate ESG portfolios are in general significant, likely due to the stronger signal from the aggregation methods.

3.4 Treynor-Black Portfolios

Along with equal-weighted portfolios, we also construct ESG portfolios using Treynor-Black weights, as given by Equation (7) in Section 1.2. In Treynor-Black portfolios, the weights are inversely proportional to the rank of the ESG score of each firm. In Table 7, we include the excess return (alpha) obtained from the time series regression using the Fama-French five-factor model and the Capital Asset Pricing Model.

Comparing the results in Tables 7 and 6, we do not observe a large difference between the alphas of the ± 25 and ± 10 portfolios, but we do find differences in alphas for the ± 40 portfolios. The effect of unequal weighting becomes more prominent when more firms are included in the portfolio and when firms at extreme percentiles on the long or short sides are weighted differently. Our other observations about excess returns described in Section 3.3 remain consistent.

Portfolio	USA ±40%	USA ±25%	USA ±10%	Europe ±40%	Europe ±25%	Europe ±10%	Japan ±40%	Japan ±25%	Japan ±10%
FF5 Alpha									
ISS: ESG	2.62***	2.20*	2.37*	2.42	2.43	1.43	5.40**	5.94***	7.03***
MSCI: ESG	3.31**	3.92***	4.49**	2.75**	2.88**	1.74**	4.66**	5.51***	3.62***
Reprisk: ESG	1.52	1.52	3.31	-0.64	0.02	1.47	1.12	1.73	2.44**
SPGlobal: ESG	0.93	0.62	1.66	2.00	2.48	3.80*	5.30***	5.95***	8.61***
TVL: ESG	1.19	0.66	-1.59	0.21	0.54	-1.28	-0.17	0.11	0.93
Moody's: ESG	2.31*	2.89*	3.94**	1.13	1.51	0.58	2.90*	2.80*	6.91**
INDI-AVG: ESG	1.98**	1.97**	2.37**	1.32	1.66	1.32	3.20**	3.67**	4.95***
AVG: ESG	4.09**	5.42***	4.64**	1.94*	2.16*	1.26*	5.87***	5.96**	6.37**
PCA: ESG	2.40*	2.88**	2.80*	2.46	2.81	3.28	5.02***	5.55**	5.90**
MAHA: ESG	4.01***	4.31**	5.17***	0.87	1.08	-0.32	5.49**	6.37***	7.62*
AVG_{vote}: ESG	3.81**	4.61***	5.12**	2.19	2.71*	2.35*	6.04***	6.63***	7.44**
STV_{vote}: ESG	1.85**	1.55**	-0.14**	1.95	3.02	6.73***	5.51**	6.52**	9.94***
OPT: ESG	4.68***	5.18***	6.19**	3.05	3.47	6.33**	6.33***	6.81***	7.08**
CAPM Alpha									
ISS: ESG	5.60***	5.37***	5.63***	3.05**	2.85**	2.93**	4.96**	5.24***	6.07**
MSCI: ESG	4.68***	5.37***	6.49***	4.34***	4.64**	4.34*	3.41**	4.10**	1.11**
Reprisk: ESG	2.04**	1.88**	3.33**	3.15	4.40*	7.34**	2.24	2.77	3.68***
SPGlobal: ESG	0.45	0.24	1.92	0.39	0.73	2.63	3.22	3.67	6.10*
TVL: ESG	2.12**	1.65**	-0.98**	2.21	2.78*	1.12*	-1.12	-1.05	0.59
Moody's: ESG	2.82*	3.33**	4.47***	-0.09	0.25	-0.38	1.33	1.15	4.78
INDI-AVG: ESG	2.95***	2.98**	3.48***	2.19**	2.63**	3.03*	2.33	2.64*	3.73**
AVG: ESG	6.11**	7.79***	7.32***	3.43**	3.80**	4.10**	4.40***	4.37**	3.79**
PCA: ESG	3.67**	4.28***	4.32**	1.54	2.02	2.89	3.30	3.68	4.00
MAHA: ESG	6.10***	6.80***	7.54***	3.64*	4.27**	4.20**	4.49**	4.84**	4.82**
AVG_{vote}: ESG	5.59***	6.74***	6.85***	3.44*	4.04**	4.67**	4.44**	4.81**	4.15**
STV_{vote}: ESG	2.57**	2.19**	0.36**	2.12	3.01	6.49***	3.76	4.44	7.37**
OPT: ESG	7.09***	8.07***	9.20***	3.69	4.20	7.22***	5.04***	5.32**	4.46**

Table 7: FF5 and CAPM alphas for Treynor-Black top-bottom ESG portfolios (±40%, ±25%, ±10%). The alphas are computed using time series regression. The standard errors are computed using heteroskedastic and autocorrelation consistent standard error estimators, with statistical significance highlighted at the 1% (***), 5% (**), and 10% (*) levels.

3.5 Combining ESG and Passive Portfolios

Once the relative weights of securities within an ESG portfolio are determined, one can combine that portfolio with any other portfolio. For example, we can also add the ESG portfolio to a suite of portfolios that mimic more traditional asset pricing factors, such as value, size, or momentum.

Perhaps the most natural application is to combine the ESG portfolio with a passive index fund such as the market portfolio. In this section, we combine the active Treynor-Black ESG portfolios with market portfolios.[16] The weight of the market portfolio is fixed to be 0.5.[17] The market portfolios we use for different regions are the MSCI USA, the MSCI Europe, and the MSCI Japan indices.

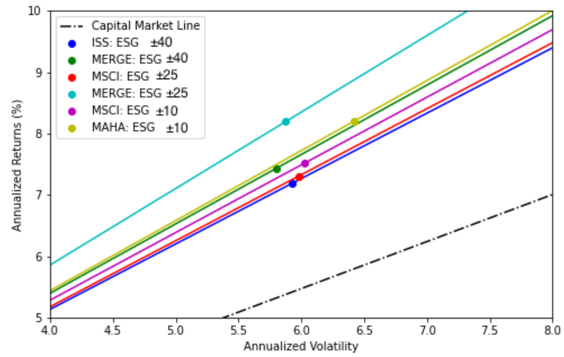
Figure 3 presents the expected return and volatility of several combined ESG portfolios. In each region, we include the top-bottom portfolios (± 40, ± 25, and ± 10) with the highest Sharpe ratio, based on single or aggregated ESG scores. The Sharpe ratios of the combined portfolios are higher than those of market portfolios, due to the signal in the ESG scores. These improved Sharpe ratios are not accessible to traditional mean-variance optimized portfolios which stay below the capital market line. This forms a "super-efficient frontier" compared to the capital market line associated with the passive portfolio, assuming that the alphas from the ESG portfolios are mispricings. Under the alternate interpretation that ESG scores capture an omitted pricing factor, the "super-efficiency" of the new frontier may be viewed as the result of additional risk premia not accessible to investors except for ESG portfolio managers.

[16] Table A.3 in the supplementary material gives the Sharpe ratio for the portfolios that are built by combining equal-weighted ESG portfolios and the passive market index.

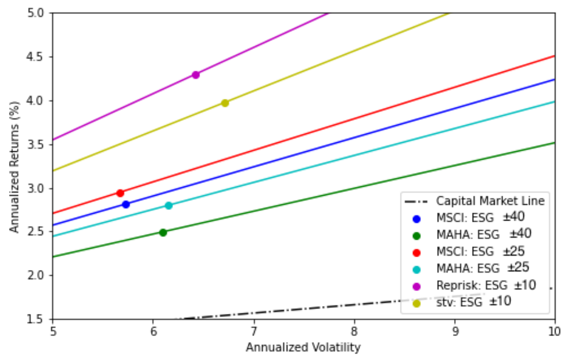
[17] More generally, weights can also be determined by other methods. For example, Lo and Zhang (2021) show that the optimal weights to maximize the Sharpe ratio ω can computed by using an ESG portfolio's excess return and idiosyncratic volatility:

$$\omega_A = \left(\frac{\alpha_A}{\sigma(\epsilon_A)^2}\right) \Big/ \left(\frac{\mathbb{E}[R_m] - R_f}{\sigma_m^2}\right) \tag{13}$$

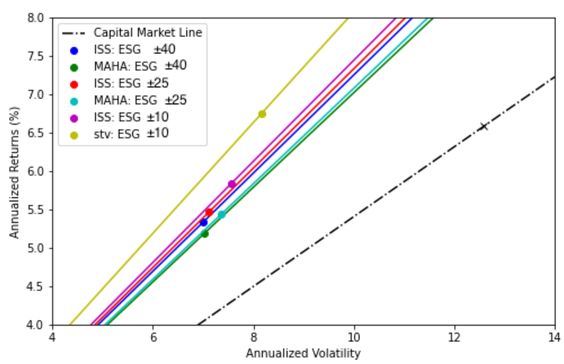
where $\mathbb{E}[R_m]$ and σ_m^2 are the expected return and variance of the passive portfolio, respectively.



(a) USA



(b) Europe



(c) Japan

Figure 3: Annualized returns (y-axis) versus volatility (x-axis). We present the return versus volatility for portfolios that combine a Treynor-Black ESG portfolio with the market portfolio. The capital market line is represented using the black dotted line. The combined portfolios lie above the capital market line. The entries on the legend are in the format: "ESG Dataset portfolio name"

In particular, the combined portfolios achieve annual Sharpe ratios reach as high as 1.25, 0.53 and 0.72 in the U.S., Europe, and Japan, respectively. As a comparison, the Sharpe ratios of the market portfolios are only 0.75, 0.05, and 0.37. Across all combined portfolios across ESG scores, the Sharpe ratios are always positive in the U.S. and Japan, while they are negative for portfolios based on Moody's scores in Europe.

4 ESG as Univariate Impact Factors

We now turn to analyzing portfolios constructed using univariate Environment (E), Social (S), and Governance (G) scores. Like our analysis of portfolios based on full ESG scores, we construct top-bottom sorted portfolios using the E, S and G scores individually, and compute their excess returns.

4.1 Environment Portfolios

We include the excess returns for Environment portfolios in Table 8. For Environment scores, we observe high and statistically significant alphas (up to 10.5%) for multiple individual vendor scores and aggregate scores for Japan. For the U.S., individual vendor scores do not achieve significant alpha, while aggregate scores generate significant positive alpha, with excess returns of up to 4%. For Europe, we do not observe significant alphas. However, CAPM alphas are positive, significant and higher for the U.S. compared to other regions.

4.2 Social Portfolios

We find there are similar patterns for Social score portfolios (see Table 9). However, these portfolios have negative significant excess returns (CAPM alpha) in Europe. Fama-French five-factor annualized alphas for Social score portfolios are positive and significant in the U.S. (up to 4.3%) and Japan (up to 7.48%).

	USA			Europe			Japan		
Portfolio	±40%	±25%	±10%	±40%	±25%	±10%	±40%	±25%	±10%
FF5 Alpha									
ISS: E	2.46*	0.76*	-0.17*	1.79	1.13	-0.04	3.21	4.19*	8.21***
MSCI: E	3.12*	4.24*	8.72**	0.73	0.24	0.16	3.68***	4.55***	6.54***
Reprisk: E	0.55	2.22	0.45	-1.70	-2.65*	-0.90*	3.06*	2.53*	1.41*
SPGlobal: E	1.60	1.66	2.20	0.01	1.36	4.02**	4.34***	5.82***	10.45***
Moody's: E	0.74	1.39	-2.35	2.05**	1.26**	-0.58**	2.11	1.83	4.42
AVG: E	2.98**	3.95**	4.49**	0.63	0.42	0.84	3.45*	7.30***	9.99***
PCA: E	2.50**	1.78**	-2.10**	0.78	1.37	0.48	3.71***	4.31***	7.54***
MAHA: E	1.67	3.30*	5.83*	1.37	1.16	0.50	4.69**	7.37***	9.65***
AVG_{vote}: E	2.29*	3.34*	4.16*	1.09	1.61	1.63	3.40*	6.94***	8.88***
STV_{vote}: E	1.95	1.88	2.26	0.06	0.33	3.53*	5.15***	6.74***	10.65***
CAPM Alpha									
ISS: E	4.96***	3.37***	2.93***	2.44**	2.15**	2.30**	2.97	3.99*	7.24**
MSCI: E	5.63**	7.72**	13.68***	0.75	0.51	0.97	2.55	3.39*	5.30*
Reprisk: E	1.66	3.17*	1.92*	0.63	0.32	4.27	4.74***	4.19**	4.09**
SPGlobal: E	2.69*	2.50*	3.85**	-1.26	-0.30	2.67*	1.90	3.34*	7.87**
Moody's: E	1.94**	3.12***	-1.31***	1.05	-0.04	-1.03	0.57	0.15	3.93*
AVG: E	5.25***	7.50***	10.27***	1.39	0.78	2.13	2.62*	5.86***	8.42**
PCA: E	4.22***	3.82**	0.14**	-0.27	0.14	-0.55	1.88	2.33	6.03**
MAHA: E	3.67***	6.32***	10.96***	2.62	3.26	3.33	4.50***	6.86***	8.95***
AVG_{vote}: E	4.47***	6.61***	10.05***	1.27	1.63	2.73	2.17	5.40**	7.66**
STV_{vote}: E	3.19*	3.13*	5.51***	-1.03	-0.88	2.70	3.26**	4.61**	7.66**

Table 8: FF5 and CAPM alphas for top-bottom **E** portfolios (±40%, ±25%, ±10%). The alphas are computed using time series regression. The stars next to the numbers represents significance levels. ***: p-val< 0.01, **: p-val<0.05, *: p-val < 0.10. The standard errors were computed using heteroskedastic autocorrelation consistent standard error estimators.

	USA			Europe			Japan		
Portfolio	±40%	±25%	±10%	±40%	±25%	±10%	±40%	±25%	±10%
				FF5 Alpha					
MSCI: S	0.86	0.37	3.04**	1.70	1.95	-0.62	2.82**	2.66**	2.22**
Reprisk: S	1.76	1.84	0.05	-0.72	-0.14	1.20	0.43	-0.60	-1.28
SPGlobal: S	1.42	1.58	-3.40	-0.78	0.15	-1.61	3.87**	5.12***	7.61***
Moody's: S	2.56**	3.28**	1.67**	-0.67	-0.80	1.60	3.44**	0.94**	3.13**
AVG: S	2.69***	3.64***	3.83*	0.44	0.11	-2.32	2.64**	3.81*	7.10**
PCA: S	1.81	1.51	-0.30	-0.88	0.20	0.87	2.79**	3.89***	5.10**
MAHA: S	3.93***	4.28***	2.54*	0.64	1.13	-1.95	3.00**	3.01*	6.19*
AVG_{vote}: S	2.29***	2.51**	4.30***	0.98	-0.48	-2.32	3.45**	4.97**	5.81*
STV_{vote}: S	1.31	1.49	-1.37	-0.43	0.31	-1.36	3.64**	5.68***	7.48***
				CAPM Alpha					
MSCI: S	0.90	-0.40	1.49	1.11	1.58	-0.80	1.19	0.57	0.05
Reprisk: S	2.35**	2.13**	-1.29**	1.71	2.98*	5.41*	1.96	1.53	1.21
SPGlobal: S	1.46	1.43	-3.20	-2.34***	-2.01*	-3.23*	1.43	3.15	5.13
Moody's: S	3.43**	4.23**	2.71**	-2.59***	-2.62**	-1.14**	1.18	-1.03	1.51
AVG: S	3.49***	4.50***	3.98*	-0.40	-0.82	-1.56	1.23	2.11	4.73
PCA: S	2.49*	1.67*	-0.06*	-3.03***	-2.50***	-2.84***	0.34	1.02	1.95
MAHA: S	5.19***	5.97***	3.29*	0.78	1.77	-0.14	1.95	2.62	4.60
AVG_{vote}: S	2.88***	2.71**	4.28**	-0.37	-1.62	-2.25	1.79	2.57	3.20
STV_{vote}: S	1.37	1.67	-0.47	-1.93***	-1.76***	-2.72***	1.31	3.61	6.00

Table 9: FF5 and CAPM alphas for top-bottom **S** portfolios (±40%, ±25%, ±10%). The alphas are computed using time series regression. The stars next to the numbers represents significance levels. ***: p-val< 0.01, **: p-val<0.05, *: p-val < 0.10. The standard errors were computed using heteroskedastic autocorrelation consistent standard error estimators.

4.3 Governance Portfolios

For Governance score portfolios (see Table 10, the aggregation does not produce significant Fama-French five-factor alphas in the U.S. or Europe compared to individual vendor scores; however, we find there are Fama-French five-factor excess returns of up to 11.75% in Japan.

5 Conclusion

Using the quantitative framework proposed by Lo and Zhang (2021), we quantify the excess returns of arbitrary ESG portfolios via the cross-sectional standard deviation of the stock's excess returns and the correlation between the excess return and ESG factors (both combined and individual E, S, and G scores) obtained from six leading ESG score providers for firms in the U.S., Europe and Japan from 2014 to 2020. Few studies have analyzed such a comprehensive dataset and as systematically. We also propose a number of methods to aggregate ESG scores across vendors to produce the best signal within the data, simultaneously addressing measurement errors and yielding a single measure of ESG that can potentially be used for portfolio management.

Empirically, we find significant ESG excess returns in the U.S. and Japan. We also find positive and higher than market risk-adjusted returns. We construct an aggregate ESG measure based on a linear combination of ESG scores that is optimized to maximize the correlation with excess returns. The ESG portfolio properties of the optimized ESG score are comparable to the aggregate scores, implying that our methods of aggregation were successful in amplifying the signal. We evaluate the properties of ESG portfolios by investigating their exposure to various risk factors, constructing optimal Treynor-Black-weighted portfolios, and combining them optimally with passive index portfolios, which yields "super-efficient" frontiers that all investors should be interested in accessing.

One practical implication from our results is that aggregation methods help to reduce the noise and amplify the signal contained in E, S, and G metrics to yield better estimates

	USA			Europe			Japan		
Portfolio	±40%	±25%	±10%	±40%	±25%	±10%	±40%	±25%	±10%
				FF5 Alpha					
ISS: G	1.89**	2.32*	3.98*	-0.37	0.31	-0.19	4.18***	4.12***	3.91**
MSCI: G	2.43**	3.66***	4.01***	1.08	0.17	1.90	1.99	2.99**	5.23***
Reprisk: G	0.34	2.32**	1.79*	0.51	0.71	4.60*	-0.14	1.34	4.89***
SPGlobal: G	-0.25	0.42	2.72	-0.13	1.00	3.98**	3.45**	5.12***	11.75***
Moody's: G	0.29	1.21	1.30	0.83	0.45	0.83	1.71	2.88	3.09
AVG: G	2.25**	3.44**	5.84**	0.75	0.81	0.31	4.44***	5.01***	6.68*
PCA: G	2.05	1.39	0.86	0.26	1.28	2.79	0.18	-0.44	-3.86
MAHA: G	1.57	1.91	4.27*	0.83	0.54	-1.33	3.33*	5.44***	3.45***
AVG_{vote}: G	1.74*	2.43*	3.72*	0.79	0.85	0.31	4.50***	4.85**	7.42***
STV_{vote}: G	-0.28	0.40	2.58	0.18	1.36	3.98**	3.46**	5.05***	9.79***
				CAPM Alpha					
ISS: G	2.32**	2.65**	4.02**	1.15	1.79	1.20	3.60***	3.24***	2.40***
MSCI: G	1.51	2.51**	1.91**	3.09***	3.34**	7.46**	1.57	2.78	5.31***
Reprisk: G	0.42	2.22**	1.19**	2.61	3.36*	8.61***	0.85	2.89	6.78***
SPGlobal: G	-2.26	-0.82	3.30	-1.86*	-1.69**	0.29**	1.15	1.80	7.56***
Moody's: G	-0.08	0.60	-0.43	0.67	-0.13	1.36	-0.29	0.61	-1.06
AVG: G	1.42	2.19	4.03	2.64***	3.51*	2.45*	3.39**	3.36*	5.58*
PCA: G	1.49	0.58	0.19	-0.27	1.03	2.00***	-0.33	-0.48	-3.98*
MAHA: G	1.01	0.69	1.95	2.71**	3.33**	1.48**	2.77*	4.54**	2.62**
AVG_{vote}: G	0.60	1.20	2.06	2.65***	3.38**	1.74**	3.25**	2.98*	4.70*
STV_{vote}: G	-2.22	-0.55	2.50	-1.36	-1.22	0.87	1.29	2.02	5.82**

Table 10: FF5 and CAPM alphas for top-bottom **G** portfolios (±40%, ±25%, ±10%). The alphas are computed using time series regression. The stars next to the numbers represents significance levels. ***: p-val< 0.01, **: p-val<0.05, *: p-val < 0.10. The standard errors were computed using heteroskedastic autocorrelation consistent standard error estimators.

of ESG portfolio properties, even though individual ESG ratings are noisy and the portfolios constructed using ESG scores from any single vendor may be quite noisy. This aggregation method can be selected at the preference of the portfolio manager, since different methods will weight the noise and signal from rating agency scores in different ways. However, since the true noise and signal component remains unknown, it is hard to establish the superiority of any particular aggregation method and we leave this important topic for future research.

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A Internet Appendix

A.1 Rank Autocorrelation

In Table A.1, we present the cross-sectional rank autocorrelation between vendor ESG scores and aggregate scores averaged over time. We find there is a 99% autocorrelation computed with a delay of one month, implying that ESG scores do not change significantly over short periods. However, lower values of rank autocorrelation at longer delay windows implies that scores change significantly over longer time windows. This pattern is consistent across regions. Hence, to rebalance our ESG portfolios, we use a time window of 12 months.

	USA				Europe				Japan			
Delay (Months)	1	3	6	12	1	3	6	12	1	3	6	12
ISS: ESG	99	98	97	94	99	98	97	95	99	98	97	95
MSCI: ESG	99	97	95	90	99	97	94	90	99	97	94	89
Reprisk: ESG	98	96	93	88	98	96	93	86	98	94	89	79
SPGlobal: ESG	99	98	96	92	99	98	97	94	99	99	98	96
TVL: ESG	98	94	86	73	99	95	88	75	99	94	85	69
Moody's: ESG	99	98	96	94	99	98	97	95	99	98	96	94
AVG: ESG	99	98	96	92	99	98	97	94	99	98	96	92
PCA: ESG	99	99	98	97	99	99	98	97	99	99	98	97
MAHA: ESG	98	96	93	86	98	96	92	86	98	95	91	82
AVG_V: ESG	99	98	96	93	99	98	97	94	99	98	96	92
STV_V: ESG	95	88	82	71	95	90	83	74	96	91	85	76

Table A.1: Cross-sectional rank autocorrelation between vendor ESG scores and aggregate scores.

A.2 Implied Realized Alphas

In Table A.2, we present the realized and implied alphas of the individual portfolios using the Fama-French five-factor model. There is a high degree of consistency between the realized and implied alphas, hence validating the model described in Section 1.1.

ESG-Data	Q-1 (R)	Q-1 (I)	Q-2 (R)	Q-2 (I)	Q-3 (R)	Q-3 (I)	Q-4 (R)	Q-4 (I)
				US				
MSCI	-0.9 (1.4)	-0.0 (0.5)	1.9 (1.2)	0.7 (0.5)	1.8 (1.1)	1.3 (0.5)	1.3 (1.1)	2.1 (0.5)
SPGlobal	2.1 (1.3)	1.1 (0.5)	-0.0 (1.2)	1.0 (0.5)	0.8 (1.1)	1.0 (0.5)	1.3 (1.1)	1.0 (0.5)
ISS	0.5 (1.3)	0.5 (0.5)	0.3 (1.3)	0.9 (0.5)	1.9 (1.2)	1.1 (0.5)	1.4 (1.1)	1.5 (0.5)
Moody's	1.2 (1.4)	0.8 (0.5)	1.1 (1.2)	1.0 (0.5)	0.2 (1.1)	1.1 (0.5)	1.5 (1.2)	1.3 (0.5)
Reprisk	0.2 (1.1)	-0.4 (0.5)	-0.3 (1.2)	0.7 (0.5)	2.0 (1.3)	1.4 (0.5)	2.1 (1.3)	2.4 (0.5)
TVL	-0.3 (1.2)	0.7 (0.5)	1.8 (1.1)	0.9 (0.5)	1.0 (1.2)	1.1 (0.5)	1.6 (1.4)	1.3 (0.5)
				Europe				
MSCI	7.5 (2.5)	7.2 (0.6)	7.7 (2.2)	8.1 (0.6)	9.7 (2.3)	8.7 (0.6)	9.6 (2.1)	9.6 (0.6)
SPGlobal	7.8 (2.3)	7.1 (0.6)	7.7 (2.4)	8.1 (0.6)	8.8 (2.3)	8.7 (0.6)	10.0 (2.2)	9.7 (0.6)
ISS	6.6 (2.4)	6.7 (0.6)	9.0 (2.4)	8.0 (0.6)	8.9 (2.3)	8.8 (0.6)	9.8 (2.1)	10.1 (0.6)
Moody's	7.7 (2.3)	7.2 (0.6)	8.2 (2.4)	8.1 (0.6)	9.1 (2.2)	8.7 (0.6)	9.3 (2.2)	9.6 (0.6)
Reprisk	9.0 (2.3)	9.0 (0.6)	9.9 (2.3)	8.6 (0.6)	6.8 (2.3)	8.2 (0.6)	8.5 (2.3)	7.8 (0.6)
TVL	7.8 (2.3)	8.2 (0.6)	8.6 (2.2)	8.3 (0.6)	9.8 (2.3)	8.5 (0.6)	8.3 (2.4)	8.7 (0.6)
				Japan				
MSCI	6.9 (3.2)	7.4 (0.5)	7.8 (3.1)	7.9 (0.5)	9.2 (3.2)	8.3 (0.5)	8.4 (3.1)	8.8 (0.5)
SPGlobal	6.4 (3.2)	6.2 (0.5)	7.2 (3.2)	7.6 (0.5)	8.3 (3.2)	8.6 (0.5)	10.4 (3.1)	10.0 (0.5)
ISS	6.5 (3.2)	6.6 (0.5)	7.1 (3.2)	7.7 (0.5)	8.6 (3.2)	8.5 (0.5)	10.2 (3.1)	9.6 (0.5)
Moody's	6.8 (3.2)	6.9 (0.5)	8.1 (3.3)	7.8 (0.5)	8.7 (3.2)	8.4 (0.5)	8.7 (3.1)	9.3 (0.5)
Reprisk	7.5 (3.3)	7.5 (0.5)	8.7 (3.2)	7.9 (0.5)	7.0 (3.1)	8.2 (0.5)	9.2 (3.1)	8.6 (0.5)
TVL	9.0 (3.1)	8.1 (0.5)	6.6 (3.2)	8.1 (0.5)	8.0 (3.1)	8.1 (0.5)	8.8 (3.2)	8.0 (0.5)

Table A.2: Average annual model-implied and realized alphas of quantile ESG portfolios with respect to Fama-French five-factor regressions, based on data from 2014 to 2020. Portfolios are rebalanced once a year.

A.3 Sharpe Ratios of Combined Market and Treynor-Black ESG Portfolios

	USA			Europe			Japan		
Portfolio	±40%	±25%	±10%	±40%	±25%	±10%	±40%	±25%	±10%
Mkt		0.75			0.05			0.37	
ISS: ESG	1.07	1.03	1.01	0.20	0.18	0.18	**0.64**	**0.65**	0.66
MSCI: ESG	1.03	1.08	1.10	**0.33**	**0.36**	0.32	0.54	0.58	0.34
Reprisk: ESG	0.81	0.79	0.87	0.22	0.31	**0.53**	0.45	0.48	0.52
SPGlobal: ESG	0.68	0.66	0.76	0.01	0.03	0.16	0.49	0.51	0.62
TVL: ESG	0.80	0.75	0.54	0.14	0.18	0.06	0.23	0.24	0.33
Moody's: ESG	0.87	0.91	0.95	-0.03	-0.01	-0.05	0.38	0.36	0.55
INDI-AVG: ESG	0.91	0.91	0.94	0.14	0.18	0.21	0.47	0.49	0.56
AVG: ESG	**1.13**	**1.25**	1.13	0.24	0.26	0.28	0.59	0.58	0.50
PCA: ESG	0.94	0.98	0.94	0.09	0.12	0.18	0.51	0.52	0.51
MAHA: ESG	1.12	1.15	**1.14**	0.26	0.31	0.30	0.62	0.62	0.57
AVG_{vote}: ESG	1.09	1.16	1.10	0.24	0.28	0.33	0.58	0.59	0.51
STV_{vote}: ESG	0.84	0.79	0.63	0.14	0.20	0.46	0.55	0.57	**0.72**
OPT: ESG	1.21	1.26	1.25	0.25	0.29	0.52	0.64	0.65	0.53

Table A.3: Sharpe ratios of combined market and ESG Treynor-Black portfolios. The market portfolios used for different regions are the MSCI USA, MSCI Europe and MSCI Japan indices. The weight of the market index is fixed at 0.5. The highest realizable Sharpe ratio in each portfolio is given in bold.