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Research

Toward ESG Alpha: Analyzing ESG Exposures through a Factor Lens

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Using data on 1,312 active US equity mutual funds with $3.9 trillion in assets under management, we analyzed the link between funds' bottom-up, holdings-based environmental, social, and governance (ESG) scores and funds' active returns, style factor loadings, and alphas. We found that funds with high ESG scores have profiles of factor loadings that are different from those of low-scoring ESG funds. In particular, funds with high environmental scores tend to have high quality and momentum factor loadings. In partitioning the ESG scores into components that are related to factors and idiosyncratic components, we found strong positive relationships between fund alphas and factor ESG scores.

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In a relatively short time, environmental, social, and governance (ESG) considerations in investing have become mainstream.[1] The largest asset managers have prominently espoused support for ESG investing and taken steps toward integrating ESG factors into their investment processes; the largest trade groups, including the Business Roundtable, have issued letters saying that corporations must consider societal needs and purpose as well as business needs; and leading consultants and rating companies now rank all active mutual fund managers on ESG attributes.[2]

A natural question, given that ESG considerations are now important for asset owners and individual investors, is how investment managers can achieve those outcomes in portfolios. One way is to select companies with attractive underlying ESG profiles without regard to their risk-and-return characteristics. The evidence that ESG factors are directly related, in a causal sense, to higher returns is mixed.[3] Kempf and Ostho (2007), Eccles, Ioannou, and Serafeim (2014), Ashwin Kumar, Smith, Badis, Wang, Ambrosy, and Tavares (2016), Khan (2019), and Serafeim (2020) found a link between ESG scores and higher returns. Conversely, Hong and Kacperczyk (2009) showed that so-called sin stocks (i.e., companies in such industries as alcohol, tobacco, and gaming) outperform non-sin stocks. Cheng, Hong, and Shue (2013) found a negative relationship between ESG scores and returns. Barber, Morse, and Yasuda (2018) showed that venture capital funds that seek a significant social impact earn lower returns than traditional funds. Chan, Hogan, Schwaiger, and Ang (2020) found underperformance of portfolios optimized purely on ESG scores relative to other benchmarks.

Other than security selection, another way that investment managers can obtain desired ESG outcomes for their portfolios is to target factor exposures. Unlike most ESG data, the factors of value, quality, momentum, size, and minimum volatility have samples that extend for decades. Ang (2014), while providing a comprehensive summary

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of the literature on factors, emphasized that their risk premiums result from economic rationales of a reward for bearing risk, structural impediments, or behavioral biases.[4] Because the effect of factors is systematic (see Ross 1976)—that is, their broad effects have been observed for thousands of stocks—and they carry a risk premium, an active fund manager's choice to include ESG concerns may be correlated with the fund's factor exposures. Even in the absence of long time series for certain ESG data, a reasonable assumption is that if factors correlate highly with ESG attributes today, they did so in the past. In other words, deliberate or inadvertent factor tilts might have relationships with ESG variables that extend back decades even if ESG data may not be observable that long ago. Indeed, Melas (2016), Dunn, Fitzgibbons, and Pomorski (2018), and Chan et al. (2020) showed that, historically, the quality and minimum-volatility factors have significantly positive ESG scores as compared with the market.

Active managers may manage factor exposures to achieve ESG profiles either directly, by using factor funds or strategies that may be related to ESG scores, or indirectly through, say, targeting ESG characteristics that are related to factors. Whether a manager chooses the indirect or direct route to manage ESG characteristics matters for two reasons. First, because the factors have long empirical evidence of being linked to excess returns (or, synonymously, alpha),[5] if certain ESG scores are linked to positive, rewarded factor exposures, those ESG components are more likely to be associated with high excess returns. Investors might prefer managers whose ESG characteristics are associated with factors' long-run risk-adjusted returns, which provides transparency into the economic sensibility for positive performance. Second, to benchmark active funds correctly, we should consider factor exposures, as literature stretching back to Jensen (1968) makes clear. If ESG-friendly funds have low returns in excess of their benchmark, they still might be beating those benchmarks on a risk-adjusted basis. Measuring how factor exposures are related to ESG scores allows investors to make these risk-adjusted comparisons.

In the study reported here, we examined how ESG attributes are linked to factors. Using data on 1,312 US active equity mutual funds with $3.9 trillion in assets under management (AUM), we investigated the relationship between a fund's bottom-up, holdings-based ESG score and its alpha and factor loadings. We used the methodology of Lo (2008) and Hsu, Kalesnik, and Myers (2010) adapted by Ang, Madhavan, and Sobczyk (2017).[6] This approach uses holdings data viewed through the lens of a factor model to attribute a fund's alpha (the return in excess of the fund's benchmark return) into (1) returns to static factor exposures, such as a constant tilt to quality, (2) factor timing, where the manager varies the exposure to factors, such as momentum, over time, and (3) manager selection over individual securities. Using stock holdings, we related the alphas and ESG scores of funds to factor loadings—which may vary over time. Using holdings, rather than time-series regressions, permits greater statistical power in testing how ESG scores affect alpha than do time-series regressions.

We found that funds with significantly large ESG attributes—both as to aggregate ESG measures and to separate "E," "S," and "G" components—have factor exposures that differ from the market in important respects. Environmental considerations are particularly important in driving factor tilts, which is consistent with, among others, Kulkarni, Alighanbari, and Doole (2017). We found that 75% of the variation in fund-level E scores can be explained by style factors, but factors have much lower explanatory power for fund S and G scores. In particular, funds with the highest environmental scores have high momentum and quality exposures, and the relationship as one moves from the funds with low E to high E scores results in nearly monotonic increases in momentum and quality factor exposures.

We separated the impact of ESG attributes into Factor ESG and Idiosyncratic ESG. On the one hand, Factor ESG is the component of fund ESG scores that is related to factors—and because factor tilts carry risk premiums, we expected that the factors might be related to alphas and active returns. Idiosyncratic ESG, on the other hand, is the ESG components that are uncorrelated with factors and may not have a relationship with fund returns. Factor ESG components are positively related to fund alphas and active returns, and the relationship is highly statistically significant. In contrast, we could not reject the lack of a relationship between Idiosyncratic ESG components and alphas or active returns; in some specifications, the point estimates for the Idiosyncratic ESG variable were negative.

In addition to being part of the growing ESG literature, our study is related to an extensive body of research on mutual fund returns. Recently, Hartzmark and Sussman (2019) found that mutual fund flows are responsive to newly introduced

Morningstar sustainability ratings, which indicate the sensitivity of investments to ESG factors. Furthermore, they found that flows to mutual funds seeking sustainable investing objectives are less volatile than flows to other funds, confirming an earlier result by Bollen (2007). An added benefit for fund managers who increase their ESG scores is that investors in socially responsible funds may be willing to forgo financial performance for social preferences (Riedl and Smeets 2017). Our study differs from these papers in examining the specific relationship between ESG scores and factor exposures.

Fund Data

The active US equity mutual fund industry is huge. As reported by the Morningstar Flow Report of August 2019, the industry's AUM of $4.25 trillion is roughly equal to the assets in US equity index mutual funds and exchange-traded funds (ETFs). Our initial sample consisted of 1,576 active US equity mutual funds with $4.2 trillion in assets, which is largely the entire US-domiciled, US-focused universe of active funds. We performed all our analyses at the master fund class level because at the share class level, holdings and ESG attributes are not independent observations. We used holdings from 30 June 2014 to 30 June 2019 at the quarterly frequency. Although our initial dataset is large from a cross-sectional perspective, in that it consists of stock-level holdings information for a high proportion of the assets held by all US active equity mutual funds, it is short from a time-series perspective. In particular, for this sample, the market return is high, but certain factors, such as value, have underperformed (see, for example, Lev and Srivastava 2020).

ESG Data

Our ESG data are from MSCI, which constructs ESG data at the stock level and then aggregates up to the fund level.[7] The MSCI ESG scores and metrics are applied to more than 600,000 equity and fixed-income securities globally and based on more than 200 metrics in three categories: sustainable impact, values alignment, and risks. The MSCI ESG Ratings for funds are designed to measure the resiliency of portfolios to long-term ESG risks and opportunities. The most highly rated funds consist of issuers with leading or improving management of key ESG risks. The ESG Ratings are calculated as a direct mapping of ESG Quality Scores to letter rating categories (e.g., AAA = 8.6–10). The ESG Ratings range from leader (AAA, AA) to average (A, BBB, BB) to laggard (B, CCC).

The ESG categories considered by MSCI in their fund ratings include, among others, carbon intensity, alcohol, gambling, tobacco, controversial weapons, and female directors. MSCI requires a minimum coverage of 65% of stocks held to give the fund a rating, so not all the 1,576 funds have an ESG score. Typically, the uncovered funds are small funds that are relatively new or are focused on narrow segments of the equity market.

Of particular interest for the E category is that MSCI computes a "weighted average carbon intensity," a measure of a fund's exposure to carbon-intensive companies. Weighted average carbon intensity is the weighted average, by portfolio weight, of carbon intensity for each fund constituent. Carbon intensity for a company is computed as the total metric tons of CO_2 emissions (Scope 1 + Scope 2) divided by sales in millions of dollars. Scope 1 emissions are those from sources owned by the company, typically from direct combustion of fuel; Scope 2 emissions are caused by the generation of electricity purchased by the company. Other measures for fund-level exposure to greenhouse emissions are strongly correlated with weighted carbon intensity.

The MSCI ESG Quality Score (from 0 to 10) for funds is calculated from the weighted average of the ESG scores of fund holdings. This score also considers the ESG Ratings trend of the fund holdings and the fund exposure to holdings in the laggard category. MSCI rates underlying holdings according to their exposure to 37 industry-specific ESG risks and the fund's ability to manage those risks relative to peers. These issuer-level ESG ratings correspond to an issuer-level ESG score. The MSCI ESG Quality Score "peer percentile" for funds is the percentile of funds in the same peer group, based on ESG Quality Scores.

The sample of funds for which we had both ESG scores and holdings data consists of 1,312 active US equity mutual funds with AUM of $3.9 trillion—that is, 93% of the total AUM in active US equity funds. For all 1,312 funds, we used Morningstar quarterly holdings data for the period 30 June 2014–30 June 2019 to compute the return performance of the fund relative to each fund's prospectus benchmark. We also computed annualized return volatility, in percentages, from the monthly returns for each fund. Active returns were defined as fund returns minus prospectus benchmark returns and were measured net of fees.

Summary Statistics

Table 1 provides a snapshot of the full sample broken down by the familiar nine Morningstar style boxes. Values reported for "All funds" under "Number of Funds" and "AUM" are the totals for each style category; all other fields are sample means. We observed the greatest number of funds (300 of the 1,312) and the largest dollar assets ($1.35 trillion of the $3.9 trillion) in the large-cap growth category. The small-cap value category has the smallest asset base, $97 billion.

Looking at the average returns, we see that the mean active return across all funds is −1.19% per year. Weighted by AUM, however, this figure is −0.33% because the larger funds had higher active returns. This evidence goes against the concept of diseconomies of scale in the managed fund industry in the theoretical model and the empirical evidence of Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004). It is consistent with the more recent data, however, of Phillips, Pukthuanthong, and Rau (2018). The overall negative return is driven by negative average active returns in eight of the nine style boxes—the only exception is small-cap growth. Thus, there is not much evidence that the small-cap universe overall offers greater manager selection opportunities, based on realized manager outperformance.

Table 1 shows that the large-cap funds have the lowest average expense ratio, but the variation in mean expense ratios across the style boxes is not large. The mean expense ratio (unweighted) is 0.87%, and weighted by AUM, this figure is 0.60%. Finally, the last column of Table 1 reports average ESG scores. There is, on average, little differentiation in ESG scores across funds, but the small differentiation that exists points to fund managers in large caps having slightly higher ESG scores (around 5.0) than their counterparts in small caps (around 4.6). In the results that follow, we use the significant differentiation of ESG scores to draw results on the relationships between ESG components and factor loadings, alpha, and active returns. The fact that Table 1 shows little dispersion in average ESG scores across the style boxes indicates that our results are not driven by specific style effects.

Table 1. Descriptive Statistics by Morningstar Style Box Category, 30 June 2014–30 June 2019

Style		Number of Funds	Total AUM ($ billion)	Active Return (%)	Expense Ratio (%)	ESG Score
	Growth	300	1,349.9	−1.68	0.86	5.0
Large cap	Blend	176	665.5	−1.95	0.77	5.1
	Value	227	871.4	−0.69	0.78	4.9
	Growth	115	286.2	−0.60	0.92	4.8
Midcap	Blend	82	137.4	−2.63	1.03	4.8
	Value	53	132.6	−0.89	0.83	4.9
	Growth	133	203.1	0.91	0.96	4.6
Small cap	Blend	153	135.6	−1.55	0.95	4.6
	Value	73	96.8	−1.58	0.96	4.6
	All funds	1,312	3,878.6	−1.19	0.87	4.9

Source: BlackRock, based on Morningstar data for the five-year period using quarterly holdings.

Notes: Figures for all funds, number of funds, and AUM are totals for each nine-box category; all other fields are the mean values for the category. Funds are grouped together at the master share class level to avoid double counting. Here, Active Return represents fund returns in excess of prospectus benchmark and net of fees. ESG is the average MSCI rating for the fund based on its (weighted) stock-level holdings. Past performance does not guarantee future results. Indexes are unmanaged and cannot be invested in directly.

Factor Portfolios

We used seven long-only factor portfolios in our analysis that were proxied by the following MSCI indexes:

- value: MSCI USA Enhanced Value Index
- size: MSCI USA Risk Weighted Index
- quality: MSCI USA Sector Neutral Quality Index
- momentum: MSCI USA Momentum Index
- minimum volatility: MSCI USA Minimum Volatility Index
- large-cap multifactor: MSCI USA Diversified Multiple-Factor Index
- small-cap multifactor: MSCI USA Small Cap Diversified Multiple-Factor Index

All these factors have a long academic history. The size and value factors were made famous by Fama and French (1993) and have been used in many other studies. The MSCI Risk Weighted Index, which we used for the size portfolio, seeks to capture a broad equity universe with lower risk attributes than comparable market cap–weighted indexes. It does so by reweighting all the constituents of a standard MSCI parent index to give more weight to stocks with minimum volatility. In practice, this weighting scheme is a proxy for small-cap and mid-cap size ranges. Standard references for supporting the use of quality, momentum, and minimum volatility are, respectively, Sloan (1996), Jegadeesh and Titman (1993), and Ang, Hodrick, Xing, and Zhang (2006). The large-cap and small-cap multifactor indexes combine value, momentum, size, and quality factors. We can interpret the large-cap and small-cap multifactor portfolios as a balanced factor mix that serves as a base for, respectively, large-cap and small-cap stocks with the single factors (value, size, quality, momentum, minimum volatility) as additional tilts beyond the multifactor benchmark.

Much of the academic literature uses long–short factor portfolios (following Fama and French 1993), but in our main analysis, we used long-only factors similar to the approach of Sharpe (1992) and Madhavan, Sobczyk, and Ang (2018). This approach is most relevant to investors who cannot short, which applies to many retail investors in mutual funds and also to many mutual fund managers, as Almazan, Brown, Carlson, and Chapman (2004) reported. All the factors in the list have investible representations in transparent and low-cost vehicles, such as ETFs.

In our analysis, we also compared factor loadings with the more traditional long–short factor portfolios. Note that these portfolios do *not* correspond to investible vehicles. We used the Fama–French–Carhart four-factor model (see Carhart 1997), which includes factors for the market, value, size, and momentum. This factor model—with data sourced from Kenneth French's website—is widely used in the academic literature (see Ang 2014; Fama and French 2010; and Madhavan, Sobcyzk, and Ang 2020, among many others.)[8] We also examined the AQR six-factor model (labeled here "AQR"), which adds the factors for betting against beta (BAB) and quality minus junk (QMJ). This model, with data obtained from www.aqr.com, was presented by Asness, Frazzini, and Pedersen (2019) and Frazzini and Pedersen (2014).

Analytical Framework for Factors and ESG Components

In this section, we describe a model to link alpha estimates (either through return regressions or holdings attribution) with ESG considerations, return decompositions, and portfolio factor loadings. We then lay out the factor model of securities. We model how fund managers seeking to outperform benchmarks hold active weights, deviating from benchmark weights, in securities. In traditional mean–variance analysis, the active holdings of a stock would be proportional to the stock's alpha. To introduce ESG preferences, stocks would also have ESG characteristics that are not related to factor loadings or stock alphas. We then present the holdings-based attribution model, which considers static factor components, time-varying factors, and security selection. The last term includes both true alpha, which is the return in excess of factor loadings, and ESG characteristics. Because ESG components are correlated with factor loadings, we have introduced an orthogonalization method to examine the ESG components related to factors and those that are idiosyncratic.

Factor Model of Returns. Our starting point is a Ross (1976) multifactor model of a security's returns with time-varying factor loadings. We assume there are N securities, which we take as US stocks held by active mutual funds, indexed by $i = 1, \ldots, N$ with K risk factors (momentum, quality, etc.) indexed by $k = 1, \ldots, K$:

$$r_{i,t} = \alpha_{i,t} + \sum_{k=1}^{K} \beta_{i,k,t} F_{k,t} + \varepsilon_{i,t}, \tag{1}$$

where $F_{k,t}$ is the kth factor return at time $t = 1, \ldots, T$ and $\beta_{i,k,t}$ denotes the exposure of security i to factor k. In Equation 1, $\alpha_{i,t}$ is the stock's true alpha—that is, the stock's return in excess of its factor exposures. Returns are also subject to idiosyncratic return shocks, with a mean of zero, denoted by $\varepsilon_{i,t}$. In our attribution, we take into account the time-varying factor loadings, $\beta_{i,k,t}$.

Equation 1 defines an $N \times N$ variance–covariance matrix $\mathbf{V}$ that depends on the factor loadings. For example, if $K = 1$, which is the case for a single-factor model such as the capital asset pricing model, $\mathbf{V} = \beta'\beta\sigma_M^2 + \mathbf{D}$, where β is the $N \times 1$ vector of betas, σ_M^2 is the variance of the market factor, and $\mathbf{D}$ is an $N \times N$ diagonal matrix of idiosyncratic risk. The generalization to K factors is straightforward.

Manager Preferences for ESG. The active fund manager universe we described previously consists of J funds. These funds invest in the universe of N stocks. A fund j's active return, $R_{j,t}$, in period t is

$$R_{j,t} = \sum_{i=1}^{N} w_{j,i,t} r_{i,t}, \tag{2}$$

where $w_{j,i,t}$ is the active stock weight—the weight in excess of the benchmark weight—of security i ($i = 1, \ldots, N$) in portfolio j at the beginning of period t and $r_{i,t}$ represents the security's return for period t, inclusive of any dividends.

ESG considerations at the fund level are modeled by assuming that manager j's estimate of the excess return (alpha) for stock i, which is denoted by $\mathrm{E}_j[\alpha_{i,t}]$, is affected by ESG considerations, denoted by $\gamma_{j,i}$. The manager's return forecast is

$$\mu_{j,i,t} = \gamma_{j,i} + \mathrm{E}_j[\alpha_{i,t}]. \tag{3}$$

In Equation 3, $\gamma_{j,i}$ is a fund-specific return that reflects "ESG values" (translated into returns) that are orthogonal to alpha forecasts. Managers who do not care about ESG attributes have $\gamma_{j,i} = 0$. For example, managers who attribute value to stocks in green industries (e.g., wind power) might overweight their return forecast by $\gamma_{j,i} > 0$, whereas stocks in other industries (e.g., fossil fuels, weapons, tobacco) might be underweighted (or excluded) by setting $\gamma_{j,i}$ sufficiently negative. The notation with $\gamma_{j,i}$ is general; that is, the ESG preferences may include E considerations (e.g., management plans to reduce carbon), S considerations (e.g., employee satisfaction), or G considerations (e.g., diversity in senior management). This setup is similar to that of Pedersen, Fitzgibbons, and Pomorski (2020), where a company's ESG score affects investor preferences and is correlated with company fundamentals. In our data, we take $\gamma_{j,i}$ as the ESG data described previously.

In our analysis, we followed Grinold and Kahn (2000) and assumed that active managers solve a mean–variance objective function and hold weights in stocks proportional to their alpha estimates. Let $\mathbf{w_{j,t}}$ be the $N \times 1$ vector of weights where the ith element is $w_{j,i,t}$. Similarly, let $\boldsymbol{\mu}_{\mathbf{j,t}}$ be the $N \times 1$ vector of ESG alphas. Then, manager active weights are given by

$$\mathbf{w_{j,t}} = \lambda_j^{-1}\mathbf{V}^{-1}\left(\gamma_{j,i} + \mathrm{E}_j[\alpha_{i,t}]\right), \tag{4}$$

where $\lambda_j > 0$ is the manager's risk aversion coefficient. In Equation 4, we implicitly assume that managers have different forecasts for expected returns, $\boldsymbol{\mu}_{\mathbf{j,i,t}}$, but the same forecasts for risk. To a first-order approximation, this assumption is reasonable because Merton (1980) showed that expected returns are an order of magnitude more difficult to forecast than second moments. Equation 4 shows the dependence of active weights on risk aversion (through λ), the factor loadings of stocks (through $\mathbf{V}$), ESG considerations (through γ), and standard alpha forecasts (through α).

The empirical question then becomes, Once factor exposures have been controlled for, how do ESG characteristics $\gamma_{j,i}$ affect manager security selection alpha?

Holdings-Based Attribution. We followed Ang et al. (2017) to estimate time-varying factor loadings by using cross-sectional risk characteristics and then used these estimates to compute the static and time-varying factor components of active equity returns.

The expected return of a fund j can, using the definition of covariance, be expressed as

$$\begin{aligned}\mathrm{E}[R_{j,t}] &= \sum_{i=1}^{N} \mathrm{E}[w_{i,j,t} r_{i,t}] \\ &= \sum_{i=1}^{N} \mathrm{E}\left(w_{i,j,t}\right)\mathrm{E}\left(r_{i,t}\right) + \sum_{i=1}^{N} \mathrm{cov}\left(w_{i,j,t}, r_{i,t}\right).\end{aligned} \tag{5}$$

The first element of the decomposition in Equation 5—the cross-product of expected values of holdings and expected security returns—reflects the expected return from passive allocation to each security in the portfolio. The second term—the covariance between weights and returns—is the dynamic security selection effect. A positive covariance means active weights are larger for securities with positive returns, which Lo (2008) and Hsu et al. (2010) interpreted as a measure of skill in security selection. Note that in Equation 5, the security weights vary over time.

Because managers have the same factor model of returns in Equation 1 driving the covariance matrix, we can substitute the factor structure into Equation 5, but the expected excess return of fund j is dependent on manager j's expected return beliefs. Thus, the expected active return of the portfolio can be written as

$$E[R_{j,t}] = \alpha^S_{j,t} + \sum_{k=1}^{K} E\left(\hat{\beta}_{j,k,t}\right) E\left(F_{k,t}\right) + \sum_{k=1}^{K} \operatorname{cov}\left(\hat{\beta}_{j,k,t}, F_{k,t}\right) \tag{6}$$

where the weighted average portfolio exposure of the kth factor is

$$\hat{\beta}_{j,k,t} = \sum_{i=1}^{N} w_{j,i,t} \beta_{i,k,t} \tag{7}$$

and $\alpha^s_{j,t}$ is the security selection component of manager j's alpha:

$$\alpha^s_{j,t} = \sum_{i=1}^{N} w_{j,i,t} \left(\gamma_{j,i} + E_j[\alpha_{i,t}]\right). \tag{8}$$

Recall that the weights in Equation 7 are active weights relative to the benchmark, so the realized return is $R_{j,t} = E[R_{j,t}] + \alpha^s_{j,t}$, where $\alpha^s_{j,t}$ is the security selection component of alpha. Then, we can use Equation 6 to express the manager's active return as the sum of static factor returns, dynamic timing, and security selection:

$$R_{j,t} = \sum_{k=1}^{K} E\left(\hat{\beta}_{j,k,t}\right) E\left(F_{k,t}\right) + \sum_{k=1}^{K} \operatorname{cov}\left(\hat{\beta}_{j,k,t}, F_{k,t}\right) + \alpha^s_{j,t}. \tag{9}$$

In Equation 9, we have the following attribution of fund returns:

1. static factor contribution from tilts to quality and other factors—given by the term $\sum_{k=1}^{K} E\left(\hat{\beta}_{j,k,t}\right) E\left(F_{k,t}\right)$;
2. dynamic timing (factor timing alpha), given by the term $\sum_{k=1}^{K} \operatorname{cov}\left(\hat{\beta}_{j,k,t}, F_{k,t}\right)$; and
3. manager selection or security selection alpha, $\alpha^s_{j,t}$, which is decomposed into green tilts and true alpha from Equation 8.

Factor Representation of Portfolios. Our final stage was to estimate the time-varying factor loadings, $\hat{\beta}_{j,k,t}$. We did this by finding the best fit to the fund's K factor characteristics with M factor-mimicking portfolios by matching the stock-by-stock style scores as described by Madhavan et al. (2018). At a given time, for a particular fund j, define a *factor-mimicking portfolio* as a set of weights $w^{ETF}_{j,m}$ on $m = 1, \ldots, M$ investible factor indexes described previously, where *ETF* refers to exchange-traded fund. The factor-mimicking portfolio is required to be long only and fully invested, and we further require that the number of factor funds in mimicking portfolio M not exceed the number of K risk factors.

Denote by $\hat{\beta}^{ETF}_{m,k}$ the exposure of an investible vehicle (such as an ETF), m, to risk factor k taken as the weighted average exposure to factor k over the individual stocks held by m. This exposure does not depend on fund j. Note that because index factor funds are constructed as passive vehicles, the timing and alpha components in the decomposition in Equation 9 are zero by construction, so the expected return contribution from a position in investible ETF m to risk factor k is $E\left(\hat{\beta}^{ETF}_{m,k}\right) E\left(F_k\right)$—that is, the product of the beta of the ETF and the expected factor return—or only the static factor in the attribution in Equation 9. This interpretation is reinforced by the factors we adopted, described earlier, being represented in terms of indexes that are investible through low-cost ETFs.

The expected return from a position in m across all K factors is $\sum_{k=1}^{K} E\left(\hat{\beta}^{ETF}_{m,k}\right) E\left(F_k\right)$. Then, the expected return of the factor-mimicking portfolio for fund j with weights $w^{ETF}_{j,m}$ (where $m = 1, \ldots, M$) is $E\left[R^{ETF}_j\right]$, where

$$\mathrm{E}\left[R_j^{ETF}\right]=\sum_{m=1}^{M} w_{j,m}^{ETF}\left[\sum_{k=1}^{K}\mathrm{E}\left(\hat{\beta}_{m,k}^{ETF}\right)\mathrm{E}\left(F_k\right)\right]. \tag{10}$$

The difference at time t between fund j's expected total return attributable to static exposures to the K risk factors and the expected return of the index factor portfolio (from Equations 9 and 10) is denoted by $\hat{\eta}_j$, where (with the time subscript omitted)

$$\hat{\eta}_j=\sum_{k=1}^{K}\mathrm{E}\left(\hat{\beta}_{j,k}\right)\mathrm{E}\left(F_k\right)-\sum_{m=1}^{M} w_{j,m}^{ETF}\left[\sum_{k=1}^{K}\mathrm{E}\left(\hat{\beta}_{m,k}^{ETF}\right)\mathrm{E}\left(F_k\right)\right]. \tag{11}$$

Then, the ordinary least-squares (OLS) estimate for the index factor portfolio is the set of M weights $w_{j,m}^{ETF}$ that minimizes the squared residual in Equation 11 subject to the following constraints:

$$\sum_{m=1}^{M} w_{j,m}^{ETF}=1, \tag{12a}$$

and

$$0 \le w_{j,m}^{ETF} \le 1, \text{ for each } m = 1, \ldots, M. \tag{12b}$$

The estimation procedure is equivalent to a root-mean-square minimization, fund by fund.

We estimated the weights by using stock-level characteristics to minimize the squared residuals given in Equation 12. Specifically, every stock had a value Z-score based on such stock characteristics as forward earnings/price or book/price and a momentum Z-score from past returns. Each fund also had a value score and a momentum score, which could be computed from the weight of the value and momentum Z-scores of each constituent stock by using the property that we could aggregate Z-scores from stocks to funds.

Suppose a particular fund had portfolio Z-scores of 0.4 and 0.25 for value and momentum, respectively. We then assume two investible long-only factor portfolios, A and B. These portfolios could be ETFs or other vehicles, but the point is that they are accessible to investors. For example, suppose Portfolio A is a value fund and is assumed to have an average factor loading of 0.8 to value and –0.2 to momentum and Portfolio B has a loading of 0.0 to value and 0.7 to momentum. Then, we can exactly reproduce the factor exposure of a fund with an equally weighted factor portfolio of investible Portfolios A and B because a portfolio of (½ A and ½ B) has the same factor scores as the fund. We call that portfolio (½ A and ½ B) a "factor-mimicking portfolio" for the index. In practice, this decomposition does not hold exactly, because the residual is nonzero (Equation 11), but we found the factor-mimicking portfolio by minimizing this squared residual.

Factor Breadth. We can quantify the extent to which factor exposures are concentrated by the *factor breadth* of an index. We define the breadth at the fund level as the inverse of the Herfindahl–Hirschman Index, which is the sum of squares of the dynamic weights $w_{j,m}^{ETF}$ in the M investible factor portfolios:[9]

$$\text{Factor breadth}_j = 1/\sum_{m=1}^{M}\left(w_{j,m}^{ETF}\right)^2. \tag{13}$$

We were interested in (1) whether more successful funds have wide or narrow breadth and (2) whether highly scoring ESG funds are more or less diversified in terms of factor exposures.

Comparison with Regression-Based Methods of Attribution. We compared our holdings-based attribution with factor loadings typically estimated by using rolling regressions of portfolio returns on factor returns. With T observations, the estimates of the manager's alpha α_j and beta exposures $\beta_{j,k}$ are based on the OLS regression with beta assumed to be constant:

$$R_{j,t}=\alpha_j+\sum_{k=1}^{K}\beta_{j,k}F_{k,t}+\varepsilon_{j,t}. \tag{14}$$

The time-series approach is attractive because it requires only data on returns, but the estimates update only slowly over time. Moreover, it assumes that the beta coefficients are constant for the estimation window, rather than taking on a new value in the most recent period. This assumption can be a problem if managers dynamically time factors—which Ang et al. (2017), Laipply Madhavan, Sobczyk, and Tucker (2020), and others have shown is the case.[10]

ESG Components Related to Factors. ESG scores are related to factor characteristics. We decomposed the ESG scores into a component that is related to factors and an idiosyncratic component.

To do so, we estimated regressions across all managers in which the dependent variable was the component ESG score and the independent variables were the investible factor portfolios. We performed this estimation separately for E, S, and G scores for $M - 1$ factors; because the weights sum to 1 by construction, we lost one degree of freedom:

$$\mathrm{ESG}_j = \sum_{m=1}^{M-1} \beta_m w_{j,m}^{ETF} + \varepsilon_j. \tag{15}$$

From the estimated regression Equation 15, we inferred the ESG portion related to factors:

$$\text{Factor ESG}_j = \sum_{m=1}^{M-1} \beta_m w_{j,m}^{ETF}. \tag{16}$$

Equation 16 gives the Lippy factor exposure that is predicted by the regression (Equation 15). Because factors are priced, in the sense that they have historically been associated with risk premiums, this component of ESG should be positively related to returns.

The Idiosyncratic, or nonfactor, ESG component is estimated as the residual,

$$\text{Idiosyncratic ESG}_j = \mathrm{ESG}_j - \text{Factor ESG}_j. \tag{17}$$

Thus, we decomposed the ESG preference ($\gamma_{j,i}$ in Equations 3 and 4) into

$$\mathrm{ESG}_j = \text{Factor ESG}_j + \text{Idiosyncratic ESG}_j.$$

The Idiosyncratic ESG component is not related to factor exposures, so we did not expect the nonfactor ESG component to be related to returns—unless a risk factor apart from value, size, momentum, quality, minimum volatility, and large cap and small cap is missing from our analysis.

Empirical Results

In this section, we discuss our findings related to (1) fund returns and ESG ratings and (2) factor loadings and ESG ratings. We also compare time-series regression with factor loadings, and we present our findings regarding fund alpha and ESG.

Fund Returns and ESG Ratings. Our starting point is **Table 2**, which reports mean estimates of ESG attributes of funds, including weighted carbon intensity, grouped by deciles of annual active returns. We report average ESG scores across deciles with weighted carbon intensity in Panel A. When the numerical values of the ESG scores are considered, the correlation between active returns and ESG scores is actually slightly negative, at –0.06. There seems to be more of a relationship, however, between active return and weighted carbon intensity. Funds with the highest active returns appear to have significantly lower carbon intensity scores—85.1 carbon emissions per dollar of sales. This number compares favorably with the 164.2, a little less than double, on average, for the other nine deciles. Note that the weighted average carbon intensity is unconstrained; looking across stocks and funds, we can see an empirical range from 0 to 25,610 metric tons per million dollars of revenue. MSCI reported a figure of 162.4 as of 30 April 2020 for the MSCI World Index and 170.1 for the MSCI North America Index.

In Panel B of Table 2, we report average fund characteristics of active returns, AUM, and expense ratios. The range in annual performance goes from the lowest decile, with an annualized active return of –5.66%, to the top decile, with an annual active return of 2.95%. Only the top three deciles show positive active performance, and Decile 8 is just barely positive. The poor active returns, on average, are consistent with the large mutual fund literature. Similar to reported results in Carhart (1997), Wermers (2000), and others, the worst funds also tend to have higher expense ratios and are smaller in AUM, possibly reflecting outflows associated with poor performance.

Fund Factor Loadings and ESG Ratings. Although we found little relationship in Table 2, which reports sorting first on active returns and then on ESG scores, we found some interesting patterns when we reversed the exercise, which we show in **Table 3** and **Table 4**.

In Table 3, the sort is on the separate E, S, and G components in, respectively, Panels A, B, and C, and we report factor-mimicking portfolio weights (see Equation 10). Overall, Table 3 shows a significant relationship between ESG components and factor exposures. In Panel A for the environmental sort, the investible factors have nearly monotonic positive relationships with momentum and quality exposures and a negative relationship with the small-cap multifactor group as we move from the lowest to the highest E deciles. For example, the

Table 2. Summary Statistics by Decile of Active Return, 30 June 2014–30 June 2019

A. ESG scores

Decile	A+ Rated (%)	B+ Rated (%)	CCC Rated (%)	No Rating (%)	Weighted Carbon Intensity
1 (low)	31.9	58.0	1.8	8.3	184.8
2	33.2	58.6	1.2	7.0	160.6
3	32.8	59.8	1.7	5.7	148.8
4	31.7	61.0	1.4	5.9	166.2
5	33.4	59.0	1.8	5.9	182.8
6	33.4	58.4	1.8	6.4	162.4
7	34.7	58.6	1.5	5.2	156.2
8	33.9	59.5	1.3	5.3	157.8
9	31.7	60.0	1.4	6.9	157.8
10 (high)	27.7	61.9	0.9	9.5	85.1

B. Fund characteristics

Decile	Active Return (%)	AUM ($ billion)	Expense Ratio (%)
1 (low)	–5.66	0.51	1.12
2	–3.35	1.45	0.98
3	–2.47	2.32	0.87
4	–1.87	2.61	0.88
5	–1.37	2.22	0.85
6	–0.90	4.53	0.75
7	–0.43	2.99	0.80
8	0.13	3.58	0.76
9	1.03	5.21	0.81
10 (high)	2.95	4.15	0.93

Source: BlackRock, based on Morningstar data for 1,312 funds over the five-year period using quarterly holdings.

Notes: Active return decile portfolios were formed on the basis of the fund's return less its prospectus benchmark. AUM is reported as the average assets under management as of 30 June 2019 in billions of dollars. ESG ratings and weighted carbon intensity are based on MSCI's fund (weighted) stock-level holdings: A+ refers to MSCI ratings of A and above, and B+ refers to ratings of B, BB, and BBB. Past performance does not guarantee future results.

momentum and quality factor loadings are 34% and 37%, respectively, for Decile 10, compared with 1% and 1% for the lowest decile. This result is remarkable because the mimicking factor procedure uses stock-level *Z*-scores related to the factors only and does not use any ESG characteristics. The funds with the highest environmental scores take on momentum and value exposure. The funds with the lowest environmental scores effectively take on only the small size factor exposure. The results for the social and governance sorts in Panels B and C show similar patterns, but the effects are strongest for the environmental sort in Panel A.

To further characterize the relationship between the ESG components with investible factors, we report in Table 4 cross-sectional regression coefficients of the E, S, and G scores on the long-only factor-mimicking portfolios. Because of an "adding-up" constraint (the factor weights sum to 1.0),

Table 3. Long-Only Factor Investible Weights (%) of Decile Portfolios Sorted by E, S, and G Characteristics, 30 June 2014–30 June 2019

Decile	Momentum	Value	Quality	Low Volatility	Small	Large-Cap Multifactor	Small-Cap Multifactor
A. Decile sort by environmental score							
1 (low)	1.0	3.3	1.1	0.0	7.8	0.4	86.5
2	1.4	3.1	0.6	0.0	15.4	0.0	79.5
3	1.5	5.1	2.4	0.1	22.0	1.7	67.3
4	2.9	11.5	9.1	1.2	35.1	3.0	37.2
5	8.2	18.1	16.6	2.6	28.3	5.2	21.0
6	16.3	19.1	26.5	2.2	20.9	4.2	10.8
7	22.3	22.4	28.9	5.7	11.7	3.5	5.6
8	29.4	23.8	30.4	3.6	8.1	2.0	2.7
9	27.8	21.6	30.6	6.8	8.3	1.6	3.4
10 (high)	33.9	13.9	37.3	5.6	5.7	0.8	2.8
B. Decile sort by social score							
1 (low)	4.6	16.8	1.7	1.2	17.9	1.2	56.6
2	4.9	18.4	5.2	2.6	20.4	2.9	45.6
3	7.8	16.2	9.2	2.8	18.6	3.1	42.3
4	11.8	16.0	10.9	1.8	15.6	2.8	41.2
5	12.3	11.9	14.0	2.5	20.7	2.1	36.5
6	18.3	16.9	18.6	4.4	16.8	2.7	22.3
7	21.4	14.5	21.9	3.7	13.0	2.4	23.1
8	20.0	12.8	30.7	1.9	17.4	2.2	15.2
9	20.3	9.1	36.2	3.6	9.6	2.0	19.2
10 (high)	23.1	9.2	35.3	3.4	13.2	1.1	14.8
C. Decile sort by governance score							
1 (low)	17.8	26.3	17.8	1.3	11.7	1.0	24.2
2	21.0	23.6	15.0	4.2	10.7	1.4	24.2
3	21.0	16.5	22.3	4.0	10.5	1.7	24.0
4	19.8	14.4	25.0	3.2	10.3	1.7	25.6
5	17.2	12.3	23.0	2.8	16.4	1.8	26.6
6	16.9	9.6	21.8	2.3	17.2	3.3	28.7
7	12.3	9.2	19.9	2.1	18.3	3.3	35.0
8	10.3	8.7	20.7	3.5	20.7	3.0	33.1
9	4.8	8.6	11.7	2.5	21.3	2.4	48.8
10 (high)	3.1	12.4	6.4	2.0	26.2	2.8	47.1

Source: BlackRock, based on Morningstar data for the five-year period using quarterly holdings.

Table 4. Cross-Sectional Regressions of ESG Component Scores on Long-Only Factor-Mimicking Portfolios, 30 June 2014–30 June 2019

	Environmental Score		Social Score		Governance Score	
	Coefficient	*t*-Stat.	Coefficient	*t*-Stat.	Coefficient	*t*-Stat.
Intercept	4.85	141.15*	4.35	194.47*	5.59	212.79*
Momentum	1.03	15.72*	0.25	5.89*	–0.39	–7.83*
Value	0.11	1.88	–0.24	–6.04*	–0.36	–7.76*
Quality	0.35	6.90*	0.20	6.07*	–0.15	–3.78*
Low volatility	0.69	6.87*	0.19	2.89*	0.08	1.05
Large-cap multifactor	–0.36	–2.95*	–0.08	–0.98	0.27	2.84*
Small-cap multifactor	–1.00	–22.31*	–0.14	–4.61*	–0.08	–2.26*
Adjusted R^2	0.75		0.26		0.14	
F-statistic	664.0		74.4		35.9	

Source: BlackRock, based on Morningstar data.

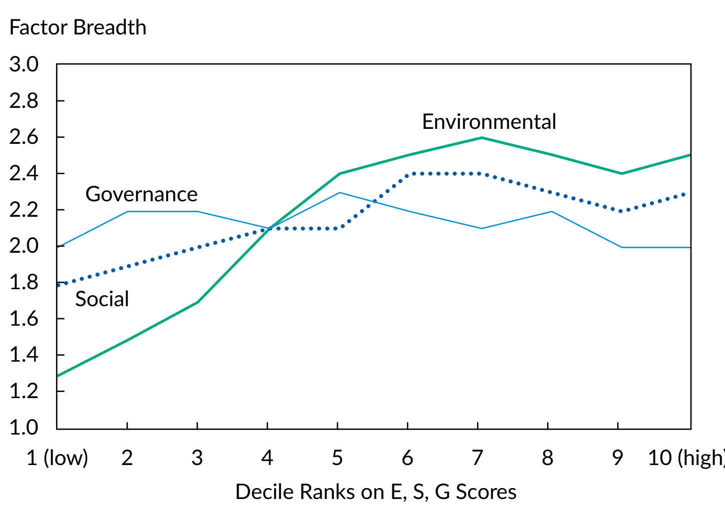
Note: The size factor is subsumed in the intercept because the sum of the weights is one.

*Significant at the 5% level.

we omitted the small size factor proxied by the MSCI USA Risk Weighted Index. Immediately, we see that the adjusted R^2 for the E scores of 0.75 is much higher than those for the S and G scores, 0.26 and 0.14, respectively. This finding confirms the strong relationship between environmental scores and factor loadings, with lower explanatory power for social and governance scores. High E scores of funds can be explained by those active managers effectively holding large momentum (1.03), quality (0.35), and low-volatility (0.69) factors, and they tend to favor large companies (inferred by the strong –1.00 coefficient on small-cap multifactor). The fact that E scores can be largely explained by factors is noteworthy because MSCI does not use factor definitions in its environmental scores.

Figure 1 shows a graph of the factor breadth (see Equation 13) with sorting on the separate E, S, and G components from Decile 1 (low rank) to Decile 10 (high rank). For the environmental score, the factor breadth noticeably increases from 1.3 for the lowest

Figure 1. Factor Breadth for Decile Portfolios Sorted by ESG Characteristics, 30 June 2014–30 June 2019



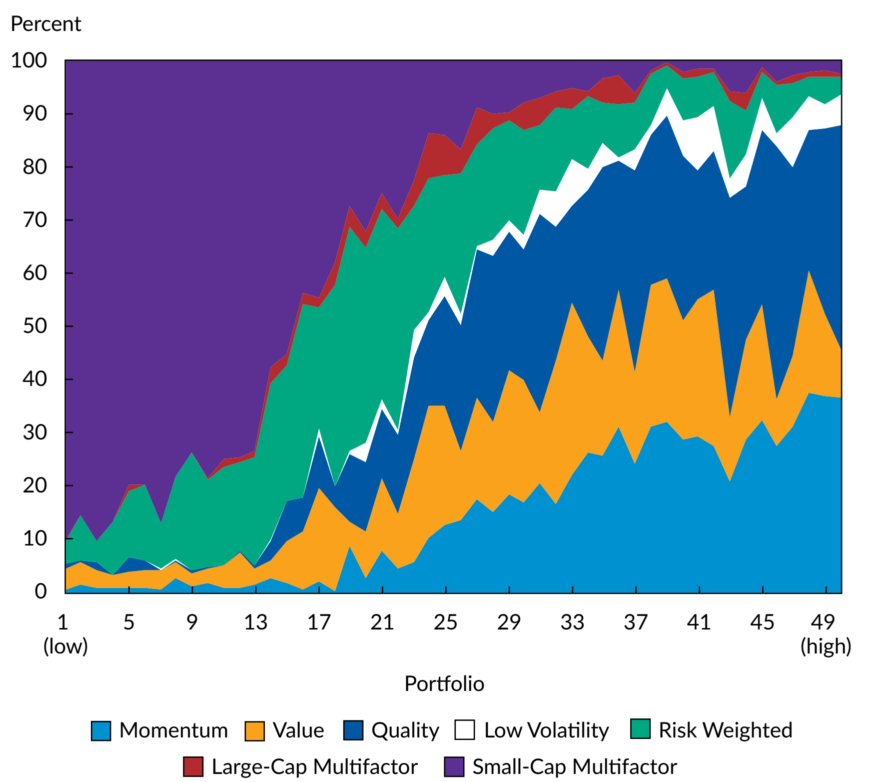
Source: BlackRock, based on Morningstar quarterly holdings data.

decile to 2.6 for the highest decile. This increase is relatively steep compared with the graphs for the social and governance scores and is monotonic from Deciles 1 to 7. Moving from the lowest to the highest E decile is equivalent to adding 1.2 factors to the portfolio! This boon is not the case for social and governance scores. For both S and G, the number of factors is in a fairly tight range around 2.0. Because active returns are a combination of static factor exposures, time-varying components, and security selection (see Equation 9), we expect that the first or second of these components related to factors might lead to a relationship between alphas and E ratings but not between alpha and S or G scores. Table 3 and Table 4 confirm this expectation.

Figure 2 plots the factor weights for 50 portfolios grouped by their environmental score rank from lowest (1) to highest (50) and illustrates how the higher E score funds have much larger momentum and quality weights and much lower weights on the small factor than low score funds have. Interestingly, the plot shows that a value exposure is *nonlinearly* related to environmental rank: The value factor weight is 3.8% for Portfolio 1, increases to 23.0% for Portfolio 30, but decreases to 8.9% for Portfolio 50. Figure 2 also provides an alternative visualization of factor breadth shown in Figure 1: Only one factor—small-cap multifactor—dominates for the least environmentally friendly funds. For the highest E score funds, large loadings can be seen on quality and momentum. In addition, low volatility is completely absent from the low E score funds but is present in the highest E score funds. Because these factors had different experiences over the sample period, this finding may have return implications, which we will explore.

Although the power for factors to explain variation in the social and governance scores of funds is weaker than it is for the environmental scores, some of the coefficients on the factors have the opposite sign of those in the environmental regression. In particular, top-scoring environmental funds correspond to high momentum, but the opposite is true for governance. High S and high G funds also tend to take positions in growth companies, which is implied by the negative factor loadings on value.

Figure 2. Long-Only Factor Composition of Decile Portfolios Ranked by Environmental Score at 30 June 2019



Source: BlackRock, based on Morningstar data.
Note: Morningstar quarterly holdings data of the mutual funds were grouped into 50 portfolios (with equal numbers of funds) based on their MSCI Environmental Score rank from lowest (1) to highest (50).

Comparison with Time-Series Regression Factor Loadings. In **Table 5** and **Table 6**, we report factor loadings estimated by using time-series regressions following Equation 14. In these regressions, the coefficients were unconstrained, so we used the long–short factors of the Fama–French–Carhart model in Table 5 and the AQR model in Table 6.

Recall that Table 5 shows only small differences in the factor loadings of funds that scored high in terms of ESG metrics. Table 5 also shows no immediately obvious relationship between active return and ESG score. The highest ESG deciles in Table 5 generally have (1) lower exposure to the market beta and less volatility, (2) more focus on large companies, and (3) negative exposure to value. The differences in betas across deciles are difficult to interpret, however, in terms of their economic significance. For example, are the differences in market exposure in the Fama–French–Carhart model from highest to lowest (1.04 to 0.93) meaningful?

The QMJ betas in Table 6 are small and do not vary much across the decile portfolios—from 0.15 in the lowest decile to 0.05 in the highest decile. Beyond the lack of interpretation of the factor betas, this approach suffers from low power because fund factor loadings are dominated by the market factor. In contrast, the holdings-based approach to measuring alpha offers a clear delineation of the factor loadings of the funds and, hence, has potentially greater power. We now turn to this analysis.

Fund Alpha and ESG Scores. So far, we have focused on how the funds' active returns or factor loadings compare with ESG scores. We now turn our attention to funds' alphas. In our attribution model (see Equation 9), we decomposed active returns into static factor exposures, time-varying factors, and security selection. Only the security selection component does not involve factor exposures.

Table 7 reports two cross-sectional regressions: Regression I for the composite ESG score and Regression II for the environmental score only. We focus on the E score because of the strong relationships it has with the style factors in Tables 3–5. For both regressions, the dependent variable is the security selection alpha (based on quarterly holdings sourced from Morningstar and measured in percentages) for the five-year period from 30 June 2014 to 30 June 2019. On the right-hand side of the regressions, we used the Idiosyncratic ESG score,

Table 5. Fama–French–Carhart Time-Series Regression Factor Loadings Sorted by Decile ESG Score

		Factor Betas			
ESG Decile	Active Return (%)	Market	Size	Value	Momentum
1 (low)	−0.54	1.04	0.71	0.08	0.05
2	−0.85	1.01	0.61	0.15	0.06
3	−0.95	1.01	0.49	0.09	0.00
4	−1.60	1.00	0.28	0.04	−0.02
5	−1.40	0.98	0.18	0.01	−0.03
6	−1.59	0.98	0.07	−0.01	−0.03
7	−1.39	0.98	0.02	−0.05	−0.02
8	−0.97	0.97	−0.02	−0.05	−0.01
9	−1.18	0.96	−0.05	−0.07	0.01
10 (high)	−1.48	0.93	−0.07	−0.10	0.01
Mean	−1.20	0.99	0.22	0.01	0.00
Weighted mean	−0.33	0.97	0.06	−0.06	−0.02

Source: BlackRock, based on Morningstar data.

Notes: Factor betas were estimated over 30 June 2014–30 June 2019 using monthly returns for 1,312 funds. Active return is defined as the fund's return less its prospectus benchmark. Past performance does not guarantee future results.

Table 6. AQR Time-Series Regression Factor Loadings Sorted by Decile ESG Score

	Factor Betas					
ESG Decile	Market	Size	Value	Momentum	QMJ	BAB
1 (low)	1.08	0.90	−0.01	0.11	0.15	−0.03
2	1.07	0.81	0.08	0.10	0.23	0.02
3	1.06	0.64	0.03	0.05	0.17	−0.02
4	1.04	0.35	0.00	0.02	0.08	−0.01
5	1.01	0.21	−0.01	0.00	0.06	−0.01
6	1.00	0.06	−0.05	−0.01	0.02	0.00
7	0.99	−0.01	−0.09	0.00	0.00	−0.02
8	0.99	−0.05	−0.08	0.00	0.02	−0.01
9	0.98	−0.10	−0.11	0.01	0.01	−0.01
10 (high)	0.95	−0.12	−0.14	0.00	0.05	−0.01
Mean	1.02	0.27	−0.04	0.03	0.08	−0.01
Weighted mean	0.99	0.03	−0.10	0.01	−0.01	−0.02

Source: BlackRock, based on Morningstar data.

Notes: Factor betas were estimated over 30 June 2014–30 June 2019 using monthly returns for 1,312 funds. Here, QMJ and BAB represent the quality minus junk and betting against beta factors described in Asness et al. (2019) and Frazzini and Pedersen (2014), respectively. Active return is defined as the fund's return less its prospectus benchmark. Past performance does not guarantee future results.

which is unrelated to factors, and the Factor ESG score (see Equations 16 and 17), which picks up the components of ESG that are related to factors. For Regression II, we performed this nonfactor and factor decomposition for just the E score. We also included several control variables that Table 2 suggests are important in explaining active returns—namely, the fund's net expense ratio (in basis points), the log of AUM, annualized fund volatility for the sample computed from monthly returns measured in percentages, and dummy variables for the manager style benchmarks (large-cap value, blend, and growth), midcap, and small cap. The large-cap blend dummy variable was subsumed in the intercept.

The results in Table 7 indicate that only the factor component of ESG is positively related to active managers' stock selection abilities. In Regression I for the composite ESG score, Factor ESG has a coefficient of 3.22 (t-statistic of 4.51). In Regression II, which focuses only on the E score, the Factor ESG variable has a coefficient of 0.74 (t-statistic of 2.77). The Idiosyncratic ESG components in both regressions are negative and are not significant. Thus, security selection alpha by fund managers is related to ESG scores, but only the style factor component of ESG is rewarded; no significant relationship was found with the security selection alpha or the Idiosyncratic ESG components not related to style factors.

For the other variables in Table 7, we note that all the style dummies are positive, which means that the large-cap blend constant (embedded in the intercept) must have a negative alpha. This finding is consistent with the challenges large-cap managers have in beating broad benchmarks, such as the S&P 500 Index. The negative coefficient on the expense ratio and the positive coefficient on AUM are similar to those previously shown in Table 2. Finally, the positive coefficient on volatility is consistent with the model of Grinold (1994), where active managers take positions in positive-alpha stocks proportional to volatility.

For robustness, we present in **Table 8** the same regressions as in Table 7 except that we replaced security selection with active return (defined as the annualized fund return, in percentage, in excess of the prospectus benchmark) as the dependent variable. A marginal improvement occurs in R^2s and overall goodness of fit, as measured by the F-statistic. This result is to be expected because

Table 7. Cross-Sectional Regressions of Security Selection Alpha (%)

	Regression I: ESG Score		Regression II: Environmental Score	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Intercept	–21.61	–5.68*	–8.93	–5.51*
Expense ratio	–0.01	–6.01*	–0.01	–5.82*
log AUM	0.16	5.79*	0.17	5.96*
Idiosyncratic ESG	–0.40	–1.33	–0.25	–1.72
Factor ESG	3.22	4.51*	0.74	2.77*
Volatility	26.91	8.09*	23.43	7.39*
Large-cap growth	0.25	1.55	0.39	2.50*
Large-cap value	0.57	3.43*	0.39	2.41*
Midcap	1.17	5.71*	0.99	4.45*
Small cap	1.43	4.70*	1.07	3.26*
Adjusted R^2	0.16		0.15	
F-statistic	28.2		26.6	

Notes: The table shows two cross-sectional regressions for the composite ESG score (Regression I) and the environmental score only (Regression II) for 1,312 funds: In both, the dependent variable is stock selection alpha for the five-year period from 30 June 2014–30 June 2019 using quarterly holdings sourced from Morningstar and measured in percent. Here, the Idiosyncratic ESG and Factor ESG scores are given by Equations 16 and 17, with the Factor ESG being the fitted value of the regressions of ESG elements on factors. Annualized fund volatility for the five-year period is measured in percent. The large-cap blend dummy variable is subsumed in the intercept.

*Significant at the 5% level.

the active return is the sum of security selection alpha, dynamic timing alpha (albeit small in economic magnitude), and the returns to static factor tilts and because the factor loadings help explain the variation across all three elements. The results from Table 8 are consistent with Table 7; the Factor ESG component in both regressions (overall ESG and environmental score only) is highly statistically significant, but the Idiosyncratic ESG element is not. Overall, these results are consistent with the finding that the effect of ESG scores on alpha tends to manifest through factor tilts.

Conclusions

Fund managers can target ESG levels by taking on factor exposures or by concentrating on the Idiosyncratic ESG components that are unrelated to style factors. Because compelling theoretical and empirical evidence over the long run links style factors with risk premiums, whether fund ESG components related to factors are linked to returns is interesting to consider. Using bottom-up holdings data, we investigated the relationship between funds' ESG scores, factor loadings, and alpha in 1,312 active US equity mutual funds with $3.9 trillion in AUM. We found that ESG outcomes are correlated with style factors—value, momentum, quality, minimum volatility, and size—and that funds with high ESG scores exhibit interesting patterns in relation to factors. In particular, funds with high environmental scores have particularly strong exposures to quality and momentum factors. We showed that fund alphas and active returns are linked to Factor ESG components, but we found no link between fund alphas and active returns to ESG components unrelated to style factors.

Note that our analysis covers a recent period when ESG investing was relatively small. In the future, stocks that exhibit high ESG characteristics may exhibit alpha as their names are added to ESG

Table 8. Cross-Sectional Regressions of Active Return (%), 30 June 2014–30 June 2019

	Regression I: ESG Score		Regression II: Environmental Score	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Intercept	–44.06	–9.10*	–15.96	–7.68*
Expense ratio	–0.01	–3.02*	–0.01	–2.75*
log AUM	0.33	9.31*	0.34	9.39*
Idiosyncratic ESG	0.03	0.08	0.25	1.34
Factor ESG	7.67	8.43*	2.12	6.17*
Volatility	14.52	3.43*	8.10	1.99*
Large-cap growth	0.21	1.04	0.54	2.73*
Large-cap value	2.01	9.47*	1.60	7.78*
Midcap	2.48	9.49*	2.33	8.12*
Small cap	4.56	11.76*	4.09	9.70*
Adjusted R^2	0.22		0.20	
F-statistic	40.1		35.9	

Notes: This table shows two cross-sectional regressions for the composite ESG score (Regression I) and the environmental score only (Regression II) for 1,312 funds: In both, the dependent variable is annual active return (fund return in excess of prospectus benchmark) for the five-year period using quarterly holdings sourced from Morningstar and measured in percent. Here, the Idiosyncratic ESG and Factor ESG scores are given by Equations 16 and 17, with the Factor ESG being the fitted value of the regressions of ESG elements on factors. Annualized fund volatility for the five-year period from 30 June 2014 to 30 June 2019 using monthly return series is measured in percent. The large-cap blend dummy variable is subsumed in the intercept.

*Significant at the 5% level.

indexes that continue to see inflows. Another important caveat about our analysis is that we used ESG scores from only one provider, MSCI. Given the "aggregate confusion" (see Berg, Kölbel, and Rigobon 2019) about ESG ratings that may be weakly correlated across providers, an extension of this research would be to examine the relationship between alphas and ESG scores from other scoring systems.

From a practical perspective, our results suggest two main take-aways. First, when investors select funds with high ESG scores, those funds tend to also have significant factor exposures. Investors need to be aware of how ESG considerations may lead to factor tilts that differ from the market as a whole. To the extent that those factor exposures are desired, they may, over the long run, provide higher returns associated with those factor premiums. If the exposures are not desired, however, investors will need to adjust their portfolios while trying to maintain their ESG score. Second, we found that in our sample period, ESG exposure was rewarded—especially for funds with high environmental scores associated with large quality and momentum factor loadings. But the link between high ESG ratings and high returns is only through the ESG components that are correlated with factor components. Other ESG components unrelated to factors carry insignificant excess return premiums that are economically small.

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Notes

1. Biehl, Hoepner, and Liu (2012) documented several notable examples of ESG investing at the beginning of the 20th century—in particular, the Methodist Church and Quakers avoiding "sin" stocks. A wave of ESG investing occurred during the 1960s as investors debated and disinvested from companies engaging with apartheid, experiencing labor issues, and violating civil rights. Thus, ESG factors have long been considered by investors, but only recently have these issues been endorsed by the largest investors and corporations.

2. See, for example, the 2020 letter by BlackRock's CEO at www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter. The 2019 statement by the Business Roundtable is available at https://opportunity.businessroundtable.org/ourcommitment. Hartzmark and Sussman (2019) studied the natural experiment of Morningstar's adoption of ESG scores in active mutual funds for flows and performance.

3. See Clark, Feiner, and Viehs (2015), Friede, Busch, and Bassen (2015), and Gerard (2018) for reviews of past research. In addition to the references in the main text, Hoepner, Oikonomou, Sautner, Starks, and Zhou (2019) showed that ESG engagement reduces company downside risk and exposure to a downside-risk factor, and Ilhan, Sautner, and Vilkov (2019) showed that companies with higher carbon emissions have greater tail risk and are more volatile than companies with low emissions. Several individual metrics often used in the construction of ESG metrics have been linked to returns and risk. Companies with higher employee satisfaction (Edmans 2011), strong shareholder rights (Gompers, Ishii, and Metrick 2003), and strong corporate culture (Guiso, Sapienza, and Zingales 2015) outperform. Bolton and Kacperczyk (2020) found that stocks of firms with higher total CO_2 emissions earn higher returns after controlling for size and other factors and concluded that investors demand a risk premium for their exposure to carbon emission risk.

4. Seminal studies are Banz (1981) for size, Basu (1977) for value, Jegadeesh and Titman (1993) for momentum, Sloan (1996) for quality, and Ang, Hodrick, Xing, and Zhang (2006) for minimum volatility.

5. Ang (2014) provided a detailed summary of this research.

6. See also Brinson and Fachler (1985), Brinson, Hood, and Beebower (1995), Grinold (2006), and Cremers and Petajisto (2009). Dynamic timing by managers can confound traditional regression-based approaches that treat factor loadings as constant, as shown by Henriksson (1984) and Henriksson and Merton (1981). More recently, Chaudhuri and Lo (2018) used spectral analysis to decompose the return from factor timing further into its frequency components.

7. For further details, see www.msci.com/documents/1296102/15388113/MSCI+ESG+Fund+Ratings+Exec+Summary+Methodology.pdf/ec622acc-42a7-158f-6a47-ed7aa4503d4f?t=1562690846881.

8. The French data library is found at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

9. The Herfindahl–Hirschman Index (HHI) is widely used in economics to measure industry concentration and the distribution of individual attributes, such as income inequality. Its inverse reflects breadth. For example, suppose the HHI for market share in a given industry is 0.25. One way to interpret this number is that it corresponds to that of an industry with just 4 (= 1/0.25) equally sized companies (because $4 \times 0.25^2 = 0.25$).

10. Holdings-based characteristics are well suited to capturing dynamic effects—especially as many authors, including Henriksson and Merton (1981), have documented the existence of skilled managers who dynamically change factor loadings in response to changing economic environments. Return-based attribution methods can be adjusted for dynamic portfolio changes: Treynor and Mazuy (1966), Henriksson and Merton, and Henriksson (1984) added nonlinear terms to a time-series regression to capture market-timing components, but these approaches do not yield estimates of time-varying factor loadings.

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