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The contributions of betas versus characteristics to the ESG premium

Rocco Ciciretti [a,b], Ambrogio Dalò [c,*], Lammertjan Dam [c]

[a] University of Rome "Tor Vergata", Italy
[b] RCEA-Rimini, Italy
[c] University of Groningen, The Netherlands

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ABSTRACT

Firms that score high on environmental, social, and governance (ESG) indicators exhibit lower expected returns. This negative ESG premium might be driven by the lower risk associated with high ESG scores (betas), or it could signal investors' preferences for firms with high ESG scores (characteristics). We show that ESG as a characteristic mainly drives the premium. Specifically, a one standard deviation increase in the ESG characteristic is associated with a decrease in expected returns of 2.73% annually. In addition, the ESG characteristic explains a higher proportion of the cross-sectional variation in expected returns compared to ESG betas. We further caution for the presence of an ESG bias within the ESG premium that is due to positive *realized* returns preceding lower long-term *expected* returns. When correcting our estimates for the ESG bias the decrease in expected returns turns out to be 3.41% on an annual basis. The ESG bias correction, together with a firm-level methodology, can help clarify the mixed findings documented in the literature.

1. Introduction

Socially responsible investment (SRI) funds incorporate firms' environmental, social, and governance (ESG) characteristics in their investment decisions. The US Social Investment Foundation (2020, 2018) reports that the total value of assets under management (AUM) subject to SRI screening amounted to $17.1 trillion in 2020 —an increase of 42% relative to 2018. Consistent with such anecdotal evidence, Hartzmark and Sussman (2019) show that within the US mutual fund market, investors are channeling funds away from low-rated towards high-rated ESG funds. Globally, the AUM subject to SRI screening reached $35.3 trillion, an increase of 15% since 2018 (Global Sustainable Investment Alliance, 2020, 2018).

The incorporation of ESG characteristics in investment decisions reflects two main reasons: (1) ESG characteristics underscore investor preferences unrelated to risk and return[1], or (2) ESG characteristics relate to loadings (betas) on some underlying common risk factor. Either way, these motivations suggest a likely ESG premium on expected returns. We first verify that there is such a premium, and we next aim to identify the separate contributions of systematic ESG risk factor betas and firm-specific ESG characteristics for generating the ESG premium. In addition, we provide evidence that positive realized returns generated by temporary increases in demand for ESG assets biases the monthly ESG premium estimates, given that these increases precede lower long-run expected returns.

* Corresponding author.
E-mail addresses: rocco.ciciretti@uniroma2.it (R. Ciciretti), a.dalo@rug.nl (A. Dalò), l.dam@rug.nl (L. Dam).

[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.

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The most common form of SRI is negative/exclusionary screening, which entails excluding firms that underperform on various ESG indicators from the investment portfolio.[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—so the return difference will not abate (for formal theoretical treatments of this mechanism, see e.g. Pástor et al., 2021a, Pedersen et al., 2021, Dam and Scholtens, 2015, Heinkel et al., 2001, and Merton, 1987). Intuitively, systematically higher demand for firms scoring high on ESG indicators should lead to a systematically higher stock price and thus a lower dividend-price ratio. Therefore, if SRI is purely driven by investor preferences, ESG characteristics should directly explain some of the differences in expected returns. However, SRI might also reduce exposure to e.g. stakeholder risk, by reducing stakeholder frictions (Freeman, 1984). In this case, ESG characteristics seemingly relate to an underlying common ESG risk factor.

To verify first that there exists an ESG premium, we rely on a standard portfolio-level sorting exercise. Next, to assess the relative contribution of ESG factor betas versus ESG characteristics in generating the differences in expected returns, we adopt the firm-level methodology proposed by Chordia, Goyal, and Shanken (2017). In the spirit of Fama and MacBeth (1973), this firm-level two-pass estimation accounts for the error-in-variables (EIV) problem, and allows for time-varying betas and risk premiums to assess the fraction of cross-sectional return variation explained by betas compared to the fraction explained by characteristics. We find that the monthly ESG premium is mostly driven by ESG characteristics, and not betas. We finally argue theoretically, and aim to show empirically that the observed increases in demand for ESG assets generates (temporarily) an increase in *realized* returns, and biases the estimate for the monthly ESG premium. We perform our analysis on a global sample of 7,772 unique firms using ESG data from the ASSET4 database for the period 2003–2020.

Our results add three insights to the literature on ESG investing. As a first contribution, we corroborate the idea that there exists an ESG premium to be explained in the first place. In line with previous empirical studies, we show that such a premium appears to be negative and significant (Albuquerque et al., 2019; Luo and Balvers, 2017; Hong and Kacperczyk, 2009; Galema et al., 2008; Renneboog et al., 2008; Bauer et al., 2007). Second, we show that the negative ESG premium is driven mainly by investor preferences (characteristics) rather than risk (betas). In economic terms, a one standard deviation increase in the ESG characteristic is associated with a decrease in expected returns of 2.73% annually—ESG characteristics indeed are much better able to explain the cross-sectional variation in expected returns compared to ESG betas. As a final contribution, we show that when estimating the ESG premium one should correct for the ESG bias generated by positive realized returns resulting from sudden shifts in demand towards ESG assets that we have seen in recent years on financial markets (Global Sustainable Investment Alliance, 2020, 2018). After correcting for the ESG bias in the estimate of the monthly unbiased ESG premium, the negative premium in expected returns turns out to be equal to 3.41% annually. As such, independently from the sign of the ESG premium previously reported by the literature, our results show that such estimates are conservative and that the reduction in expected returns may be even larger than previously thought. Even when the ESG premium is estimated to be positive (Statman and Glushkov, 2009) or non significant (Bauer et al., 2007), it might be due to the absence of the ESG bias correction.

We conduct multiple robustness checks. First, we 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 firms in our sample. Second, in the spirit of Fama and French (2012, 2017), we repeat our analysis at single investment area level. Third, we repeat our analysis with ESG indicators from a different data source, namely, VIGEO-EIRIS, that provides the ESG ratings of 3,696 unique firms. We find qualitatively and quantitatively similar results across all three robustness checks.

Despite the rather clear theoretical prediction provided recently by Pástor et al. (2021a) and Pedersen et al. (2021), prior SRI literature offers mixed evidence of the existence of an ESG premium, as well as whether the premium is positive or negative, and commonly neglects to identify to what extent it is driven by betas or characteristics. The majority of the literature finds that investing in firms with higher ESG scores leads to lower risk-adjusted returns (alphas) (see e.g. Albuquerque et al., 2019; Luo and Balvers, 2017; Hong and Kacperczyk, 2009; Galema et al., 2008; Renneboog et al., 2008; Bauer et al., 2007). Specifically, 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. (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. A second smaller strand of literature finds that investing in firms with higher ESG scores leads to greater risk-adjusted returns (e.g. Statman and Glushkov, 2009; Kempf and Osthoff, 2007; Bauer et al., 2005). In this respect however, Pástor et al. (2021b) show that the higher returns delivered by green assets are mainly due to an unexpected strong increase in environmental concerns, rather than high expected returns. All studies mentioned above 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). Yet, some literature instead finds that there is no difference at all in terms of returns between ESG and conventional investing (e.g. Bauer et al., 2007, 2006; Hamilton et al., 1993). 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.

We argue that this lack of consensus may stem from various methodological issues. First, most of these studies exclusively investigate the ESG effect at the aggregated portfolio level or ESG fund level and focus on risk-adjusted returns based on multi-factor

[2] The most common sustainable investment strategy is ESG integration, followed by negative screening, corporate engagement and shareholder action, norms-based screening and sustainability-themed investment. (Global Sustainable Investment Alliance, 2020).

time-series regressions. Looking at risk-adjusted returns (alphas) based on time series regressions and trying to relate these to ESG scores, as proposed by Brennan et al. (1998), constrains the factor-risk premia to be equal to the sample average of the risk factors. This can be problematic as these constraints may not provide the best estimate for the risk premium, in particular because in most ESG studies the sample period is relatively short due to limited data availability on ESG investing. Moreover, 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 any asset pricing model. Additionally, trying to dissect the contribution of betas versus characteristics using information at portfolio level is usually unfeasible due to the mechanically high correlation between the two variables (Ferson et al., 1999). Second, all previous studies ignore a potential ESG bias due to positive realized returns on the ESG premium estimate. It may well be that lower expected returns are preceded by higher realized returns (in the form of pure capital gains) generated by sudden increases in demand for ESG assets that we observe on financial markets (Pástor et al., 2021b; Hartzmark and Sussman, 2019). As such, positive realized returns bias the estimate for the ESG premium, and this mechanism may also explain the mixed findings documented in the literature so far, on top of the other methodological concerns regarding the use of a pure portfolio-level analysis.

To the best of our knowledge we are the first to explicitly address both these methodological issues. Specifically, using the methodology proposed by Chordia, Goyal, and Shanken (2017), and by using all firm-level data in the cross-section, we do not constrain the premium to be equal to the sample average of the risk factors. Moreover, a firm-level approach (with lower correlation between betas and characteristics) does allow us to pin down the impact of both betas and characteristics on expected returns. On top of that, we are the first to suggest a methodology that is able to correct the estimate of the ESG premium for the potential ESG bias due to positive realized returns.

Our findings have several implications for, investors, policy makers and researchers. First, on average, investor preference for ESG assets comes with the cost of lower expected future returns, which is only temporarily compensated by positive realized returns. Specifically, investors may expect to face a reduction in expected return of about 2.73% on an annual basis. Such a reduction becomes even more pronounced when correcting the biased ESG premium for the ESG bias and translates to a decrease in expected returns of about 3.41% on an annual basis. Even if the difference between the two may seem rather small, it is worth mentioning that the decrease in expected returns tends to increase as investors: (1) tilt their portfolios even more towards stocks with the best ESG performance (e.g., by using a two standard deviation increase of the ESG characteristic instead of one), and (2) if they keep following such a strategy for a prolonged period. To put it concisely, the insights provided by our results may help investors better calibrate their needs in terms of both ESG and financial performance to allocate their portfolios optimally. The consequences faced by investors are of importance for policymakers too, especially in light of the new possibilities for pension funds to implement ESG criteria when allocating their portfolios. Our results indeed show that ESG investing cannot be seen as a free lunch, and policy aiming to make available ESG investments to a broader investor base should carefully consider the long-term implications behind the adoption of such policies. The implications for investors and policy makers mentioned above also highlight an important message for researchers. If one wants to assess the existing relation between ESG performance and expected returns, it is essential to realize that "shifts in equilibrium" in terms of increased demand for ESG assets may bias the estimate for the ESG premium upward. That is, the magnitude of the negative ESG premium may be larger than previously thought, and typical estimates can even be insignificant or positive if the bias is not adequately addressed. This would explain, on top of the other methodological concerns regarding the use of a pure portfolio-level analysis, the mixed results outlined so far by the literature on ESG investing.

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 the 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 to the ESG premium, 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 ($k_1 \times 1$), F_t is a vector of factors ($k_1 \times 1$), 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 $\hat{B}_{t-1}$ $(k_1 \times N_t)$, and the matrix of observed firm characteristics Zsc_t $(k_2 \times N_t)$; 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 $(k_1 \times 1)$, and γ_2 is a vector of characteristic premiums $(k_2 \times 1)$. 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 Eq. (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, $\hat{\Gamma}^{Eiv}_t$, is defined as follows:

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

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 $\hat{\Sigma}_{\hat{B}_{i,t}}$ $(k_1 \times k_1)$ 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 $\Gamma^{Eiv}_t := (\gamma_{0,t}, \gamma_{1,t}', \gamma_{2,t}')'$. The ultimate estimate for Γ is calculated by taking the time-series average of Γ^{Eiv}_t.

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:

$$E_{t-1}[R^e_t] = \hat{\gamma}_0 + E^{\hat{B}}_{t-1}[R^e_t] + E^{Zcs}_{t-1}[R^e_t],$$

where

$$E^{\hat{B}}_{t-1}[R^e_t] = \hat{B}_{t-1}\hat{\gamma}_1, \text{ and } E^{Zcs}_{t-1}[R^e_t] = Zcs_{t-1}\hat{\gamma}_2.$$

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

$$C_{\hat{B},t} = \frac{\sigma^2_{cs}\left(E^{\hat{B}}_{t-1}[R^e_t]\right)}{\sigma^2_{cs}\left(E_{t-1}[R^e_t]\right)}, \tag{3}$$

$$C_{Zcs,t} = \frac{\sigma^2_{cs}\left(E^{Zcs}_{t-1}[R^e_t]\right)}{\sigma^2_{cs}\left(E_{t-1}[R^e_t]\right)}, \tag{4}$$

where $\sigma^2_{cs}\left(E_{t-1}[R^e_t]\right)$ is the cross-sectional variance of expected returns, $\sigma^2_{cs}\left(E^{\hat{B}}_{t-1}[R^e_t]\right)$ is the beta component of cross-sectional variance, and $\sigma^2_{cs}\left(E^{Zcs}_{t-1}[R^e_t]\right)$ is the characteristic component of cross-sectional variance. 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 various sources. Our main data on ESG scores at the firm level are from the Refinitiv ASSET4 database (previously known as Thomson Reuters).[3,4] 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

[3] 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.

[4] We provide full results using additional ESG data by VIGEO-EIRIS. See Section 5.2.

Table 1
Descriptive statistics for the firm-level characteristics and the estimated 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	$\hat{\beta}_{mk}$	$\hat{\beta}_{s}$	$\hat{\beta}_{h}$	$\hat{\beta}_{r}$	$\hat{\beta}_{c}$	$\hat{\beta}_{w}$	$\hat{\beta}_{ESG}$
$Mean$	14.206	−0.684	0.232	0.226	0.013	39.686	1.034	0.496	−0.051	−0.284	−0.128	−0.102	0.012
$St.dev.$	1.826	0.902	0.928	0.975	0.317	18.945	0.463	0.831	1.196	1.447	1.496	0.587	1.038
10%	11.926	−1.789	−0.106	−0.131	−0.300	16.170	0.495	−0.422	−1.332	−1.953	−1.884	−0.755	−1.351
25%	13.080	−1.175	0.093	−0.027	−0.106	24.650	0.752	−0.046	−0.617	−0.946	−0.887	−0.382	−0.651
50%	14.261	−0.588	0.211	0.064	0.034	37.730	1.010	0.397	−0.031	−0.147	−0.046	−0.073	0.035
75%	15.368	−0.091	0.353	0.198	0.162	53.200	1.294	0.921	0.571	0.553	0.743	0.203	0.684
90%	16.484	0.287	0.599	0.489	0.306	66.890	1.604	1.533	1.273	1.264	1.511	0.511	1.276
	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												
$lBtM$	−0.161	1.000											
Pro	0.126	−0.192	1.000										
Inv	−0.066	−0.101	−0.026	1.000									
$lRet6$	0.125	−0.200	0.036	0.100	1.000								
ESG	0.465	−0.001	0.063	−0.110	0.008	1.000							
$\hat{\beta}_{mk}$	0.074	0.009	−0.012	−0.028	−0.066	−0.007	1.000						
$\hat{\beta}_{s}$	−0.319	0.098	−0.059	0.035	−0.047	−0.170	0.210	1.000					
$\hat{\beta}_{h}$	0.024	0.229	0.029	−0.045	−0.016	0.015	−0.003	0.067	1.000				
$\hat{\beta}_{r}$	0.091	0.057	0.069	−0.026	0.038	0.049	−0.006	0.075	0.419	1.000			
$\hat{\beta}_{c}$	0.021	−0.033	0.020	−0.048	0.017	0.034	0.071	0.003	−0.324	0.033	1.000		
$\hat{\beta}_{w}$	0.093	−0.114	0.023	0.076	0.114	−0.001	−0.160	−0.140	0.048	0.045	−0.121	1.000	
$\hat{\beta}_{ESG}$	−0.040	−0.050	−0.026	0.005	−0.017	−0.240	0.185	−0.094	0.041	0.001	0.172	−0.129	1.000

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 in Eq. (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: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 betas estimated, panel B provides correlations. The sample consist of 7,772 global firms for 180 months (July 2005–June 2020), and we require at least 400 observations over two years to estimate the betas.

estimation of monthly rolling-window betas.[5] From the Fama and French (2017) and Fama and French (2012) global and area specific 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 investment risk factor (CMA).[6] We build the ESG risk factor following the methodology of Becchetti et al. (2018), that is consistent with the Fama–French procedure for risk factor construction. Specifically, we define the Worst-minus-Best (WMB) ESG risk factor as the difference between the two equally-weighted Worst and Best portfolios in terms of ESG score and market capitalization (for details, see Becchetti et al., 2018).

We filter out ADRs, units, preferred shares, and stapled securities (Fama and French, 1992, 1993), and we keep only firms in the following four areas: Asia Pacific ex-Japan, Europe, Japan, and North America. (Fama and French, 2012, 2017). We end up with a sample of 7772 unique firms, resulting in an unbalanced panel of 692,973 firm-month observations, between July 2003 and June 2020 (204 months), and the firms are divided among the four areas as follows: Asia Pacific ex-Japan (905), Europe (2,030), Japan (513), and North America (4,324). 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 two years.[7]

Table 1 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 in Eq. (1), including the Fama–French five factors (Fama and French, 2017), the momentum risk factor (Carhart, 1997), and the ESG-risk factor (Becchetti et al., 2018).[8] It shows that our sample is characterized by firms with a low exposure to the ESG risk factor (Panel A, column [13]). The correlations exhibit the expected sign, including a negative one between the ESG risk factor loadings and ESG characteristics (Panel B, columns [1]–[6]). The negative correlations between size, investment, and ESG characteristics with their 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

[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), Return Index (RI), and Price Index (PI).

[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 2003 to June 2005. We then roll the window monthly, requiring at least 400 data points for the beta estimation.

[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.

positive correlations among the book-to-market, profitability, and momentum characteristics and their related betas. Moreover, consistent with Albuquerque et al. (2019), the ESG characteristics appear to be positively correlated with firms' profitability and negatively correlated with the market betas. As such, higher ESG ratings imply higher revenues and lower market risk exposure. Crucially, 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

We start our analysis by shedding 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 month using the last ESG score available before month t. The first column of Table 2 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. As we move from the $Worst$ to the $Best$ portfolio we see a decreasing pattern in average returns. Moreover, we report the average return for a long-short portfolio ($Diff$), defined as the difference in monthly returns between the $Best$ and $Worst$ decile portfolio in terms of ESG performance. It reveals a monthly ESG premium equal to -0.71% (Panel A, column [1]). The monthly negative ESG premium based on the $Diff$ portfolio is also statistically significant ($t = -1.657$). This result is in line with previous empirical studies that investigate the relation between ESG ratings and returns (Albuquerque et al., 2019; Luo and Balvers, 2017; Hong and Kacperczyk, 2009; Galema et al., 2008; Renneboog et al., 2008; Bauer et al., 2007).

Table 2 also verifies whether the monthly ESG premium disappears for the decile portfolios when controlling for an ESG-risk factor (a Worst-minus-Best factor; WMB, Becchetti et al., 2018) constructed using the standard procedure proposed by Fama and French (1993). The resulting pricing errors (alphas) are estimated using different specifications of the time-series multi-factor model in Eq. (1); all specifications include the ESG-risk factor (Panel B). In terms of pricing errors, the decreasing pattern survives when we move from $Worst$ to $Best$ portfolio for all specifications. Moreover, all the alphas of the $Diff$ portfolio are negative and statistically significant irrespective of the specification used. In particular, alpha is equal to: -0.610 ($t = -4.667$) for the 2-factor specification, -0.610 ($t = -4.899$) for the 4-factor specification, and -0.679 ($t = -5.617$ and $t = -5.606$) for the 6-factor and 7-factor specifications, respectively. The inability of the multi-factor models to correctly price the portfolios is also formally assessed with the GRS (Gibbons et al., 1989) test, rejecting at 1% the null that the alphas are jointly equal to zero for all specifications. As such, investor preferences (related to ESG characteristics) might play a prominent role in explaining this pricing "anomaly".

To summarize Table 2: (1) there exists an ESG premium; expected returns decrease as ESG scores increase, and (2) such a premium is likely not exclusively driven by pure risk/return considerations (Albuquerque et al., 2019; Luo and Balvers, 2017; Hong and Kacperczyk, 2009). We therefore proceed in disentangling the separate contribution of risk and preferences in generating such a premium by assessing their ability to explain the cross-sectional variation of expected returns using the firm-level methodology proposed by Chordia, Goyal, and Shanken (2017).

Table 3 reports the results for the cross-sectional regressions using Eq. (2) with the EIV-bias correction for the betas (Chordia et al., 2017) for the following models: a global 2-factor model that includes both the market and the ESG-risk factor (Becchetti et al., 2018), a 4-factor model that additionally includes the SMB and HML-risk factor (Fama and French, 2012), a 6-factor model that additionally includes the RMW and CMA-risk factor (Fama and French, 2017), and a 7-factor model that augments the 6-factor model with the momentum factor (Carhart, 1997).

The results show that the monthly premium for the ESG characteristic is negative and significant for all specifications. The coefficients vary between -0.013 and -0.012 (Table 3, columns [1]–[4]). In economic terms, a one standard deviation increase in the ESG score decreases the expected return about 2.73% annually ($-0.012 \times 18.945 \times 12$). The ESG-risk factor betas, however, are insignificant across all specifications. These results thus indicate that investor preferences for ESG-related issues mainly drive the ESG premium, rather than that systematic risk components are captured by ESG scores (columns [1]–[4]). This result is further supported by the proportion of the cross-sectional variation explained by the ESG characteristic ($\bar{C}_{ESG}$), which is always greater than that of the ESG beta ($\bar{C}_{\hat{\beta}_{ESG}}$). For all specifications, the intercepts (which can be interpreted as the expected return on a zero-beta portfolio) are mostly negative and significant (Black et al., 1972, Fama and MacBeth, 1973). In line with Chordia, Goyal, and Shanken (2017), the monthly premium on the investment (Inv) characteristic is negative and significant, while the monthly premium for the profitability (Pro) characteristic is positive and significant. In contrast with Chordia, Goyal, and Shanken (2017), we find a significant and positive monthly premium for the size characteristic (lME), a significant and negative monthly premium for the book-to-market characteristic ($lBtM$), and a negative but not significant monthly premium for the past 6-month return ($lRet6$). The monthly premiums on the betas are insignificant, except for the size, value and momentum risk premium (columns [2]–[4]). Moreover, the negative and mostly insignificant monthly market premium is in line with Albuquerque et al. (2019), as well as the descriptive evidence provided in Table 1. Looking at the percentage of cross-sectional variance explained by characteristics ($\bar{C}_{Zcs}$) and betas ($\bar{C}_{\hat{\beta}}$), we find that the maximum variation in expected returns that the betas can explain is slightly above 32%. The characteristics appear to explain most of the cross-sectional variation in expected returns.

The absence of a monthly 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 4 reports the results,

Table 2
Properties of decile portfolios sorted on ESG score.

	[1]	[2]	[3]	[4]
	Panel A: Descriptives			
	$\bar{R}_p^e$	σ_p	ShR_p	$\overline{ESG}_p$
$Worst$	1.686	4.455	0.379	11.036
2	1.614	4.626	0.349	18.755
3	1.581	4.935	0.320	24.096
4	1.456	4.958	0.294	29.061
5	1.237	4.596	0.269	34.086
6	1.273	4.168	0.305	39.436
7	1.067	4.117	0.259	45.140
8	1.059	4.310	0.246	51.574
9	1.192	4.131	0.289	59.568
$Best$	0.975	4.207	0.232	72.069
$Diff$	−0.711**			
	(−1.657)			
	Panel B: Multifactor time-series regression alphas and GRS test.			
	$2-Factor$	$4-Factor$	$6-Factor$	$7-Factor$
$Worst$	0.501***	0.449**	0.572***	0.571***
	(2.842)	(2.556)	(3.428)	(3.478)
2	0.337**	0.238	0.32**	0.319**
	(2.003)	(1.446)	(1.978)	(1.993)
3	0.259	0.171	0.268	0.267
	(1.345)	(0.899)	(1.442)	(1.473)
4	0.163	0.05	0.134	0.134
	(0.817)	(0.255)	(0.694)	(0.696)
5	0.021	−0.045	0.023	0.022
	(0.119)	(−0.252)	(0.129)	(0.125)
6	0.155	0.12	0.171	0.17
	(1.028)	(0.789)	(1.121)	(1.133)
7	−0.022	−0.057	−0.001	−0.003
	(−0.149)	(−0.386)	(−0.009)	(−0.018)
8	−0.054	−0.109	−0.061	−0.062
	(−0.352)	(−0.703)	(−0.39)	(−0.406)
9	0.11	0.069	0.147	0.146
	(0.765)	(0.477)	(1.047)	(1.056)
$Best$	−0.109	−0.161	−0.107	−0.108
	(−0.737)	(−1.09)	(−0.728)	(−0.745)
$Diff$	−0.61***	−0.61***	−0.679***	−0.679***
	(−4.677)	(−4.899)	(−5.617)	(−5.606)
GRS	[3.203]	[3.428]	[4.555]	[4.537]

The table reports in Panel A the overall period average of the monthly excess return ($\bar{R}_p^e$) for the ESG portfolios in percentage, standard deviation (σ_p), Sharpe Ratio (ShR_p), and the average ESG score ($\overline{ESG}_p$). Panel B reports the pricing errors in percentage estimated for the decile portfolios and the difference portfolio ($Diff$) using different versions of factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML and WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). $Worst$ is the portfolio composed of firms with the lowest ESG score, $Best$ is the portfolio composed of firms with the highest ESG score, and $Diff$ is the long-short portfolio defined as the difference of the monthly return series between the $Best$ and $Worst$ decile portfolio. The sample consist of 7,772 global firms for 204 months (July 2003–June 2020). t-statistics are reported in round brackets. The GRS test is on the regression alphas of the 10 ESG portfolios (Gibbons et al., 1989). ***,** and * denote 1%, 5%, and 10% significance.

and they are by and large consistent with those in Table 3. Critically, the ESG characteristic is still negative, strongly significant, and varies between −0.013 and −0.011 (column [1]–[4]). In economic terms, a one standard deviation increase in the ESG score decreases the expected return about 2.50% annually ($-0.011 \times 18.945 \times 12$). In three out of four specifications, the ESG characteristic explains better the variation in expected returns than the ESG beta. Moreover, the intercept and all the remaining characteristics but momentum ($lRet6$) are significant across all specifications, and consistent in terms of sign with the results of Table 3. Similar reasoning applies to the betas. Again, in terms of cross-sectional variation of expected returns, the characteristics seem to play a more prominent role compared to the betas.

In summary, the results so far show that it is the ESG characteristic (preferences) rather than beta (risk) that drives the ESG premium, and the related cross-sectional variation of expected returns. As such, our results corroborate the strand of literature showing a negative premium for ESG investments. We acknowledge however that part of the literature documents opposite findings (e.g., Statman and Glushkov, 2009; Bauer et al., 2005), or the absence of an ESG premium in the first place (e.g., Bauer et al., 2007; Hamilton et al., 1993). We conjecture that the opposite findings documented so far are driven by the portfolio-level analysis used, and by a potential ESG bias, which we will address next. That is, a sudden increase in relative demand for firms with large ESG

Table 3
Cross-sectional regressions.

	[1] 2-factor	[2] 4-factor	[3] 6-factor	[4] 7-factor
$Const.$	−2.362	−3.004**	−3.122***	−3.477***
	(−1.535)	(−2.325)	(−2.83)	(−3.357)
lME	0.165**	0.234***	0.238***	0.255***
	(1.988)	(3.302)	(3.808)	(4.469)
$lBtM$	−1.129***	−1.266***	−1.198***	−1.203***
	(−13.352)	(−16.181)	(−16.153)	(−16.81)
Pro	0.602***	0.677***	0.684***	0.684***
	(3.697)	(4.061)	(4.24)	(4.381)
Inv	−0.508***	−0.573***	−0.52***	−0.513***
	(−5.697)	(−6.681)	(−6.113)	(−6.069)
$lRet6$	−0.344	−0.260	−0.386	−0.328
	(−0.672)	(−0.512)	(−0.94)	(−0.843)
ESG	−0.013***	−0.013***	−0.012***	−0.012***
	(−6.619)	(−7.278)	(−7.006)	(−6.46)
$\hat{\beta}_{mk}$	0.223	−0.456*	−0.394*	−0.341
	(1.568)	(−1.854)	(−1.968)	(−1.06)
$\hat{\beta}_s$		0.477**	0.508**	0.537**
		(2.276)	(2.404)	(2.59)
$\hat{\beta}_h$		0.386***	0.265**	0.256
		(3.033)	(2.24)	(1.642)
$\hat{\beta}_r$			−0.096	−0.052
			(−1.111)	(−0.431)
$\hat{\beta}_c$			0.050	0.068
			(0.613)	(0.822)
$\hat{\beta}_w$				−0.550*
				(−1.749)
$\hat{\beta}_{ESG}$	−0.189	−0.187	−0.076	0.060
	(−1.406)	(−0.91)	(−0.296)	(0.165)
$\bar{C}_{Zcs}$	104.269	105.100	107.471	105.450
$\bar{C}_{\hat{B}}$	4.000	30.095	23.328	32.182
$\bar{C}_{ESG}$	5.593	4.117	4.163	4.139
$\bar{C}_{\hat{\beta}_{ESG}}$	3.592	2.785	0.527	0.317

The table reports the time-series averages of γ coefficients estimated using Eq. (2) that accounts for the EIV-bias correction:

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

The betas are estimated using different versions of the factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consist of 7,772 global firms for 180 months (July 2005–June 2020). 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. $\bar{C}_{ESG}$ and $\bar{C}_{\hat{\beta}_{ESG}}$ represent the proportions of variation in expected returns explained by the ESG characteristics and ESG betas, respectively. ***,** and * denote 1%, 5%, and 10% significance.

scores leads to a systematic shift in equilibrium price levels. Such a trend may confound the analysis, because *realized* returns rise temporarily through capital gains as *expected* returns fall. Put differently, increased screening using ESG scores over time may bias the ESG premium that we predict, and as a result obfuscates the economic interpretation provided by the literature so far. In the next section we first further motivate the mechanism that we have in mind, formalize it, and then suggest a way to estimate the resulting ESG bias.

4.1. Correcting the ESG premium for the ESG bias

We start our motivation for the subsequent analysis with some observations on ESG-related developments on financial markets, where there have been some shifts in market demand towards ESG assets. In this respect, Pástor et al. (2021b) show that due to an unexpected increase in environmental concerns, green assets have delivered higher realized returns in recent years but not higher expected returns. In the same spirit, Hartzmark and Sussman (2019) show that within the US mutual fund market, investors are channeling funds away from low-rated towards high-rated ESG funds. This trend appears to be in line with the anecdotal evidence in formal reports on assets under management subject to ESG criteria (Global Sustainable Investment Alliance, 2020, 2018). The

Table 4
Cross-sectional regressions using in-sample constructed risk factors.

	[1] 2-factor	[2] 4-factor	[3] 6-factor	[4] 7-factor
$Const.$	−2.348	−2.676*	−3.115***	−3.112***
	(−2.676)	(−1.966)	(−2.713)	(−2.649)
lME	0.165*	0.223***	0.233***	0.241***
	(0.223)	(3.041)	(3.551)	(3.611)
$lBtM$	−1.129***	−1.173***	−1.192***	−1.20***
	(−1.173)	(−14.264)	(−15.449)	(−15.767)
Pro	0.599***	0.683***	0.683***	0.665***
	(0.683)	(4.421)	(4.484)	(4.362)
Inv	−0.509***	−0.549***	−0.526***	−0.537***
	(−0.549)	(−5.952)	(−5.981)	(−6.176)
$lRet6$	−0.34	−0.295	−0.155	−0.186
	−0.662	−0.607	−0.334	−0.399
ESG	−0.013***	−0.013***	−0.012***	−0.011***
	(−0.013)	(−7.289)	(−6.285)	(−6.56)
$\hat{\beta}_{mk}$	0.236*	−0.448**	−0.217	−0.401*
	(−0.448)	(−2.405)	(−1.022)	(−1.973)
$\hat{\beta}_s$		0.114	0.195**	0.045
		(0.631)	(1.986)	(0.214)
$\hat{\beta}_h$		0.544**	0.584***	0.89**
		(2.087)	(3.587)	(2.304)
$\hat{\beta}_r$			−0.32***	−0.663
			(−2.648)	(−1.466)
$\hat{\beta}_c$			−0.08	−0.32
			(−0.459)	(−1.202)
$\hat{\beta}_w$				−0.23
				(−0.904)
$\hat{\beta}_{ESG}$	−0.204	−0.242*	−0.147*	−0.26
	(−0.242)	(−1.831)	(−1.72)	(−1.225)
$\bar{C}_{Zcs}$	104.570	105.796	107.342	76.257
$\bar{C}_{\hat{B}}$	4.518	25.071	35.427	70.547
$\bar{C}_{ESG}$	5.792	4.830	4.118	2.586
$\bar{C}_{\hat{\beta}_{ESG}}$	4.250	5.628	2.176	4.330

The table reports the time-series averages of γ coefficients estimated using Eq. (2) that accounts for the EIV-bias correction:

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

The betas are estimated using different versions of the factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consist of 7,772 global firms for 180 months (July 2005–June 2020). 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. $\bar{C}_{ESG}$ and $\bar{C}_{\hat{\beta}_{ESG}}$ represent the proportions of variation in expected returns explained by the ESG characteristics and ESG betas, respectively. ***,** and * denote 1%, 5%, and 10% significance.

market shifts towards ESG assets cannot be explained by on average larger expected returns of higher scoring ESG firms, as we have shown in Table 2 that average returns are actually lower for higher scoring ESG firms. Such shifts towards ESG assets can however lead to a temporary increase in realized returns which in turn might bias the estimate of the ESG premium, and more generally could explain some of the mixed findings documented by the literature so far.

To assess whether temporary price increases due to the shift in demand for ESG assets have biased our estimates of the monthly ESG premium, we use insights from the return predictability literature and take inspiration from Campbell and Vuolteenaho (2004)'s application of the Campbell and Shiller (1988) return decomposition. Specifically, Campbell and Vuolteenaho (2004) decompose the *unexpected* log-return of a generic asset i ($\tilde{r}_{i,t}$) into two components:

$$\tilde{r}_{i,t} = r_{i,t} - E_{t-1}[r_{i,t}] = \underbrace{(E_t - E_{t-1})\left[\sum_{j=0}^{\infty}\rho^j \Delta d_{i,t+j}\right]}_{=N_{CF,i,t}} - \underbrace{(E_t - E_{t-1})\left[\sum_{j=1}^{\infty}\rho^j r_{i,t+j}\right]}_{=N_{DR,i,t}}, \tag{5}$$

where $r_{i,t} = \log(R_{i,t})$ is the log return at time t for stock i, $\Delta d_{i,t+j} = \log(D_{i,t+j}/D_{i,t})$ is log dividend growth at time $t+j$ for stock i, and ρ is a constant of log-linearization. $N_{CF,i,t}$ represents revisions in expected future dividends (cash-flow news, e.g., higher earnings/dividends than expected) and $N_{DR,i,t}$ represents revisions in expected returns (expected returns news, e.g., increases in discount rates). By definition, the above decomposition of the unexpected return equals the error term of our cross-sectional Eq. (2). Combining the above decomposition of the unexpected return for each asset with our Eq. (2) for expected returns, we have:

$$r_{i,t} = \underbrace{\gamma_0 + \gamma_1' B_{i,t-1} + \gamma_2' Zsc_{i,t-1}}_{E_{t-1}[r_{i,t}]} + \underbrace{N_{CFi,t} - N_{DRi,t}}_{\epsilon_{i,t}}. \tag{6}$$

The equation above implies that a drop in expected returns, $N_{DR,i,t} < 0$, is preceded by higher realized returns. In our setting, the drop in the expectation is driven by the increased interest in ESG assets. That is, investors that are tilting their portfolios towards assets with higher ESG scores may require a lower expected return on these assets, but the associated capital flows generate a positive effect on the *realized* return at time t.[9] Formally, we postulate that the OLS assumption that the ESG characteristic is uncorrelated with the error term may be violated, i.e. $Cov(N_{DRi,t}, Zsc_{i,t}) \neq 0$. For example, if there is a negative correlation, it biases upward our estimates for the ESG premium. To be precise, if the ESG scores are indeed correlated with changes in expected returns, $N_{DRi,t} = \theta_2' Zsc_{i,t-1} + \epsilon_{DRi,t}$, we can (theoretically) observe this bias directly by substituting this expression in Eq. (6):

$$r_{i,t} = \gamma_0 + \gamma_1' B_{i,t-1} + \underbrace{(\gamma_2' - \theta_2')}_{\tilde{\gamma}_2} Zsc_{i,t-1} + \tilde{\epsilon}_{i,t}. \tag{7}$$

Eq. (7) tells us that if a researcher is interested in the parameter γ_2, by running the cross-sectional Eq. (2) he/she is in fact estimating $\tilde{\gamma}_2 = (\gamma_2 - \theta_2)$ that includes the negative ESG bias (θ_2), when it is reasonable to assume that some of the characteristic is correlated with the error term, as in our case with the ESG score.[10] The question now is how to correct the monthly biased ESG premium ($\tilde{\gamma}_2$) in such a way that we are then able to retrieve the monthly unbiased ESG premmium (γ_2) of interest. In particular, we need to proxy and model the component capturing changes in expected returns, $N_{DRi,t+1}$, and relate such a proxy to the ESG scores, i.e. find a measure for $Cov(N_{DRi,t}, Zsc_{i,t})$ to correct the bias.

To do so, we rely again on the insights from the return predictability literature based on the Campbell and Shiller (1988) log-linearized return identity for a generic stock i, and express the $N_{DRi,t+1}$ in terms of the scaled dividend-price ratio ($\widetilde{dp}_{i,t}$) as follows:

$$N_{DRi,t} = (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{i,t+j} = \widetilde{dp}_t - E_{t-1}[\widetilde{dp}_{i,t}]. \tag{8}$$

For details of this derivation see Appendix A. Here, $\widetilde{dp}_{i,t} := \rho dp_{i,t}$ is the log dividend-price ratio, $dp_{i,t} = \log(D_{i,t}/P_{i,t})$, scaled with ρ, the constant of linearization of the Campbell and Shiller (1988) return identity. We further adopted the empirical stylized fact that the dividend-price ratio does not predict dividend growth as an identifying assumption.[11] Eq. (8) thus tells us that we can use the innovations in the scaled dividend-price ratio as a proxy for revisions in expected returns.

Using Eq. (8), we specify the hypothesized relation between changes in expected returns ($N_{DRi,t}$) and the characteristics ($Zsc_{i,t-1}$) in terms of dividend-price ratios, and rewrite, to obtain:

$$\widetilde{dp}_{i,t} = \theta_0 + \theta_1 \widetilde{dp}_{i,t-1} + \theta_2' Zsc_{i,t-1} + \upsilon_{i,t}, \forall t \tag{9}$$

where we use the text-book approach (Cochrane, 2009) to model persistence in the expected dividend-price ratio $E_{t-1}[dp_t]$ with an $AR(1)$ process, with constant θ_0 and error term $\upsilon_{i,t}$. Intuitively, θ_2 tells us that the more the shift towards ESG assets exceeds initial investor expectations, the higher the drop in the dividend-price ratio will be due to the associated price increase (that is, increase in realized returns), and so the greater will be the correction on the estimate of the monthly biased ESG premium due to the ESG bias.

We proceed by estimating Eq. (9) at the firm level using a standard (Fama and MacBeth, 1973) two-step procedure, since (9) does not involve the use of the betas at firm level. Hence it does not require the use of the EIV correction (Chordia et al., 2017).

Table 5 reports the estimates for Eq. (9) for the entire estimation period, and the corrected estimate of the monthly ESG premium coefficient (γ_2), i.e. adjusted for the monthly ESG bias (θ_2). We estimate the parameter θ_2 at -0.003, which confirms our notion that there is a negative relation between the ESG characteristic and changes in expected returns. This shows that higher ESG scores are associated with lower dividend-price ratios, which in term drive long-run expected returns, corroborating the negative ESG premium. Such an increase translates to an unbiased monthly ESG premium (γ_2) of about -0.015 instead of -0.012 as previously estimated without correcting for the monthly ESG bias in Table 3. From an economic perspective, a one standard deviation increase in the ESG score results in a reduction in expected returns of about 3.41% annually ($-0.015 \times 18.945 \times 12$). Instead, with the monthly biased ESG premium ($\tilde{\gamma}_2$) the same estimate yields a smaller reduction in expected returns of about 2.73% annually. As such, when

[9] Campbell and Vuolteenaho (2004) use the decomposition to measure "good" and "bad" betas; in our setting the economic interpretation is somewhat different, but the spirit of the mechanism is the same.

[10] Note that, we implicitly assume that the characteristics known at $t-1$ do not provide relevant cash-flow news at t ($N_{CFi,t}$), rendering it more likely that prices respond directly to relevant expected returns news. The effect we are after is in a sense not so much a cash-flow news effect, but a historical shift in investment style that has only become clear in hindsight. Moreover, the error term is now defined as $\tilde{\epsilon}_{i,t} = N_{CFi,t} + \epsilon_{DRi,t}$.

[11] We have in fact empirically checked whether dividend-price ratios predict returns in our dataset. These results are available upon request.

Fig. 1. The three-year moving average of the monthly biased ESG premium (left axis) and the monthly ESG bias (right axis).
The figure shows the three-year moving average of the monthly biased ESG premium $\tilde{\gamma}_2$ (continuous line) based on Eq. (2), and the monthly ESG bias θ_2 (dashed line) based on Eq. (9). The more negative the ESG bias, the larger is the correction in the monthly biased ESG permium.

correcting the estimates of the monthly biased ESG premium for the monthly ESG bias, the additional loss in terms of expected returns is roughly 0.7%. We acknowledge however that such a difference is not huge, but it is not innocuous either. In particular, the difference between the two estimates builds up quickly: (1) when we consider a less conservative interpretation of the difference in the unbiased versus biased ESG premium, and (2) when investors hold their ESG portfolios for more than one year, as small return differences compound quickly. For example, a two standard deviation increase in the ESG score translates to a reduction in expected returns of about 1.4% annually. Compounding such a small difference over several years can have an additional and large economic impact.

Table 5
Cross-sectional regressions for the dividend-price ratio.

[1]	[2]	[3]	[4]	[5]
$\tilde{\gamma}_2$	θ_0	θ_1	θ_2	γ_2
−0.012	3.451***	3.605***	−0.003*	−0.015***
	(44.722)	(7.042)	(−1.674)	(−57.723)

The table reports the estimates of Eq. (9):

$$\widetilde{dp}_{i,t} = \theta_0 + \theta_1 \widetilde{dp}_{i,t-1} + \theta_2' Zsc_{i,t-1} + v_{i,t}$$

$\widetilde{dp}_{i,t}$ and $\widetilde{dp}_{i,t-1}$ represents the current and one-month lagged scaled dividend price ratio; $Zsc_{i,t-1}$ is a vector including the ESG characteristic only. $\tilde{\gamma}_2$ is the monthly biased ESG premium estimated in Table 3 via specification [4]of Eq. (2), and $\gamma_2 = \tilde{\gamma}_2 + \theta_2$ is the monthly unbiased ESG premium once the monthly biased ESG premium ($\tilde{\gamma}_2$) is corrected for the monthly ESG bias (θ_2). The coefficients are multiplied by 100 and t-statistics are in brackets. ***,** and * denote 1%, 5%, and 10% significance.

Fig. 1 visualizes the three-year moving average of the monthly biased ESG premium ($\tilde{\gamma}_2$), and the monthly ESG bias (θ_2). Over the sample period we observe in line with the expected mechanism that the dashed and solid line move roughly in opposite directions, implying that an increase/decrease in the *realized* returns, indeed precedes a drop/rise in the expected returns.

In sum, while our method relies on some identifying assumptions based on stylized facts from the equity return predictability literature, we feel that the circumstantial evidence on capital flows and the economic logic of our argument point out that previous estimates of the negative ESG premium were conservative and that the reduction in expected returns may be even larger than previously thought (cf. Albuquerque et al., 2019 and Luo and Balvers, 2017 among others). An additional implication of our finding is that even when the literature shows a positive ESG premium, it might be due to the absence of the ESG bias correction, on top of the other methodological concerns regarding the use of a pure portfolio-level analysis (Statman and Glushkov, 2009 and Bauer et al., 2007 among others).

As such, we feel comfortable in arguing that in shorter time series during periods of sudden increased demand for ESG assets, estimates for the ESG premium might be significantly biased, both statistically and economically. Put differently, the magnitude of the ESG premium is perhaps larger than we previously thought.

5. Robustness checks

5.1. Specific investment area

Some of the small differences in the results for some of the characteristics premiums compared with Chordia, Goyal, and Shanken (2017) might be due to the use of a global sample. Alternatively, such differences might be due to peculiar features of ESG assets. Either way, these concerns deserve additional investigation. Table 6 reports the results for the cross-sectional regression using Eq. (2)

Table 6
Cross-sectional regressions at area-specific level.

	[1] Asia Pacific ex-Japan	[2] Europe	[3] Japan	[4] North America
$Const$	0.436	−5.207***	−5.078***	−4.042***
	(0.086)	(−4.784)	(−3.653)	(−3.82)
lME	0.169	0.37***	0.373***	0.276***
	(0.795)	(5.60)	(4.154)	(4.808)
$lBtM$	−1.668***	−1.089***	−1.546***	−1.195***
	(−9.287)	(−12.575)	(−11.914)	(−13.45)
Pro	0.38	0.791***	−0.015	0.948***
	(1.379)	(4.82)	(−0.047)	(6.136)
Inv	−0.812***	−0.491***	−1.016***	−0.535***
	(−3.241)	(−3.471)	(−2.641)	(−6.484)
$lRet6$	0.404	0.215	−1.112**	−0.622
	(0.541)	(0.478)	(−2.277)	(−1.329)
ESG	−0.03***	−0.009***	−0.009***	−0.009***
	(−2.727)	(−4.261)	(−3.759)	(−4.153)
$\hat{\beta}_{mk}$	−1.734	−0.364	−0.118	−0.531*
	(−1.232)	(−1.023)	(−0.347)	(−1.717)
$\hat{\beta}_{s}$	1.134**	0.523***	0.554***	0.638***
	(2.562)	(2.791)	(2.967)	(4.651)
$\hat{\beta}_{h}$	1.748*	0.494***	0.69***	0.386**
	(1.883)	(3.174)	(4.334)	(2.563)
$\hat{\beta}_{r}$	−0.711***	−0.34***	−0.30***	−0.048
	(−2.793)	(−3.47)	(−2.827)	(−0.432)
$\hat{\beta}_{c}$	−0.626	0.055	0.207**	0.141
	(−0.727)	(0.629)	(2.029)	(1.40)
$\hat{\beta}_{w}$	−1.461*	−0.222	−0.845***	−0.643**
	(−1.901)	(−0.909)	(−4.352)	(−2.376)
$\hat{\beta}_{ESG}$	−0.134	−0.019	−0.186	−0.147
	(−0.673)	(−0.147)	(−1.055)	(−1.341)
$\bar{C}_{Zcs}$	58.555	120.801	133.453	109.909
$\bar{C}_{\hat{B}}$	59.255	23.422	48.116	28.660
$\bar{C}_{ESG}$	5.162	2.518	4.706	2.107
$\bar{C}_{\hat{\beta}_{ESG}}$	0.139	0.012	2.081	1.111

The table reports the time-series averages of the estimated using Eq. (2) that accounts for the EIV-bias for each of the investment areas as defined by Fama and French (2017):

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

The betas are estimated using different versions of the factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consist of 7,772 global firms for 180 months (July 2005–June 2020). 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. $\bar{C}_{ESG}$ and $\bar{C}_{\hat{\beta}_{ESG}}$ represent the proportions of variation in expected returns explained by the ESG characteristics and ESG betas, respectively. ***,** and * denote 1%, 5%, and 10% significance.

with the EIV-bias correction for the betas and the area specific 7-factor specification. In line with Table 3, the monthly premiums for the ESG characteristic is still negative and significant across all the four areas (column [1]–[4]). Crucially, the ESG-risk factor betas are always insignificant. Moreover, in all the areas, the cross-sectional variation explained by the ESG characteristic ($\bar{C}_{ESG}$) exceeds the one for ESG beta ($\bar{C}_{\hat{\beta}_{ESG}}$). Concerning the remaining results, the constant turns out to be not significant for the Asia Pacific ex-Japan area. The monthly premiums for the lME and the Pro characteristic are still positive and significant across the four regions, whereas the $lBtM$ and Inv are still negative and significant. In contrast to the results in Table 3, the monthly premium for the $lRet6$ characteristic is now significant for Japan.

For the monthly beta premiums, the most notable difference with the results in Table 3 is that the market beta is still negative but now mainly insignificant. In contrast, the size beta is always significant, whereas the significance for the profitability, investment, and momentum beta appear to vary somewhat across the areas. Yet, the characteristics are still the main explanatory variables for the variation in the cross-section of expected returns.

Overall, the results in Table 6 confirm by and large those provided by Table 3. However, the findings do outline some heterogeneity in terms of significance for some of the monthly beta premiums across the regions. We conclude that the differences with the findings of Chordia, Goyal, and Shanken (2017) do not depend either on the area-specific attributes, and the peculiar characteristics of responsible assets.

5.2. Alternative ESG data

Another concern regarding the robustness of our results relates to the ESG ratings used. Even though the methodology used within the rating agency is consistently applied across all the firms rated, it is not always clear how ESG ratings are exactly constructed, nor whether a large enough investor base takes these ratings (directly or indirectly) 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. Applying the same sample selection steps used for the ASSET4 database, we obtain a final VIGEO-EIRIS sample that comprises 3,696 unique firms, for the period July 2005 to June 2018 (156 months), for four areas: Asia Pacific Ex-Japan (518), Europe (1,357), Japan (543), and North America (1,278).

Table B.1 in Appendix B reports the descriptive statistics of the cross-sectional distributions of the firm-specific accounting variables and ESG scores. Table B.2 reports the descriptive statistics for the ESG decile portfolios composed of firms from the VIGEO-EIRIS database. Again, in line with the (theoretical) notion of the existence of an ESG premium, we observe a decreasing pattern in the average excess returns as we move from the *Worst* to *Best* portfolio. In line with Table 2, the pattern translates into a monthly negative ESG premium based on the difference portfolio, $Diff$, that is long in the $Best$ and short in the $Worst$ (Panel A, column [1]). In contrast to Table 2, the return on the $Diff$ portfolio is not statistically significant, and all the portfolios are correctly priced according to the GRS-test statistics for the 6-/7-Factor specification. It is worth noting however that the differences with respect to Table 2 might be explained by the smaller variation in terms of ESG score levels, yielding relatively smaller differences in ESG characteristics between the *Worst* and *Best* portfolio.

Table 7 reports the results for the cross-sectional regressions using the ESG data from VIGEO-EIRIS. The coefficient for the ESG characteristic is still negative and significant for all specifications (columns [1]–[4]), and it ranges between -0.022 and -0.024 per month. Again, the ESG characteristics explain better the variation of cross-sectional expected returns in comparison to the ESG beta. As such, 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. The intercept is insignificant in all specifications (columns [2]–[4]), and the premiums on firm characteristics are all insignificant for each specification, with the exception of lME. Different from the results in Table 3, the size risk betas are barely priced in the 7-factor specification, but the profitability risk factor is priced. Finally, the percentage of cross-sectional variation explained by the factor loadings reaches its maximum for the 7-factor specification (column [4]) and is slightly above 22%. The characteristics explain most of the cross-sectional variation in expected returns (columns [1]–[4]).

We also verify for the VIGEO-EIRIS database whether demand shifts have biased the estimate of the monthly ESG premium in Table 7. In this respect, Fig. 2 shows the three-year moving average of the monthly biased ESG premium ($\tilde{\gamma}_2$), and the monthly ESG bias (θ_2). Again, an increase/decrease in the realized returns precedes a drop/rise in the expected returns. Correcting the monthly biased ESG premium ($\tilde{\gamma}_2$) for the ESG bias (θ_2) results into an unbiased ESG premium (γ_2) of -0.026 and it is statically significant at 1% (Table 8).

As a final robustness check, we also conducted the analysis with in-sample constructed Fama–French risk factors (Table B.3), and repeat our analysis at area specific level (Table B.4). The results again corroborate those provided by Table 3, and those based on the Asset4 database. Specifically, the coefficient for the ESG characteristic is always negative, and the ESG characteristic explains more variation in cross-sectional expected returns in comparison to the ESG beta.

Table 7
Cross-sectional regressions – VIGEO-EIRIS.

	[1] 2-factor	[2] 4-factor	[3] 6-factor	[4] 7-factor
$Const$	−0.134	−0.021	−0.102	−0.143
	(−0.273)	(−0.047)	(−0.240)	(−0.342)
lME	0.488***	0.507***	0.524***	0.498***
	(7.140)	(7.162)	(7.673)	(7.604)
$lBtM$	−0.124	−0.112	−0.100	−0.101
	(−0.984)	(−0.950)	(−0.902)	(−0.954)
Inv	−0.374	−0.328	−0.254	−0.273
	(−1.310)	(−1.214)	(−0.947)	(−1.072)
Pro	−0.046	−0.040	−0.057	−0.054
	(−0.286)	(−0.272)	(−0.369)	(−0.346)
$lRet6$	−0.859	−0.528	−0.341	−0.270
	(−1.505)	(−1.060)	(−0.761)	(−0.598)
ESG	−0.024***	−0.024***	−0.022***	−0.023***
	(−4.053)	(−4.367)	(−4.083)	(−4.273)
$\hat{\beta}_{mk}$	0.182	−0.046	−0.010	0.079
	(0.907)	(−0.165)	(−0.035)	(0.228)
$\hat{\beta}_{s}$		0.203	0.235	0.257*
		(1.198)	(1.523)	(1.720)
$\hat{\beta}_{h}$		0.061	0.084	0.087
		(0.399)	(0.551)	(0.615)
$\hat{\beta}_{r}$			−0.194**	−0.202**
			(−2.020)	(−2.127)
$\hat{\beta}_{c}$			0.019	0.061
			(0.172)	(0.560)
$\hat{\beta}_{w}$				−0.098
				(−0.359)
$\hat{\beta}_{ESG}$	−0.189	−0.220	−0.134	−0.185
	(−0.836)	(−1.143)	(−0.688)	(−0.958)
$\bar{C}_{Zcs}$	116.264	130.525	119.858	123.691
$\bar{C}_{\hat{B}}$	6.640	12.937	16.466	22.536
$\bar{C}_{ESG}$	24.708	25.440	19.278	23.090
$\bar{C}_{\hat{\beta}_{ESG}}$	4.487	6.556	2.167	4.648

The table reports the time-series averages of γ coefficients estimated using Eq. (2) that accounts for the EIV-bias correction:

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

The betas are estimated using different versions of the factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 3,696 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. $\bar{C}_{ESG}$ and $\bar{C}_{\hat{\beta}_{ESG}}$ represent the proportions of variation in expected returns explained by the ESG characteristics and ESG betas, respectively. ***,** and * denote 1%, 5%, and 10% significance.

Table 8
Cross-sectional regressions for the dividend price-ratio – VIGEO-EIRIS.

[1]	[2]	[3]	[4]	[5]
$\tilde{\gamma}_2$	θ_0	θ_1	θ_2	γ_2
−0.023	0.445***	5.3804***	−0.0035***	−0.026***
	(15.489)	(3.496)	(−4.899)	(−29.839)

The table reports the estimates of Eq. (9):

$$\widetilde{dp}_{i,t} = \theta_0 + \theta_1\widetilde{dp}_{i,t-1} + \theta'_2 Zsc_{i,t-1} + v_{i,t}$$

$\widetilde{dp}_{i,t}$ and $\widetilde{dp}_{i,t-1}$ represents the current and one-month lagged scaled dividend price ratio; $Zsc_{i,t-1}$ is a vector including the ESG characteristic only. $\tilde{\gamma}_2$ is the monthly biased ESG premium estimated in Table 3 via specification [4]of Eq. (2), and $\gamma_2 = \tilde{\gamma}_2 + \theta_2$ is the monthly unbiased ESG premium once the monthly biased ESG premium ($\tilde{\gamma}_2$) is corrected for the monthly ESG bias (θ_2). The coefficients are multiplied by 100 and t-statistics are in brackets. ***,** and * denote 1%, 5%, and 10% significance.

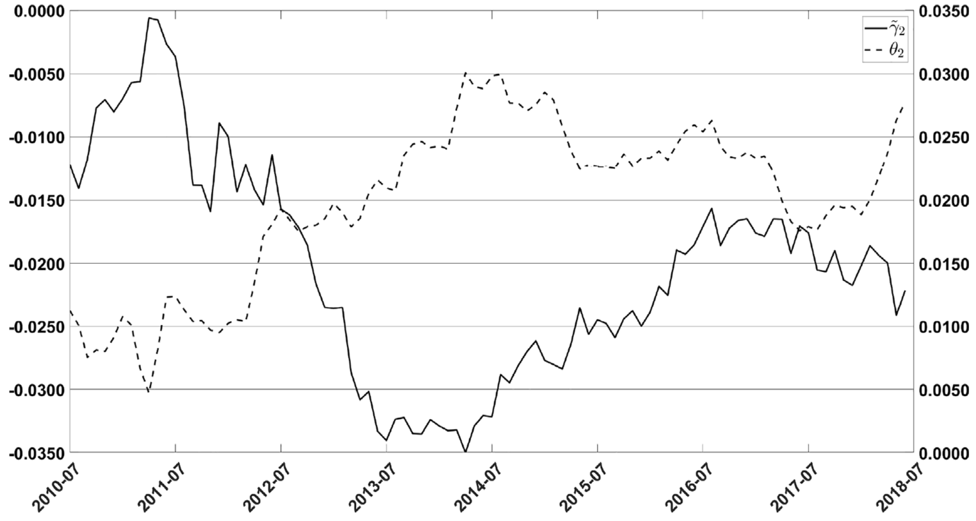

Fig. 2. The three-year moving average of the monthly biased ESG premium (left axis) and the monthly ESG bias (right axis) – VIGEO-EIRIS.
The figure shows the three-year moving average of the monthly biased ESG premium $\tilde{\gamma}_2$ (continuous line) based on Eq. (2), and the monthly ESG bias θ_2 (dashed line) based on Eq. (9). The more negative the ESG bias, the larger is the correction in the monthly biased ESG permium.

6. Conclusion

ESG screening in investment decisions might exist 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. Furthermore, we address a potential bias in assessing the ESG premium.

We first establish the existence of a negative ESG premium, and we show that investor preferences primarily drive such a premium for these assets. We explicitly dissect the separate impact of ESG risk and ESG preferences on the cross-sectional variation in expected returns and empirically support the recent theory in this respect. On top of that, we show how temporary increases in realized returns may bias the estimates of the ESG premium. This last finding, together with a firm-level methodology, enables us to better assess the ESG premium and potentially explains why the literature has documented mixed findings.

Using a global sample of firms for the period 2003 to 2020, and accounting for the EIV problem, we find evidence of a negative ESG premium. In addition, ESG characteristics appear to be the only determinant of the ESG premium and not ESG risk factor betas. Specifically, a one standard deviation increase in the ESG score is associated with a decrease in expected returns of about 2.73% annually. We additionally postulate that sudden ESG-related demand increases may cause a bias in the baseline estimation. ESG-related changes in demand may be associated with changes in expected returns – reflected by temporary higher realized returns – and this in turn biases our estimate of the ESG premium. Using Fama-MacBeth regressions of dividend-price ratios on ESG characteristics, the unbiased ESG premium turns out to be equal to 3.41% on an annual basis. These results are consistent across four investment areas, the two ESG data sets, and robust to various specifications and different proxies for the risk factors. Our results reveal that investors are only willing to hold firms with low ESG scores if they are compensated with higher expected returns, irrespective of risk considerations. Moreover, the decrease in expected returns tends to increase as investors: (1) tilt their portfolios even more towards stocks with the best ESG performance (e.g., by a using two standard deviation increase of the ESG characteristic instead of one), and (2) if they keep following such a strategy for a prolonged period. Such implications deliver an important message for policy makers and researchers too. The former might want to carefully implement policy aiming to make available ESG investments to a broader investor base. For the latter it is essential to realize that "shifts in equilibrium" in terms of increased demand for ESG assets may bias the estimates for the ESG premium upward. This finding is rather encouraging, as it points out that previous estimates, at minimum, have been conservative—the magnitude of the ESG premium is perhaps larger than we thought. Future research may focus on improving the bias correction of the ESG premium estimate.

CRediT authorship contribution statement

Rocco Ciciretti: Conceptualization, Methodology, Data curation, Writing – review & editing, Supervision. **Ambrogio Dalò:** Conceptualization, Methodology, Software, Data curation, Writing – original draft, Writing – review & editing. **Lammertjan Dam:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

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Appendix A. Proofs and derivations

Derivation of Eq. (8)

The Campbell and Shiller (1988) log-linearized return identity for a generic stock i reads:

$$r_{i,t+1} = \Delta d_{i,t+1} + dp_{i,t} - \rho dp_{i,t+1} \tag{A.1}$$

where $r_{i,t+1} = \log(R_{i,t+1})$ is the log return at time $t+1$ for stock i, $\Delta d_{i,t+1} = \log(D_{i,t+1}/D_{i,t})$ is log dividend growth, $dp_{i,t} = \log(D_{i,t}/P_{i,t})$ is the log dividend-price ratio at time t, and ρ is a constant of log-linearization. Campbell and Vuolteenaho (2004) iterate this equation forward and take the difference between the return at time $t+1$ and its expectation at time t to obtain Eq. (5) in the main text. We take similar steps, but focus directly on obtaining a proxy for $N_{DRi,t}$. We rearrange (A.1), and express it in terms of current dividend-price ratio ($dp_{i,t}$),

$$dp_{i,t} = \rho dp_{i,t+1} + r_{i,t+1} - \Delta d_{i,t+1},$$

and iterate forward up to infinity to obtain the following identity:

$$dp_{i,t} = \sum_{j=1}^{\infty} \rho^{j-1}(r_{i,t+j} - \Delta d_{i,t+j}) \tag{A.2}$$

To match the right-hand side term in Eq. (5), we scale Eq. (A.2) with the constant of linearization (ρ), and label the scaled dividend-price ratios as $\widetilde{dp}_{i,t}$, as introduced in Eq. (8) of the paper:

$$\widetilde{dp}_{i,t} = \sum_{j=1}^{\infty} \rho^{j}(r_{i,t+j} - \Delta d_{i,t+j}) \tag{A.3}$$

A stylized fact from the literature on return predictability (Cochrane, 2009) is that the dividend-price ratio predicts returns but does not predict dividend growth. So as an identifying assumption we render the dividend-growth term unpredictable by the dividend-price ratio (or i.i.d), such that $\mu_{i,d} := E_{t-1}\left[\sum_{j=1}^{\infty} \rho^j \Delta d_{i,t+j}\right] = E_t\left[\sum_{j=1}^{\infty} \rho^j \Delta d_{i,t+j}\right]$. We then take the difference in expectation at t ($E_t[.]$) and $t-1$ ($E_{t-1}[.]$) of Eq. (A.3) and obtain:

$$\widetilde{dp}_t - E_{t-1}[\widetilde{dp}_{i,t}] = E_t\left[\sum_{j=1}^{\infty} \rho^j r_{i,t+j}\right] - E_{t-1}\left[\sum_{j=1}^{\infty} \rho^j r_{i,t+j}\right] = (E_t - E_{t-1})\sum_{j=1}^{\infty} \rho^j r_{i,t+j} = N_{DRi,t}, \tag{A.4}$$

which is Eq. (8) in the paper.

Appendix B. VIGEO-EIRIS ESG data set

See Tables B.1–B.4.

Table B.1
Descriptive statistics for the firm-level characteristics and the estimated betas – VIGEO-EIRIS.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
	Panel A: Cross-Sectional Distributions												
	lME	$lBtM$	Pro	Inv	$lRet6$	ESG	$\hat{\beta}_{mk}$	$\hat{\beta}_s$	$\hat{\beta}_h$	$\hat{\beta}_r$	$\hat{\beta}_c$	$\hat{\beta}_w$	$\hat{\beta}_{ESG}$
$Mean$	1.267	−0.701	0.292	0.116	0.020	33.466	1.031	0.401	0.064	0.098	−0.120	−0.068	−0.113
$St.dev.$	1.577	0.860	0.470	0.353	0.245	11.797	0.396	0.726	0.905	1.196	1.207	0.461	0.629
10%	−0.649	−1.799	0.046	−0.127	−0.241	19.000	0.541	−0.450	−0.976	−1.403	−1.639	−0.603	−0.989
25%	0.332	−1.205	0.142	−0.037	−0.081	25.000	0.780	−0.104	−0.458	−0.554	−0.741	−0.291	−0.529
50%	1.278	−0.625	0.242	0.051	0.033	32.000	1.015	0.323	0.027	0.188	−0.003	−0.038	−0.035
75%	2.268	−0.106	0.381	0.165	0.149	42.000	1.269	0.818	0.563	0.839	0.624	0.195	0.333
90%	3.247	0.285	0.598	0.358	0.271	50.000	1.536	1.354	1.186	1.515	1.240	0.439	0.630
	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												
$lBtM$	−0.140	1.000											
Pro	0.113	−0.399	1.000										
Inv	−0.042	−0.125	−0.029	1.000									
$lRet6$	0.085	−0.040	0.016	−0.015	1.000								
ESG	0.297	0.025	0.083	−0.101	0.005	1.000							
$\hat{\beta}_{mk}$	−0.011	0.050	−0.023	0.012	−0.034	0.075	1.000						
$\hat{\beta}_s$	−0.440	0.154	−0.087	−0.014	−0.031	−0.174	0.148	1.000					
$\hat{\beta}_h$	−0.069	0.304	−0.020	−0.099	−0.036	−0.010	0.025	0.178	1.000				
$\hat{\beta}_r$	−0.069	0.086	0.046	−0.074	0.007	−0.020	−0.023	0.242	0.365	1.000			
$\hat{\beta}_c$	0.077	0.005	0.018	−0.121	0.019	0.008	0.018	0.047	−0.277	0.099	1.000		
$\hat{\beta}_w$	0.079	−0.158	0.025	0.069	0.121	−0.038	−0.134	−0.107	−0.010	0.036	−0.061	1.000	
$\hat{\beta}_{ESG}$	0.120	−0.002	−0.035	0.013	0.023	−0.389	0.050	0.017	0.037	0.063	0.146	−0.044	1.000

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 in Eq. (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 3,696 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.

Table B.2
Properties of decile portfolios sorted on ESG score – VIGEO-EIRIS.

	Panel A: Descriptives			
	$\bar{R}_p^e$	σ_p	ShR_p	$\overline{ESG}_p$
$Worst$	1.146	5.487	0.209	14.488
2	1.561	5.014	0.311	21.412
3	1.424	4.768	0.299	25.485
4	1.260	5.133	0.245	28.766
5	1.308	5.067	0.258	32.195
6	1.185	4.504	0.263	35.374
7	0.723	4.881	0.148	38.857
8	0.993	4.621	0.215	42.593
9	1.001	4.603	0.217	47.252
$Best$	0.758	4.881	0.155	55.152
$Diff$	−0.387			
	(−0.659)			

	Panel B: Multifactor time-series regression alphas and GRS test.			
	$2-Factor$	$4-Factor$	$6-Factor$	$7-Factor$
$Worst$	−0.286	−0.226	−0.224	−0.23
	(−1.153)	(−0.942)	(−0.883)	(−0.911)
2	0.182	0.212	0.232	0.232
	(1.034)	(1.228)	(1.278)	(1.274)
3	0.097	0.098	0.195	0.194
	(0.556)	(0.572)	(1.088)	(1.081)
4	−0.004	0.016	0.016	0.015
	(−0.018)	(0.076)	(0.071)	(0.07)
5	0.098	0.109	0.16	0.161
	(0.469)	(0.533)	(0.746)	(0.746)
6	0.076	0.038	0.053	0.053
	(0.399)	(0.206)	(0.271)	(0.268)
7	−0.469***	−0.481***	−0.421**	−0.423**
	(−2.717)	(−2.767)	(−2.304)	(−2.309)
8	−0.145	−0.163	−0.178	−0.178
	(−0.862)	(−0.982)	(−1.026)	(−1.02)
9	−0.051	−0.069	−0.017	−0.019
	(−0.384)	(−0.515)	(−0.12)	(−0.139)
$Best$	−0.203	−0.219	−0.134	−0.133
	(−1.34)	(−1.455)	(−0.867)	(−0.857)
$Diff$	−0.083	−0.007	−0.089	−0.097
	(−0.301)	(−0.026)	(−0.318)	(−0.345)
GRS	[1.726]	[1.858]	[1.614]	[1.605]

The table reports in Panel A the overall period average of the monthly excess return ($\bar{R}_p^e$) for the ESG portfolios in percentage, standard deviation (σ_p), Sharpe Ratio (ShR_p), and the average ESG score ($\overline{ESG}_p$). Panel B reports the pricing errors in percentage estimated for the decile portfolios and the difference portfolio ($Diff$) using different versions of factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML and WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). $Worst$ is the portfolio composed of firms with the lowest ESG score, $Best$ is the portfolio composed of firms with the highest ESG score, and $Diff$ is the long-short portfolio defined as the difference of the monthly return series between the $Worst$ and $Best$ decile portfolio. The sample consist of 3,696 global firms for 156 months (July 2005–June 2018). t-statistics are reported in round brackets. The GRS test is on the alphas of the 10 ESG portfolios (Gibbons et al., 1989). ***,** and * denote 1%, 5%, and 10% significance.

Table B.3
Cross-sectional regressions using in-sample constructed risk factors – VIGEO-EIRIS.

	[1] 2-factor	[2] 4-factor	[3] 6-factor	[4] 7-factor
$Const$	0.005	−0.046	−0.093	−0.006
	(0.010)	(−0.103)	(−0.225)	(−0.014)
lME	0.486***	0.525***	0.502***	0.489***
	(7.118)	(7.068)	(7.054)	(6.943)
$lBtM$	−0.131	−0.164	−0.110	−0.140
	(−1.030)	(−1.335)	(−0.895)	(−1.231)
Pro	−0.058	−0.104	−0.034	−0.097
	(−0.366)	(−0.703)	(−0.225)	(−0.655)
Inv	−0.353	−0.275	−0.311	−0.271
	(−1.253)	(−1.002)	(−1.153)	(−1.004)
$lRet6$	−0.897	−0.483	−0.068	−0.109
	(−1.566)	(−0.885)	(−0.139)	(−0.224)
ESG	−0.025***	−0.024***	−0.021***	−0.020***
	(−4.193)	(−4.498)	(−4.036)	(−3.905)
$\hat{\beta}_{mk}$	0.115	−0.132	−0.113	−0.202
	(0.547)	(−0.434)	(−0.322)	(−0.554)
$\hat{\beta}_s$		0.069	0.241**	0.279**
		(0.369)	(2.127)	(2.491)
$\hat{\beta}_h$		0.208	0.028	0.155
		(1.093)	(0.152)	(0.933)
$\hat{\beta}_r$			−0.241**	−0.214
			(−1.982)	(−1.587)
$\hat{\beta}_c$			0.138	0.192
			(0.574)	(0.835)
$\hat{\beta}_w$				−0.182
				(−0.894)
$\hat{\beta}_{ESG}$	−0.229	−0.145	−0.054	−0.028
	(−1.006)	(−0.707)	(−0.265)	(−0.144)
$\bar{C}_{Zcs}$	116.391	120.859	107.893	111.514
$\bar{C}_{\hat{B}}$	7.351	8.749	22.955	33.959
$\bar{C}_{ESG}$	24.626	22.381	17.506	16.717
$\bar{C}_{\hat{\beta}_{ESG}}$	4.657	2.491	0.300	0.083

The table reports the time-series averages of γ coefficients estimated using Eq. (2) that accounts for the EIV-bias correction:

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

The betas are estimated using different versions of the factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 3,696 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. $\bar{C}_{ESG}$ and $\bar{C}_{\hat{\beta}_{ESG}}$ represent the proportions of variation in expected returns explained by the ESG characteristics and ESG betas, respectively. ***,** and * denote 1%, 5%, and 10% significance.

Table B.4
Cross-sectional regressions at area-specific level – VIGEO-EIRIS.

	[1] Asia Pacific ex-Japan	[2] Europe	[3] Japan	[4] North America
$Const$	0.372	0.358	0.479	−0.240
	(0.698)	(0.689)	(0.889)	(−0.547)
lME	0.373***	0.601***	0.482***	0.490***
	(3.000)	(6.969)	(5.253)	[8.255)
$lBtM$	−0.398**	−0.002	−0.137	0.008
	(−2.165)	(−0.012)	(−0.716)	(0.080)
Pro	−1.376***	0.222	0.691	−0.420***
	(−2.605)	(0.908)	(0.929)	(−3.119)
Inv	0.641	0.269	−0.859	−0.604***
	(0.981)	(0.729)	(−0.920)	(−2.746)
$lRet6$	0.847	0.612	−0.368	−0.627
	(0.854)	(1.033)	(−0.538)	(−1.180)
ESG	−0.010	−0.022***	−0.014*	−0.014**
	(−0.765)	(−3.698)	(−1.958)	(−2.252)
$\hat{\beta}_{mk}$	−0.120	−0.530	0.091	0.317
	(−0.332)	(−1.151)	(0.227)	(0.931)
$\hat{\beta}_s$	0.312	0.754***	1.193***	0.578***
	(0.932)	(3.396)	(4.913)	(2.754)
$\hat{\beta}_h$	0.443	0.199	−0.067	−0.778***
	(1.470)	(1.021)	(−0.269)	(−3.713)
$\hat{\beta}_r$	0.042	−0.398***	−0.255*	0.296**
	(0.133)	(−2.830)	(−1.837)	(2.551)
$\hat{\beta}_c$	0.492**	0.068	−0.192	−0.089
	(2.030)	(0.570)	(−1.436)	(−0.656)
$\hat{\beta}_w$	−1.179***	−0.132	−0.570***	−0.076
	(−2.720)	(−0.423)	(−2.123)	(−0.271)
$\hat{\beta}_{ESG}$	0.007	0.037	−0.192	−0.246
	(0.015)	(0.230)	(−0.784)	(−1.382)
$\bar{C}_{Zcs}$	79.416	124.980	87.036	74.439
$\bar{C}_{\hat{B}}$	71.159	47.194	98.334	55.612
$\bar{C}_{ESG}$	2.565	18.555	7.099	3.317
$\bar{C}_{\hat{\beta}_{ESG}}$	0.001	0.056	1.560	3.615

The table reports the time-series averages of the estimated using Eq. (2) that accounts for the EIV-bias for each of the investment areas as defined by Fama and French (2017):

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

The betas are estimated using different versions of the factor model in Eq. (1), namely, 2-factor (Mkt and WMB), 4-factor (Mkt, SMB, HML WMB), 6-factor (Mkt, SMB, HML, RMW, CMA and WMB), and 7-factor (Mkt, SMB, HML, RMW, CMA, WML and WMB). The cross-sectional characteristics ($Zcs_{i,t-1}$) are: logarithm of market capitalization (lME), logarithm of the book-to-market ratio ($lBtM$), operating profitability (Pro), assets growth (Inv), logarithm of one 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: 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 time-series regressions using past two years of daily data; we require at least 400 observations to estimate betas. The sample consists of 3,696 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. $\bar{C}_{ESG}$ and $\bar{C}_{\hat{\beta}_{ESG}}$ represent the proportions of variation in expected returns explained by the ESG characteristics and ESG betas, respectively. ***,** and * denote 1%, 5%, and 10% significance.

References

Albuquerque, R., Koskinen, Y., Zhang, C., 2019. Corporate social responsibility and firm risk: Theory and empirical evidence. Manage. Sci. 65 (10), 4451–4469.
Bauer, R., Derwall, J., Guenster, N., Koedijk, K., 2005. The eco-efficiency premium puzzle. Financ. Anal. J. 61 (2), 51–63.
Bauer, R., Derwall, J., Otten, R., 2007. The ethical mutual fund performance debate: New evidence from Canada. J. Business Ethics 70 (2), 111–124.
Bauer, R., Otten, R., Rad, A., 2006. Ethical investing in australia: Is there a financial penalty? Pac.-Basin Finance J. 14 (1), 33–48.
Becchetti, L., Ciciretti, R., Dalò, A., 2018. Fishing the corporate social responsibility risk factors. J. Financial Stab. 37, 25–48.
Black, F., Jensen, M., Scholes, M., 1972. The capital asset pricing model: some empirical tests. In: Studies in the Theory of Capital Markets.
Brennan, M., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. J. Financ. Econ. 49 (3), 345–373.
Campbell, J., Shiller, R., 1988. The dividend-price ratio and expectations of future dividends and discount factors. Rev. Financ. Stud. 1 (3), 195–228.
Campbell, J.Y., Vuolteenaho, T., 2004. Bad beta, good beta. Amer. Econ. Rev. 94 (5), 1249–1275.
Carhart, M., 1997. On persistence in mutual fund performance. J. Finance 52 (1), 57–82.
Chordia, T., Goyal, A., Shanken, J., 2017. Cross-Sectional Asset Pricing with Individual Stocks: Betas Versus Characteristics. Working Paper.

Cochrane, J.H. (Ed.), 2009. Asset Pricing, revised ed. Princeton University Press.
Dam, L., Scholtens, B., 2015. Toward a theory of responsible investing: On the economic foundations of corporate social responsibility. Resour. Energy Econ. 41, 103–121.
De Haan, M., Dam, L., Scholtens, B., 2012. The drivers of the relationship between corporate environmental performance and stock market returns. J. Sustain. Finance Invest. 2 (3–4), 338–375.
Derwall, J., Koedijk, K., Ter Horst, J., 2011. A tale of values-driven and profit-seeking social investor. J. Bank. Financ. 35 (8), 2137–2147.
Fama, E., French, K., 1992. The cross-section of expected stock returns. J. Finance 47 (2), 427–465.
Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–53.
Fama, E., French, K., 2012. Size, value, and momentum in international stock returns. J. Financ. Econ. 105 (3), 457–472.
Fama, E., French, K., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22.
Fama, E., French, K., 2017. International tests of a five-factor asset pricing model. J. Financ. Econ. 123 (3), 441–463.
Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. J. Polit. Econ. 81 (3), 607–636.
Ferson, W., Sarkissian, S., Simin, T., 1999. The alpha factor asset pricing model: A parable. J. Financial Mark. 2 (1), 49–68.
Freeman, E. (Ed.), 1984. Strategic Management: A Stakeholder Approach. Pitman.
Galema, R., Plantinga, A., Scholtens, B., 2008. The stocks at stake: Return and risk in socially responsible investment. J. Bank. Financ. 32 (12), 2646–2654.
Gibbons, M.R., Ross, S.A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57 (5), 1121–1152.
Global Sustainable Investment Alliance, 2018. Global Sustainable Investment Review. Technical report.
Global Sustainable Investment Alliance, 2020. Global Sustainable Investment Review. Technical report.
Hamilton, S., Jo, H., Statman, M., 1993. Doing well while doing good? the investment performance of socially responsible mutual funds. Financ. Anal. J. 49 (7), 62–66.
Hartzmark, S., Sussman, A., 2019. Do investors value sustainability? a natural experiment examining ranking and fund flows. J. Finance 74 (6), 2789–2837.
Heinkel, R., Kraus, A., Zechner, J., 2001. The effect of green investment on corporate behavior. J. Financ. Quant. Anal. 36 (4), 431–449.
Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. J. Financ. Econ. 93 (1), 15–36.
Kempf, A., Osthoff, P., 2007. The effect of socially responsible investing on portfolio performance. Eur. Financial Manag. 13 (5), 908–922.
Lewellen, J., Nagel, S., Shanken, J., 2010. A skeptical appraisal of asset pricing tests. J. Financ. Econ. 96 (2), 175–194.
Luo, A., Balvers, R., 2017. Social screens and systematic investor boycott risk. J. Financ. Quant. Anal. 52 (1), 365–399.
Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. J. Finance 42 (3), 483–510.
Pástor, L., Stambaugh, R.F., Taylor, L.A., 2021a. Sustainable investing in equilibrium. J. Financ. Econ. 142 (2), 550–571.
Pástor, L., Stambaugh, R.F., Taylor, L.A., 2021b. Dissecting Green Returns. Working Paper.
Pedersen, L.H., Fitzgibbons, S., Pomorski, L., 2021. Responsible investing: The esg-efficient frontier. J. Financ. Econ. 142 (2), 572–597.
Renneboog, L., Ter Horst, J., Zhang, C., 2008. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. J. Corp. Finance 14 (3), 302–322.
Statman, M., Glushkov, D., 2009. The wages of social responsibility. Financ. Anal. J. 65 (4), 33–46.
US Social Investment Foundation, 2018. The Impact of Sustainable and Responsible Investment. Technical report.
US Social Investment Foundation, 2020. Report on Us Sustainable and Impact Investing Trends. Technical report.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 817–838.