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Abstract

Firms that score low on environmental, social, and governance (ESG) indicators exhibit higher expected returns. This negative ESG premium might be driven by higher risk associated with low ESG scores, or it could signal investors' preferences for firms with high ESG scores. The first driver implies an underlying, systematic ESG risk factor, such that ESG risk factor betas explain differences in expected returns. The second driver implies that firm-specific ESG characteristics explain the ESG premium. To identify the separate contributions of ESG betas and ESG characteristics for explaining variation in expected returns, this study uses two global data sets from 2004-2018 and reveals that ESG characteristics mainly explain variation in expected returns. A one standard deviation decrease in ESG scores is associated with an increase of 13 basis points in monthly expected returns. This study also sheds new light on how the term structure of the ESG premium has changed over time.

Keywords: Socially Responsible Investment, ESG Premium, EIV correction.
JEL: G11, C58

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1 Introduction

Socially responsible investment (SRI) funds incorporate firms' environmental, social, and governance (ESG) characteristics in their investment decisions. The US Social Investment Foundation (2016, 2018) reports that the total value of assets under management in the United States that are subject to SRI screening amounted to $11.06 trillion in 2018 – an increase of 44% relative to 2016. Globally, it reached $30.07 trillion, an increase of 34% since 2016 (Global Sustainable Investment Alliance, 2016, 2018). Thus, SRI now accounts for one out of every four dollars under professional management in the United States and one out of every two dollars in Europe. The incorporation of ESG characteristics in investment decisions reflects two main reasons: (1) ESG characteristics reflect investor preferences, unrelated to risk and return[1], or (2) ESG characteristics relate to their loadings (betas) on some underlying common risk factor. Either way, these motivations suggest a likely ESG premium on expected returns. We therefore aim to identify the separate contributions of systematic ESG risk factor betas and firm-specific ESG characteristics for generating the ESG premium. In doing so, we also shed some new light on how the term structure of the ESG premium has changed over time.

The most common form of SRI is negative/exclusionary screening, which excludes firms that underperform on various ESG indicators.[2] In general, systematic screening of assets based on investors' preferences leads to a return premium on the screened assets, in equilibrium, and such return differences cannot be arbitraged away by "neutral" investors (e.g. Merton, 1987, Heinkel et al., 2001, Dam and Scholtens, 2015). Systematically lower demand should lead to a systematically lower price and thus a higher dividend-price ratio. Even if responsible firms encounter higher operating costs, investors' preferences for SRI may make them willing to invest in such firms, despite the threat of lower returns. Therefore, if SRI is purely driven by investor preferences, ESG characteristics should explain any differences in expected returns. However, SRI might also reduce exposure to stakeholder risk (Freeman, 1984), by reducing stakeholder frictions. In

[1] Different labels designate (ESG) preferences unrelated to risk and return. For example, Derwall et al. (2011) use the term "values-driven investment approach" to identify social investments with non-pecuniary motivations, whereas Renneboog et al. (2008) use the terminology "the price of ethics" to refer to the price paid by investors, in terms of lower expected returns, for investing in responsible firms.

[2] The most common ESG strategy in Europe is negative screening, whereas ESG integration dominates in the United States, Canada, Australia, New Zealand, and Asia, with the exception of Japan, where corporate engagement and shareholder activism are primary strategies in Japan (Global Sustainable Investment Alliance, 2016, 2018).

this case, ESG characteristics seemingly relate to an underlying common ESG risk factor, and the associated factor betas should explain any differences in expected returns. De Haan et al. (2012) and Becchetti et al. (2018) attempt to construct such ESG risk factors.

To assess the relative contribution of ESG factor betas versus ESG characteristics in generating expected returns, we adopt a methodology suggested by Chordia, Goyal, and Shanken (2017). This firm-level, two-pass estimation, in the spirit of Fama and MacBeth (1973), accounts for the error-in-variables (EIV) problem and allows for time-varying betas and risk premiums. With the obtained estimates, they assess the fraction of cross-sectional return variation explained by betas compared with the fraction explained by characteristics. We apply their method to a global sample of 5,972 unique firms using ESG data from the ASSET4 database for the period 2004-2018. As asset pricing models, we consider the CAPM, the global Fama-French three- and five-factor models, and augmented versions of these models that include the momentum (Carhart, 1997) and the ESG risk factor, in the spirit of Becchetti et al. (2018). We find evidence of a negative ESG premium, in that firms with lower ESG scores exhibit higher expected returns. This negative premium is driven mainly by ESG characteristics, not ESG risk factor betas. In economic terms, a one standard deviation decrease in ESG characteristic is associated with an increase in expected returns of 13 basis points, on a monthly basis.

Our interpretation of the results relies on an equilibrium argument; irrespective of risk considerations, investors are willing to forgo potential returns if a firm scores well on ESG items (or alternatively, investors are only willing to hold firms that score low on ESG items if they are compensated with higher returns). However, considering the reported shift in demand toward SRI funds, the equilibrium we anticipate might have shifted too. An increase in the portfolio weights of firms that score high on ESG ratings leads to short-term capital gains for these firms. This way, *realized* returns may rise temporarily, even as *expected* long-run returns fall. Such a change in the term structure of the ESG premium would obfuscate our economic inferences. Motivated by the stylized facts established in return predictability literature (e.g., Campbell and Shiller, 1988), we investigate how the long-run ESG premium evolves over time by running Fama-Macbeth regressions of dividend-price ratios on the ESG characteristics. We confront the time series of this long-run component of the ESG premium with the time series of the one period component that is based on Fama-MacBeth regressions that use monthly returns as the dependent variable. For

both the one-period and long-run expected return the ESG premium is negative on average. However, for certain time periods, the one period component decreases as the long-run component increases, confirming our notion of equilibrium shifts. The observed changes in market capitalization weights during these periods corroborate our interpretation.

We also conduct multiple robustness checks. Our main sample uses ESG data from ASSET4, but we repeat our analysis with ESG indicators from a different data source, namely, VIGEO-EIRIS, which provides the ESG ratings of 2,160 unique firms. We also acknowledge that it might not be appropriate to adopt the global risk factors provided by Fama and French (2012), which are not representative of the firms in our data set. For example, their global factor model is not able to explain local returns very well. To mitigate this concern, we construct the global risk factors according to their methodology but by using only the stock returns in our sample. For both data sets, we find qualitatively and quantitatively similar results using these in-sample constructed risk factors.

Prior SRI literature offers mixed evidence of the existence of an ESG premium, as well as whether the premium is positive or negative and to what extent it is driven by betas or characteristics. Hong and Kacperczyk (2009) find that so-called sin stocks earn a positive risk-adjusted return of about 2.5% annually. In line with these findings, Bauer et al. (2005b, 2006, 2007), Galema et al. (2008), and Renneboog et al. (2008) find that firms that score positively on ESG items generate negative risk-adjusted returns, whereas Bauer et al. (2005a), Kempf and Osthoff (2007), and Glushkov and Statman (2009) find a positive relation between ESG characteristics and risk-adjusted returns. These studies mainly focus on differences in risk-adjusted returns, though occasionally researchers consider the relation among ESG characteristics, factor loadings, and expected returns (e.g., Galema et al., 2008). De Haan et al. (2012) and Becchetti et al. (2018) pay more explicit attention to factor loadings and construct an additional risk factor in a conventional way, by sorting assets along an ESG dimension and constructing a long-short portfolio of "worst" scoring minus "best" scoring firms. Their results provide some evidence of a priced ESG risk factor.

This lack of consensus may stem from various methodological issues that have been identified in recent literature (see Chordia, Goyal, and Shanken, 2017). For example, it is well known that because betas are generated regressors, they suffer from an error-in-variables (EIV) problem. A

common practice groups stocks into portfolios to improve the estimates of the betas and avoid this problem. However, Lewellen et al. (2010) point out that the method chosen to conduct the portfolio grouping can have a dramatic impact on the test results of an asset pricing model. Studies that use risk-adjusted returns also can avoid the EIV problem (Brennan et al., 1988), but such an approach cannot identify the separate contributions of loadings and characteristics, because the risk premiums are constrained to be equal to the sample mean of the risk factor. Another concern is the potentially mechanical relationship between factor loadings and characteristics, which would imply that the relation between factor loadings and expected returns might be mechanical as well (Ferson et al., 1999). A mechanical correlation between loadings and characteristics potentially complicates the identification of the relative contribution to expected returns. Finally, studies that use a global sample often adopt the global risk factors provided by Fama and French in their analysis. However, the constituents included among the Fama and French risk factors are often very different from the firms used in a particular sample. Using risk factors that are not representative for the investment universe under investigation likely reduces the pricing performance of a multi-factor model (Fama and French, 2012, 2017).

Therefore, as our first contribution to literature, we rule out the possibility that the mixed findings in SRI literature are due to methodological issues. As a second contribution, we explicitly estimate and compare the relative contribution of ESG characteristics and ESG factor betas to the cross-sectional variation in expected returns. This way, we advance discussions about whether ESG screening is driven by risk considerations or by investors' "taste for assets" (Fama and French, 2007). Furthermore, there has been relatively little discussion about whether the ESG premium has changed over time; to the best of our knowledge, this study is the first to highlight how changes in the term structure of the ESG premium due to changes in demand for SRI funds may obfuscate statistical and economic inferences about the ESG premium.

The paper is organized as follows: In the next section, we explain our methodology. In section 3, we describe our data set and provide the descriptive statistics. Section 4 reports the results and their economic interpretation of the ESG premium, Section 5 contains the robustness checks, and Section 6 concludes.

2 Methodology

To assess the relative contribution of ESG characteristics and ESG factor betas in explaining cross-sectional expected return variation, we adopt the approach suggested by Chordia, Goyal, and Shanken (2017). Their method consists of a two-pass procedure as in Fama and MacBeth (1973), but applied to individual stocks. In the second-stage cross-sectional regressions, they include both betas and firm characteristics. They deal with the EIV problem and finite-sample issues in the estimation, then use the obtained estimates to calculate measures of the relative contribution of betas and characteristics. We highlight the main steps here; for more details, we refer readers to their paper.

2.1 Time-Series Regressions

First, factor betas are estimated through time-series regressions of excess stock returns on the factors:

$$R^e_{i,t} = B_{0,i} + B_i' F_t + \epsilon_{i,t}, \tag{1}$$

where $R^e_{i,t}$ is stock i's excess return over the risk-free rate, $B_{0,i}$ is the intercept, B_i is a vector of factor betas ($\mathbf{k_1} \times \mathbf{1}$), F_t is a vector of factors ($\mathbf{k_1} \times \mathbf{1}$), and $\epsilon_{i,t}$ is the error term. We run this regression for rolling windows of two years of past daily stock returns to obtain estimates for monthly time-varying betas.

2.2 Cross-Sectional Regressions with Error-in-Variables Correction

For the cross-sections, given N_t active stocks, we specify the expected excess returns in terms of betas and factor risk premiums but allow for pricing errors to be related to a vector of firm characteristics, $Zsc_{i,t}$:

$$E_{t-1}[R^e_{i,t}] = \gamma_0 + \gamma_1' B_{i,t-1} + \gamma_2' Zsc_{i,t-1} =: \hat{X}_t \Gamma, \tag{2}$$

where $\hat{X}_t := [1_{N_t}, \hat{B}_{t-1}, Zsc_{t-1}]$ consists of a constant, the estimated matrix of factor betas $\hat{B}_{t-1}$ ($\mathbf{k_1} \times \mathbf{N_t}$), and the matrix of observed firm characteristics Zsc_t ($\mathbf{k_2} \times \mathbf{N_t}$); and $\Gamma := (\gamma_0, \gamma_1', \gamma_2')'$, where γ_0 is the excess zero-beta rate, γ_1 is a vector of factor beta premiums ($\mathbf{k_1} \times \mathbf{1}$), and γ_2

is a vector of characteristic premiums ($\mathbf{k_2} \times \mathbf{1}$). We thus consider models with constant beta premiums. As mentioned by Chordia, Goyal, and Shanken (2017), the patterns in unconditional premiums are of interest even if the conditional premiums vary over time; including them also facilitates comparisons with previous literature. When we explicitly discuss the ESG premium, we allow for a time-varying premium though.

To estimate Γ in Equation (2), we run a cross-sectional regression for each month, using $\hat{X}_t$ as independent variables. For each cross-sectional estimation, we apply an EIV correction. The EIV-corrected estimator, $\hat{\Gamma}_t^{Eiv}$, is defined as follows:

$$\hat{\Gamma}_t^{Eiv} = \left(\hat{X_t}'\hat{X_t} - \sum_{1=i}^{N_t} M'\hat{\Sigma}_{\hat{B}_{i,t-1}}M\right)^{-1}\hat{X}_t'R_t^e,$$

where the matrix $M = [0_{k_1\times 1}, I_{k_1\times k_1}, 0_{k_1\times k_2}]$ ensures that the adjustment only applies to the k_1 factor betas and not the constant or the k_2 characteristics. The matrix $\hat{\Sigma}_{\hat{B}_{i,t}}$ ($\mathbf{k_1} \times \mathbf{k_1}$) is the White (1980) heteroskedasticity-consistent covariance matrix for the time-series estimates of $\hat{B}_{i,t-1}$. This approach yields a time-series of cross-sectional coefficients $\Gamma_t^{Eiv} := (\gamma_{0,t}, \gamma_{1,t}', \gamma_{2,t}')'$. The ultimate estimate for Γ is calculated by taking the time-series average of Γ_t^{Eiv}.

2.3 Relative Contribution of Betas and Characteristics

With the estimate for Γ at hand, we calculate the expected excess returns in each month as:

$$E_{t-1}[R_t^e] = \hat{\gamma}_0 + E_{t-1}^{\hat{B}}[R_t^e] + E_{t-1}^{Zcs}[R_t^e],$$

where

$$E_{t-1}^{\hat{B}}[R_t^e] = \hat{B}_{t-1}\hat{\gamma}_1, \text{ and } E_{t-1}^{Zcs}[R_t^e] = Zcs_{t-1}\hat{\gamma}_2.$$

Next, we calculate the relative contribution of betas and characteristics in each month as:

$$C_{\hat{B},t} = \frac{\sigma_{cs}^2\left(E_{t-1}^{\hat{B}}[R_t^e]\right)}{\sigma_{cs}^2\left(E_{t-1}[R_t^e]\right)} \quad (3), \qquad C_{Zcs,t} = \frac{\sigma_{cs}^2\left(E_{t-1}^{Zcs}[R_t^e]\right)}{\sigma_{cs}^2\left(E_{t-1}[R_t^e]\right)}, \quad (4)$$

where $\sigma_{cs}^2\left(E_{t-1}[R_t^e]\right)$ is the cross-sectional variance of expected returns, $\sigma_{cs}^2\left(E_{t-1}^{\hat{B}}[R_t^e]\right)$ is the beta component of cross-sectional variance, and $\sigma_{cs}^2\left(E_{t-1}^{Zcs}[R_t^e]\right)$ is the characteristic component of cross-

sectional variance.[3] The ratio $C_{\hat{B},t}$ gives the contribution of the factor betas in the variation of cross-sectional expected returns at month t. Likewise, the ratio $C_{Zcs,t}$ gives the contribution of the characteristics in the variation of cross-sectional expected returns. These ratios are calculated for each month, and we report their time-series averages. Note that the average ratios need not add to 1 because of covariance between the two components.

3 Data and Descriptive Statistics

We collect data from different sources. Our main data on ESG scores at the firm level are from the Refinitiv ASSET4 database (previously known as Thomson Reuters).[4] In addition, we retrieve ESG scores from the VIGEO-EIRIS data set (provided by Moody's), and we repeat the entire analysis with these data as a robustness check. The number of unique firms per year ranges from 1,359 in 2004 to 5,219 in 2017, covering North America, Europe, Japan, Asia Pacific ex Japan, South America, and Africa.

We retrieve from Refinitiv DATASTREAM the following firm-level data on an annual basis: market value of equity; common equity; total assets; deferred taxes; net sales or revenues; selling, general, and administrative expenses; interest expense on debt; and cost of goods sold. We use these variables to create size (ME), book-to-market (BE/ME), operating profitability (Pro), and assets growth (Inv) characteristics, following the Fama and French (2015) approach. Furthermore, we collect monthly returns and dividend yields to be used in the cross-sectional regressions, along with daily returns for the estimation of monthly rolling-window betas.[5] From the Fama and French (2012, 2017) global risk-factor database, we obtain the monthly and daily excess return of the market (Mkt), the one-month T-bill rate (R_f), the size risk factor (SMB), the value risk factor (HML), the momentum risk factor (WML), the profitability risk factor (RMW), and the

[3]The calculation of the cross-sectional variances is subject to a similar adjustment, because of the estimation error for the betas. For details on how to construct the difference estimator that we report later in the tables; see Chordia, Goyal, and Shanken (2017)

[4]For a complete overview of the universe and the methodology used to assess the ESG score of a firm see: https://www.refinitiv.com/content/dam/gl/en/documents/methodology/esg-scores-methodology.pdf.

[5]The data types of the variables retrieved are as follows: $WC08001$ (market value of equity), $WC02999$ (total assets), $WC03501$ (common shareholders' equity), $WC03263$ (deferred taxes), $WC01001$ (net sales or revenues), $WC01101$ (selling, general, and administrative expenses), $WC01251$ (interest expense on debt), $WC01051$ (cost of goods sold), RI (Return Index), and dividend per share (DPS).

investment risk factor (CMA).[6] We filter out ADRs, units, preferred shares, and stapled securities. We exclude all firms with missing return data over the sample period and firms with an average monthly return greater than the 0.995 or lower than the 0.005 fractile.

In line with prior literature (Fama and French, 1992, 1993), all the accounting variables, including the ESG score, are assumed to be known by investors six months after the fiscal year-end. We end up with a sample of $5,972$ unique firms, resulting in an unbalanced panel of $697,790$ firm-month observations, between July 2007 and June 2018 (132 months). We use our sample of firm-month return observations in our estimations, while time-varying monthly betas are calculated using daily returns for a rolling-window period of 2 years.[7]

Before proceeding with our analysis, we shed some light on whether there is an ESG premium to explain in the first place. To this end, we construct ten portfolios based on ESG score deciles. The portfolios are rebalanced each year, six months after the fiscal year-end.

The first column of Table I shows the average monthly excess return for each ESG decile portfolio, where the portfolio labeled *Worst* consists of the firms with the lowest ESG scores, and the portfolio labeled *Best* consists of the firms with the highest ESG scores. Table I shows that the average excess return decreases as the ESG score increases (columns 1-2), though not monotonically. The question is whether these return differences are due to risk (factor betas) or investor preferences (characteristics). Moreover, the market capitalization of the *Best* portfolio is the largest of the ten portfolios, much larger than the *Worst* portfolio (column 3). At the same time, the differences in the average number of ordinary shares issued (column 4) are small, implying that the price per share is larger for firms with high ESG scores. Figure I shows the evolution over time of the relative market capitalization for the ESG decile portfolios. The market capitalization weight of the *Best* portfolio increases over time, which might be a reflection of the increase in demand for responsible assets.

[6] Fama–French web page: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[7] Our first estimation window for the rolling betas uses daily returns from July 2005 to June 2006. We then roll the window monthly, requiring at least 400 data points for the beta estimation. For each loading and characteristic, values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile each month. See Chordia, Goyal, and Shanken (2017) for additional details on the variable definitions.

Table I. Descriptive Statistics for Value Weighted ESG Decile Portfolios

The table reports the overall period average monthly excess return ($\bar{R}^e_p$) for the ESG decile portfolios as a percentage; the average ESG score ($\overline{Esg}_p$); average portfolio market capitalization, over the total market capitalization both in logs ($\overline{lME}_p$); and the average number of ordinary shares over the total number of ordinary shares outstanding, in logs as well ($\overline{lNs}_p$). The sample consists of 5,972 global firms for 132 months (July 2007 - June 2018). *Worst* is the portfolio composed of firms with the lowest ESG score, and *Best* is the portfolio composed of firms with the highest ESG score.

	(1)	(2)	(3)	(4)
	$\bar{R}^e_p$	$\overline{Esg}_p$	$\overline{lME}_p$	$\overline{lNs}_p$
Worst	0.588	21.232	0.068	0.098
2	0.608	28.879	0.074	0.098
3	0.585	33.673	0.090	0.099
4	0.495	37.707	0.103	0.100
5	0.416	41.551	0.107	0.101
6	0.417	45.554	0.110	0.101
7	0.553	50.585	0.097	0.100
8	0.535	56.968	0.098	0.100
9	0.439	64.551	0.114	0.101
Best	0.534	75.447	0.139	0.103

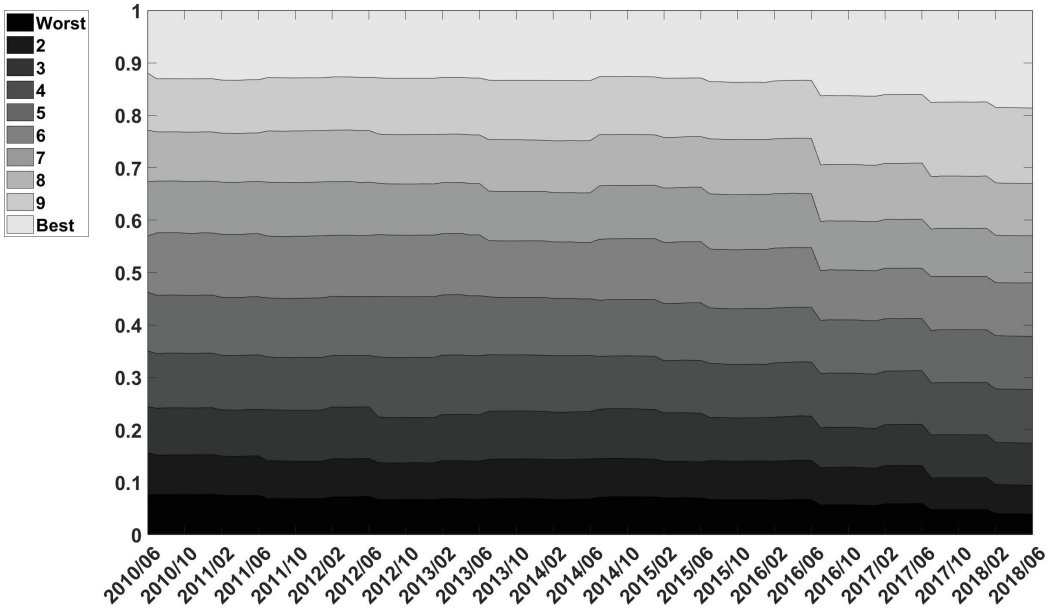


Figure I. Market Capitalization Weights over Time for ESG Decile Portfolios

The figure shows the evolution over time of the relative market capitalization of the value-weighted ESG decile portfolios relative to the total market capitalization.

Because we conduct our main analysis at the firm level instead of the portfolio level, we provide descriptive statistics at the firm level, too. Table II reports the cross-sectional distribution of the firm-specific characteristics (Panel A, columns 1-6) and the firm-level factor loading estimates (Panel A, columns 7-13), using factor model (1), including the ESG-risk factor (Becchetti et al., 2018), the Fama-French five factors (Fama and French, 2017), and the momentum risk factor (Carhart, 1997).[8] With at the average factor betas, Table II shows that our sample is characterized by firms with a relatively low exposure to the size, value, investment, and profitability factor, compared with Fama and French (2015, 2017). We also observe that our firms generally have a low exposure to the ESG risk factor (Panel A, columns 7-13).

The correlations exhibit the expected sign, including a negative one between the ESG risk factor and ESG characteristics (Panel B, columns 1-6). The negative correlations between size, investment, and ESG characteristics with the related betas indicate that larger firms with low investment growth and a higher ESG score are considered less risky by the market. In contrast, we find positive correlations among the book-to-market, profitability, and momentum characteristics and their related betas. Overall, the correlations between characteristics and betas are low. This evidence implies considerable independent variation of the characteristics and their related betas, which allows us to dissect the separate contributions of characteristics and risk to the cross-section of expected returns.

4 Results

Table III reports the results for the cross-sectional regressions using model (2) with the EIV-bias correction for the betas (Chordia, Goyal, and Shanken, 2017) for the following models: CAPM, global Fama and French (2012) 3-factor model, global Fama and French (2017) 5-factor model, a 6-factor model that augments the global 5-factor model with the momentum factor (Carhart, 1997), and a 7-factor model that augments the 6-factor model with the ESG risk factor (Becchetti et al., 2018).

For all model specifications, the intercepts (which can be interpreted as the expected return

[8] For each characteristic and beta, we first compute the cross-sectional means, standard deviations, and percentiles. We then take the time-series average of these summary statistics.

Table II. Descriptive Statistics for the Firm-Level Characteristics and the Estimated Betas

The table reports the time-series averages of the cross-sectional distributions for the monthly characteristics from column (1) to (6), and betas from column (7) to (13), estimated using factor model (1) that includes the following factors: the excess return of the market (Mkt), the size risk factor (SMB), the value risk factor (HML), the profitability risk factor (RMW), the investment risk factor (CMA), the momentum risk factor (WML), and the ESG risk factor (WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are the logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of 1 plus the last six-month return ($lRet6$) lagged one month, and the overall ESG score (ESG). The cross-sectional betas ($\hat{B}_{i,t-1}$) are the market beta ($\hat{\beta}_{mk}$), size beta ($\hat{\beta}_s$), value beta ($\hat{\beta}_h$), profitability beta ($\hat{\beta}_r$), investment beta ($\hat{\beta}_c$), momentum beta ($\hat{\beta}_w$), and ESG beta ($\hat{\beta}_{ESG}$). Panel A provides descriptive statistics for the distribution of the characteristics and estimated betas, Panel B provides correlations. The sample consists of 2,160 global firms for 132 months (July 2007 - June 2018), and we require at least 400 observations of daily returns to estimate the rolling-window betas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A: Cross-Sectional Distributions													
	lME	$lBtM$	Pro	Inv	$lRet6$	ESG	$\hat{\beta}_{mk}$	$\hat{\beta}_s$	$\hat{\beta}_h$	$\hat{\beta}_r$	$\hat{\beta}_c$	$\hat{\beta}_w$	$\hat{\beta}_{ESG}$
$Mean$	0.867	-0.696	0.372	0.174	0.020	45.284	1.038	0.448	-0.012	-0.210	-0.191	-0.086	-0.034
$St.dev.$	1.605	0.864	0.787	0.603	0.283	16.210	0.451	0.793	1.046	1.315	1.347	0.526	1.336
10%	-1.139	-1.800	0.016	-0.129	-0.286	25.380	0.500	-0.433	-1.127	-1.737	-1.845	-0.681	-1.740
25%	-0.149	-1.194	0.134	-0.029	-0.101	33.230	0.753	-0.078	-0.542	-0.850	-0.880	-0.331	-0.987
50%	0.886	-0.619	0.258	0.064	0.039	43.080	1.012	0.350	-0.013	-0.111	-0.083	-0.046	-0.098
75%	1.905	-0.124	0.456	0.197	0.165	56.790	1.295	0.868	0.530	0.570	0.620	0.203	0.951
90%	2.890	0.278	0.843	0.437	0.307	68.850	1.602	1.467	1.165	1.253	1.294	0.471	1.661

Panel B: Correlations

	lME	$lBtM$	Pro	Inv	$lRet6$	ESG	$\hat{\beta}_{mk}$	$\hat{\beta}_s$	$\hat{\beta}_h$	$\hat{\beta}_r$	$\hat{\beta}_c$	$\hat{\beta}_w$	$\hat{\beta}_{ESG}$
lME	1.000												
$lBtM$	-0.165	1.000											
Pro	0.132	-0.214	1.000										
Inv	-0.044	-0.103	-0.047	1.000									
$lRet6$	0.110	-0.026	0.008	-0.010	1.000								
ESG	0.184	-0.008	0.051	-0.061	0.003	1.000							
$\hat{\beta}_{mk}$	-0.092	0.035	-0.021	0.001	-0.055	0.018	1.000						
$\hat{\beta}_s$	-0.374	0.106	-0.112	0.028	-0.033	-0.103	0.269	1.000					
$\hat{\beta}_h$	0.002	0.249	0.062	-0.080	-0.028	-0.013	-0.032	0.066	1.000				
$\hat{\beta}_r$	0.076	0.068	0.017	-0.069	0.025	0.027	-0.003	0.087	0.384	1.000			
$\hat{\beta}_c$	0.006	-0.006	0.021	-0.097	0.024	0.032	0.136	0.064	-0.300	0.071	1.000		
$\hat{\beta}_w$	0.144	-0.160	-0.001	0.078	0.123	-0.006	-0.209	-0.172	0.023	0.026	-0.139	1.000	
$\hat{\beta}_{ESG}$	-0.111	-0.073	-0.043	0.015	0.033	-0.212	0.225	0.165	0.077	-0.033	0.129	-0.176	1.000

Table III. Cross-Sectional Regressions

The table reports the time-series averages of the estimated coefficients of the Fama-MacBeth cross-sectional regressions, accounting for the EIV bias:

$$R^e_{i,t} = \gamma_{0,t} + \gamma'_{1,t}\hat{B}_{i,t-1} + \gamma'_{2,t}Zcs_{i,t-1} + \epsilon_{i,t}.$$

The betas are estimated using different versions of factor model (1), namely, 1-factor (Mkt), 3-factor (Mkt, SMB and HML), 5-factor (Mkt, SMB, HML, RMW and CMA), 6-factor (Mkt, SMB, HML, RMW, CMA and WML), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are the logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of 1 plus the last six-month return ($lRet6$) lagged one month, and the overall ESG score (ESG). The cross-sectional betas ($\hat{B}_{i,t-1}$) are the market beta ($\hat{\beta}_{mk}$), size beta ($\hat{\beta}_s$), value beta ($\hat{\beta}_h$), profitability beta ($\hat{\beta}_r$), investment beta ($\hat{\beta}_c$), momentum beta ($\hat{\beta}_w$), and ESG beta ($\hat{\beta}_{ESG}$). Betas are estimated from rolling-window time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 5,972 global firms for 132 months (July 2007 - June 2018). The table reports the coefficients multiplied by 100 and t-statistics in brackets. $\bar{C}_{Zcs}$ and $\bar{C}_{\hat{B}}$ are the proportions of variation in expected returns explained by characteristics and betas, respectively. $Diff$ is the difference between these two values, and the square brackets contain the 95% confidence interval of this difference estimator. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)	(4)	(5)
	1-factor	**3-factor**	**5-factor**	**6-factor**	**7-factor**
$Const$	0.373	0.417	0.299	0.199	0.274
	[1.283]	[0.896]	[0.857]	[0.674]	[0.967]
lME	0.361***	0.411***	0.413***	0.415***	0.416***
	[6.221]	[5.601]	[6.581]	[7.183]	[7.233]
$lBtM$	0.017	0.044	0.024	0.026	0.049
	[0.191]	[0.507]	[0.320]	[0.389]	[0.774]
Pro	-0.113	-0.080	-0.084	-0.076	-0.074
	[-1.652]	[-1.345]	[-1.582]	[-1.564]	[-1.548]
Inv	-0.271***	-0.312***	-0.257***	-0.265***	-0.250***
	[-2.634]	[-3.056]	[-3.145]	[-3.341]	[-3.334]
$lRet6$	-0.288	-0.254	-0.235	-0.190	-0.192
	[-0.530]	[-0.422]	[-0.452]	[-0.396]	[-0.404]
ESG	-0.009***	-0.010***	-0.009***	-0.010***	-0.008***
	[-4.625]	[-5.104]	[-5.166]	[-5.830]	[-5.489]
$\hat{\beta}_{mk}$	-0.180	-0.312	-0.250	-0.157	-0.275
	[-0.412]	[-1.736]	[-1.260]	[-0.630]	[-1.051]
$\hat{\beta}_s$		0.224	0.312***	0.339***	0.354***
		[1.560]	[2.699]	[3.058]	[3.157]
$\hat{\beta}_h$		-0.045	-0.014	-0.014	-0.015
		[-0.344]	[-0.138]	[-0.131]	[-0.141]
$\hat{\beta}_r$			-0.084	-0.075	-0.039
			[-1.025]	[-1.012]	[-0.544]
$\hat{\beta}_c$			0.028	0.057	0.057
			[0.297]	[0.632]	[0.634]
$\hat{\beta}_w$				-0.146	-0.171
				[-0.671]	[-0.802]
$\hat{\beta}_{ESG}$					0.089
					[1.082]
$\bar{C}_{Zcs}$	92.564	95.108	97.187	100.511	93.104
$\bar{C}_{\hat{B}}$	2.682	13.610	20.269	26.484	30.777
$Diff$	89.882	81.498	76.918	74.027	62.327
	[41.240, 101.204]	[72.737, 89.168]	[60.401, 84.201]	[66.214, 82.598]	[53.889, 71.463]

on a zero-beta portfolio) are insignificant (Black et al., 1972, Fama and MacBeth, 1973). The premiums on firm characteristics are significant for each model specification, with the exception of the premium on book-to-market ($lBtM$), profitability (Pro), and past 6-month return ($lRet6$), indicating that these three characteristics present no explanatory power for the cross-section of expected returns. In contrast with Chordia, Goyal, and Shanken (2017), we find a positive sign for the size characteristic (lME). However, because we use a global sample, and the size characteristic is not scale free, these results are not directly comparable; a "large" firm in a country where the average market cap is small would be considered "small" globally. The premiums on the betas are insignificant, with the exception of the size risk premium. Specifically, the size risk premium varies between 0.312 (column 3) and 0.354 (column 5). Looking at the percentage of cross-sectional variance explained by characteristics ($\bar{C}_{Zcs}$) and betas ($\bar{C}_{\hat{B}}$), we find that the maximum variation in expected returns that the betas are able to explain is slightly above 30%, in line with the findings of Chordia, Goyal, and Shanken (2017). The characteristics appear to explain most of the cross-sectional variation in expected returns.

The premium on the ESG characteristic is negative and significant for all model specifications, including the 7-factor model that controls for ESG-risk exposure. The coefficients vary between -0.008 and -0.010 (Table III , columns 1-5). In economic terms, a one standard deviation decrease in the ESG score increases the monthly expected return by 13 ($16.210 \times |-0.008|$) basis points. The ESG risk factor betas are insignificant. In summary, these results indicate that the cross-sectional variation of expected returns related to the ESG premium is mainly driven by investor preferences for ESG-related issues, rather than that systematic risk components are captured by ESG scores (columns 1-5).

4.1 Interpretation and Term Structure of the ESG Premium

The main interpretation of our results relies on an equilibrium argument: The average investor is only willing to hold stocks with low ESG scores if compensated with higher expected returns. It is a "taste for assets" (Fama and French, 2007), that drives the ESG premium, not risk. However, the US Social Investment Foundation (2016, 2018) reports increased screening for ESG items over time, so the ESG characteristics premium could have changed over time too. An increase in relative demand for firms with large ESG scores leads to a systematic shift in equilibrium

price levels. Such a trend may confound our analysis, because *realized* returns rise temporarily as *expected* returns fall. In particular, it would impose an upward bias on our results, because the temporary positive (or "less negative") realized returns would be due to a drop in long-run returns. Put differently, increased screening of ESG scores over time may shift the equilibrium we predict, which would lead to changes in the term structure of expected returns.

These concerns warrant some additional investigation. As such, we try to formalize the notion that a rise in long-run returns implies a drop in realized returns. However, the sample period of our data set is relatively short. To address how economic inferences about the ESG premium using short-term returns may be confounded by changes in long-run expected returns, we rely on the stylized facts from return predictability literature (e.g., Campbell and Shiller, 1988).

First consider Campbell and Shiller (1988) log-linearization of the realized return identity in present value form:

$$dp_t = \left[\sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j} - \Delta d_{t+j}) \right], \tag{5}$$

where $dp_t = \log(D_t/P_t)$ is the log dividend-price ratio at time t, r_t is the log return, Δd_{t+j} is log dividend growth, and ρ is a constant. From return predictability literature, we know that virtually all variation in dividend-price ratios corresponds to variation in long-run expected returns. For ease of exposition and to be able to identify the changes in long-run expected returns, we assume that dividend growth is i.i.d. Then:

$$dp_t = E_t \left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} \right] - \mu_d, \tag{6}$$

where $\mu_d = E_t[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}]$, for all t, and we take the conditional expectation at time t. This equation shows that in the absence of dividend-growth predictability or rational "bubbles," dividend-price ratios are associated with long-run returns. By combining Equations (5) and (6), lagging the result one period, and subtracting the risk-free from both sides, we have:

$$E_{t-1}[r_t^e] = \underbrace{\underbrace{\mu_d - r_f + dp_{t-1}}_{Short-Run} - \underbrace{\rho E_{t-1}[dp_t]}_{Long-Run}}_{One-Period}, \tag{7}$$

so that the expected excess return can be decomposed in short- and long-run components. Equation (7) formalizes the idea that returns may go up temporarily due to the shift in demand for responsible assets, but it might reflect lower expected returns in the long run.

With Fama and MacBeth (1973) cross-sectional expected return regressions, we cannot disentangle short-run effects from long-run effects of ESG characteristics on expected returns. To assess the contribution of ESG characteristics to the cross-sectional variation in long-run expected returns, we relate the characteristics directly to the divided-price ratio by running the following T Fama-MacBeth regressions:

$$E_{t-1}\left[\frac{D_{i,t}}{P_{i,t}}\right] = \theta_{0,t} + \theta'_{2,t} Zsc_{i,t-1}, \forall t. \tag{8}$$

This procedure yields a time-series for the vector of parameters, $\theta_{2,t}$. Equation (8) is estimated at the portfolio level using the ESG decile portfolios introduced in Table I, instead of at the firm level, because individual firms pay out dividends too infrequently to obtain a monthly dividend-price ratio.

We assume that Equation (2) holds for one-period expected returns and captures the information about both short-run and long-run components in Equation (7). The cross-sectional regression for the expected returns can be rewritten as:

$$E_{t-1}[R^e_{i,t}] = \tilde{\gamma}_0 + \gamma'_1 B_{i,t-1} + \tilde{\gamma}'_2 Zsc_{i,t-1}$$

where $\tilde{\gamma}_0 = \gamma_0 - \rho\,\theta_0$, and $\tilde{\gamma}_2 = \gamma_2 - \rho\,\theta_2$. With $\theta_{ESG,t}$ and $\tilde{\gamma}_{ESG,t}$, we denote the time series of estimated parameters of Equations (2) and (8) for the ESG characteristic, respectively. For ease of exposition, we refer to $\tilde{\gamma}_{ESG,t}$ as the one-period component and $\theta_{ESG,t}$ as the long-run component of the ESG characteristic premium.

Figure II shows the three-year moving average of both the one-period component $\tilde{\gamma}_{ESG,t}$ (dashed line) and the long-run component $\theta_{ESG,t}$ (continuous line) of the ESG characteristic premium. Both time series have negative values for the entire sample period, so an increase in ESG scores is associated with lower expected returns for both the short run and the long run. Moreover and as

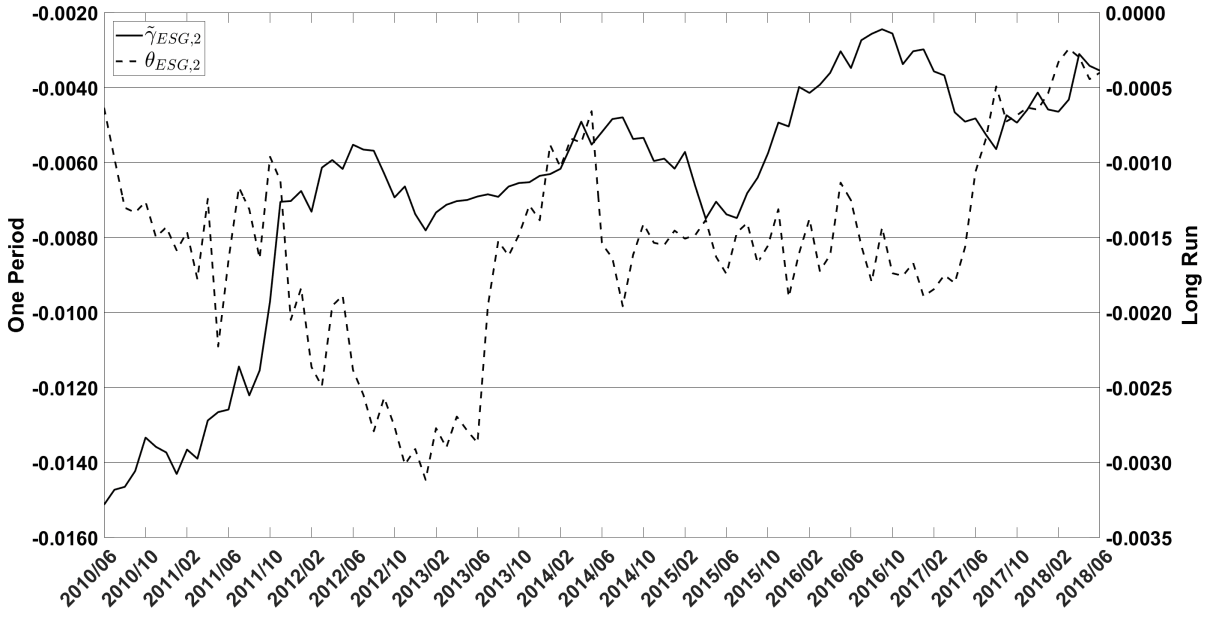


Figure II. Three-Year Moving Average of the One-Period and Long-Run Component of the ESG Characteristic Premium Over Time

The figure shows the three-year moving average of the ESG characteristics premium for the one-period component $\tilde{\gamma}_{ESG,t}$ (continuous line) based on Equation (2) estimated at the firm level, for the long-run component $\theta_{ESG,t}$ (dashed line) based on Equation (8) and estimated at the portfolio level.

expected, the figure also shows a slight negative correlation between the long-run and one-period component; for periods when the long-run component decreases, the one-period component increases, and vice versa. For example, the one-period ESG premium seems smaller (less negative) for the period June 2013 - June 2017, but the long-run premium increases substantially (becomes more negative) during this period. From Figure I we see that the portfolio weight in the *Best* decile portfolio also increased substantially for this period.

Taken together, we interpret these findings as follows: Shifts in demand lead to larger portfolio weights in assets with high *ESG* scores. These shifts mitigate the associated lower expected returns temporarily because of capital gains, but not in the long-run. A more sophisticated understanding of how ESG screening interacts with the term structure of expected returns requires a more thorough investigation, which is beyond the scope of our paper. Nonetheless, our exercise illustrates that researchers should be cautious when trying to assess the ESG premium, in particular for periods of increased ESG screening.

5 Robustness Checks

The absence of a significant premium for most of the risk factors, as well as the low explanatory power of the betas for the cross-sectional variation in expected returns, could result because the global risk factors provided by Fama and French are not representative for the investment universe that we investigate. Fama and French (2012) report that the global multi-factor model is not able to explain local returns very well, for example. In light of this concern, we first construct Fama and French risk factors based on the returns of the firms in our sample, then repeat our estimations with these risk factors.

Table IV reports the results, and they are by and large consistent with those in Table III. Again, the intercept is insignificant for each model specification, and the characteristics are all insignificant with the exception of lME and Inv. Critically, the ESG characteristic is still negative, strongly significant, and equal to -0.009 (column 3-4). In economic terms, a one standard deviation decrease in the ESG score increases the monthly expected return by 14.6 basis points. The results for the betas are also consistent with those in Table III. What we learn from Table IV is that the in-sample constructed risk factors confirm our results for the out-of-sample Fama-French risk factors. Again, the characteristics mainly drive the cross-sectional variation in expected returns.

Another concern relates to the ESG ratings. It is not always clear how ESG ratings are exactly constructed, nor whether a large enough investor base takes these ratings into account to have an effect on returns. Furthermore, many (arguably) subjective or ambiguous choices inform the construction or aggregation of the ratings. Therefore, as a second robustness check, we repeat the entire analysis with the ESG scores from the VIGEO-EIRIS database for the same time period. Starting with an unbalanced panel of 5,128 unique firms with 28,678 firm-year observations, and applying the same steps used for the ASSET4 database, we obtain a final VIGEO-EIRIS sample that is considerably smaller than ASSET4; it comprises 2,160 unique firms with 13,998 firm-year and 267,358 firm-month observations, from July 2007 to June 2018 (132 months).[9]

Table A-I in the appendix reports the descriptive statistics for the ESG decile portfolios composed of firms from the VIGEO-EIRIS database. Again, we observe a decreasing but non-monotonic

[9]The ASSET4 sample and VIGEO-EIRIS share 28% overlap in firms. Following the VIGEO-EIRIS methodological approach, we discard all firms with an ESG score lower then 30. In doing so, we exclude firms for which there is not enough information to construct an ESG rating.

Table IV. Cross-Sectional Regressions Using In-Sample Constructed Risk Factors

The table reports the time-series averages of the estimated coefficients of the Fama-MacBeth cross-sectional regressions, accounting for the EIV-bias:

$$R^e_{i,t} = \gamma_{0,t} + \gamma'_{1,t}\hat{B}_{i,t-1} + \gamma'_{2,t}Zcs_{i,t-1} + \epsilon_{i,t}$$

The betas are estimated using different versions of factor model (1), namely, 1-factor (Mkt), 3-factor (Mkt, SMB and HML), 5-factor (Mkt, SMB, HML, RMW and CMA), 6-factor (Mkt, SMB, HML, RMW, CMA and WML), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are the logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of 1 plus the last six-month return ($lRet6$) lagged one month, and the overall ESG score (ESG). The cross-sectional betas ($\hat{B}_{i,t-1}$) are the market beta ($\hat{\beta}_{mk}$), size beta ($\hat{\beta}_s$), value beta ($\hat{\beta}_h$), profitability beta ($\hat{\beta}_r$), investment beta ($\hat{\beta}_c$), momentum beta ($\hat{\beta}_w$), and ESG beta ($\hat{\beta}_{ESG}$). Betas are estimated from rolling-window time-series regressions using the past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 5,972 global firms for 132 months (July 2007 - June 2018). The table reports the coefficients multiplied by 100 and t-statistics in brackets. $\bar{C}_{Zcs}$ and $\bar{C}_{\hat{B}}$ are the proportions of variation in expected returns explained by characteristics and betas, respectively. $Diff$ is the difference between these two values; the square brackets contain the 95% confidence interval of this difference estimator. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)	(4)	(5)
	1-factor	**3-factor**	**5-factor**	**6-factor**	**7-factor**
$Const$	0.407	0.318	0.371	0.389	0.405
	[1.417]	[0.794]	[1.298]	[1.417]	[1.541]
lME	0.359***	0.404***	0.409***	0.422***	0.421***
	[6.178]	[6.340]	[6.947]	[7.574]	[7.748]
$lBtM$	0.029	0.031	0.038	0.040	0.041
	[0.324]	[0.354]	[0.584]	[0.651]	[0.685]
Pro	-0.109	-0.122**	-0.081	-0.079	-0.075
	[-1.594]	[-2.018]	[-1.599]	[-1.624]	[-1.561]
Inv	-0.265***	-0.305***	-0.244***	-0.241***	-0.234***
	[-2.612]	[-2.487]	[-3.083]	[-3.194]	[-3.177]
$lRet6$	-0.277	-0.262**	-0.200	-0.235	-0.198
	[-0.510]	[-0.460]	[-0.406]	[-0.491]	[-0.415]
ESG	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	[-4.601]	[-4.456]	[-5.011]	[-5.474]	[-6.052]
$\hat{\beta}_{mk}$	-0.157	-0.241	-0.295	-0.344	-0.375
	[-0.343]	[-1.309]	[-1.138]	[-1.194]	[-1.251]
$\hat{\beta}_s$		0.253***	0.260***	0.308***	0.329***
		[2.148]	[2.369]	[2.947]	[3.245]
$\hat{\beta}_h$		-0.107	-0.071	-0.034	-0.021
		[-0.577]	[-0.448]	[-0.212]	[-0.134]
$\hat{\beta}_r$			0.075	0.076	0.101
			[0.849]	[0.872]	[1.148]
$\hat{\beta}_c$			-0.005	0.016	-0.030
			[-0.026]	[0.104]	[-0.204]
$\hat{\beta}_w$				-0.047	-0.071
				[-0.265]	[-0.385]
$\hat{\beta}_{ESG}$					0.052
					[0.680]
$\bar{C}_{Zcs}$	93.443	94.961	99.254	100.142	100.493
$\bar{C}_{\hat{B}}$	1.979	22.414	22.427	25.270	29.387
$Diff$	91.463	72.546	76.828	74.872	71.106
	[41.848, 101.542]	[61.764, 81.303]	[65.647, 87.116]	[62.915, 84.380]	[58.046, 81.591]

Table V. Cross-Sectional Regressions Using ESG Data from VIGEO-EIRIS

The table reports the time-series averages of the estimated coefficients of the Fama-MacBeth cross-sectional regressions, accounting for the EIV bias:

$$R^e_{i,t} = \gamma_{0,t} + \gamma'_{1,t}\hat{B}_{i,t-1} + \gamma'_{2,t}Zcs_{i,t-1} + \epsilon_{i,t}$$

The betas are estimated using different versions of factor model (1), namely, 1-factor (Mkt), 3-factor (Mkt, SMB and HML), 5-factor (Mkt, SMB, HML, RMW and CMA), 6-factor (Mkt, SMB, HML, RMW, CMA and WML), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are the logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of 1 plus the last six-month return ($lRet6$) lagged one month, and the overall ESG score (ESG). The cross-sectional betas ($\hat{B}_{i,t-1}$) are the market beta ($\hat{\beta}_{mk}$), size beta ($\hat{\beta}_s$), value beta ($\hat{\beta}_h$), profitability beta ($\hat{\beta}_r$), investment beta ($\hat{\beta}_c$), momentum beta ($\hat{\beta}_w$), and ESG beta ($\hat{\beta}_{ESG}$). Betas are estimated from rolling-window time-series regressions using the past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 2,160 global firms for 132 months (July 2007 - June 2018). The table reports the coefficients multiplied by 100 and t-statistics in brackets. $\bar{C}_{Zcs}$ and $\bar{C}_{\hat{B}}$ are the proportions of variation in expected returns explained by characteristics and betas, respectively. $Diff$ is the difference between these two values; the square brackets contain the 95% confidence interval of this difference estimator. ***,** and * denotes 1%, 5%, and 10% significance.

	(1)	(2)	(3)	(4)	(5)
	1-factor	**3-factor**	**5-factor**	**6-factor**	**7-factor**
$Const$	0.837**	0.378	0.226	0.040	0.161
	[1.983]	[0.719]	[0.546]	[0.116]	[0.476]
lME	0.322***	0.376***	0.394***	0.395***	0.386***
	[4.278]	[4.484]	[5.130]	[5.417]	[5.691]
$lBtM$	-0.078	-0.047	-0.093	-0.114	-0.113
	[-0.761]	[-0.471]	[-1.101]	[-1.516]	[-1.500]
Pro	-0.044	-0.022	-0.044	-0.035	-0.042
	[-0.567]	[-0.315]	[-0.695]	[-0.597]	[-0.722]
Inv	-0.469*	-0.556**	-0.408*	-0.485**	-0.405*
	[-1.928]	[-2.369]	[-1.821]	[-2.248]	[-1.893]
$lRet6$	-0.592	-0.683	-0.460	-0.460	-0.370
	[-0.918]	[-1.011]	[-0.755]	[-0.862]	[-0.709]
ESG	-0.019***	-0.020***	-0.018***	-0.018***	-0.018***
	[-2.782]	[-3.007]	[-2.845]	[-2.827]	[-3.548]
$\hat{\beta}_{mk}$	-0.491	-0.156	-0.152	-0.046	-0.142
	[-0.864]	[-0.774]	[-0.722]	[-0.171]	[-0.477]
$\hat{\beta}_s$		0.162	0.249*	0.185	0.156
		[0.940]	[1.783]	[1.345]	[1.193]
$\hat{\beta}_h$		-0.128	-0.097	-0.052	-0.015
		[-0.846]	[-0.775]	[-0.377]	[-0.110]
$\hat{\beta}_r$			-0.009	0.016	-0.027
			[-0.100]	[0.167]	[-0.279]
$\hat{\beta}_c$			-0.001	0.054	0.087
			[-0.009]	[0.557]	[0.907]
$\hat{\beta}_w$				-0.156	-0.182
				[-0.573]	[-0.667]
$\hat{\beta}_{ESG}$					0.123
					[0.807]
$\bar{C}_{Zcs}$	65.841	84.380	88.964	101.722	85.712
$\bar{C}_{\hat{B}}$	18.049	11.113	12.131	11.255	12.569
$Diff$	47.791	73.267	76.833	90.467	73.144
	[-25.637, 102.800]	[57.983, 86.001]	[65.985, 86.402]	[82.355, 100.393]	[62.915, 87.305]

pattern in the average excess returns as we move from the *Best* to *Worst* portfolio, confirming an ESG premium. Moreover, the market capitalization of the *Best* portfolio as a percentage of the total market capitalization is on average among the highest, though the difference with respect to the *Worst* portfolio is not as pronounced as in Table I (column 3). Figure A-II is qualitatively similar to Figure I and confirms that investors increase their portfolio weights in assets with high ESG scores, though again the pattern is not as pronounced. Table A-II in the appendix reports the descriptive statistics of the cross-sectional distributions of the firm-specific accounting variables and ESG scores. Compared with ASSET4, the VIGEO-EIRIS database appears to be composed of firms with a high book-to-market ratios and "robust" profitability.

Table V reports the results for the cross-sectional regressions using the ESG data from VIGEO-EIRIS. The intercept is insignificant in almost all model specifications (columns 2-5), and the premiums on firm characteristics are insignificant for each model specification, with the exception of market capitalization (lME) and asset growth (Inv). The premium on the ESG characteristic is still negative and significant for all model specifications (columns 1-5), and it ranges between -0.018 and -0.020 per month. In economic terms, a one standard deviation decrease in the ESG score increases the monthly expected return by approximately 15 basis points ($8.34 \times |-0.018|$). Despite the difference in the methods that the two data providers use to construct ESG scores, the sign of the ESG characteristics premium is consistently negative, with comparable magnitudes. Different from the results in Table III, none of the risk factors appears to be priced. Finally, the percentage of cross-sectional variation explained by the factor loadings reaches its maximum for the 7-factor specification (column 5) and is slightly above 12%. Again, the characteristics explain most of the cross-sectional variation in expected returns (columns 1-5).

As a final robustness check, we conducted the analysis with in-sample constructed Fama-French risk factors for the VIGEO-EIRIS database. Table VI reports the results for the cross-sectional regressions with the EIV bias correction. The intercept and coefficients for the characteristics are consistent with those of Table IV in terms of significance. The ESG characteristic is again negative and significant in all model specifications and of the same magnitude; a one standard deviation increase in the ESG score decreases the monthly expected return by 16 basis points. Finally, with in-sample constructed risk factors, the size risk factor (columns 3-5) appears to be priced, and overall, the factor betas are better able to explain the cross-sectional varia-

Table VI. Cross-Sectional Regressions Using ESG Data from VIGEO-EIRIS and In-Sample Constructed Risk Factors

The table reports the time-series averages of the estimated coefficients of the Fama-MacBeth cross-sectional regressions, accounting for the EIV bias:

$$R^e_{i,t} = \gamma_{0,t} + \gamma'_{1,t}\hat{B}_{i,t-1} + \gamma'_{2,t}Zcs_{i,t-1} + \epsilon_{i,t}$$

The betas are estimated using different versions of factor model (1), namely, 1-factor (Mkt), 3-factor (Mkt, SMB and HML), 5-factor (Mkt, SMB, HML, RMW and CMA), 6-factor (Mkt, SMB, HML, RMW, CMA and WML), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are the logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of 1 plus the last six-month return ($lRet6$) lagged one month, and the overall ESG score (ESG). The cross-sectional betas ($\hat{B}_{i,t-1}$) are the market beta ($\hat{\beta}_{mk}$), size beta ($\hat{\beta}_s$), value beta ($\hat{\beta}_h$), profitability beta ($\hat{\beta}_r$), investment beta ($\hat{\beta}_c$), momentum beta ($\hat{\beta}_w$), and ESG beta ($\hat{\beta}_{ESG}$). Betas are estimated from rolling-window time-series regressions using the past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 2,160 global firms for 132 months (July 2007 - June 2018). The table reports the coefficients multiplied by 100 and t-statistics in brackets. $\bar{C}_{Zcs}$ and $\bar{C}_{\hat{B}}$ are the proportions of variation in expected returns explained by characteristics and betas, respectively. $Diff$ is the difference between these two values; the square brackets contain the 95% confidence interval of this difference estimator. ***,** and * denote 1%, 5%, and 10% significance.

	(1)	(2)	(3)	(4)	(5)
	1-factor	**3-factor**	**5-factor**	**6-factor**	**7-factor**
$Const$	0.368	0.253	0.516	0.391	0.223
	[1.077]	[0.522]	[1.375]	[1.173]	[0.702]
lME	0.336***	0.457***	0.463***	0.458***	0.459***
	[4.467]	[6.165]	[6.774]	[6.687]	[6.876]
$lBtM$	-0.115	-0.089	-0.049	-0.047	-0.069
	[-1.173]	[-1.017]	[-0.622]	[-0.602]	[-0.906]
Pro	-0.041	-0.053	-0.029	-0.023	-0.063
	[-0.535]	[-0.712]	[-0.466]	[-0.359]	[-1.027]
Inv	-0.569**	-0.734***	-0.500**	-0.456**	-0.466**
	[-2.383]	[-2.977]	[-2.378]	[-2.165]	[-2.196]
$lRet6$	-0.525	-0.674	-0.423	-0.408	-0.411
	[-0.808]	[-1.079]	[-0.729]	[-0.735]	[-0.757]
ESG	-0.019***	-0.021***	-0.025***	-0.025***	-0.019***
	[-2.783]	[-3.370]	[-4.291]	[-4.388]	[-3.644]
$\hat{\beta}_{mk}$	-0.147	-0.420*	-0.429	-0.309	-0.358
	[-0.273]	[-1.657]	[-1.246]	[-0.849]	[-0.983]
$\hat{\beta}_s$		0.323***	0.307***	0.315***	0.342***
		[2.682]	[2.509]	[2.566]	[2.758]
$\hat{\beta}_h$		0.009	0.007	0.056	0.006
		[0.041]	[0.031]	[0.267]	[0.027]
$\hat{\beta}_r$			0.082	0.109	0.017
			[0.629]	[0.917]	[0.145]
$\hat{\beta}_c$			0.005**	0.109	-0.033
			[0.020]	[0.620]	[-0.169]
$\hat{\beta}_w$				-0.293	-0.209
				-1.398	-1.015
				[0.165]	[0.312]
$\hat{\beta}_{ESG}$					0.220
					[1.398]
$\bar{C}_{Zcs}$	90.769	128.422	124.621	112.448	114.813
$\bar{C}_{\hat{B}}$	1.844	35.908	33.256	36.238	33.239
$Diff$	88.925	92.514	91.365	76.211	81.574
	[23.448, 104.905]	[79.675, 105.077]	[72.652, 108.708]	[59.420, 93.892]	[70.152, 96.984]

tion in expected returns (columns 1-5) compared with Table V. Nevertheless, the characteristics still mainly drive the cross-sectional variation in expected returns. In summary, we find robust evidence that the ESG premium is mostly driven by characteristics and not factor betas.

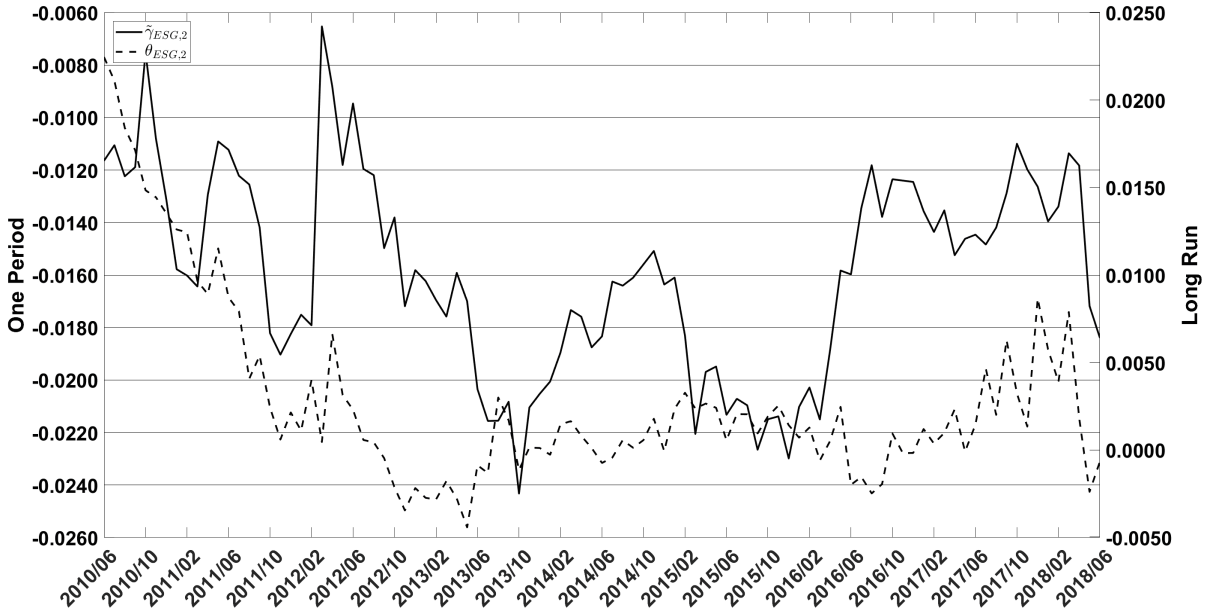


Figure III. Three-Year Moving Average of the One-Period and Long-Run Component of the ESG Characteristic Premium Over Time Using ESG Data from VIGEO-EIRIS

The figure shows the three-year moving average of the ESG characteristics premium for the one-period component $\tilde{\gamma}_{ESG,t}$ (continuous line) based on Equation (2) and estimated at the firm level, as well as for the long-run component $\theta_{ESG,t}$ (dashed line) based on Equation (8) and estimated at the portfolio level.

We also repeat our expected return decomposition for the VIGEO-EIRIS data. Figure III shows the three-year moving average of both the one-period component $\tilde{\gamma}_{ESG,t}$ (continuous line) and the long-run component $\theta_{ESG,t}$ (dashed line) of the ESG characteristic premium. The figure indicates a slight negative correlation between the long-run and one-period components. The most interesting period is at the beginning of the sample, when the long-run component decreases rapidly, while the one-period component spikes. Again, we interpret this result as a shift in equilibrium; increased weights in firms with high SRI scores result in less negative short-term returns due to capital gains, but long-run expected returns decrease. In Figure A-II, we note the shift in terms of market capitalization from the *Worst* to the *Best* portfolio, though it is not as pronounced as the shift in Figure I based on the ASSET4 data. After 2012, there is no clear trend in the time

series depicted in Figure III; both the one-period and long-term components of the ESG premium appear relatively stable.

6 Conclusion

The inclusion of ESG characteristics in investment decisions result from for two different reasons, namely: ESG characteristics simply reflect investor preferences, unrelated to risk and return or ESG characteristics relate to loadings (betas) on some underlying common risk factor. Either way, these motivations potentially lead to an ESG premium on expected returns. With this study, we identify the separate contributions of systematic ESG risk factor betas and firm-specific ESG characteristics in generating the ESG premium.

Using a global sample of firms for the period 2004 to 2018, and accounting for the EIV problem, we find evidence of an ESG premium. In addition, ESG characteristics appear to explain a much larger proportion of the cross-sectional variation in expected returns relative to the ESG risk factor betas. Specifically, a one standard deviation decrease in the ESG score is associated with an increase in monthly expected returns of about 13 basis points. These results are consistent across two ESG data sets and robust to various model specifications and different proxies for the risk factors.

Our interpretation of the results relies on an equilibrium argument. Investors are only willing to hold firms with low ESG scores if they are compensated with higher expected returns, irrespective of risk considerations. With this interpretation, we also check whether the ESG premium is stable over time. We observe a decrease in the premium and postulate that increased interest in SRI may have caused this decrease. Specifically, using Fama-MacBeth regressions of dividend-price ratios on ESG characteristics, we show that the long-run component of expected returns might blur our analysis; realized returns drop temporarily as expected returns rise. Even though the ESG premium is present for both long-run and short-run returns, the term structure of expected returns appears to change during periods of increased screening of ESG items.

A potential direction for continued research would be to attempt to disaggregate the overall ESG indicators. Overall ESG scores currently aggregate ratings from several dimensions. The ESG characteristics effect may depend on the interaction of highly heterogeneous ESG dimensions.

Specifically, corporate governance measures are oriented at protecting shareholder rights, but most other ESG measures in the environmental or social domains are oriented toward protecting the rights of other stakeholders. The various dimensions therefore might interact, which may affect the assessments of the premium earned from each ESG characteristic. Furthermore, a more thorough investigation of how increased screening of ESG items interacts with the term structure of expected returns seems a fruitful direction for research.

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Appendix: Descriptive Statistics for the VIGEO-EIRIS ESG Data Set

Table A-I. Descriptive Statistics for Value Weighted ESG Decile Portfolios Using ESG Data from VIGEO-EIRIS

The table reports the overall period average monthly excess return ($\bar{R}_p^e$) for the ESG decile portfolios as a percentage; the average ESG score ($\overline{Esg}_p$); average portfolio market capitalization over the total market capitalization, both in logs ($\overline{lME}_p$); and the average number of ordinary shares over the total number of ordinary shares outstanding, both in logs as well ($\overline{lNs}_p$). The sample consist of 2,160 global firms for 132 months (July 2007 - June 2018). *Worst* is the portfolio composed of firms with the lowest ESG score, and *Best* is the portfolio composed of firms with the highest ESG score.

	(1)	(2)	(3)	(4)
	$\bar{R}_p^e$	$\overline{Esg}_p$	$\overline{lME}_p$	$\overline{lNs}_p$
$Worst$	0.538	30.690	0.100	0.124
2	0.538	32.858	0.079	0.090
3	0.665	34.774	0.095	0.103
4	0.579	36.764	0.085	0.090
5	0.658	39.021	0.100	0.104
6	0.453	41.478	0.096	0.096
7	0.579	44.150	0.109	0.105
8	0.295	47.041	0.097	0.089
9	0.429	51.050	0.125	0.106
$Best$	0.144	57.698	0.113	0.094

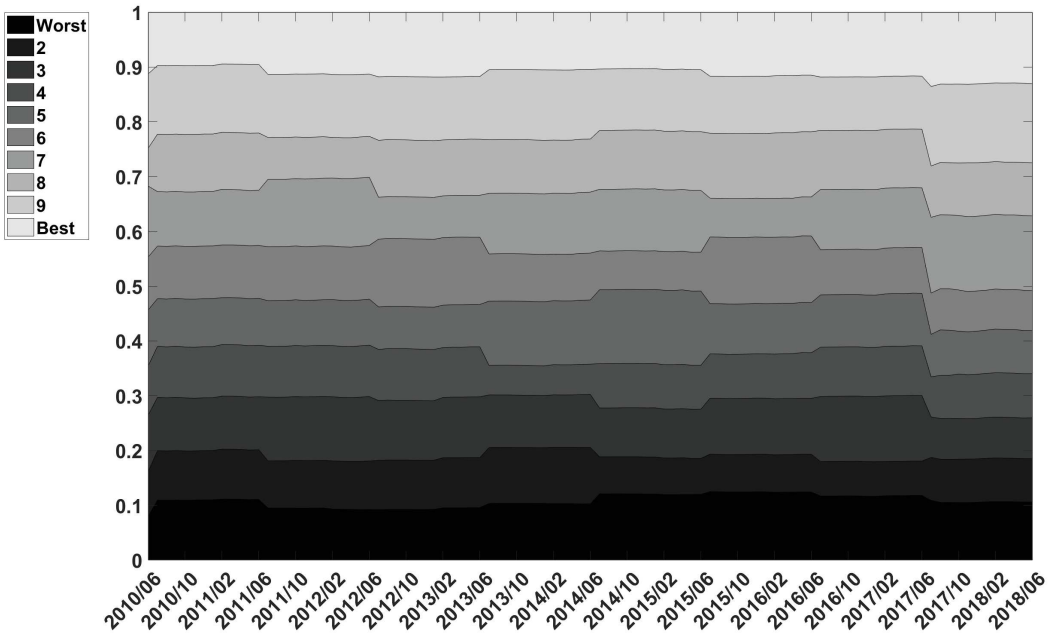


Figure A-II. Market Capitalization Weights over Time for ESG Decile Portfolios Using ESG Data from VIGEO-EIRIS

The figure shows the evolution over time of the relative market capitalization of the value-weighted ESG decile portfolios relative to the total market capitalization.

Table A-II. Descriptive Statistics for the Firm-Level Characteristics and Estimated Betas Using ESG Data from VIGEO-EIRIS

The table reports the time-series averages of the cross-sectional distributions for the monthly characteristics from column (1) to (6), and betas from column (7) to (13), estimated using factor model (1) that includes the following factors: the excess return of the market (Mkt), the size risk factor (SMB), the value risk factor (HML), the profitability risk factor (RMW), the investment risk factor (CMA), the momentum risk factor (WML), and the ESG risk factor (WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are the logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of 1 plus the last six-month return ($lRet6$) lagged one month, and the overall ESG score (ESG). The cross-sectional betas ($\hat{B}_{i,t-1}$) are the market beta ($\hat{\beta}_{mk}$), size beta ($\hat{\beta}_s$), value beta ($\hat{\beta}_h$), profitability beta ($\hat{\beta}_r$), investment beta ($\hat{\beta}_c$), momentum beta ($\hat{\beta}_w$), and ESG beta ($\hat{\beta}_{ESG}$). Panel A provides descriptive statistics for the distribution of the characteristics and estimated betas; Panel B provides the correlations. The sample consists of 2,160 global firms for 132 months (July 2007 - June 2018), and we require at least 400 observations of daily returns to estimate the rolling-window betas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)

Panel A: Cross-Sectional Distributions

	lME	$lBtM$	Pro	Inv	$lRet6$	ESG	$\hat{\beta}_{mk}$	$\hat{\beta}_s$	$\hat{\beta}_h$	$\hat{\beta}_r$	$\hat{\beta}_c$	$\hat{\beta}_w$	$\hat{\beta}_{ESG}$
$Mean$	1.905	-0.691	0.479	0.092	0.016	40.745	1.030	0.216	0.129	0.095	-0.210	-0.072	-0.278
$St.dev.$	1.337	0.827	0.766	0.333	0.246	8.340	0.409	0.684	0.875	1.118	1.223	0.460	0.781
10%	0.267	-1.743	0.097	-0.132	-0.244	31.000	0.520	-0.556	-0.869	-1.264	-1.736	-0.591	-1.390
25%	1.001	-1.187	0.191	-0.045	-0.083	34.000	0.784	-0.235	-0.394	-0.498	-0.825	-0.284	-0.834
50%	1.867	-0.627	0.314	0.042	0.032	39.000	1.019	0.149	0.064	0.161	-0.091	-0.041	-0.141
75%	2.780	-0.126	0.542	0.150	0.145	46.000	1.273	0.575	0.590	0.759	0.520	0.182	0.302
90%	3.651	0.271	1.040	0.309	0.264	53.000	1.535	1.077	1.225	1.400	1.159	0.419	0.619

Panel B: Correlations

	lME	$lBtM$	Pro	Inv	$lRet6$	ESG	$\hat{\beta}_{mk}$	$\hat{\beta}_s$	$\hat{\beta}_h$	$\hat{\beta}_r$	$\hat{\beta}_c$	$\hat{\beta}_w$	$\hat{\beta}_{ESG}$
lME	1.000												
$lBtM$	-0.199	1.000											
Pro	0.091	-0.330	1.000										
Inv	0.020	-0.077	-0.034	1.000									
$lRet6$	0.104	-0.035	-0.003	-0.011	1.000								
ESG	0.235	0.091	0.075	-0.043	-0.010	1.000							
$\hat{\beta}_{mk}$	-0.061	0.113	-0.009	-0.010	-0.020	-0.009	1.000						
$\hat{\beta}_s$	-0.369	0.158	-0.114	-0.031	-0.041	-0.100	0.106	1.000					
$\hat{\beta}_h$	-0.096	0.308	0.031	-0.078	-0.047	0.026	0.058	0.167	1.000				
$\hat{\beta}_r$	-0.048	0.019	-0.070	-0.043	0.018	-0.031	0.012	0.257	0.267	1.000			
$\hat{\beta}_c$	0.082	-0.049	0.020	-0.097	0.032	-0.017	0.038	0.045	-0.342	0.098	1.000		
$\hat{\beta}_w$	0.114	-0.191	-0.010	0.086	0.132	0.008	-0.154	-0.155	-0.045	0.010	-0.086	1.000	
$\hat{\beta}_{ESG}$	0.187	-0.094	-0.066	0.058	0.042	-0.340	0.071	-0.001	-0.036	0.081	0.119	-0.013	1.000

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