The impact of ESG momentum in stock prices

Carolina Sverner[†]
Andrea Minardi[‡]
Fernando Tassinari Moraes[*]

Abstract This paper investigates whether ESG (environmental, social and governance) practices impact stock prices. We collected data of the stocks that compose the S&P500 from June 2014 to June 2021. First, we tested the hypothesis that there is a negative relation between stock returns and the ESG rating. We built an ESG factor, following the Fama and French (1993) procedure, with the Sustainalytics ESG score. The results of the two-stage cross-section regressions indicate the existence of an ESG risk premium: we estimated that the portfolio of companies with the worst ESG ratings has a return between 0.20% and 0.29% higher than the portfolio of companies with the best ratings when controlled for other risk factors. Following, we tested the hypothesis that the variation in ESG scores has a significant impact on stock returns. For that, we created an ESG Momentum factor using the same procedure described in Fama and French (1993) and the two-stage cross-sectional regression estimated a return premium between 0.23% and 0.35%—that is, the excess return of a portfolio that is long on the shares with the highest ESG score upgrade, and short on the shares with the highest downgrades. The rating upgrades had a more expressive impact on the returns than the rating downgrades. This is evidence that the improvement in the quality of ESG practices causes an appreciation in the stock prices. However, both results lose significance when we utilize the generalized method of moments (GMM) for estimation.

Keywords: ESG; ESG momentum; Equities risk factor; Sustainability; ESG risk premium.
JEL Code: G11, G12.

1. Introduction

Investment strategies that, besides the traditional risk and return approach, take into account the exposition of companies to Environmental, Social and Governance (ESG) issues have become mainframe. According to Global Sustainable Investment Alliance (GSIA, 2020), more than US$35.5 trillion were invested in funds that claimed to be focused or to address ESG issues: a cumulative growth of 15% in two years, and 55% between 2016 e 2020. ESG investments represent around 36% of the total assets under management in

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[†]Insper, Brazil: carolinass2@al.insper.edu.br
[‡]Insper, Brazil: minardi@insper.edu.br
[*]Insper, Brazil: fernandotm@al.insper.edu.br

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the five markets analyzed by the report.[1] Both ethical reasons and the impact of ESG issues in the long-term performance are behind this behavior. Many financial analysts believe that the winner corporations will be those that treat Environmental, Social and Governance issues as key factors in their strategy.

Several studies propose that the ESG profile is negatively related to idiosyncratic and systematic risks. According to Bénabou and Tirole (2010), the ESG profile of a company can affect its systematic risk because the sustainable practices impact the resilience of the corporation during periods of crises. Factors such as change of regulations, supply chain, technological and reputational risks also affect the idiosyncratic risk (Starks, 2009). Sayani and Kaplan (2020) and Bae et al. (2021) show that a higher ESG score reduces the risk of an abrupt drop in the share price. Dunn et al. (2018) find evidences that the stocks of companies with the lowest MSCI ESG score have a volatility 15% higher and a beta up to 3% higher than the stocks of companies with the highest scores. As ESG characteristics are reflected in the corporate risks, we can assume that they also impact the corporation cost of capital. Therefore, we should expect an appreciation in the share prices of companies that improve its sustainable practices.

Similar to Pástor et al. (2021), we raised the hypothesis that companies with better ESG practices have lower risks, and are preferred by investors who appreciate sustainability. In equilibrium, the shares of companies with better ESG practices are priced higher and consequently have lower expected returns. Therefore, in equilibrium, investors require a return premium to invest in companies with poor ESG practices.

We built the ESG factor, which is linked to the ESG rank of the corporations. Our first hypothesis proposes that the ESG factor is negatively related to the cross-section returns of the stocks.

Most of the studies in the academic literature find a positive relation between the quality of sustainable practices and firm value, but the causal effect of the ESG attributes in firm value can be either positive or negative (Gillan et al., 2021). On the one hand, ESG practices can create shareholder value because they increase future cash flows (ie: consumers pay a premium price on brands that have high reputation on sustainability issues, those companies hire more talented employees which are more productive), or because they reduce the cost of capital either due to the increase in shareholder utility or due to risk reduction. On the other hand, ESG practices can reflect agency problems, and top management can engage on those practices to maximize their utility instead of shareholders' utility (Bénabou and Tirole, 2010). Several ESG practices reduce firm value, because they require heavy investments

[1] Europe, United States, Japan, Canada, Australia and New Zealand.

in CAPEX and incur in high short-term costs and expenses, while it produces uncertain positive returns in the long term (Cornell and Damodaran, 2020). Companies with better operational performance and lower risks are more able to, and have more resources to implement the best environmental, social and governance practices, and therefore, the causal direction is in the opposite direction: higher valuations and better operation performance lead to better ESG performance. Both causal directions predict a positive (negative) relation between stock price (return) and ESG score, and the identification of the causal direction is an econometric concern.

There is little consensus on what is material for each specific industry and region, which results in a lack of convergence in ESG scores of different providers (Berg et al., 2022). Consequently, there are still many inefficiencies in the pricing of environmental, social and governance practices (Pástor et al., 2021).

By logical extension of the first assumption, we can conclude that a change in the ESG profile can also provide useful information on equity valuation. Therefore, our second proposed hypothesis is that if the market appreciates sustainable practices, an improvement in the ESG performance should result in an appreciation on the stock price, while a deterioration in the ESG performance should bring about a stock price reduction. This second hypothesis tests how the stock price reacts to a change in the sustainable practice quality, reducing the identification problem of the first hypothesis.

We built a factor linked to the upward trend of the ESG rank, and called it ESG Momentum (ESGM). Our hypothesis is that the ESG Momentum should result in a significant return premium in the explanation of the cross-section returns, because as sustainable practices improve, there is a reduction in the ESG risk, and consequently an appreciation in the stock price.

We used the relative position in the ESG scores (ESG rank) of Sustainatytics Morningstar as a proxy for ESG profile, and collected data of the stocks that compose the S& P 500 index to test both hypotheses during the period between June 2014 and June 2020.

This article brings two main contributions. Firstly, it addresses the relation between the current ESG profile of a company and its return, without investigating the direction of the causality. The second is related to the explanation power of the improvements in the quality of ESG practices on the stock returns. Both results are in accordance to our proposed hypotheses. We find evidence, yet weak, of a premium for poor ESG practices, that is, a negative relation between stock return and ESG score, and a premium for the ESGM factor, indicating that improvement in the quality of the ESG practices result in the stock price appreciation.

Evidences that share price reacts positively to ESG practices may motivate more players in the financial market to incorporate ESG momentum in their investment decision, creates incentives for the launch of funds focused on buying shares of companies improving ESG practices, and also support board members and top management in defending the implementation of corporate sustainability initiatives.

2. Theoretical framework and hypotheses formulation

Halbritter and Dorfleitner (2015), Nagy and Giese (2018), Dunn et al. (2018), Giese et al. (2019a,b), Lee et al. (2021), Pástor et al. (2021) are some of the academic studies that investigate the relation between ESG ratings, risk metrics and returns. There is a lack of consensus in the literature, and this is expected, since the disclosure of sustainable practices of different companies and countries are heterogeneous (Baldini et al., 2018), ESG scores of different providers often diverge (Berg et al., 2022), and there is a broad spectrum about what is considered as an ESG investment.

Initially, social responsible investments (SRI) were limited to *negative screening*, that is, to exclude from the investment portfolio securities of companies with low ESG classification, or even whole sectors like tobacco, weapons and cigars, regardless of the specific sustainability conduct of a company. According Kotsantonis et al. (2016), this approach of ESG investing fails in capturing the value added by sustainable practices.

However, even among studies which consider other ESG investment strategies, as for instance positive screening (search for the companies with the best ESG score in relation to the peers), or ESG integration (systematic integration of ESG issues in the analysis and investment decisions,[2]) there is divergence in the findings.

Dunn et al. (2018) find evidences that stocks with lower ESG scores have higher total, specific and systematic risks. They also found that the ESG classification can predict future risks up to five years. Sayani and Kaplan (2020), and Bae et al. (2021) showed that, once controlled for other risk factors, companies with the highest MSCI ESG scores have historically lower frequency of tail risk, that is, sudden drops in stock prices.

Hong and Kacperczyk (2009) found evidences of a return premium in the “sin” stocks (alcohol, tobacco, and gaming). According to the authors, some investors, especially those that are norm constrained, like pension funds, abstain from investing in stocks that promote vice. A lower demand for those securities imply in lower stock prices, and consequently higher future re-

[2] According to PRI (Principle for Responsible Investment)

turns. Kotsantonis et al. (2016) propose that investors that are attracted by a company's sustainable practices may accept lower returns, and as a consequence, reduce its cost of capital. Both articles are in accordance to Pástor et al. (2021), which propose that in equilibrium, assets with better sustainable practices have lower expected returns than assets with poor practices, and this is due either to the investors preference for holding sustainable securities, or for a recognition that those assets have lower risk.

Halbritter and Dorfleitner (2015) observed that the explanation power of ESG score in stock returns is reduced along time. They built a portfolio long in the shares of companies with the highest ESG score and short in the shares of companies with the lowest ESG scores, and found a positive alpha in the period between 1991 and 2001. They observed a drop in the alpha after this period, and after 2012 the alpha found became not significantly different from zero. As more investors value good sustainable practices, the share price of companies with better ESG profiles rises, and their expected rate of return become lower than those of companies with poor practices.

Accordingly, we raised the hypothesis that companies with higher ESG scores should have lower returns than companies with lower scores. That is, we propose that there is a premium for corporate sustainability—investors require an excess return to invest in companies with the worst sustainable practices.

H_1: A factor linked to ESG has a negative relationship with the cross-section returns.

Materiality is a relevant issue regarding the impact of sustainable practices on firm value. A specific ESG topic may be very relevant to a certain industry (material factor), and peripheric to another one (immaterial factor). Khan et al. (2016) classified sustainable issues reported by corporations as material and immaterial according to the industry materiality map of the Sustainability Accounting Standard Boards (SASB), and built a material (immaterial) firm specific rating. Results indicated that firms with high residual changes on material issues outperformed firms with low residual changes on the same issues. However, firms with high residual chances on immaterial sustainability issues do not outperform firms with low residual changes on these topics.

The disclosure of sustainability practices and the concept of what is material across different sectors, companies and regions are heterogenous (Baldini et al., 2018). Berg et al. (2022) observed that the ESG ratings of the six main providers disagree substantially– the mean correlation of the ESG scores assigned by different providers is only 0.54. The main sources of divergence are the sets of attributes they use, different indicators used to measure each attribute and the weight divergence. This lack of standardization makes it difficult to evaluate the ESG performance of companies, funds and portfolios. It also creates mixed signals and decreases the incentive of companies to improve their sustainable practices, and disperses the effect of ESG performance on investors' preference and asset prices. It also represents a challenge for academic research, since the choice of utilizing the rating of one provider versus another may change the results and conclusions. Halbritter and Dorfleitner (2015) did not find consistent results in terms of return predictability when using ESG classifications of different providers.

Nagy and Giese (2018) argues that the analysis of the change in ESG score, that is, the ESG momentum, is a more useful approach to understand how the market prices sustainability practices than using static scores, since it provides evidences of the direction of the causality. The authors concluded that the upgrade of the ESG score leads to an appreciation of the equity value, while the downgrade of the ESG score leads to a depreciation of the stock price. They also observe that the impact in valuation is higher for companies with ESG scores in the intermediate range rather than for companies with extreme scores.

Giese et al. (2019b) point that the assignment of ESG ratings to companies is relatively recent, and the time series of scores are short, resulting in a lower statistic confidence level when compared to other usual risk factors. Given the amount of data and the short time horizon of the available data, the impact of changes in the ESG score (ESG Momentum) is more immediate and measurable than the impact of the static score on ESG corporate performance. The authors also observe that ESG momentum had a higher correlation to ESG performance, and it was the most consistent variable across time when comparing to other ESG dimensions.

Based on this discussion, we raised a second hypothesis: an improvement on ESG performance leads to equity value appreciation, and consequently, to abnormal return to investors. The variation of the ESG classification is related to a change in the firm risk, and generates abnormal returns.

H_2: A risk factor linked to the variation of ESG score (ESG Momentum) has a positive relationship to the cross-section returns.

3. Data base and methodology

We collected monthly closing price data of the stocks that compose the S& P500 index during the period between June 2014 and June 2021 in Bloomberg. We excluded stocks with missing price information, and which did not have an ESG classification by Sustainalytics. Our final sample was comprised of 451 companies. The reason why we chose the S& P index lies on a high percentage of stocks that are ESG ranked by Sustainalytics, and as well receive good coverage by financial analysts, with prices that reflect current information.

We used the relative ESG score (ESG rank) as a proxy for ESG firm profile. We collected data of the ESG score of Sustainalytics of Morningstar in Bloomberg, during the period between June 2014 and June 2021. Unfortunately, we did not have access to data of different main providers to check if our results hold to other ESG ratings' datasets. We had access only to the time series of Sustainalytics ESG rank, and not to time series of absolute scores. Although the use of ESG rank reduces the data sensitiveness to outliers and problems due to kurtosis and skewness in the series (Baldini et al., 2018), we recognize that it would be advisable to analyze as well the impact of changes of absolute scores on stock returns, and that the impossibility of doing so is a limitation to our analysis.

The aggregate ESG score of Sustainalytics consolidates the level of preparation, disclosure and involvement in controversies of the company in all three pillars: E, S and G. ESG rank is a classification of a company in the environmental, social and governance pillars of a company relatively to its peers in the industrial sector. The top 1%, corresponds to the percentile 99%, and the bottom 1% to the percentile 1%. Higher scores in ESG rank represent less risky ESG profile. Therefore, score upgrades represent a positive momentum, and score downgrade a negative momentum.

In order to build the ESG Momentum (ESGM), we firstly estimated the annual variation of the company ESG score. For example, the ESG momentum of a certain stock in June 2019 will be measured as the change in the ESG rank of this stock between June 2018 and June 2019. We used annual variation because we did not observe significant score variation in shorter periods. As we need 12-month lag to estimate the score variation in year t, the ESG momentum series start in June 2015 and ends in June 2021, summing up to 72 time series observations for each stock.

In June of each year t, from 2015 to 2021, we ranked stocks in descending order according to their ESG Momentum. Based on this ranking, we allocated the stocks in three portfolios: high (H) – the tercile of the stocks with the highest ESG score, medium (M) – the tercile of stocks with the intermediary ESG scores, and low (L) – the tercile of stocks with the bottom ESG scores.

In order to avoid the influence of company size on ESG-related factors, we control the factors for this characteristic. For this, in June of each year t, from 2015 to 2021, all shares in the database were classified by size (price times number of shares). The median size was then used to divide the database into two groups, one of small companies and the other of big companies called “small” and “big” (S and B respectively).

From the intersections of the two size groups with the three ESG momentum groups, six equally weighted portfolios were constructed: Small Low (S|L), Small Medium (S|M), Small High (S|H), Big Low (B|L), Big Medium (B|M), Big High (B|H). The B|H portfolio, for example, contains the stocks of high ESG momentum (H) among the stocks of the large size group (B).

The monthly returns of the six portfolios were calculated from July of year t to June of $t+1$, and the portfolios were rebalanced in June of $t+1$. The choice of annual rebalancing was due to the findings of Nagy and Giese (2018), who pointed out that changes in the ESG characteristics of a company led to more expressive variations in the price of shares in a time horizon of one year, compared to shorter and longer periods.

The return of the high, medium and low Momentum ESG portfolios is the simple average between the returns of the big and small portfolios of each of the three momentum groups, as presented in equations (1), (2) and (3). The ESGM factor, intended to capture the effect on the returns resulting from the variation of the ESG profile, is the monthly difference between the portfolios of high ESG momentum (H) and low ESG momentum (L), as shown in equation (4). Thus, the difference between the two returns must be independent of the size factor, evidencing instead the different return behaviors of high and low ESGM companies

$$R(\text{High}) = \frac{R(\text{Small}|\text{High}) + R(\text{Big}|\text{High})}{2} \tag{1}$$

$$R(\text{Medium}) = \frac{R(\text{Small}|\text{Medium}) + R(\text{Big}|\text{Medium})}{2} \tag{2}$$

$$R(\text{Low}) = \frac{R(\text{Small}|\text{Low}) + R(\text{Big}|\text{Low})}{2} \tag{3}$$

$$\text{Risk Factor} = R(\text{High}) - R(\text{Low}) \tag{4}$$

The ESG factor was constructed in the same way as the ESGM factor, using, however, the ESG rank score instead of its annual variation to define the high (H), medium (M) and low (L) groups.

Table 1 presents the median and cut-off point of the 1st and 2nd tercile of ESG momentum for small (S) and large (B) companies in each year of the sample. We can observe that in some years the medians move away from zero, indicating that there are more score upgrades (years with a positive median) or score downgrades (years with a negative median). In addition, the dispersion of ESG momentum for smaller companies was higher than for larger

Table 1
Distribution of ESG Moments

	SMALL			BIG		
	Median	Min 1st tercile (High)	Min 2nd tercile (Low)	Median	Min 1st tercile (High)	Min 2nd tercile (Low)
2015-06-30	0.64%	9.03%	−5.95%	0.48%	6.06%	−3.61%
2016-06-30	−0.10%	6.70%	−6.75%	−1.66%	2.75%	−6.76%
2017-06-30	−0.79%	6.21%	−9.10%	−0.13%	4.44%	−7.79%
2018-06-29	3.74%	13.90%	−0.85%	3.55%	12.00%	−0.43%
2019-06-28	1.68%	8.74%	−5.83%	0.60%	7.26%	−6.53%
2020-06-30	1.05%	9.52%	−6.63%	−0.60%	4.49%	−6.62%
2021-06-30	−2.05%	5.20%	−7.59%	−1.84%	3.90%	−7.00%

Table 2
Distribution of ESG scores

	SMALL			BIG		
	Median	Min 1st tercile (High)	Min 2nd tercile (Low)	Median	Min 1st tercile (High)	Min 2nd tercile (Low)
2015-06-30	48.80	60.10	34.60	61.10	71.80	45.30
2016-06-30	48.70	61.70	35.80	58.90	70.70	45.60
2017-06-30	47.50	57.50	36.30	58.10	68.70	43.90
2018-06-29	51.70	63.20	36.20	61.90	73.00	50.50
2019-06-28	50	65.10	36.70	61.90	72.50	49.30
2020-06-30	51.40	65.10	37.30	61.70	73.40	50.40
2021-06-30	51.90	63.40	40.40	59.90	74.10	45.80

companies, so that the tercile's cut-off points were more distant from each other for smaller companies.

Table 2 presents the same information as the previous table, but referring to ESG rank scores. We were able to observe that the largest 50% companies in the sample have higher ESG scores than the smallest 50%, confirming our choice to control ESG and ESGM factors for size.

Figures 1 to 4 shows the cumulative return of each of the 12 portfolios (6 ESGM portfolios and 6 ESG portfolios) during the analyzed period.

Tables 3 and 4 present the descriptive analysis of the returns of the 6 ESGM and 6 ESG portfolios, respectively. We can verify that, among the portfolios built based on ESG momentum, the ones that produced the best annualized cumulative returns were the high-momentum ones, and the worst annualized cumulative returns were obtained by purchasing the average-momentum portfolios. Among the portfolios built on ESG scores, the ones that produced the best annualized cumulative returns were those with medium scores, followed by high grades and finally low grades. However, it was not possible to observe statistical significance in the t-tests for the comparison between the

Figure 1
Cumulative return of ESG Momentum portfolios of small companies (S|H, S|M and S|L)

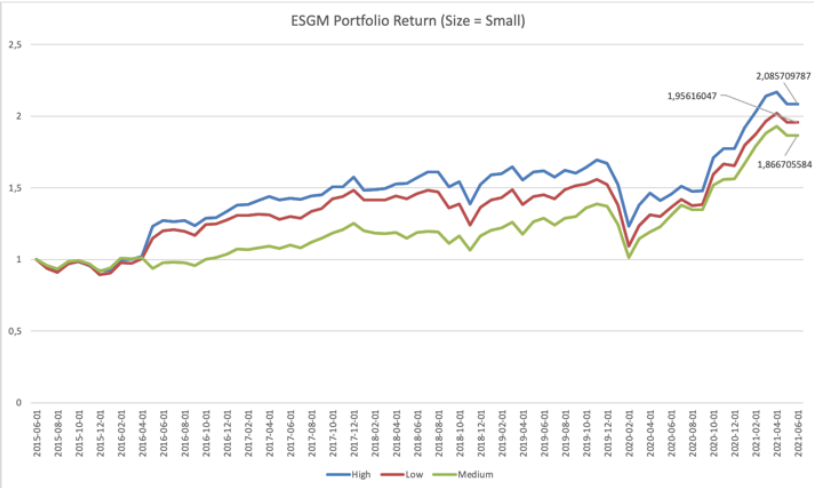


Figure 2
Cumulative return of ESG Momentum portfolios of big companies (B/H, B/M and B/L)

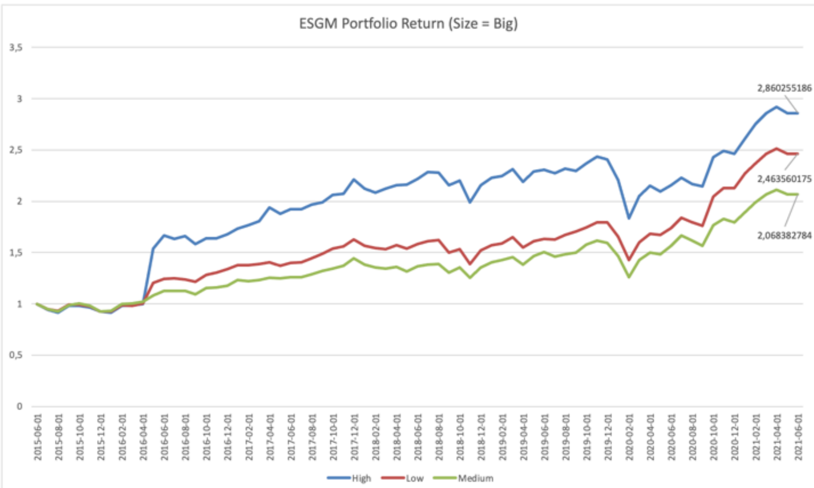


Figure 3
Cumulative return of ESG portfolios of small companies (S|H, S|M e S|L)

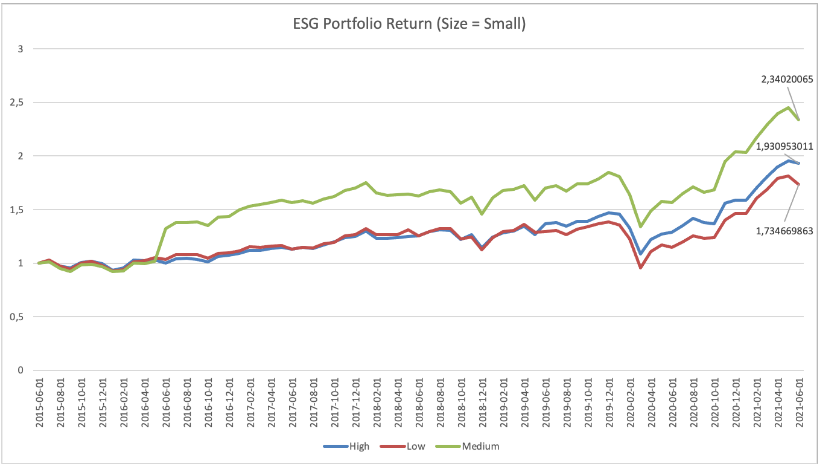


Figure 4
Cumulative return of ESG portfolios of big companies (B|H, B|M e B|L)

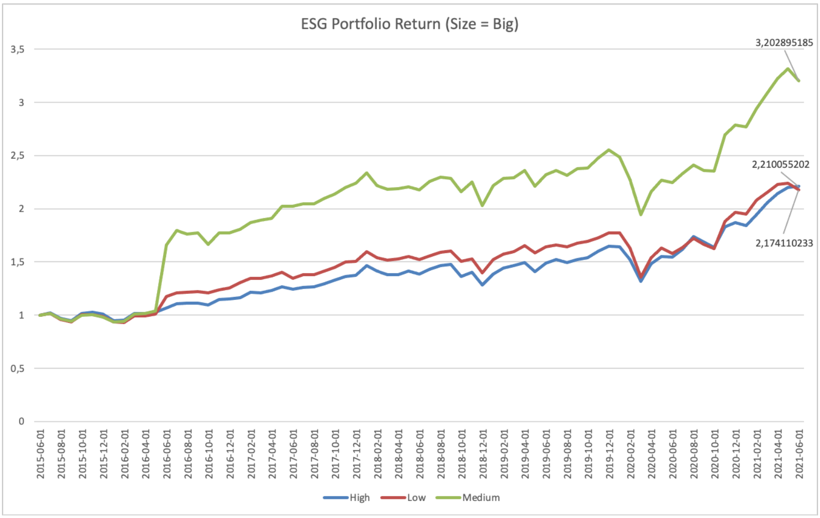


Table 3
Annualized Cumulative Return of 6 portfolios formed by ESGM and size

			ESGM				Difference		
			High	Medium	Low				
			1	2	3		(1 – 3)	(1 – 2)	(2 – 3)
SIZE	Big		19.52%	13.08%	16.68%		3.08%	5.99%	−3.62%
		Sd	0.27	0.16	0.17	Sd	0.15	0.20	0.07
						p-value*	0.76	0.56	0.72
	Small		13.33%	11.46%	12.14%		0.91%	1.22%	−1.49%
		Sd	0.19	0.17	0.19	Sd	0.05	0.13	0.10
						p-value*	0.93	0.85	0.93
			5.99%	0.94%	3.64%				
	Difference	Sd	0.14	0.07	0.05				
		p-value*	0.62	0.90	0.72				

Note: * – p-value for t-test for two populations.

Table 4
Annualized Cumulative Return of 6 portfolios formed by ESG and size

			ESG				Difference		
			High	Medium	Low				
			1	2	3		(1 – 3)	(1 – 2)	(2 – 3)
SIZE	Big		14.13%	21.41%	13.82%		−0.28%	−12.16 %	7.29%
		Sd	0.15	0.29	0.17	Sd	0.07	0.24	0.19
						p-value*	0.99	0.53	0.54
	Small		11.59%	15.22%	9.61%		1.28%	−5.08%	4.64%
		Sd	0.16	0.21	0.18	Sd	0.06	0.14	0.14
						p-value*	0.89	0.72	0.64
			1.94%	6.04%	3.20%				
	Difference	Sd	0.05	0.13	0.09				
		p-value*	0.82	0.65	0.73				

Note: * – p-value for t-test for two populations.

different portfolios. This result is probably due to the restricted size of the database, which ends up converting into lower statistical confidence levels.

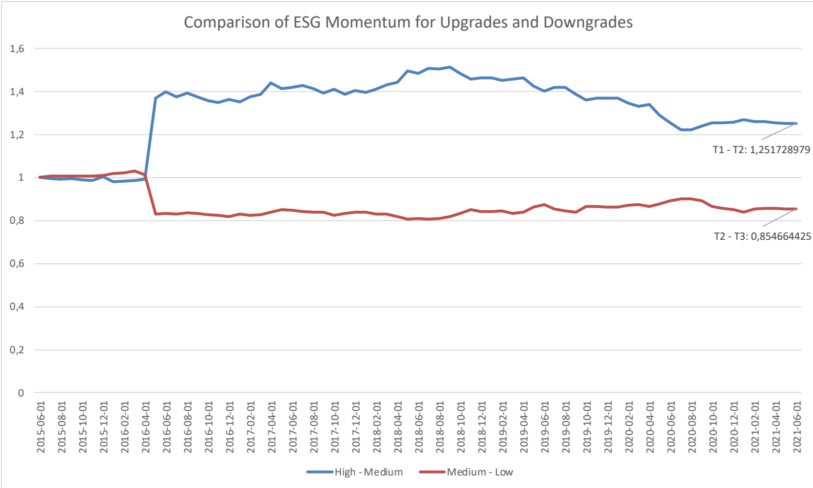
Following the procedure adopted by Nagy and Giese (2018) to assess the divergence of the impact of upgrades and downgrades of ESG scores on equity return, we measured the return due to upgrades as the difference between the portfolio high (H) and medium (M) ESG Momentum, while the return due to downgrades was calculated as the difference between the medium (M) and low (L) portfolio of ESG Momentum, according to equations (5) and (6).

$$R(\text{Upgrade}) = R(\text{High}) - R(\text{Medium}) \tag{5}$$

$$R(\text{Downgrade}) = R(\text{Medium}) - R(\text{Low}) \tag{6}$$

We observe in Table 3 that there is an apparent asymmetry in the magnitude of the variation of returns, since upgrades ("Difference 1-2") have a

Figure 5
Comparison of cumulative return performance due to ESG score upgrades and downgrades



stronger performance than downgrades ("Difference 2-3") in both large and small companies. Figure 5 displays this result graphically.

We controlled the return for four other risk factors: Mkt (market), SMB (small minus big), HML (high minus low) and QMJ (quality minus junk). We collected monthly time series data of Mkt, SMB and HML returns on Kenneth Fama[3] website. The monthly return data of QMJ was collected on AQR[4] website. The definition of the four factors are as follows:

Mkt is the "market" factor, measured as the difference between the market portfolio return (capitalization weighted) and the risk-free rate return (1-month US treasury bond).

SMB is the "size" factor, measured as the difference between the return on a diversified portfolio of small stocks and one of big stocks.

HML is the "value" factor, measured as the difference between the return on a diversified portfolio of high and low Book to Market value (book value over market value).

QMJ is the "quality" factor, measured through the difference between the

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

[4] https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly

return on a diversified portfolio of high and low quality stocks (Asness et al 2019). The quality is measured as a function of the company's profitability, security and growth. The quality factor was included in the model to control for the correlation between ESG and quality.

To estimate risk factor premiums, we used two methodologies: 1) two-step regression and; 2) generalized method of moments (GMM). According to Goyal (2012), the two-step regression consists of, firstly, estimating a time series regression in which, for each asset, the beta vector ($\boldsymbol{\beta}_i$) is estimated in relation to the risk factors. The second step is to estimate a cross-sectional regression in which the estimated betas from the first step are used to estimate the vector of the risk premium of the factors. Equations (7) and (8) describe the first and second stage respectively:

$$R_{i,t} = \alpha_i + \boldsymbol{\beta}_i \boldsymbol{F}_t + \varepsilon_{i,t} \tag{7}$$

$$\bar{R}_i = a + \widehat{\boldsymbol{\beta}}_i \boldsymbol{\lambda} + e_i, \tag{8}$$

Where $R_{i,t}$ corresponds to the monthly excess return of asset i in period t, $\boldsymbol{F}_t$ is the vector of risk factors, $\bar{R}_i$ is the average monthly excess return of asset i in the time period we analyzed, and $\boldsymbol{\lambda}$ is the vector of risk premium for the factors.

The GMM is a more robust method to estimate risk premium returns than the two-step regression, because it estimates equations (7) and (8) simultaneously, addressing the problems of autocorrelation and heteroscedasticity of residuals. In addition, the methodology avoids possible standard error problems that can arise with two-step regression.[5]

Considering equations (7) and (8), by construction, we have that $E(\varepsilon_{i,t}) = 0$ and$E(\varepsilon_{i,t}) = 0$,, and the GMM conditions are given by (9).

$$g_t(a,\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\lambda}) = \begin{bmatrix} (\boldsymbol{R}_t - \boldsymbol{\alpha} - \boldsymbol{\beta}\boldsymbol{F}_t) \\ (\boldsymbol{r}_t - \boldsymbol{\alpha} - \boldsymbol{\beta}\boldsymbol{F}_t) \otimes \boldsymbol{F}_t \\ (\mathbf{1},\boldsymbol{\beta}')(\boldsymbol{R}_t - a - \boldsymbol{\beta}\boldsymbol{\lambda}) \end{bmatrix} \tag{9}$$

where $\boldsymbol{R}_t$ corresponds to the vector of monthly excess return of all stocks in the sample, $\otimes$ is the operator of the Kroecker product, and $\mathbf{1}$ is the unit vector. The parameters are estimated according to (10),

$$\left\{\hat{a},\widehat{\boldsymbol{\beta}},\widehat{\boldsymbol{\alpha}},\widehat{\boldsymbol{\lambda}}\right\} = \operatorname{argmin}_{\{a,\beta,\alpha,\lambda\}} \sum_{t=1}^{T} [g_t(a,\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\lambda})]' \boldsymbol{I} \sum_{t=1}^{T} [g_t(a,\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\lambda})], \tag{10}$$

[5] See Shanken (1992) for more details about the standard error estimation problem in equations (7) and (8).

Table 5
Descriptive statistics of risk factors

	annualized		
Risk Factor	av. return	st. deviation	Sharpe Ratio
ESG	0.01	0.05	0.11
ESGM	0.02	0.09	0.23
Mkt	0.15	0.16	0.94
SMB	0.01	0.09	0.06
HML	–0.06	0.13	–0.49
QMJ	0.03	0.09	0.34

and the R^2 is calculated according to (11) since our focus is on the accuracy of the factor risk premia.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(\bar{R}_i - \widehat{a} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{i}}\widehat{\boldsymbol{\lambda}}\right)^2}{\sum_{i=1}^{N}\left(\bar{R}_i\right)^2}. \tag{11}$$

4. Discussion of the results

Table 5 contains descriptive statistics of the risk factors. It can be seen that the Sharpe ratio of the ESGM factor is positive, indicating that the variation of ESG scores is directly related to returns (i.e., the greater the ESG momentum of a company, the greater its returns). These results corroborate with Nagy and Giese (2018), who associate increases in a company's ESG score (positive ESG moment) with equity value appreciation.

Table 6 presents the correlation matrix between the factors used, in which we can verify that the ESGM factor controlled by size has a low correlation with the other factors, including the factor linked to quality. The ESG factor, in turn, has a slightly higher correlation with the other factors.

In Figure 6, it is possible to visualize the accumulated return of all the factors considered. We can see that the ESGM factor has the third best accumulated positive performance, behind the market and quality factors. In module, however, the accumulated return of the factor lags behind the other factors already established in the literature, with the exception of the factor linked to size, which had a lower performance than the ESG Momentum factor.

We ran four time series regressions (TS1 to TS4) of the ESG and ESGM factors. Table 7 indicates the factors used as dependent and explanatory in

Table 6
Correlation matrix of risk factors

	ESG	ESGM	Miot	SMB	HML	QMJ
ESG	1	–0.48	–0.11	–0.15	–0.13	0.22
ESGM	–0.48	1	–0.11	–0.08	–0.09	0.08
Miot	–0.11	–0.11	1	0.35	0.18	–0.50
SMB	–0.15	–0.08	0.35	1	0.22	–0.59
HML	–0.13	–0.09	0.18	0.22	1	0.02
QMJ	0.22	0.08	–0.50	–0.59	0.02	1

Figure 6
Cumulative return of risk factors

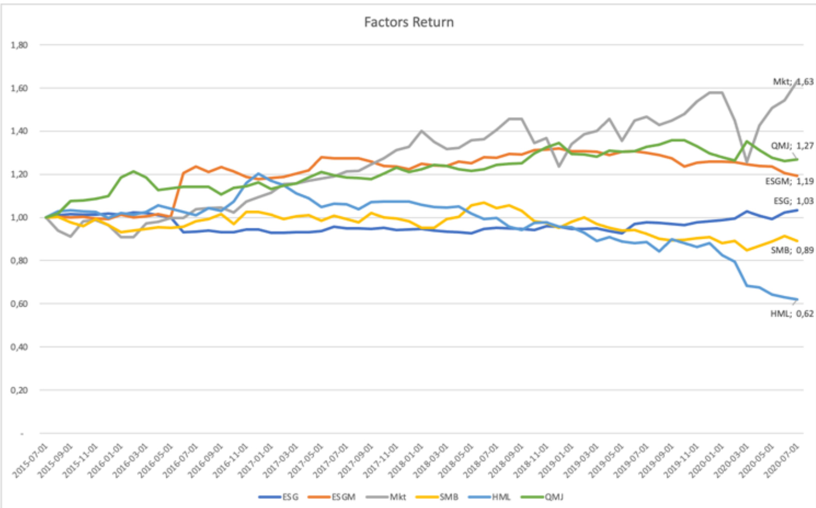


Table 7
Dependent and explanatory factors in different time series regression models

Modelo	Rt	Ft
TS1	ESG	Mkt + SMB + HML
TS2	ESG	Mkt + SMB + HML + QMJ
TS3	ESGM	Mkt + SMB + HML
TS4	ESGM	Mkt + SMB + HML + QMJ

each time series regression (defined by equation (12)).

$$R_{i,t} = \alpha_i + \boldsymbol{\beta}_i \boldsymbol{F}_t + \varepsilon_{i,t}. \tag{12}$$

The results of these regressions are shown in Table 8. Both the ESG factor and the ESGM could not be explained by any of the other four factors, since all the four regressions presented an adjusted R^2 close to zero and statistical insignificance. This result indicates possible new information brought by the ESG and ESGM factors that are not contained in the other factors. However, none of the time series regressions showed a significant intercept.

Table 9 contains the result of the two-step cross-section regression (equations (7) and (8)) using as dependent variable the excess return of the 451 stocks in the sample. The regressions showed a very high adjusted R^2, approximately 90%, demonstrating the high explanatory power of these factors on cross-section returns. The risk premiums of all the factors were significant in all regressions. However, we observe a significant intercept in all the models, indicating the persistence of idiosyncratic risk not explained by the factors, and therefore our factors were insufficient to explain the stock returns in its entirety.

The ESG factor showed consistently negative and significant lambda between –0.2% and –0.28%. This result corroborates our hypothesis H_1, according to which there is a significant risk premium related to ESG scores: higher (lower) sustainability reduces (increases) stock returns between 0.2% and 0.28%. This result is consistent with the equilibrium advocated by Pástor et al. (2021), which establishes that the higher the ESG rating of a company, the lower the return required by investors for its shares.

The ESGM factor showed consistently positive and significant lambda, between 0.23% and 0.32%. This result validates our hypothesis H_2, according to which there is a risk premium linked to the variation of the ESG scores This is evidence that share prices adjust positively to ESG score upgrades, resulting in abnormal gains for the investor, and it is in accordance to Nagy and Giese (2018) and Giese et al. (2019a).

Table 8
Time series regressions of factors ESG and ESGM on the other four risk factors

Time series regression		TS1	TS2	TS3	TS4
Coefficient		ESG	ESG	ESGM	ESGM
Intercept	Estimate	0.00	–0.00	0.00	0.00
	std. error	0.00	0.00	0.00	0.00
	t value	0.36	–0.14	0.74	0.63
	p-value	0.72	0.89	0.46	0.53
Mkt	Estimate	–0.02	0.01	–0.05	–0.04
	std. error	0.04	0.05	0.08	0.09
	t value	–0.40	0.27	–0.64	–0.49
	p-value	0.69	0.79	0.52	0.62
SMB	Estimate	–0.06	0.01	–0.03	–0.01
	std. error	0.07	0.09	0.13	0.16
	t value	–0.83	0.15	–0.26	–0.09
	p-value	0.41	0.88	0.80	0.93
HLM	Estimate	–0.04	–0.06	–0.05	–0.06
	std. error	0.05	0.05	0.09	0.10
	t value	–0.78	–1.14	–0.58	–0.61
	p-value	0.44	0.26	0.57	0.55
QMJ	Estimate		0.15		0.04
	std. error		0.10		0.18
	t value		1.53		0.22
	p-value		0.13		0.83
Adjusted-R2		–0.01	0.01	–0.03	–0.04

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

Table 10 shows the results of the two-stage cross-section regression according to equations (7) and (8), but using as dependent variable an aggregate of 150 portfolios constructed from the factors size, value, profitability and investment, available on Kenneth French[6] website. These portfolios represent 6 sets of 25 portfolios formed from the two-by-two intersection of 5 portfolios created from each factor. Both ESG and ESGM factors presented significant risk premiums. However, the explanatory power of the models was reduced to approximately 30%. The magnitude of the ESG factor premium was similar to the test applied to individual stocks: between 0.25% and 0.29%. However, the magnitude of the ESGM factor premium: between 0.78% and 0.8% was more than double the previous test.

Table 11 shows the results for two-stage cross-section regression according to equations (7) and (8), using as the dependent variable 96 portfolios available on Kenneth French's website as the response variable. These portfolios represent 3 sets of 32 portfolios formed from the three-to-three intersection of 2 categories of size, 4 of value, 4 of profitability and 4 of investment. The lambdas of the ESG and ESGM factors were not significant in any of the models. The only factors with a statistically risk premium different from zero were size (SMB), value (HML) and investment (CMA), which managed to explain up to 50% of the returns.

Tables 12, 13 and 14 show the results of the tests in Tables 9, 10 and 11 respectively, but using the GMM method described in equations (9), (10) and (11).[7] We can verify that when we eliminate the bias in the estimation of the standard errors of the coefficients of the cross-section regression, most of the risk premiums lose their statistical significance.

In Table 12 we see that the only factor that presented a significant risk premium in all the models was the value factor (HML). With the exception of the M2 model in the table, the intercepts remained significant, indicating the existence of additional returns not explained by the models. Despite being statistically insignificant, we observe a positive lambda for ESGM factor in all the models.

In Tables 13 and 14, we see that none of the factors considered presented a significant risk premium and, with the exception of one model, all presented intercepts statistically different from zero, once again reiterating the insufficiency of the models in explaining the excess return of the portfolios.

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

[7]It is important to notice that the GMM described by equations (9) and (10) is exactly identified, so the Sargan-Hansen test is not applied in this case. Furthermore, instrumental variables are not employed in this case since the GMM is used only to estimate equations (7) and (8) simultaneously and to account for autocorrelation and heteroscedasticity of residuals.

Table 9
Two-stage cross-sectional regression, where the dependent variable is the excess return of the 451 stocks

2-step cross-sectional

Coefficient		M1	M2	M3	M4	M5	M6
Intercept	Estimate	0.0087	0.0069	0.0080	0.0068	0.0085	0.0071
	std. error	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012
	t value	7.5160	5.9560	6.7680	5.6530	7.2260	6.1090
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
Mkt	Estimate	0.0060	0.0078	0.0069	0.0081	0.0062	0.0075
	std. error	0.0011	0.0011	0.0011	0.0012	0.0012	0.0011
	t value	5.3850	6.8940	6.0290	6.9880	5.3590	6.6030
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
SMB	Estimate	0.0040	0.0048	0.0042	0.0049	0.0040	0.0050
	std. error	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008
	t value	4.8490	5.9050	4.9680	5.7970	4.8330	6.0530
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
HLM	Estimate	−0.0117	−0.0115	−0.0115	−0.0114	−0.0117	−0.0116
	std. error	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008
	t value	−14.5830	−14.7410	−14.0870	−14.1650	−14.4280	−14.8630
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
QMJ	Estimate		−0.0023		−0.0026		−0.0022
	std. error		0.0007		0.0007		0.0007
	t value		−3.2790		−3.5550		−3.0490
	p-value		0.0011‡		0.0004‡		0.0024‡
ESG	Estimate	−0.0026	−0.0020			−0.0024	−0.0028
	std. error	0.0001	0.0001			0.0005	0.0005
	t value	−33.6170	−13.8620			−4.6800	−5.6390
	p-value	0.0000‡	0.0000‡			0.0000‡	0.0000‡
ESGM	Estimate			0.0032	0.0031	0.0028	0.0023
	std. error			0.0001	0.0001	0.0002	0.0002
	t value			36.7430	32.4660	18.2260	13.4880
	p-value			0.0000‡	0.0000‡	0.0000‡	0.0000‡
Adjusted-R2		0.9080	0.9140	0.9060	0.9100	0.9080	0.9140

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

Table 10
Two-stage cross-sectional regression with 150 Fama and French portfolios as the response variable

2-step cross-sectional – FF 150 portfolios (6 × 25)

Coefficient		M1	M2	M3	M4	M5	M6
Intercept	Estimate	0.0169	0.0171	0.0160	0.0163	0.0163	0.0165
	std. error	0.0017	0.0017	0.0015	0.0016	0.0017	0.0017
	t value	10.2210	10.0070	10.3380	9.9910	9.8560	9.6930
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
Mkt	Estimate	−0.0049	−0.0050	−0.0039	−0.0041	−0.0043	−0.0044
	std. error	0.0016	0.0016	0.0014	0.0015	0.0016	0.0016
	t value	−3.1060	−3.1280	−2.6850	−2.7590	−2.6800	−2.7220
	p-value	0.0023‡	0.0021‡	0.0081‡	0.0065‡	0.0082‡	0.0073‡
SMB	Estimate	0.0025	0.0022	0.0031	0.0027	0.0029	0.0027
	std. error	0.0005	0.0007	0.0005	0.0007	0.0005	0.0007
	t value	5.2440	3.2500	6.3940	3.8350	5.7160	3.7710
	p-value	0.0000‡	0.0014‡	0.0000‡	0.0002‡	0.0000‡	0.0002‡
HLM	Estimate	−0.0018	−0.0016	−0.0024	−0.0023	−0.0024	−0.0023
	std. error	0.0006	0.0007	0.0007	0.0007	0.0007	0.0007
	t value	−2.7570	−2.3980	−3.4660	−3.0720	−3.4430	−3.0830
	p-value	0.0066‡	0.0178†	0.0007‡	0.0025‡	0.0008‡	0.0025‡
QMJ	Estimate		−0.0013		−0.0013		−0.0013
	std. error		0.0007		0.0007		0.0007
	t value		−1.8910		−1.8880		−1.9010
	p-value		0.0606*		0.0611*		0.0593*
ESG	Estimate	−0.0026	−0.0025			−0.0029	−0.0028
	S Error	0.0015	0.0015			0.0014	0.0015
	t value	−1.8130	−1.6940			−2.0210	−1.8860
	p-value	0.0720*	0.0924*			0.0451†	0.0613*
ESGM	Estimate			0.0080	0.0078	0.0080	0.0078
	S Error			0.0028	0.0028	0.0028	0.0029
	t value			2.8200	2.7410	2.8250	2.7500
	p-value			0.0055‡	0.0069‡	0.0054‡	0.0067‡
Adjusted-R2		0.2260	0.2220	0.2480	0.2460	0.2450	0.2410

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

Table 11
Two-stage cross-sectional regression with 96 Fama and French portfolios as the response variable

2-step cross-sectional – FF 96 portfolios (3 × 32)

Coefficient		M1	M2	M3	M4	M5	M6
Intercept	Estimate	0.0129	0.0147	0.0132	0.0148	0.0127	0.0143
	std. error	0.0017	0.0023	0.0017	0.0023	0.0017	0.0023
	t value	7.4520	6.3740	7.6410	6.3360	7.3890	6.2030
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
Mkt	Estimate	−0.0012	−0.0028	−0.0016	−0.0031	−0.0008	−0.0023
	std. error	0.0016	0.0021	0.0016	0.0022	0.0016	0.0022
	t value	−0.7100	−1.3200	−0.9920	−1.4150	−0.4820	−1.0540
	p-value	0.4798	0.1903	0.3240	0.1606	0.6309	0.2946
SMB	Estimate	0.0041	0.0035	0.0040	0.0035	0.0044	0.0039
	std. error	0.0006	0.0007	0.0005	0.0008	0.0006	0.0008
	t value	7.4270	4.7820	7.2620	4.5910	7.6630	5.0910
	p-value	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡	0.0000‡
HLM	Estimate	−0.0018	−0.0016	−0.0024	−0.0022	−0.0025	−0.0023
	std. error	0.0008	0.0008	0.0009	0.0009	0.0009	0.0009
	t value	−2.3080	−2.0170	−2.7230	−2.4260	−2.8750	−2.5680
	p-value	0.0232†	0.0466†	0.0078‡	0.0173†	0.0050‡	0.0119†
QMJ	Estimate		−0.0020		−0.0024		−0.0018
	std. error		0.0007		0.0007		0.0007
	t value		−2.8160		−3.6130		−2.5860
	p-value		0.0060‡		0.0005‡		0.0113†
ESG	Estimate	0.0026	0.0026			0.0020	0.0020
	std. error	0.0018	0.0017			0.0018	0.0018
	t value	1.4820	1.4690			1.1490	1.1540
	p-value	0.1417	0.1452			0.2536	0.2516
ESGM	Estimate			0.0035	0.0031	0.0029	0.0026
	std. error			0.0036	0.0036	0.0036	0.0036
	t value			0.9520	0.8530	0.8270	0.7250
	p-value			0.3434	0.3958	0.4102	0.4703
Adjusted-R2		0.3750	0.3780	0.3650	0.3650	0.3880	0.3890

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

Table 12
GMM cross-section regression using as dependent variable the excess return of the 451 stocks

GMM cross-sectional

Coefficient		M1	M2	M3	M4	M5	M6
Intercept	Estimate	0.0087	0.0069	0.0080	0.0068	0.0085	0.0071
	std. error	0.0045	0.0043	0.0043	0.0042	0.0043	0.0043
	t value	19.1640	1.6216	1.8604	1.5938	1.9763	1.6584
	p-value	0.0550*	0.1050	0.0630*	0.1110	0.0480†	0.0970*
Mkt	Estimate	0.0060	0.0078	0.0069	0.0081	0.0062	0.0075
	std. error	0.0060	0.0062	0.0061	0.0063	0.0062	0.0064
	t value	0.9945	1.2507	1.1338	1.2907	0.9911	1.1835
	p-value	0.3200	0.2110	0.2570	0.1970	0.3220	0.2370
SMB	Estimate	0.0040	0.0048	0.0042	0.0049	0.0040	0.0050
	std. error	0.0044	0.0044	0.0043	0.0044	0.0044	0.0043
	t value	0.9202	1.1100	0.9609	1.1143	0.9199	1.1479
	p-value	0.3570	0.2670	0.3370	0.2650	0.3580	0.2510
HLM	Estimate	−0.0117	−0.0115	−0.0115	−0.0113	−0.0117	−0.0116
	std. error	0.0048	0.0047	0.0048	0.0048	0.0048	0.0047
	t value	−2.4501	−2.4220	−2.3854	−2.3753	−2.4377	−2.4860
	p-value	0.0140†	0.0150†	0.0170†	0.0180†	0.0150†	0.0130†
QMJ	Estimate		−0.0023		−0.0026		−0.0022
	std. error		0.0033		0.0033		0.0033
	t value		−0.6979		−0.7750		−0.6546
	p-value		0.4850		0.4380		0.5130
ESG	Estimate	−0.0026	−0.0020			−0.0024	−0.0028
	std. error	0.0014	0.0014			0.0025	0.0024
	t value	−1.8974	−1.4194			−0.9531	−1.1803
	p-value	0.0580*	0.1560			0.3410	0.2380
ESGM	Estimate			0.0032	0.0031	0.0028	0.0023
	std. error			0.0029	0.0029	0.0030	0.0030
	t value			1.1052	1.0449	0.9542	0.7903
	p-value			0.2690	0.2960	0.3400	0.4290
Adjusted-R		0.9080	0.9140	0.9060	0.9090	0.9080	914

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

The ESG factor lambda remained negative in all models of Tables 12 and 13, but significant at a 10% level only in M1 of Table 12.

The ESGM factor lambda was insignificant but positive in all regressions in Tables 12, 13 and 14.

5. Conclusion

In this article we investigate whether good ESG practices lead to a lower cost of capital and higher equity valuation. We built an ESG factor based

Table 13
GMM cross-section regression using as dependent variable the 150 Fama and French portfolios

GMM – FF 150 (6 × 25)

Coefficient		M1	M2	M3	M4	M5	M6
Intercept	Estimate	0.0169	0.0171	0.0160	0.0163	0.0163	0.0165
	std. error	0.0050	0.0052	0.0053	0.0054	0.0053	0.0054
	t value	3.3656	3.2890	3.0074	3.0148	3.0727	3.0307
	p-value	0.0010‡	0.0010‡	0.0030‡	0.0030‡	0.0020‡	0.0020‡
Mkt	Estimate	−0.0049	−0.0050	−0.0389	−0.0041	−0.0043	−0.0044
	std. error	0.0076	0.0077	0.0076	0.0077	0.0076	0.0077
	t value	−0.6485	−0.6512	−0.5093	−0.5362	−0.5605	−0.5681
	p-value	0.5170	0.5150	0.6110	0.5920	0.5750	0.5700
SMB	Estimate	0.0020	0.0022	0.0031	0.0027	0.0029	0.0027
	std. error	0.0040	0.0034	0.0040	0.0034	0.0040	0.0034
	t value	0.6116	0.6651	0.7555	0.7897	0.7294	0.7782
	p-value	0.5410	0.5060	0.4500	0.4300	0.4660	0.4360
HLM	Estimate	−0.0018	−0.0016	−0.0024	−0.0023	−0.0024	−0.0023
	std. error	0.0047	0.0047	0.0045	0.0045	0.0045	0.0045
	t value	−0.3783	−0.3541	−0.5372	−0.5062	−0.5376	−0.5105
	p-value	0.7050	0.7230	0.5910	0.6130	0.5910	0.6100
QMJ	Estimate		−0.0013		−0.0013		−0.0013
	std. error		0.0039		0.0039		0.0039
	t value		−0.3401		−0.3333		−0.3357
	p-value		0.7340		0.7390		0.7370
ESG	Estimate	−0.0026	−0.0025			−0.0029	−0.0028
	std. error	0.0044	0.0043			0.0037	0.0036
	t value	−0.6084	−0.5857			−0.7826	−0.7632
	p-value	0.5430	0.5580			0.4340	0.4450
ESGM	Estimate			0.0080	0.0078	0.0080	0.0078
	std. error			0.0069	0.0069	0.0069	0.0069
	t value			1.1596	1.1252	1.1637	1.1411
	p-value			0.2460	0.2600	0.2450	0.2540
Adjusted-R2		0.2260	0.2220	0.2480	0.2450	0.2450	0.2410

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

Table 14
GMM cress-section regression using as dependent variable the 96 Fama and French portfolios

GMM – FF 96 (3 × 32)

Coefficient		M1	M2	M3	M4	M5	M6
Intercept	Estimate	0.0129	0.0147	0.0132	0.0148	0.0127	0.0143
	std. error	0.0100	0.0083	0.0096	0.0085	0.0099	0.0084
	t value	1.2874	1.7758	1.3767	1.7361	1.2736	1.6947
	p-value	0.1980	0.0760*	0.1690	0.0830*	0.2030	0.0900*
Mkt	Estimate	−0.0012	−0.0028	−0.0016	−0.0031	−0.0008	−0.0023
	std. error	0.0116	0.0102	0.0111	0.0103	0.0114	0.0102
	t value	−0.0996	−0.2770	−0.1438	−0.2956	−0.0686	−0.2233
	p-value	0.9210	0.7820	0.8860	0.7680	0.9450	0.8230
SMB	Estimate	0.0041	0.0035	0.0040	0.0035	0.0044	0.0039
	std. error	0.0040	0.0040	0.0041	0.0041	0.0040	0.0040
	t value	1.0270	0.8833	0.9661	0.8371	1.0993	0.9874
	p-value	0.3040	0.3770	0.3340	0.4030	0.2720	0.3230
HLM	Estimate	−0.0018	−0.0016	−0.0024	−0.0022	−0.0025	−0.0023
	std. error	0.0047	0.0049	0.0046	0.0047	0.0047	0.0048
	t value	−0.3802	−0.3309	−0.5315	−0.4746	−0.5384	−0.4835
	p-value	0.7040	0.7410	0.5950	0.6350	0.5900	0.6290
QMJ	Estimate		−0.0020		−0.0024		−0.0018
	std. error		0.0044		0.0047		0.0044
	t value		−0.4502		−0.5142		−0.4176
	p-value		0.6530		0.6070		0.6760
ESG	Estimate	0.0026	0.0026			0.0020	0.0020
	std. error	0.0046	0.0046			0.0041	0.0042
	t value	0.5590	0.5541			0.4989	0.4903
	p-value	0.5760	0.5800			0.6180	0.6240
ESGM	Estimate			0.0035	0.0031	0.0029	0.0026
	std. error			0.0057	0.0063	0.0060	0.0068
	t value			0.6018	0.4961	0.4936	0.3836
	p-value			0.5470	0.6200	0.6220	0.7010
Adjusted-R2		0.3750	0.3780	0.3650	0.3650	0.3880	0.3890

Note: ‡– p-value < 0.01; †– p-value < 0.05; * – p-value < 0.1.

on the static ESG score by Sustainalytics, and an ESGM factor, related to the variation of the ESG classifications—the ESG momentum. We raised a first hypothesis (H1), according to which there is a negative relation between ESG score and return. In other words, we propose that investors require a risk premium to invest in companies with poor ESG practices. We ran a two-stage cross-section regression, controlling by Fama and French factors and a quality factor. Our results indicate that the share of companies with the worst ESG scores had a return between 0.2% and 0.29% higher than companies with the highest ESG scores. However, with this test it is not possible to identify the direction of the causality.

We raised a second hypothesis, which proposes that changes in ESG score —or ESG momentum—impact the cost of capital and share price. The results of a two-stage cross-section regression indicates that there is a positive and significant relationship between the improvement of ESG practices and returns. A portfolio long in the stocks with the highest upgrades in ESG score and short in the stocks with the highest downgrades in ESG score had a return premium between 0.23% and 0.35%. The magnitude of the impact in the return is much more expressive for score upgrades than for score downgrades. This indicates that investors precify positively ESG practices, and that the improvement in the sustainable practices lead to an appreciation in the equity value. However, given the divergence of ESG ratings of different providers (Berg et al., 2022), it is not possible to generalize our results based on Sustainalityc ESG rank to other providers.

When we ran a GMM two-step regression, a more robust methodology, we found ESG and ESGM premiums of similar magnitudes, however all the results were statistically insignificant.

Some adversities may explain the lack of robustness of the proposed risk factors. (i) The divergence among ESG scores of different providers disperses the potential effect of investor preference for sustainable characteristics on asset prices. (ii) We built ESG and ESGM factors based on ESG rank, which is a relative score of a firm to its peers in the same industrial sector. Absolute scores probably would increase the magnitude of ESG momentum and the dispersion of ESG score. Unfortunately, we were not able to access time series of Sustainalytics absolute scores to test if the results would be more significant. (iii) The short history of ESG data represents a significant drawback to conducting robust research and testing. With an ESG Momentum database of only 6 years (June 2015 to June 2021), the lack of significance in some t-tests would not be entirely unexpected. Possibly, it will still take a few years of ESG quality data before it is possible to accurately test the claim that ESG momentum is a robust factor, as pointed out by Giese et al. (2019b). (iv)

Given the robustness of the GMM methodology, even risk premiums of factors widely consolidated in the literature lost significance, that is, the ESGM factor does not necessarily have less academic relevance than the other factors used in the study. Furthermore, we can argue that the maintenance of positive premiums for the ESGM factor throughout the different models, or even the failure to obtain significant negative premiums for this factor, is, in itself, a result that encourages the use of ESG momentum in the management of portfolios.

Issues related to sustainability and social responsibility should permeate the investment universe in the future. This work adds to the literature bringing favourable, yet weak, evidence that the improvement in the quality of sustainable practices lead to firm value appreciation.

Future research, with a larger and more standardized database have the potential to produce more robust results about the existence of ESG and ESGM risk factors, and this is a promising research topic in the portfolio management process for years to come.

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