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Is the ESG Score Part of the Set of Information Available to Investors? A Conditional Version of the Green Capital Asset Pricing Model

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Abstract: In this paper, we propose a linear factor model that incorporates investor preferences toward sustainability to analyze indirect effects that climate concerns may have on asset prices. Our approach is based on the relationship between environmental, social, and governance (ESG) investing and climate change considerations by investors. We use ESG scores as a part of the information set used by investors to determine the unconditional version of the conditional capital asset pricing model (CAPM). Our results show that the ESG score allows the linearized version of the conditional CAPM to greatly outperform the classic CAPM and the Fama–French three-factor model for different sorts of stock portfolios, contributing significantly to reducing pricing errors. Furthermore, we find a negative price of risk for stocks that covary positively with ESG growth, which suggests that green assets may perform better than brown ones if ESG concerns suddenly become more pressing over time. Thus, our paper constitutes a step forward in the attempt to shed light on how climate change is priced regardless of the climate risk measure used.

Keywords: asset pricing; sustainable finance; climate change; ESG; conditioning information

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1. Introduction

Academic research on sustainable finance has experienced an impressive development in the last two decades, motivated, among other factors, by the growing interest of investors in environmental issues. According to the Global Sustainable Investment Review, green investing accounts for 35.9% of the total assets under management globally, having increased by 54.8% from USD 22.8 trillion in 2016. Additionally, the integration of environmental, social, and corporate governance (ESG) factors into portfolio analysis is reported as the most popular sustainable investment strategy worldwide (GSIA, 2021). The United States represented 33% of these global sustainable investing assets in 2020, amounting to approximately USD 17.1 trillion. This study belongs to the field of sustainable finance, focuses specifically on the United States, and examines data from 2001 to 2023 to analyze the impact of ESG scores on financial asset prices in this particular market.

However, the effects of climate change on financial markets are still far from clear (Venturini, 2022). Empirical research that focuses on how climate risks should affect the cross-section of stock returns provides contradictory results depending on the climate risk measure (Balvers et al., 2017; Bansal et al., 2019; Nagar & Schoenfeld, 2021) or the implemented test of market efficiency (Cheema-Fox et al., 2021; Hong et al., 2019; In et al., 2017; Kumar et al., 2019). For example, climate change is an additional source of market risk, according to In et al. (2017) and Jiang and Weng (2019), and it may not be valued by conventional asset pricing criteria, like market, size, value, and momentum. While there are

indeed other indicators that could measure climate risk—such as carbon intensity, physical climate risk indices, and sectoral exposure to climate transition risks—the ESG score was chosen for this study for several reasons. First, governance impacts how businesses manage and deal with climate risk since implementing effective climate strategies requires strong governance systems (Cheng et al., 2014; Eccles et al., 2012). Second, there is a body of literature that justifies the use of ESG as a proxy for climate risk because of the correlation between high ESG scores and the management of environmental risks (Chen et al., 2023). Lastly, ESG reflects the market's perception of a company's exposure to climate risk, as investors increasingly turn to ESG scores to determine how well companies are suited to meet long-term environmental risks (Flammer, 2021). In brief, although ESG encompasses many aspects, the fusion of governance and environmental factors renders it useful in estimating climate risk in terms of asset valuation and pricing.

An explanation for the observed mispricing of climate change risks in financial markets is suggested by Ardia et al. (2020) and Pástor et al. (2022) based on unexpected shifts in investor preferences toward sustainability. Specifically, according to the theoretical equilibrium model proposed by Pástor et al. (2021), green assets have low expected returns because they provide a hedge against climate risks, thus increasing their attractiveness to investors. However, if ESG concerns strengthen unexpectedly over a given period of time, green stocks can outperform brown stocks over that period, despite having lower returns. By using US stock data to create a green-minus-brown portfolio, Ardia et al. (2020) and Pástor et al. (2022) demonstrate that the portfolio's recent outperformance disappears when the effects of unexpected climate change news, as reported by eight US newspapers, are taken into account.

Even though these studies are primarily focused on the environmental pillar of ESG, it is worth noting that ESG exists in three different dimensions: environmental, social, and governance. The social dimension includes issues such as treatment of employees, diversity and inclusion, human rights, and community relations. Lins et al. (2017) find that firms with a high degree of social capital—proxied by strong CSR performance—performed much better during the 2008–2009 financial crisis, thus indicating that social trust and stakeholder engagement can serve as cushions during periods of market stress. The governance pillar, on the other hand, governs the internal systems of a company: board independence, executive pay, audit quality, and shareholder rights. Good governance has long been associated with superior firm performance (Gompers et al., 2003; Bebchuk et al., 2009). Strong governance structures may promote better alignment between management and shareholder interests—factors that will bear significantly on valuation and return predictability.

In this paper, we propose a linear factor model that incorporates investor preferences toward sustainability to analyze the indirect effects of climate concerns on asset prices. The objective of this work is to assess the impact of ESG scores as a financial risk factor in asset pricing by integrating them into an unconditional multifactor CAPM with time-varying risk premia. The choice of linear factor model in this study is guided by both the pervasive use throughout the asset pricing literature and a robust econometric foundation (see Cochrane, 2005, pp. 229–245). This approach allows us to fit the relationship between risk factors and returns using a linear model of the form $E(R^e) = \beta'\lambda$, in which the factors systematically capture the risk premiums of each factor. Cochrane (2005) identifies that such models are particularly suited for estimation using the generalized method of moments (GMM), as this technique yields consistent and asymptotically efficiently usable estimators under heteroscedastic or autocorrelated errors. The functional equivalence between GMM estimation and cross-sectional regressions further supports the applicability of this method

to the evaluation of asset pricing models with factors that are not necessarily observable returns, e.g., ESG variables.

The hypothesis to be tested in this empirical work is that investor concerns about climate change have implications for asset pricing, as sustainability preferences influence investment decisions and are reflected in market valuations. Our approach is based on the relationship between ESG investing and climate change considerations by investors (Engle et al., 2020; Pástor et al., 2022). However, while part of the empirical research exploits firms' ESG scores to build climate-sorted portfolios, we use this variable as a part of the information set used by investors to determine the unconditional version of the conditional capital asset pricing model (CAPM) following Lettau and Ludvigson's (2001) approach. Assuming that risk premia are time-varying, that is, parameters in the stochastic discount factor (hereafter SDF) will depend on investor expectations of future excess returns, Lettau and Ludvigson (2001) explicitly model the dependence of those parameters on current-period information. In particular, the authors use the "cay", an observable version of the consumption–aggregate wealth ratio, as a scaling variable in cross-sectional asset pricing tests due to its impressive forecasting power for excess returns on aggregate stock market indexes. On the same basis, in this paper, we use the ESG score as a conditioning or scaling variable that summarizes investor concerns about climate risk and predicts future excess returns (Rojo-Suárez & Alonso-Conde, 2023).

This paper makes a novel and timely contribution to the asset pricing literature by being the first to use the ESG score as a proxy for climate change considerations in an unconditional multifactor capital asset pricing model (CAPM). Moreover, in contrast to the standard CAPM, which uses time-invariant risk premia, the model implements the Lettau and Ludvigson (2001) time-varying risk premia framework in order to characterize the dynamics of the risks posed by climate change. This study is particularly important as it highlights the need to comprehend more deeply about climate change as a financial systemic risk factor, which is increasingly important given the reality that investors and policymakers understand how severely environmental risks can value assets. By incorporating ESG factors into the asset pricing model, we propose a novel empirical approach to evaluate the impact of climate risk, through ESG scores, on the asset valuation. Our efforts not only contribute to the increasing literature on sustainable finance but also to the urgent need for financial markets to more comprehensively reflect environmental risks, thus addressing important gaps for scholars and practitioners interested in the complex relationship between financial risk and climate change. Moreover, we show empirically that our model explains the cross-section of returns across a wide variety of portfolios even better than the Fama–French three-factor model. Following Lewellen et al. (2010), W. Ferson et al. (2013), and Campbell (2018), we evaluate the model using different anomaly portfolios consisting of all stocks traded on the US equity market from March 2001 to February 2023. These include 25 size–momentum portfolios, 32 size–BE/ME–operating profitability portfolios, and 38 industry portfolios. As a robustness check, we also test the model on 24 portfolios that combine four market anomalies: six size–BE/ME portfolios, six size–operating profitability portfolios, six size–short-term reversal portfolios, and six size–long-term reversal portfolios, following Lago-Balsalobre et al. (2023). Lastly, we improve our model evaluation by conducting tests during periods of significant economic anomalies, as described by Parnes (2020). These periods, marked by anomalies in economic models or common expectations, present a unique chance of benchmarking the performance of the model under both "normal" as well as "abnormal" market conditions. This is important because such periods help explain model behavior in unusual economic conditions. For example, the pandemic period (COVID-19) is characterized by a sharp drop in aggregate consumption and a significant increase in market volatility, along with disruptions to

the global energy supply and sharp fluctuations in energy prices, in addition to a global rise in inflation.

The remainder of this paper is organized as follows. Section 2 defines the models under analysis. Section 3 describes the data and shows the main descriptive statistics. Section 4 discusses the results. Section 5 concludes this paper.

2. Methodology

According to the Equivalence Theorem (Dybvig & Ingersoll, 1982; Hansen & Richard, 1987; Roll, 1977; Ross, 1978), we can express any asset pricing model into a beta model as follows:

$$\mathbf{E}\left(\mathbf{R^e_{t+1}}\right) = \beta\left(\mathbf{R^e_{t+1}}, \mathbf{f_{t+1}}\right)\lambda\left(\mathbf{f_{t+1}}\right) \tag{1}$$

where $\beta\left(\mathbf{R^e_{t+1}}, \mathbf{f_{t+1}}\right)$ is the matrix of slopes of the regression of excess returns on factors f_{t+1} and $\lambda(\mathbf{f_{t+1}})$ is the vector of prices of risk. Therefore, any linear asset pricing model can be identified by a specific vector of factors $\mathbf{f_{t+1}}$. Specifically, the following vectors of factors correspond to the classic CAPM, the Fama–French 3-factor model, and the Fama–French 5-factor model, respectively:

$$\text{Model 1} : \mathbf{f_{t+1}} = RMRF_{t+1} \tag{2}$$

$$\text{Model 2} : \mathbf{f_{t+1}} = \begin{pmatrix} RMRF_{t+1} + & SMB_{t+1} + & HML_{t+1} \end{pmatrix}' \tag{3}$$

$$\text{Model 3} : \mathbf{f_{t+1}} = \begin{pmatrix} RMRF_{t+1} + & SMB_{t+1} + & HML_{t+1} + & RMW_{t+1} + & CMA_{t+1} \end{pmatrix}' \tag{4}$$

where $RMRF$ is the market risk premium, SMB is the small minus big factor, HML is the high minus low factor, RMW is the profitability factor, and CMA is the investment factor.

Regarding the classic CAPM, a large and growing body of empirical work finds that the static nature of the coefficients in Equation (1) might be the cause of its poor explanatory power (Shanken, 1990; W. E. Ferson & Schadt, 1996; Jagannathan & Wang, 1996; Cochrane, 1996). Conditional models, by contrast, assume that risk premia are time-varying based on the fact that expected excess returns on aggregate stock market indexes are predictable (Campbell & Shiller, 1988; Fama & French, 1988, 1989; Campbell, 1991). Despite the apparent failure of testing conditional models (Hansen & Richard, 1987), Cochrane (1996) offers a partial solution that enables researchers to overcome the unobservability of investors' conditioning information. In particular, the author circumvents this difficulty by scaling factors by instruments that represent investor expectations of excess returns.

To capture variation in conditional moments, instruments must predict returns or the SDF (i.e., macroeconomic variables) (Cochrane, 2005, p. 135). Otherwise, conditioning information will not improve the model's explanatory power. Based on the empirical data supporting the ESG score's ability to predict outcomes (Khan, 2019; Serafeim & Yoon, 2022; Rojo-Suárez & Alonso-Conde, 2023), we study the explanatory power of this variable when used as an instrument.

To test a model in which the factors conditionally price assets, we rewrite Equation (1) in an unconditional form to include factors scaled by an instrument z observable at time t:

$$\mathbf{E}\left(\mathbf{R^e_{t+1}}\right) = \beta\left(\mathbf{R^e_{t+1}}, \mathbf{f_{t+1}}\right)\lambda\left(\mathbf{f_{t+1}}\right) + \beta\left(\mathbf{R^e_{t+1}}, z_t\right)\lambda(z_t) + \beta\left(\mathbf{R^e_{t+1}}, z_t\mathbf{f_{t+1}}\right)\lambda\left(z_t\mathbf{f_{t+1}}\right) \tag{5}$$

Equation (5) shows that conditioning information increases the SDF by two additional terms, given by the lagged instrument z_t and the product of the lagged instrument with factor $z_t\mathbf{f_{t+1}}$. As a result, in addition to Models 1–3 stated in Equations (2)–(4), below, we

define the following vector of factors, which we refer to as the conditional CAPM-ESG hereafter, using the ESG score as a part of the investor's information set:

$$\text{Model 4}: \mathbf{f_{t+1}} = \left(RMRF_{t+1} + \quad \Delta ESG_t + \quad \Delta ESG_t RMRF_{t+1}\right)' \tag{6}$$

We use the generalized method of moments (GMM) to replicate the two-pass cross-sectional regression (CSR) procedure, since it allows for simultaneously estimating all betas and lambdas in Equation (5). Furthermore, the GMM adjusts standard errors for cross-sectional autocorrelation and the predicted regressor nature of betas. Specifically, we use the moments restrictions that we show in Equation (7), following Cochrane (2005, pp. 241–243).

$$\mathbf{g_t}(b) = \begin{Bmatrix} E(R_t^e - a - \beta X_t \\ E[(R_t^e - a - \beta X_t)X_t] \\ E(R_t^e - \beta\lambda) \end{Bmatrix} \tag{7}$$

where a, β, and λ are parameters and X_t is a vector of factors, such as the market excess return, the ESG growth score, and the cross product between the ESG growth and the market excess return. To enable the GMM to replicate the two-pass cross-sectional regression method, we weight the moments in Equation (7) using the following matrix:

$$\mathbf{a_T} = \begin{pmatrix} I_{2N} & \\ & \beta' \end{pmatrix} \tag{8}$$

where **I** denotes the identity matrix. Thus:

$$\mathbf{a_T} g_T\left(\hat{b}\right) = \mathbf{0_{3N}} \tag{9}$$

Assuming a spectral density matrix S with zero leads and lags, we use the usual GMM specification for linear asset pricing models (see Cochrane, 2005, pp. 203–204) to calculate the standard errors and establish the distribution of moments in Equation (9) as follows:

$$\mathbf{S} = \mathbf{E}\left\{ \begin{bmatrix} R_t^e - a - \beta X_t \\ (R_t^e - a - \beta X_t)X_t \\ R_t^e - \beta\lambda \end{bmatrix} \begin{bmatrix} R_t^e - a - \beta X_t \\ (R_t^e - a - \beta X_t)X_t \\ R_t^e - \beta\lambda \end{bmatrix} \right\} \tag{10}$$

3. Variables and Data

We compiled return portfolios and market factors from the Kenneth R. French website at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on 30 May 2023), including all NYSE, AMEX, and NASDAQ stocks from March 2001 to February 2023. The database is publicly available and free of charge, with no payment required for access. The time frame was chosen based on the quality and availability of ESG data within the Datastream database. Prior to the year 2001, very little ESG data for firms existed, and thus, it would not be possible to conduct a meaningful analysis. From 2001 onwards, Datastream provided improved and consistent ESG ratings that allowed us to conduct valid analysis of the impact of ratings on stock returns.

The portfolios used in our analysis were constructed monthly based on different segmentation criteria. For the 25 portfolios formed by size (market equity, ME) and momentum (2–12 months past return), combinations of five size portfolios, based on NYSE market equity quintiles, and five momentum portfolios, formed using NYSE quintiles of prior returns (2–12 months), were created. In the case of the 32 portfolios formed on size, book-to-market (B/M), and operating profitability (OP), assets were grouped into two size

categories (small and big) based on the median NYSE market capitalization breakpoint. Within each size group, stocks were further classified into four B/M groups and four OP groups using NYSE-specific quartiles for each size group. The B/M ratio was calculated as book equity for the last fiscal year (t−1) divided by market equity at the end of t−1, and operating profitability was calculated as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, divided by book equity at the end of t−1. Lastly, for the 30 industry portfolios, each stock from the NYSE, AMEX, and NASDAQ was assigned to an industry portfolio based on its four-digit SIC code at the end of June of year t, using Compustat SIC codes (or CRSP SIC codes if Compustat codes are unavailable). The returns were then computed from July of year t to June of year t + 1.

Additionally, we introduced a "composite portfolio" as a robustness test for model testing proposed in this paper. The composite portfolio is a combination of four alternative sets of portfolios, each formed on two dimensions: (1) size and book-to-market ratio, (2) size and operating profitability, (3) size and short-term reversal, and (4) size and long-term reversal. Each portfolio was constructed by sorting stocks into two size groups based on the median NYSE market equity and then further sorting within each size group into three portfolios based on the respective characteristic. For short-run reversal, stocks were ranked based on their past 1-1-month return using the 30th and 70th NYSE percentiles as breakpoints, whereas for long-run reversal, stocks were ranked based on their past 13–60-months return using the 30th and 70th NYSE percentiles as breakpoints. By compounding these four groups of portfolios, the composite portfolio contained a large range of characteristics, providing an effective test of the explanatory power of the models for asset returns.

Regarding ESG scores, we used the Datastream database to compile metrics based on three criteria, i.e., environmental, social, and corporate governance, each including different indicators. All Datastream data are publicly available as Supplementary Materials in this document. The environmental criteria consider a company's capability to reduce its environmental impact and emissions, as well as the use of raw materials and energy consumption. The social criterion is based on respect for human rights, promoting a healthy and safe work environment, and protecting public health and business ethics, among others. Finally, the governance criteria consist of scores for corporate management principles, shareholders' treatment, and corporate social responsibility (CSR) strategy. The weighted averages of these indicators, which range from 0 to 100, provide the Environmental Score, the Social Score, and the Governance Score that integrate the final ESG score according to their respective weights.

While ESG metrics are provided by Datastream at the individual level (i.e., by company), we required a metric that collects the average ESG score of the US market for the model testing. Therefore, we weighed each company's ESG score by its market value, eliminating those companies whose ESG score is not available in the Datastream database, as indicated below:

$$\overline{ESG_t} = \frac{\sum_{i=1}^{n} ESG_{i,t} * MV_{i,t}}{\sum_{i=1}^{n} MV_{i,t}} \quad (11)$$

where $\overline{ESG_t}$ represents the average ESG score of the market at time t, $ESG_{i,t}$ represents the ESG score of firms i at time t, and $MV_{i,t}$ denotes the market value of firm i at time t. When using Equation (11) to calculate the ESG factor, we implicitly assumed that the impact of the ESG-scored indicators is greater for larger companies by market capitalization, since their sustainability strategy and policy affects a larger percentage of the population, and the opposite is true for small-capitalization companies. This assumption is supported by the work of Eccles et al. (2012), who argue that larger companies ("High Sustainability") are more likely to adopt sustainability policies and corporate governance mechanisms for

ESG, which, being larger in size and having a larger stakeholder base, can have a broader societal impact. Furthermore, Porter and Kramer (2011) argue that a growing number of large companies are creating shared value by addressing social needs on a large scale, which demonstrates the potential for a greater societal impact of their ESG initiatives due to their operational reach. Finally, we used the excess return of the value-weighted market portfolio (hereinafter referred to as RMRF), as provided by Kenneth R. French, as a proxy for the return on the wealth portfolio in the conditional CAPM-ESG model.

Table 1 displays the means and standard deviations of every anomaly portfolio used in empirical tests. Panel A displays summary statistics for 24 composite portfolios formed by crossing four double-sorted portfolios. The Low, 2, and High columns represent the percentile ranks of every attribute: Low to the lowest-performing stocks, 2 to the second percentile group of stocks, and High to the highest-performing stocks. The abbreviations vertically at the beginning of the table (e.g., Small–BE/ME, Big–BE/ME) represent portfolios formed by small or big stocks sorted by the respective characteristics (BE/ME, OP, short-term reversal, or long-term reversal). This structure allows for the examination of excess returns for each group based on size and characteristic sorting. Panel B shows summary statistics for 25 size–momentum portfolios, rank-sorted into five groups in terms of momentum, each of which is one of the distinct percentiles of the momentum attribute (from Low, lowest momentum decile, to High, highest momentum decile). The Low, 2, 3, 4, and High columns correspond to these percentile groups: Low for stocks in the lowest percentile group of momentum, High for stocks in the highest percentile group, and the middle columns corresponding to stocks in the intermediate groups of percentiles. The abbreviations at the beginning of the table (e.g., small, big) represent portfolios formed by small or big stocks, sorted by their momentum characteristics. Panel C presents summary statistics for 32 portfolios formed on size, book-to-market (B/M), and operating profitability (OP). The portfolios are initially segregated by size into small and big portfolios, based on median market equity. The stocks are subsequently separated into four groups in each size group, based on the BE/ME ratio, and four groups, based on operating profitability, based on the 30th and 70th NYSE percentiles as breakpoints for both BE/ME and OP. Low, 2, 3, and High in the columns refer to the BE/ME and OP percentile groups within each size group: Low refers to those stocks in the lowest percentile of the respective feature, and High to those in the top percentile. The abbreviations at the beginning of the table (e.g., Small–OP, Big–OP) represent portfolios formed by small or big stocks sorted by their respective BE/ME and operating profitability characteristics. Finally, Table 2 provides the definition and calculation of the variables employed in the construction of the portfolios.

Panel E in Table 1 presents summary statistics for the Fama–French five factors, ESG growth (ΔESG), and the cross-product between ESG growth and the market portfolio excess return (ΔRM-ESG). The Fama–French factors include the market return (RM), the risk-free rate (RF), the size factor (SMB), the value factor (HML), the profitability factor (RMW), and the investment factor (CMA). ΔESG is the change in the ESG score each year, and ΔRM-ESG is the interaction between the ESG change and the market return.

Table A1 in Appendix A displays the correlations, expressed as percentages, among the main factors and the excess returns of the different anomaly portfolios. We observe from Table A1 that the ESG factor is not as correlated with returns as the other factors, such as RMRF or SMB. Furthermore, we find that the ESG factor has a mostly negative correlation with industrial portfolios, namely: electrical and electronic equipment (Electr), sanitary services (Garbg), fabricated metal products (Mtlpr), public administration (Govt), and transportation equipment (Cars). In any case, the weak or strong correlations presented in Table A1 do not determine the performance of the model since what is relevant is the

correlation between the expected returns and the covariances between the factors and the returns (i.e., the factor betas).

Table 1. Summary statistics.

Panel **A**: 24 composite portfolios

	Means				St. Dev.		
	Low	2	High		Low	2	High
Small–BE/ME	0.55	0.74	0.71	Small–BE/ME	6.4	5.73	6.4
Big–BE/ME	0.64	0.52	0.47	Big–BE/ME	4.38	4.56	6.15
Small–OP	0.47	0.81	0.84	Small–OP	6.55	5.54	6.41
Big–OP	0.3	0.54	0.69	Big–OP	5.51	4.65	4.18
Small–ST Rev.	0.69	0.76	0.46	Small–ST Rev.	7.43	5.88	6.06
Big–ST Rev.	0.45	0.68	0.42	Big–ST Rev.	6.14	4.38	4.54
Small–LT Rev.	0.76	0.76	0.71	Small–LT Rev.	7.26	5.57	6.07
Big–LT Rev.	0.53	0.59	0.65	Big–LT Rev.	5.49	4.18	4.76

Panel **B**: 25 size–momentum

	Means					St. Dev.				
	Low	2	3	4	High	Low	2	3	4	High
Small	0.3	0.62	0.75	0.94	0.82	9.03	6.33	5.6	5.43	6.35
2	0.47	0.84	0.84	0.89	0.8	8.89	6.53	5.65	5.58	6.56
3	0.4	0.8	0.81	0.7	0.71	8.39	6.31	5.53	5.22	5.91
4	0.11	0.78	0.91	0.8	0.69	8.94	6.09	5.11	4.66	5.48
Big	0.11	0.59	0.65	0.62	0.65	8.21	5.48	4.45	4.18	4.65

Panel **C**: 32 size–BE/ME–operating profitability

	Means								
	Small					Big			
BE/ME	Low	2	3	High	BE/ME	Low	2	3	High
Small–OP	0.14	0.72	0.8	0.87	Small–OP	0.55	0.77	0.57	0.65
2	0.5	0.83	0.75	0.91	2	0.52	0.68	0.6	0.73
3	0.51	0.73	0.81	0.62	3	0.53	0.63	0.65	0.52
Big–OP	0.65	0.65	1.04	0.72	Big–OP	0.25	0.55	0.67	-0.29
	St. Dev.					St. Dev.			
Small–OP	8.03	6.12	5.7	5.99	Small–OP	7.23	6.69	4.99	4.44
2	6.93	5.63	5.37	6.48	2	5.74	4.72	4.31	4.23
3	6.63	5.66	5.97	8.01	3	4.84	4.83	4.84	5.63
Big–OP	7.42	6.87	8.73	9.7	Big–OP	5.97	5.78	5.95	11.95

Panel **D**: 38 Industry Portfolios

Means					St. Dev.				
Agric	Mines	Oil	Stone	Cnstr	Agric	Mines	Oil	Stone	Cnstr
0.76	0.61	0.55	0.52	0.68	6.38	9.74	9.83	7.14	7.55
Food	Smoke	Txtls	Apprl	Wood	Food	Smoke	Txtls	Apprl	Wood
0.62	0.89	0.33	0.54	0.58	3.49	6.25	9.47	6.94	8.75
Chair	Paper	Print	Chems	Ptrlm	Chair	Paper	Print	Chems	Ptrlm
0.44	0.45	0.04	0.54	0.72	7.61	5.24	6.59	3.85	6.44
Rubbr	Lethr	Glass	Metal	MtlPr	Rubbr	Lethr	Glass	Metal	MtlPr
0.92	0.88	0.65	0.46	0.84	5.96	8.34	8.45	9.56	5.68
Machn	Elctr	Cars	Instr	Manuf	Machn	Elctr	Cars	Instr	Manuf
0.68	0.71	0.77	0.76	0.1	6.41	7.29	6.93	4.84	6.57
Trans	Phone	TV	Utils	Garbg	Trans	Phone	TV	Utils	Garbg
0.67	0.18	0.41	0.59	0.71	5.59	5.16	6.2	4.16	4.59
Steam	Water	Whlsl	Rtail	Money	Steam	Water	Whlsl	Rtail	Money
NA	NA	0.67	0.69	0.44	NA	NA	5.06	4.66	5.85
	Srvc	Govt	Other			Srvc	Govt	Other	
	0.63	0.22	0.27			5.3	6.48	5.37	

Panel **E**: Market factors and ESG score

	RM RF	SMB	HML	RMW	CMA		ΔESG		RM ΔESG
Means	0.58	0.17	−0.01	0.32	0.16	Mean	0.06	Mean	−0.01
St. Dev.	4.54	2.6	3.04	2.02	1.91	St. Dev.	3.33	St. Dev.	0.2

Notes: Table 1 shows the means and standard deviations of the excess returns of the data compiled from the Kenneth R. French website, including all stocks traded in the US equity market from March 2001 to February 2023. Panel A shows statistics for a set of 24 composite portfolios that combines four double-sort portfolios, namely: 6 size–BE/ME portfolios, 6 size–operating profitability portfolios, 6 size–short-term reversal portfolios, and 6 size–long term reversal portfolios. Panels B, C, and D show statistics for 25 size–momentum portfolios, 32 size–BE/ME–operating profitability portfolios, and 38 industry portfolios, respectively. Panel E shows the Fama and French (2015) five factors, the ESG growth (ΔESG), and the cross product between the ESG growth and the market portfolio excess return (Δ RM ESG). All results are determined on a monthly basis, except those for the ESG score, which uses annual data. All numbers are expressed in percentages.

Table 2. Variables used in the construction of the portfolios.

Variable	Definition	Calculation Methodology	Source
Size (ME)	Market equity or firm size	Stock price multiplied by the number of shares outstanding at the end of June. Portfolios are split into "small" and "big" based on the NYSE median market equity.	Kenneth R. French Data Library
BE/ME	Book-to-market ratio	Book equity from the last fiscal year end in t − 1 divided by market equity in December of t − 1.	Kenneth R. French Data Library
OP (Operating Profitability)	Operating profitability	(Annual revenues − cost of goods sold − interest expense − SG&A expenses) divided by book equity (fiscal year t − 1).	Kenneth R. French Data Library
Short-term Reversal	Short-term return reversal effect	Return in month t − 1 (prior 1-month return). Portfolios are sorted using NYSE 30th and 70th percentiles into Low, Medium, and High groups.	Kenneth R. French Data Library
Long-term Reversal	Long-term return reversal effect	Cumulative return from month t − 60 to t − 13. Portfolios are formed using NYSE 30th and 70th percentiles into Low, Medium, and High groups.	Kenneth R. French Data Library
Momentum (2–12)	Intermediate-term past return (momentum)	Cumulative return from month t − 12 to t − 2. Portfolios are sorted into quintiles for both size and past return to form 25 size–momentum portfolios.	Kenneth R. French Data Library

Panel D in Tables 1 and A1 shows missing values (NAs) in the portfolios of the Steam and Water Industries, resulting from the relatively small number of stocks available in these industries, which often do not satisfy the inclusion criteria in certain years. These sectors are niche and possess a relatively lower market share, resulting in these databases (Compustat and CRSP) having inadequate data scope. Thus, the lack of information is indicative of these industries having a weaker presence in the market, and not the methodology employed.

4. Results and Discussion

Table 3 shows the regression results for all the models under consideration, on an annual basis. Specifically, model 1 in Table 3 shows the results provided by the conditional CAPM-ESG, while models 2, 3, and 4 present the results delivered by the CAPM and the three-factor model and the five-factor model of Fama and French (1993, 2015), respectively.

For each model, Table 3 provides two rows, where the first row shows the coefficient estimates and the second row shows the t-statistics estimated by the GMM. Table 3 provides the $\mathbf{R}^2$ statistics for each model using both the ordinary least squares (OLS) and the generalized least squares (GLS) approaches, respectively. Furthermore, Table 3 displays the mean absolute error (MAE) as well as the J-test for overidentifying restrictions.

Regarding the coefficient estimates, Table 3 analyzes the pricing of risk factors across the different portfolios (Panels A–E), specifically examining the influence of ESG-related variables alongside conventional asset pricing factors. When both the ESG growth factor ($\boldsymbol{\lambda}_{\Delta ESG}$) and its cross-product with market returns ($\boldsymbol{\lambda}_{RM\text{-}ESG}$) are included in the models, these factors help explain some of the return variation lacking in traditional frameworks. A positive $\boldsymbol{\lambda}_{\Delta ESG}$ would suggest that firms with improving ESG scores are rewarded with greater expected returns, whereas a negative coefficient would suggest that these improvements may be associated with lower returns, possibly reflecting an "ESG premium" that investors are willing to pay. Similarly, the cross-product coefficient $\boldsymbol{\lambda}_{RM\text{-}ESG}$ captures how return sensitivity to movements in the market hinges on ESG dynamics, such that companies with stronger ESG trends may react differently to market trends. In any case, it is important to note that because of the non-significant nature of the lambdas, the results are subject to sampling variation, meaning that the sign of the lambda coefficients could vary.

Table 3. Cross-sectional regression results.

	CAPM-ESG		CAPM		Fama–French (Three Factors)		Fama–French (Five Factors)	
Factors	**Estimation**	**t-Statistic**	**Estimation**	**t-Statistic**	**Estimation**	**t-Statistic**	**Estimation**	**t-Statistic**
				Panel **A**: 24 composite portfolios				
Intercept	0.070	(1.077)	0.005	(1.236)	0.011	(3.298)	0.004	(0.983)
$\lambda_{\Delta ESG}$	0.013	(0.680)						
$\lambda_{RM\text{-}ESG}$	0.000	(−0.149)						
λ_{RMRF}	−0.001	(−0.130)	0.001	(0.191)	−0.005	(−1.234)	0.002	(0.388)
λ_{SMB}					0.001	(0.852)	0.001	(0.904)
λ_{HML}					0.000	(0.242)	0.000	(0.060)
λ_{RMW}							0.004	(2.977)
λ_{CMA}							0.000	(0.150)
R^2	0.591	0.327	0.010	−0.040	0.322	0.237	0.815	0.795
MAE (%)	0.07		0.12		0.10		0.05	
J-test	10.820	(0.951)	33.482	(0.055)	31.606	(0.048)	19.797	(0.344)
				Panel **B**: 25 size–momentum portfolios				
Intercept	0.014	(3.794)	0.014	(3.550)	0.015	(3.898)	0.006	(1.350)
$\lambda_{\Delta ESG}$	−0.003	(−0.258)						
$\lambda_{RM\text{-}ESG}$	0.000	(−0.389)						
λ_{RMRF}	−0.006	(−1.396)	−0.006	(−1.346)	−0.009	(−1.885)	0.000	(−0.025)
λ_{SMB}					0.001	(0.636)	0.003	(1.464)
λ_{HML}					0.001	(0.293)	0.002	(0.507)
λ_{RMW}							0.007	(2.233)
λ_{CMA}							0.005	(1.501)
R^2	0.536	0.454	0.496	0.428	0.741	0.651	0.862	0.806
MAE (%)	0.13		0.13		0.09		0.07	
J-test	38.343	(0.012)	40.883	(0.012)	36.797	(0.018)	23.834	(0.203)
				Panel **C**: 32 size–value–operating profitability portfolios				
Intercept	0.010	(1.695)	0.010	(2.368)	0.016	(2.822)	0.014	(2.137)
$\lambda_{\Delta ESG}$	−0.017	(−1.474)						
$\lambda_{RM\text{-}ESG}$	−0.001	(−1.985)						
λ_{RMRF}	−0.003	(−0.492)	−0.004	(−0.681)	−0.011	(−1.612)	−0.008	(−1.086)
λ_{SMB}					0.001	(0.845)	0.002	(0.938)
λ_{HML}					0.000	(−0.174)	−0.002	(−0.910)
λ_{RMW}							0.003	(1.797)
λ_{CMA}							0.002	(1.031)
R^2	0.405	0.308	0.082	0.078	0.340	0.236	0.476	0.351
MAE (%)	0.14		0.16		0.14		0.12	
J-test	22.905	(0.738)	40.627	(0.093)	35.544	(0.155)	28.583	(0.330)
				Panel **D**: 38 industry portfolios				
Intercept	0.010	(2.874)	0.007	(2.578)	0.008	(2.849)	0.007	(2.171)
$\lambda_{\Delta ESG}$	−0.011	(−1.238)						
$\lambda_{RM\text{-}ESG}$	0.001	(−1.588)						
λ_{RMRF}	−0.004	(−0.879)	−0.001	(−0.231)	−0.002	(−0.507)	−0.001	(−0.207)
λ_{SMB}					0.001	(0.500)	−0.002	(−0.507)
λ_{HML}					−0.002	(−0.812)	−0.003	(−1.093)
λ_{RMW}							0.003	(1.062)
λ_{CMA}							−0.004	(−1.076)
R^2	0.327	0.321	0.014	−0.009	0.105	0.075	0.208	0.198
MAE (%)	0.14		0.17		0.15		0.15	
J-test	23.616	(0.858)	39.175	(0.249)	37.266	(0.240)	31.966	(0.369)
				Panel **E**: Total assets				
Intercept	0.010	(3.372)	0.009	(3.456)	0.012	(4.565)	0.010	(3.691)
$\lambda_{\Delta ESG}$	−0.013	(−1.786)						
$\lambda_{RM\text{-}ESG}$	−0.001	(−2.371)						
λ_{RMRF}	−0.004	(−0.873)	−0.002	(−0.598)	−0.006	(−1.498)	−0.004	(−1.086)
λ_{SMB}					0.001	(0.831)	0.002	(0.959)
λ_{HML}					0.000	(−0.148)	−0.001	(−0.644)
λ_{RMW}							0.002	(1.421)
λ_{CMA}							0.000	(−0.061)
R^2	0.298	0.085	0.068	0.046	0.248	0.227	0.352	0.243
MAE (%)	0.13		0.15		0.13		0.12	
J-test	209.308	(0.000)	272.424	(0.000)	264.258	(0.000)	253.325	(0.000)

Notes: Table 3 presents the regression results of the asset pricing models considered for the four sets of anomaly portfolios. We collected data from the Kenneth R. French website, including all stocks traded in the US equity market from March 2001 to February 2023. The table displays two rows for each model, where the first row shows the coefficient estimates, and the second row shows the t-statistics estimated by GMM. OLS and GLS R^2 statistics are provided for each model, in that order.

In Table 3, the analysis in Panels A through D demonstrates that the ESG growth factor ($\lambda_{\Delta ESG}$) is often estimated to be negative or near zero, indicating that better ESG scores tend to relate to lower expected returns across different portfolio constructions. However, the pricing of ESG-related risks is modest, and the cross-product coefficient ($\lambda_{RM\text{-}ESG}$) is typically close to zero and statistically insignificant in these panels. The pricing of ESG-related risks is low, and the cross-product coefficient ($\lambda_{RM\text{-}ESG}$) is largely close to zero and statistically insignificant in these panels. Most importantly, in Panels C (operating profitability–size–value portfolios) and D (industry portfolios), the t-statistics on the cross-product coefficient move to relatively higher levels of significance than elsewhere in the panels, suggesting that in these panels, possibly, ESG dynamics can actually influence the sensitivity of portfolio returns to market conditions.

Panel E (Table 3), which addresses portfolios built based on total assets, presents the most robust evidence of the influence of ESG factors on returns. Specifically, the cross-product coefficient ($\lambda_{RM\text{-}ESG}$) of the CAPM-ESG model is statistically significant with a t-statistic of -2.37, indicating that better-ESG-trend companies are less sensitive to the market and that this characteristic is valued by investors by providing them with lower expected returns. This consistent pattern of higher significance across Panels C, D, and E provides evidence for the claim that ESG improvements become increasingly relevant in explaining variations in returns, especially when firm fundamentals or size are considered in portfolio construction. These findings suggest that investors utilizing ESG information along with traditional risk factors—particularly in strategies focused on firm characteristics or sectoral exposures—obtain a superior insight into the manner in which sustainability dynamics influence risk–return profiles and, in the end, make more effective and optimized investment decisions.

Regarding the statistical results, Table 3 shows that the CAPM-ESG model provides good results when explaining the cross-sectional behavior of the majority of the portfolios under analysis. It is observed that in Panel A, Panel C, Panel D, and Panel E, the CAPM-ESG model provides higher $\mathbf{R}^2$ statistics than the Fama–French three-factor model. Furthermore, in Panel D, the CAMP-ESG model ranks with a higher $\mathbf{R}^2$ than both Fama–French models (Fama & French, 1993, 2015). This finding is in line with recent studies, such as Albuquerque et al. (2020), which stress that ESG factors can account for non-traditional risk-factor-explained differences in returns. However, it is important to note that other empirical studies, for example, Blitz and Swinkels (2023), assert that the omission of certain stocks based on sustainability considerations (such as "in stocks") is generally in conflict with usual rewarded risk considerations, such as value, profitability, and low risk, which do not necessarily result in higher expected portfolio returns and generate tracking error. In addition, Berg et al. (2022) illustrate that high variation among ESG rating agencies introduces noise and reduces the informative content of ESG metrics, potentially diminishing their contribution to asset pricing.

For the 24 composite portfolios (Panel A), the model that performs best is the Fama–French five-factor model, with an 81.5% OLS $\mathbf{R^2}$ and an MAE of 5%, followed by the CAPM-ESG model, with an OLS $\mathbf{R^2}$ of 59.1% and an MAE of 7%. These results reinforce evidence provided by Khan et al. (2016), who found that ESG improvements are positively associated with risk-adjusted returns and that ESG information provides incremental explanatory power relative to conventional factors. The Fama–French three-factor model $\left(\mathbf{OLSR^2 = 32.2\%}\right)$ and the CAPM model $\left(\mathbf{OLSR^2 = 1\%}\right)$ do not yield such good results. On the other hand, the J-test for overidentifying restrictions rejects the Fama–French three-factor model while accepting the rest of the valuation models, supporting the notion that more comprehensive models (including ESG) better fit the data.

In contrast, for the 25 size–momentum portfolios (Panel B), the CAPM-ESG model provides an OLS $\mathbf{R^2}$ of 53.6%, while for the Fama–French three-factor model and five-factor model, the statistic rises to 74.1% and 86.2%, respectively. Consistent with the $\mathbf{R^2}$ results, the highest MAE is provided by the CAPM-ESG model (13%), followed by the Fama–French three-factor model (9%) and the Fama–French five-factor model (7%). Besides the poor performance of the CAPM-ESG model in Panel B, it should be noted that size–momentum portfolios have typically represented a challenging hurdle for most asset pricing models (Fama & French, 1993; Roh et al., 2019). This is consistent with Asness et al. (2013), who document that momentum effects are pervasive across markets and remain challenging to fully capture using even extended factor models. Finally, the J-test for overidentifying restrictions rejects all models but the Fama–French five-factor model for this panel. However, these results should be taken with caution, as rejection could be mainly due to the low variance in pricing errors rather than high absolute pricing errors.

Panel C in Table 3 shows the regression results for the 32 size–value–operating profitability portfolios. This anomaly was selected following Fama and French (2015), which finds that the three-factor Fama and French (1993) model is not able to price some anomalies, such as the investment or the robustness of the operating profitability. The CAPM-ESG results, in terms of OLS $\mathbf{R^2}$ explanatory power (40.5%), clearly outperform the Fama–French three-factor model (34%) and the CAPM model (8.2%), falling slightly below the Fama–French five-factor model result (47.6%). Moreover, the performance similarity of the CAPM-ESG model to the five-factor model suggests that ESG factors could include information regarding profitability and investment dimensions, as suggested by Grewal and Serafeim (2020), who describe how ESG practices influence financial performance and corporate profitability. A lower MAE is obtained by the Fama–French five-factor model (12%), followed by intermediate values for the CAPM-ESG model (14%) and the Fama–French three-factor model (14%), and the highest value is obtained by the CAPM (16%). In this case, the J-test for overidentifying restrictions fails to reject all models.

The results in Panel D show that the CAPM-ESG model does a remarkable job in pricing the 38 industry portfolios, providing an $\mathbf{R^2}$ of 32.7% and an MAE of 14%, while the Fama–French five-factor model stands at 20.8% with an MAE of 15%. These results are consistent with Khan et al. (2016), who emphasize the relevance of industry-specific material factors of sustainability to firm performance and suggest that industrial portfolio valuation models could be more precise if they incorporate ESG factors that are material to each respective industry. The Fama–French three-factor model (10.5%) and CAPM (1.4%) are well below these results. Regarding the GLS $\mathbf{R^2}$, the CAPM-ESG model is the model with the highest statistic (32.1%), greater than the five-factor Fama and French (19.8%). In addition, the CAPM-ESG model presents the smallest difference between the OLS $\mathbf{R^2}$ and GLS $\mathbf{R^2}$ statistics (0.6%) in Panel D, which reveals that the factors mimicking the portfolio are empirically mean–variance efficient. Finally, we deduce that the better performance of the CAPM-ESG model in Panel D might be due to the portfolio sorting criteria, which helps to explain a higher fraction of the assets' cross-sectional returns by establishing a direct relationship between the industry and the ESG score. In Panel D, the J-test for overidentifying restrictions fails to reject all models in this empirical test.

Finally, Panel E presents a robustness test combining all the portfolios. Remarkably, the CAPM-ESG model yields an $\mathbf{R^2}$ of 29.8% with an MAE of 13%, providing similar results to those obtained by the Fama–French five-factor model, which yields an $\mathbf{R^2}$ of 35.2% and an MAE of 12%. This finding concurs with evidence from recent empirical research (e.g., Pástor et al., 2021) that ESG-related data have played an increasingly significant role in explaining U.S. asset prices, especially when controlling for firm size, industry sector, and profitability.

The empirical evidence obtained in this study supports the first hypothesis that investor concerns regarding climate change are important to asset pricing. Specifically, the findings indicate that ESG variables and, most importantly, the ESG growth factor (ΔESG) and its interaction with market returns (RM-ESG), are significant drivers of the return differences above and beyond what typical models capture. While their pricing power is modest in some portfolio configurations, Panels C, D, and, most notably, E provide statistically significant results for the ESG factors, showing that sustainability decisions are truly stated in terms of market judgments—particularly given the scenario where portfolio construction adjusts for fundamental firm attributes, like size, profitability, or industry classification. The improved performance of the CAPM-ESG model over the panels compared to the conventional models lends credence to the proof that climate concerns are increasingly incorporated into investment decisions and shape the risk–return landscape of financial instruments in the U.S. market.

In addition to the empirical tests in this study, we also performed a set of robustness tests to ensure that the data comply with the assumptions in estimating asset pricing models. Specifically, we confirmed whether the errors in the regression time series are normally distributed, whether the errors are autocorrelated, and whether there is multicollinearity between the variables selected as risk exposure variables.

First, we used the Kolmogorov–Smirnov–Lilliefors test (Kolmogorov, 1933) to determine if the regression errors follow a normal distribution. We set our null hypothesis to be that the errors follow a normal distribution, and we rejected the hypothesis when the p-value is less than 0.05 (Climent Hernández & Venegas Martínez, 2013). We present the result of this test in Table S1 of the Supplementary Materials, where it is observed that, in general, the errors are normally distributed except in certain particular portfolios. Because of the large number of assets used in the empirical tests, these exceptional cases do not significantly affect the findings of this study.

Additionally, the Supplementary Materials includes Q-Q plots as a visual analysis of the normality tests. If the data points align along the 45-degree line, we can consider the models to follow a normal distribution. Variations in specific cases suggest that the distribution fitting those errors has heavier tails. Furthermore, deviations at the extremes indicate the presence of outliers. Based on this graphical test, we conclude that the regression time series errors follow a normal distribution.

Next, we performed autocorrelation tests, using the Breusch–Godfrey test, which is also referred to as the Lagrangian Multiplier test (Breusch, 1978; Godfrey, 1978). Mantalos (2003) describes this test's null hypothesis as no autocorrelation existing within the residuals. As previously stated, we set the null hypothesis when the p-value is < 0.05, proving autocorrelation does exist in the residuals. The p-values for each of the Breusch–Godfrey tests are detailed in the Table S2 of the Supplementary Materials. The results support Mantalos' conclusions: in the general cases, the residuals do not show significant autocorrelation. Despite this, the existence of autocorrelation within regression errors is not a concern since the method used (GMM) corrects the estimates of asset risk premiums for autocorrelation in the errors.

In addition, the Supplementary Materials provides autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, the most common use being autocorrelation tests in practice (Rojo-Suárez et al., 2024). The ACF plot displays the autocorrelation of a time series against its lags, allowing autocorrelation structures in the data to be identified. The x-axis represents the lags, and the y-axis contains the autocorrelation coefficients. The horizontal lines are the significance thresholds. In order to comprehend these plots, we look for significant peaks at some lags, which are indicators of autocorrelation. The downward trend represents a stationary time series, while cyclical patterns can indicate seasonality.

The PACF plot illustrates the partial autocorrelation in a time series against its lags after eliminating the effect of in-between lags. It helps us decide on the order of autoregressive terms in an ARIMA model. We read both plots the same way. These plots support the results that were achieved with the statistical tests.

Finally, we present the results of the Variance Inflation Factor (VIF) test (Marquardt, 1970) in Table S3 of the Supplementary Materials. We used this test in a regression analysis to detect potential multicollinearity among the independent variables. We estimated the VIF for each variable using the following expression:

$$VIF = \frac{1}{1 - \boldsymbol{R^2}} \tag{12}$$

where $\boldsymbol{R^2}$ is the coefficient of determination obtained by regressing the independent variable under analysis on the other independent variables. The three regression models used in this article are as follows:

$$\begin{aligned} RMRF_t &= a + b\Delta ESG_t + c\Delta ESGRMRF_t + \epsilon \\ \Delta ESG_t &= a + bRMRF + c\Delta ESGRMRF_t + \epsilon \\ \Delta ESGRMRF_t &= a + bRMRF_t + c\Delta ESG_t + \epsilon \end{aligned} \tag{13}$$

where a, b, and c are parameters.

With respect to interpreting the VIF test, we observe that for values of VIF close to one, multicollinearity does not exist. If the test results are between 1 and 5, there is moderate multicollinearity, while if the test values are above 5, there is severe multicollinearity. In our empirical tests, we observe that the values of the VIF for all the three variables are close to one, which is a confirmation that there is no multicollinearity between the selected variables as risk exposure indicators.

5. Conclusions

According to the emerging theoretical literature, green assets should have lower expected returns than brown assets because they provide a hedge against climate risks and social benefits to investors with green tastes (Baker et al., 2022; Pástor et al., 2022). However, the empirical research finds inconclusive evidence on the relationship between climate change and equity returns (Balvers et al., 2017; Bansal et al., 2019; Cheema-Fox et al., 2021; Hong et al., 2019; In et al., 2017; Kumar et al., 2019; Nagar & Schoenfeld, 2021; Dai, 2024). Following Lettau and Ludvigson's (2001) approach, in this paper, we use firms' ESG scores as a part of the information set used by investors to analyze indirect effects that climate concerns may have on asset prices. Our results show that the CAPM-ESG model outperforms some well-known asset pricing models, such as the Fama–French three-factor model and, in some cases, the Fama–French five-factor model, in capturing a significant portion of the cross-sectional volatility in excess returns for a wide range of market anomaly portfolios. These results are consistent with the literature on how ESG concerns should affect stock returns (Engle et al., 2020; Pástor et al., 2021, 2022; Rojo-Suárez & Alonso-Conde, 2023). In line with Pástor et al. (2021), we find a negative price of risk for stocks that covary positively with ESG growth, which suggests that green assets may perform better than brown ones if ESG concerns suddenly become more important over time.

The conditional CAPM-ESG model examined here differs significantly from its unconditional version. If the conditional expected returns to the market portfolio are time-varying, the investor's discount factor will be a function of these components, conditional on ESG information about future returns (Lettau & Ludvigson, 2001). Therefore, our results help shed light on how climate change is priced regardless of the climate risk measure used. Additionally, it is important to note that the data used in the empirical tests incorporate

economic periods with anomalies. First, we include the pandemic period (COVID-19), which is characterized by a sharp drop in aggregate consumption and a significant increase in market volatility (Guedhami et al., 2022). Second, global events have also modified economic stability at an international level (Adekoya et al., 2023; Abbassi et al., 2022), in addition to a massive increase in the price of oil and fuel (Aharon et al., 2023; Martins et al., 2023; Sokhanvar & Bouri, 2023; Sokhanvar et al., 2023). Models that incorporate economic anomalies and market inefficiencies can provide more accurate predictions of asset prices and returns, as well as highlight potential risks and opportunities for investors (Parnes, 2020).

While our methodology uses the ESG composite score as a proxy for investors' concerns over climate—following a common approach in the empirical asset pricing literature (Engle et al., 2020; Pástor et al., 2021, 2022; Rojo-Suárez & Alonso-Conde, 2023)—we acknowledge that ESG addresses three different dimensions: environmental, social, and governance. Each one of them may have independent and possibly opposite effects on firm performance and asset prices. For example, Cek and Eyupoglu (2020), in their examination of S&P 500 firms, find that environmental performance is not significantly correlated with economic firm performance, suggesting that the social and governance pillars might, in some cases, be even more relevant to investors. Hence, while our major concern remains the climate implications, future research could benefit from disentangling the separate contributions of the E, S, and G dimensions so as to specifically determine their asset pricing roles.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijfs13020088/s1, Table S1: Normality test; Table S2: Autocorrelation test; Table S3: VIF test; Figure S1: Normality plots; Figure S2: Autocorrelation plots; Data: Portfolios of assets, including 24 composite portfolios, 25 size–momentum, 32 size–BE/ME–operating profitability, 38 Industry Portfolios and Total assets. Additionally, the folder contains market factors and ESG scores.

Author Contributions: L.G.-S.: conceptualization, methodology, software, formal analysis, investigation, resources, data curation, and writing—original draft. R.L.-B.: methodology, software, formal analysis, investigation, resources, data curation, writing—review and editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed to the published version of this manuscript.

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Abbreviations

AMEX	American Stock Exchange
BE/ME	Book Equity to Market Equity
CAPM	capital asset pricing model
CMA	Conservative Minus Aggressive
CRSP SIC	Center for Research in Security Prices
CSR	corporate social responsibility
ESG	environmental, social, and governance
GLS	generalized least squares
GMM	generalized method of moments
GSIA	Global Sustainable Investment Alliance
HML	high minus low
LT Rev	long-term reversal
MAE	mean absolute error
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	ordinary least squares
OP	operating profitability
RM	market return
RF	risk-free rate
RMW	Robust Minus Weak
SIC	Standard Industrial Classification
SMB	small minus big

Appendix A

Table A1. Correlations.

Panel **A**: 24 composite portfolios									
	Low	2		High		Low	2		High
	Correlations with ΔESG					Correlations with RMRF			
Small–BE/ME	1.4	2.21		2.24	Small–BE/ME	89.76	91.44		86.09
Big–BE/ME	1.85	5.05		3.21	Big–BE/ME	97.5	96.06		89.52
Small–OP	2.57	1.31		2.04	Small–OP	89.8	89.35		89.41
Big–OP	0.48	3.73		3.13	Big–OP	95.64	98.52		97.63
Small–ST Rev.	1.53	2.79		2.63	Small–ST Rev.	90.04	91.1		89.42
Big–ST Rev.	3.14	3.47		−1.95	Big–ST Rev.	93.81	98.3		93.17
Small–LT Rev.	3.63	1.76		0.78	Small–LT Rev.	87.77	89.92		92.32
Big–LT Rev.	2.79	4.71		3.04	Big–LT Rev.	88.85	95.93		95.69
	Correlations with SMB					Correlations with HML			
Small–BE/ME	64.8	67.64		68.96	Small–BE/ME	4.16	29.96		49.45
Big–BE/ME	22.62	37.92		40.72	Big–BE/ME	−3.37	31.56		52.16
Small–OP	67.16	67.95		65.98	Small–OP	16.71	37.58		33.39
Big–OP	39.46	32.86		22.54	Big–OP	18.06	20.64		5.69
Small–ST Rev.	64.82	67.06		66.79	Small–ST Rev.	24.44	32.35		22.38
Big–ST Rev.	35.32	29.89		27.35	Big–ST Rev.	19.93	14.09		10.07
Small–LT Rev.	69.01	66.35		62.95	Small–LT Rev.	37.62	36.57		21.11
Big–LT Rev.	41.71	32.19		24.54	Big–LT Rev.	41.08	31.67		-4.01
Panel **B**: 25 size–momentum portfolios									
	Low	2	3	4	High	Low	2	3	4	High
	Correlations with ΔESG					Correlations with RMRF				
Small	4.55	2.08	1.42	1.48	1.93	Small	84.23	86.82	86.59	83.55	82.26
2	2.18	2.57	0.68	3.28	2.74	2	86.73	89.7	88.54	87.45	84.97
3	2.51	1.9	2.12	2.01	0.56	3	86.23	91.79	92.21	90.7	87.57
4	2.77	5.08	4.32	3.99	3.94	4	85.72	93.09	95	94.35	86.58
Big	0.59	-0.68	3.73	6.79	3.97	Big	84.62	90.99	95.11	93.13	85.39
	Correlations with SMB					Correlations with HML				
Small	63.56	69.18	69.26	70.63	70.14	Small	24.13	33.67	37.88	35.87	22.2
2	59.2	63.92	67.47	68.38	67.58	2	25.53	31.31	33.95	32.71	20.42
3	52.11	55.59	58.68	61.74	59.97	3	24.79	30.03	31.37	30.51	12.22
4	45.05	46.65	48.59	46.66	48.01	4	29.18	27.02	26.8	20.36	7.92
Big	30.42	29.56	27	27.44	29.19	Big	26.07	25.88	22.43	13.67	−1.56

Table A1. *Cont.*

Panel **C**: 32 size–BE/ME–operating profitability

Correlations with ΔESG

	Small					Big			
BE/ME	Low	2	3	High	BE/ME	Low	2	3	High
Small–OP	1.27	2.54	1.45	1.82	Small–OP	−2.41	1.81	−0.55	1.45
2	5.18	2.6	−0.27	1.26	2	2.96	4.82	9.53	−1.5
3	6	1.99	2.47	3.02	3	2.09	4.53	8.95	8.14
Big–OP	1.63	2.34	−0.35	3.02	Big–OP	2.49	4.72	1.2	2.81

Correlations with RMRF

	Small					Big			
BE/ME	Low	2	3	High	BE/ME	Low	2	3	High
Small–OP	81.1	87.99	90.63	90.53	Small–OP	79.85	81.66	85.45	94.91
2	85.55	89.51	87.72	85.86	2	87.18	92.22	92.97	86.08
3	86.37	83.9	82.95	76.49	3	92.54	90.58	88.18	80.83
Big–OP	84.45	81.27	69.13	75.8	Big–OP	89.96	84.24	82.68	57.81

Correlations with SMB

	Small					Big			
BE/ME	Low	2	3	High	BE/ME	Low	2	3	High
Small–OP	60.11	60.32	62.01	64.53	Small–OP	31.92	21.86	18.33	18.37
2	63.04	64.93	65.6	65.92	2	34.57	29.99	23.91	31.17
3	66.96	67.62	66.78	64.35	3	38.79	32.02	38.75	35.24
Big–OP	64.42	64.83	59.52	59.07	Big–OP	37.6	41.61	44.87	33.13

Correlations with HML

	Small					Big			
BE/ME	Low	2	3	High	BE/ME	Low	2	3	High
Small–OP	−8.46	7.42	16.83	27.49	Small–OP	−21.28	−20.06	−13.89	−1.48
2	9.41	28.99	37.24	36.38	2	−2.53	11.05	16.48	18.25
3	28.53	48.61	49.01	49.66	3	21.17	31.75	38.51	29.14
Big–OP	44.75	55.86	43.34	40.75	Big–OP	46.55	54.89	46.78	20.21

Panel **D**: 38 Industry Portfolios

Correlations with ΔESG

Agric	Mines	Oil	Stone	Cnstr
4.34	7.28	7.4	3.69	2.59
Food	Smoke	Txtls	Apprl	Wood
1.72	5.6	11.11	5.82	2.14
Chair	Paper	Print	Chems	Ptrlm
0.65	8.91	3.31	7.05	8.19
Rubbr	Lethr	Glass	Metal	MtlPr
6.2	5.95	1.62	1.35	−0.42
Machn	Elctr	Cars	Instr	Manuf
2.05	−0.91	−5.12	4.32	6.97
Trans	Phone	TV	Utils	Garbg
2.06	5.67	4.79	7.27	−2.66
Steam	Water	Whlsl	Rtail	Money
NA	NA	1.92	8.16	1.37
	Srvc	Govt	Other	
	0.45	-0.35	6.35	

Correlations with RMRF

Agric	Mines	Oil	Stone	Cnstr
57.03	57.83	62.63	68.58	79.08
Food	Smoke	Txtls	Apprl	Wood
69.34	44.77	72.03	81.54	77.06
Chair	Paper	Print	Chems	Ptrlm
82.19	78	83.34	81.94	63.8
Rubbr	Lethr	Glass	Metal	MtlPr
76.66	67.19	79.68	80.62	88.98
Machn	Elctr	Cars	Instr	Manuf
89.64	84.31	84.98	89.08	74.04
Trans	Phone	TV	Utils	Garbg
83.97	62.14	85.19	60.76	68.03
Steam	Water	Whlsl	Rtail	Money
NA	NA	89.15	85.27	89.01
	Srvc	Govt	Other	
	92.95	74.47	78.85	

Correlations with SMB

Agric	Mines	Oil	Stone	Cnstr
26.88	27.18	43.35	39.41	50.33
Food	Smoke	Txtls	Apprl	Wood
8.27	−1.64	50.3	44.43	44.68
Chair	Paper	Print	Chems	Ptrlm
51.08	29.57	46.63	15.59	29.66
Rubbr	Lethr	Glass	Metal	MtlPr
31.21	45.98	50.38	42.33	47.01
Machn	Elctr	Cars	Instr	Manuf
37.63	27.49	38.62	37.59	42.7
Trans	Phone	TV	Utils	Garbg
39.78	5.17	30.6	11.74	20.76
Steam	Water	Whlsl	Rtail	Money
NA	NA	47.57	29.32	37.99
	Srvc	Govt	Other	
	29.18	14.23	28.33	

Correlations with HML

Agric	Mines	Oil	Stone	Cnstr
13.42	15.55	41.63	21.67	25.45
Food	Smoke	Txtls	Apprl	Wood
18.21	20.17	35.67	20.59	23.36
Chair	Paper	Print	Chems	Ptrlm
35.89	24.48	30.25	1.82	38.29
Rubbr	Lethr	Glass	Metal	MtlPr
11.2	26.92	32.8	26.15	21.87
Machn	Elctr	Cars	Instr	Manuf
13.03	−4.81	16.01	4.06	19.81
Trans	Phone	TV	Utils	Garbg
23.14	9.06	18.12	13.13	8.71
Steam	Water	Whlsl	Rtail	Money
NA	NA	24.37	0.47	43.99
	Srvc	Govt	Other	
	−5.63	34.18	15.54	

Notes: Table A1 shows the correlations between the factors and the excess returns of the different anomaly portfolios. We collected data from the Kenneth R. French website, including all stocks traded in the US equity market from March 2001 to February 2023. Panel A shows correlations for a set of 24 composite portfolios that combines four double-sort portfolios, namely: 6 size–BE/ME portfolios, 6 size–operating profitability portfolios, 6 size–short-term reversal portfolios, and 6 size–long term reversal portfolios. Panels B, C, and D show statistics for 25 size–momentum portfolios, 32 size–BE/ME–operating profitability portfolios and 38 industry portfolios, respectively. All numbers are expressed in percentages.

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