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Integrating ESG factors into Capital Asset Pricing Model: ESG uncertainties and ESG betas

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Abstract: This thesis investigates the implications of ESG (Environmental, Social, Governance) scores and ESG uncertainty in asset returns on a large dataset of US stocks. The analysis gives no evidence of a market impact of ESG uncertainty in recent years. Furthermore, the model proposed by Avramov et al. (2022) [1] that incorporate the individual stock's ESG score and the market's ESG score does not yield statistically significant results of an ESG premium. We propose a different approach to integrate the ESG score in the capital asset pricing model (CAPM). The analysis confirms that the equity market prices a negative individual ESG risk premium when we neglect the non-informative market ESG score.

Key-words: ESG, CAPM, Sustainable investing, ESG uncertainty

1. Introduction

In recent years, the convergence of finance and sustainability has marked a major turning point in the investment world. As reported by Bloomberg (2021) [6], global ESG assets, i.e. financial assets that promote ESG themes, are on track to exceed \$53 trillion by 2025, representing more than a third of the \$140.5 trillion in projected total assets under management.

Growing awareness of global challenges related to the environment, social issues, and corporate governance has catalyzed a transformation in investment evaluation criteria. In addition to traditional financial indicators, more and more investors and institutions embrace valuation approaches that incorporate ESG principles in order to assess not only a company's economic performance but also its overall impact on society and the environment. Sustainable investments, which have become a significant pillar of portfolio strategies, embody this new paradigm. The goal is not only to maximize financial returns but also to contribute positively to environmental and social issues. Moreover, in this context, investors' attention is increasingly shifting to long-term profits and how green stocks are more profitable than brown stocks. A significant result is obtained from the analysis conducted by Pástor et al. (2022) [14], in which they show that green stocks strongly outperformed brown in recent years.

In this context, the adoption of ESG metrics becomes crucial to assessing and comparing the performance of different companies. The most popular and widely used of the metrics is definitely the ESG score, an index that rates a company's ability to manage environmental, social, and governance aspects. The ESG score, which provides a comprehensive and weighted assessment of these three pillars, has become a key tool for investors who wish to integrate sustainability into their financial decisions. This metric provides an in-depth perspective on a company's responsibility and sustainability, allowing investors to consider not only short-term financial performance, but also the long-term impact on the environment and society. Several ESG rating providers are already in the market, such as Bloomberg and Refinitiv. Moreover, credit rating agencies like Moody's, S&P and Fitch also provide ESG ratings. All of these providers produce an ESG rating with proprietary and black-box methodologies, as also reported by Del Vitto et al. (2023) [9]. This creates discrepancies between the different ratings in the market and an issue regarding the regulation and objectivity of these ratings, as shown by Berg et al. (2022) [4] and Billio et al. (2021) [5]. Thus, the issue of uncertainty related to the ESG score emerges in the literature, as reported by Avramov et al. (2022) [1].

In recent years, in parallel with the increased attention to sustainability issues in the financial world, there is also a marked increase in regulation regarding sustainability metrics. One example is the adoption of the European Sustainability Reporting Standards (ESRS) in July 2023 by the European Commission. This development reflects the recognition by regulators and governments of the crucial role that sustainability plays in ensuring the stability and accountability of the global financial system. Regulation focuses on standardizing reporting practices and promoting greater transparency by companies regarding their environmental, social and governance impacts. Regulatory bodies introduce specific guidelines and reporting requirements that require companies to disclose detailed information about their sustainable performance, including data on ESG indicators. Thus, the ESG score strengthens as a crucial tool for sustainable investing.

We investigate at this point whether ESG factors really impact investment performances. Several theories can be found in the literature, among them, Bennani et al. (2018) [3] claim that ESG investing impacts investment performance in two different ways. First, ESG can be viewed as an alternative risk assessment model for corporate firms. Second, ESG generates investment flows that can impact asset prices, as also reported by Bams et al. (2022) [2], and subsequently portfolio returns, as also reported by Pelizzon et al. (2021) [16].

On this second point, several capital asset pricing models that consider ESG implications are developed and tested, such as the ESG-adjusted CAPM derived by Pedersen et al. (2021) [15], which model heterogeneity in how investors use ESG information. Another important contribution was brought by Pastor et al. (2021) [13], who show a two-factor asset pricing model, where the factors are the market portfolio and an ESG factor. In addition, consistent with the model presented by Pastor et al. (2021) [13], Avramov et al. (2022) [1] derive a model in which the equilibrium expected returns depend on (1) the market risk factor and (2) an ESG-based factor. In particular, the ESG factor proposed by Avramov et al. (2022) [1] is the difference between the firm's own ESG score and the market ESG score multiplied by the stock's CAPM beta. Moreover, they propose another model in which they consider an ESG uncertainty factor, which is the uncertainty related to the corporate ESG profile. Indeed, they claim that in the presence of ESG uncertainty, the model needs to take into account an additional risk premium attributable to it. However, in the paper of Avramov et al. (2022) [1], they do not conduct an empirical evaluation of the presented model on market data to test whether the negative ESG premium is priced. Therefore, this thesis fills this blind spot.

In this framework, we focus on the models presented by Avramov et al. (2022) [1]. Indeed, there is evidence in the literature that the current landscape in sustainable investing is now mature enough that there is no significant evidence of uncertainty within ESG data. Moreover, some institutional investors incorporate ESG targets in their investment strategies, which they tend to enhance in the market. Against this backdrop, the potential uncertainty in ESG scores emerges as a secondary consideration for institutional investors. Thus we claim that no additional factor is needed in the asset pricing model to account for ESG uncertainty.

In order to test our hypothesis, we calibrate the model presented by Avramov et al. (2022) [1] which does not consider the uncertainty factor, and show that it can explain well the expected asset returns of the market. Thus, we proceed and reformulate in our analysis the model presented by Avramov et al. (2022) [1] which does not consider the uncertainty factor. We then look at the components of the Russell3000 index from 2004 to 2022 to build a large dataset of ESG and returns data to proceed with our analysis. We use Refinitiv to collect all financial and ESG data related to the stocks in the Russell3000 index. In a first analysis, we observe that only from 2017 onward we have a significant percentage of ESG data available. Therefore, we proceed with the subsequent analysis using 2017-2022 as the reference time range. Moreover, we perform an analysis and preprocessing of the data in order to have a complete and usable dataset for further analysis.

We calibrate the model of Avramov et al. (2022) [1] on each stock of the sample and, following the approach of Brennan et al. (2008) [7], we divide the stocks into 27 portfolios according to the values of the estimated regression coefficients found. We then calibrate the model on each portfolio using the OLS method. In particular, we test the significance of ESG-related coefficients, the negative dependence of asset expected excess returns on portfolios' ESG score, and the dependence between coefficients of the regression model. However, the results of the statistical analysis on the model are not very significant and do not allow us to give evidence to support our assumptions.

We proceed to test the model and the different hypotheses with different statistical approaches. We first test for the presence of dependence between the regression coefficients using the maximum likelihood estimation method and the likelihood-ratio test. This analysis shows that in most portfolios the relationship between the coefficients is confirmed and that therefore the model succeeds in correctly calibrating the expected excess returns. We then examine the cross-sectional regression of the beta values found in the first stage regression in order to investigate the negative dependence of expected excess returns on portfolios' ESG score. In this case, the results obtained fail to support our thesis. Finally, we perform a robustness check and we find that the results are robust controlling returns for firm characteristics in Fama et al. 1993 [10].

The results obtained do not significantly support the assumptions of the presented model. In particular, we do not verify the negative sign of the coefficient related to portfolio ESG score. This result leads us to the formulation of another model. In particular, we observe that market ESG score is a linear increasing function over time and so it is not very informative in the model. Therefore, we propose a new model that does not take into account the market ESG score, but only the portfolio ESG factor.

We test the proposed new model. First, we reformulate the division of the Russell3000 index stocks into 9 new portfolios, divided according to the new estimated values of the two coefficients in the regression model. Then, we calibrate the regression model without the ESG market factor on the constructed datasets. As we expected, we find that the factor related to market premium is significant in all portfolios, while the coefficients related to the ESG factor are not significant in all portfolios. We continue with the calibration of a cross-sectional regression for the beta values found in the previous regression. We observe that the coefficient related to the portfolio's ESG score beta is negative and highly significant, proving that a negative risk premium is associated with the portfolio's ESG score. The results obtained allow us to state that the model without the ESG market factor succeeds in calibrating the data better and has a higher level of significance than the general model presented by Avramov et al. (2022) [1]. Furthermore, we can state that there is no evidence of uncertainty within our data. Indeed, the market data used in the analysis, collected only from one data provider (Refinitiv), are explained well by our model in which the uncertainty factor is not present. This result adds to the present and growing literature regarding the implications of ESG factors in asset pricing models.

The next part of the thesis is structured as follows. In section 2 we present the model that we use in the following analysis. In section 3 we describe the constructed datasets for the development of the analysis and the preprocessing performed. In section 4 we calibrate the model and perform a series of statistical tests to verify the model's assumptions. In section 5 we present a new simplified model, calibrate it and test the assumptions. Finally, in section 6 we report the conclusions that emerged from the analysis.

2. ESG CAPM

In this section, we report the model presented by Avramov et al. (2022) [1] and our reformulation to proceed in the subsequent analysis.

We investigate the asset return implications of ESG preferences in the market. In literature, there are already different approaches and theories about the impact of the sustainability theme on investment decisions. In this thesis, we focus on the model presented by Avramov et al. (2022) [1] to model the equilibrium expected returns of the risky assets.

We consider an economy consisting of I optimizing agents, N risky assets, and a riskless asset. We follow the assumptions of Avramov et al. (2022) [1], which model the excess returns and ESG scores on N assets as

$$\tilde{r} = \mu_r + \tilde{\epsilon_r} \tag{1}$$

$$\tilde{g} = \mu_g + \tilde{\epsilon_g} \tag{2}$$

where the residuals are assumed to follow a 2N-variate normal distribution and μ_r, μ_g are the N-vectors of expected excess returns and expected ESG scores, respectively. Moreover, in the paper, they assume that agent preferences follow a CARA function.

Under these assumptions, Avramov et al. (2022) [1] present the following model for stock expected returns when no ESG uncertanty is take into account

$$\mu_r = \beta\mu_M - b_M(\mu_g - \beta\mu_{g,M}) \tag{3}$$

where β is the equilibrium CAPM beta, μ_M is the equilibrium market premium, b_M is the aggregate brown aversion, μ_g is the expected ESG score and $\mu_{g,M}$ is the aggregate market greenness. They claim that the expected returns are affected by the market factor and by the effective ESG score, which is the difference between the ESG score of the stock and the ESG score of the market. In particular, the term $b_M(\mu_g - \beta\mu_{g,M})$ should reflect the negative ESG risk premium.

In the presence of ESG uncertainty, the model needs to take into account an additional risk premium attributable to it. They present another asset pricing model, in which they consider the ESG uncertainty factor, which is the uncertainty related to the corporate ESG profile. In the latter case, the expected stock returns are modeled by

$$\mu_r = \beta\mu_M + (\beta_{eff} - \beta)\mu_M - b_M(\mu_{g,U} - \beta_{eff}\mu_{g,M,U}) \tag{4}$$

where β is the equilibrium CAPM beta, μ_M is the equilibrium market premium,b_M is the aggregate brown aversion, $\mu_{g,U}$ is the perceived aggregate ESG scores of individual assets, $\mu_{g,M,U}$ is the perceived aggregate market ESG score, β_{eff} is the effective beta.

We encountered problems regarding the uncertainty of data in past years, when data and information related to the sustainability profile of companies were not so widespread and there were not many government policies regulating the publication of this type of non-financial data. However, many European countries have already introduced mandatory disclosure of non-financial information, as shown by Singhania et al. (2022) [19]. Moreover, following the European example, many other countries are beginning to consider adopting mandatory policies to encourage the dissemination of the sustainability theme. Another factor to consider is the growing influence of ESG factors in the investment world with respect to the relevance of data reliability underlying ESG score computation. For example, as reported by Rau et al. (2023) [17], institutional investors might incorporate ESG factors in portfolio selection and management as this attracts more considerable flows. Moreover, some of them have ESG targets in their investment choices, which they tend to enhance in the market. In this context, the possible uncertainty in the ESG score becomes a secondary factor for institutional investors.

To support this thesis, in the following sections, we perform a calibration of model (3) to test the hypothesis that no additional factor is needed in the asset pricing model to account for ESG uncertainty. The model (3) can be rewritten as

$$\mu_r = \beta\mu_M - b_M\mu_g + b_M\beta\mu_{g,M} \tag{5}$$

where we can clearly identify a three-factor regression model in which the coefficients are not independent of each other. We initially disregard the dependence between the coefficients in the model and consider a general three-factor regression model. Then, we perform some statistical tests to investigate the relationships present in the equation (5). Therefore, to perform an initial regression on the data, we reformulate the model (5) as

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g + \beta_3\mu_{g,m} + \epsilon \tag{6}$$

where $\beta_1 = \beta$, $\beta_2 = -b_M$, $\beta_3 = b_M\beta$ and ϵ is an error term.

3. Data

In this section, we construct large datasets of US stocks. In particular, we construct datasets containing ESG data and financial data. We perform data preprocessing necessary for the purpose of subsequent analysis.

3.1. Data source

Our reference sample consists of the components of the Russell3000 index from 2004 to 2022. In order to implement our analysis, we need to construct a comprehensive dataset of annual ESG scores of the sample companies in the reference years. For this purpose, we collect annual ESG scores from Refinitiv, as it offers one of the most comprehensive ESG databases in the industry, covering over 85% of the global market cap (Refinitiv 2022 [18]). However, due to the fact that computation and publication of ESG scores for companies has only become more widely used in recent years, we conduct a statistical investigation on the availability of ESG data to determine the time interval to consider in the subsequent analysis.

We observe a significant number of ESG data only from 2017. Moreover, we assume that if an investor is interested in a stock, but the latest ESG score has not yet been published, the investor considers the last ESG score available. Using this convention, in the construction of our dataset if the ESG data is missing for a given year we consider the previous year's value. We remove from the sample all components that have no value for any year and we kept those components that do not have an ESG score for some years, because they can be used in the later analysis considering a narrow time interval.

For the Russell3000 index components remaining in the sample, we then construct a dataset containing monthly stock returns. We extract also from Refinitiv stocks return data and cleaned them so that we have a complete dataset that can be used in the subsequent analysis. Finally, we extract from Refinitiv the financial data that we need, as the market capitalization of the stocks.

In Table 1, we provide a summary analysis on the components of the Russell3000 remaining in the final sample for each year and their relative market capitalization value.

Year	Left comp	Tot comp	% comp	Left MC	Tot MC	% MC
2017	954	2960	32.23 %	26,349 bln	31,012 bln	84.96 %
2018	1575	3012	52.29 %	26,150 bln	28,339 bln	92.28 %
2019	2145	2992	71.69 %	34,121 bln	35,742 bln	95.46 %
2020	2422	3059	79.18 %	41,080 bln	43,627 bln	94.16 %
2021	2294	3065	74.84 %	51,706 bln	54,800 bln	94.35 %
2022	2159	2963	72.86 %	40,237 bln	42,340 bln	95.03 %

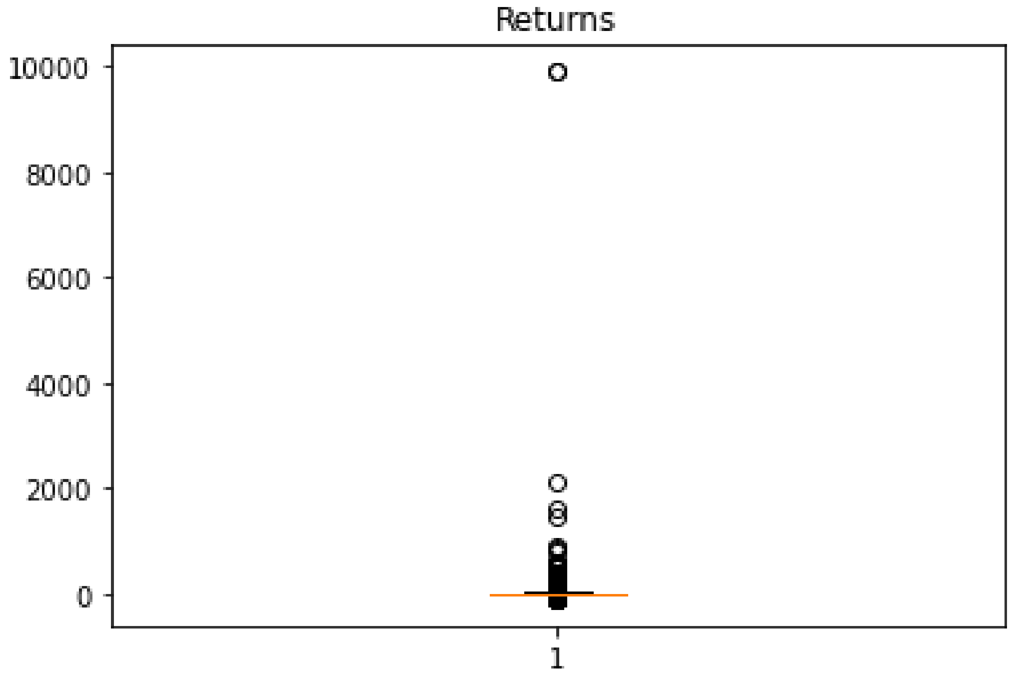
Table 1: Components left of the Russell3000 index from 2017 to 2022 for subsequent analysis. Market capitalization value related to the left components and all Russell3000 index components from 2017 to 2022 and its percentage value. "MC" stands for Market Capitalization.

The analysis of previous data led to the final sample covering the time interval from January 2017 to December 2022, with a total number of 2727 Russell3000 components. As we expected, Table 1 shows that in more recent years the availability of ESG data is higher, leading to more than 70% components left. However, in 2017 the percentage of market capitalization related to the remaining components is very high, more than 80%, allowing us to perform a meaningful analysis on the sample.

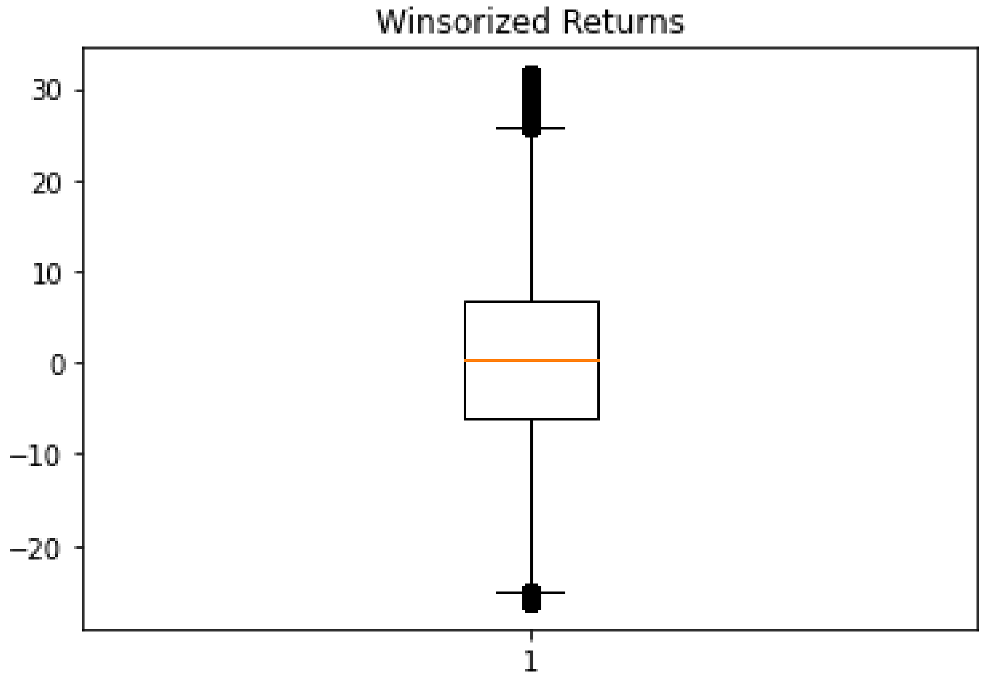
3.2. Preprocessing

Before carrying out the analysis, it is necessary to perform a preprocessing of the data. First, we demean the ESG scores by computing the global average of the stocks' ESG scores and subtracting the latter from each ESG score.

Looking at the monthly returns of the stocks, we notice the presence of outliers. Indeed, our reference sample contains in its time range some years that have been very volatile for the markets. We note particularly high volatility in returns in February 2020, corresponding to the onset of the global COVID-19 pandemic which significantly impacted many companies. We subsequently observe another period of high volatility at the onset of the war involving Russia and Ukraine in February 2022. The impact of these events on the market can be seen in our data, where we reach thresholds of almost 10000%, as shown in the Figure 1a.



(a) Monthly returns



(b) Winsorized monthly returns

Figure 1: Winsorization 95% on monthly returns of the components of Russell3000 index. Figure (a) shows the boxplot of monthly stock returns. Figure (b) shows the boxplot of monthly stock returns after applying winsorization.

Therefore, we perform a winsorization on returns data, which limits extreme values in the statistical data and reduces the effect of possible outliers. We use a 95% winsorization which sets all data below the 2.5th percentile to the 2.5th percentile, and data above the 97.5th percentile to the 97.5th percentile. Following this method, we do not eliminate outliers but we limit their effect, as shown by Hawkins (1993) [11]. Thus, we limit extreme values of outliers present in our sample, as shown in Figure 1b.

4. Model Estimation

In this section, we present the results of the analysis performed on the model presented by Avramov et al. (2022) [1]. We construct 27 portfolios based on the β values found in the regression analysis performed on each stock. We fit a linear regression on each portfolio and estimate the coefficients of the model in 4.2. We perform a regression analysis with the maximum likelihood estimation method and a likelihood-ratio test in 4.3. We then fit a cross-sectional regression on β values found in 4.4 and a robustness check considering Fama-French factors in 4.5. Additional robusteness results are available in the Appendix.

After defining the final sample, we test the reliability of the model presented by Avramov et al. (2022) [1] performing a calibration of the model (6) and some statistical analysis on the results obtained. Moreover, we want to estimate the β_1,β_2 and β_3 factors and assess their significance within the model.

4.1. Portfolios formation

The first step we perform in order to proceed with our analysis is to divide our sample of Russell3000 stocks into different portfolios. We perform a first calibration of the regression model (6) on each stock to estimate β_1,β_2 and β_3. Then we divide the stocks into 27 portfolios based on the β values found previously. In particular, for each factor β_1,β_2 and β_3 the stocks are divided into three quantiles and then are combined with each other. The result is the construction of 27 different portfolios.

4.2. Regression analysis

After the formation of the 27 different portfolios from the stocks of the Russell3000 index from 2017 to 2022, we estimate the other factors presented in the model.

We first estimate the return for each portfolio and each month. Specifically, during this procedure, for every year we consider only the current components of the Russell3000 index with an ESG value during the reference year. The portfolio returns are estimated by weighing the returns of each stock by the annual market capitalization

$$\mu_r = \frac{\sum_{i=1}^{N}(Return_i * MarketCapAnnual_i)}{\sum_{i=1}^{N} MarketCapAnnual_i} \tag{7}$$

where N is the number of stocks in every portfolio in the reference year.

Similarly to portfolio returns, the portfolio's ESG score is estimated for each month. The ESG score of a portfolio is estimated by weighing the ESG score of each stock by the annual market capitalization

$$\mu_g = \frac{\sum_{i=1}^{N}(ESGscore_i * MarketCapAnnual_i)}{\sum_{i=1}^{N} MarketCapAnnual_i} \tag{8}$$

where N is the number of stocks in every portfolio in the reference year. In Appendix A, we report summary tables of the 27 portfolio data.

In order to perform the calibration of the regression model, we estimate the market data. In particular, we estimate the market returns and the ESG scores of the market considering only stocks belonging to the portfolios and the Russell3000 index in the reference year. For this computations, we use the monthly market capitalization data retrieved from Refinitiv with the following formula

$$\mu_m = \frac{\sum_{i=1}^{N}(Return_i * MarketCapMonthly_i)}{\sum_{i=1}^{N} MarketCapMonthly_i} \tag{9}$$

where N is the number of stocks considered in the reference year.

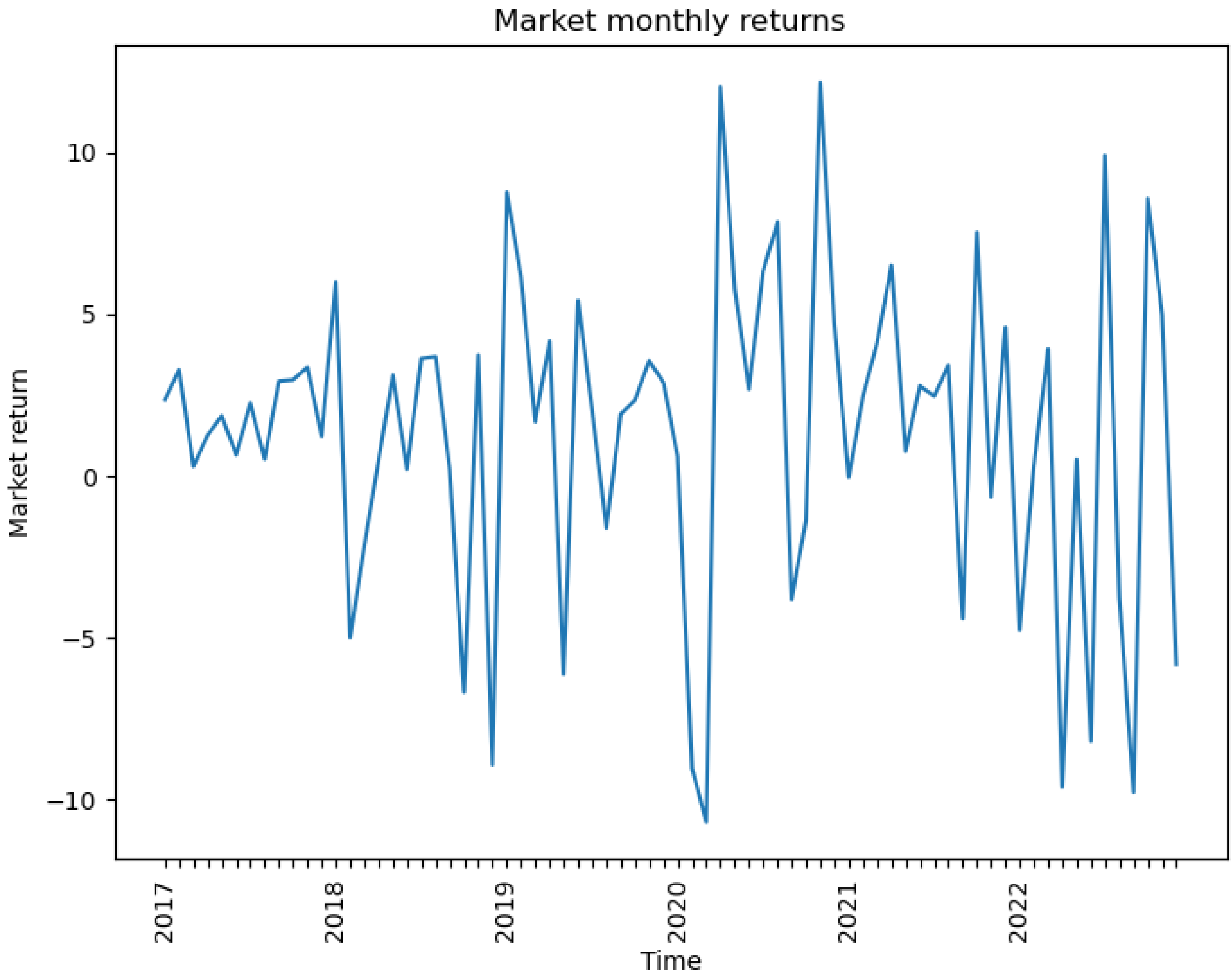


Figure 2: Market monthly returns for the reference period (2017-2022).

From Figure 2, we observe that from 2018 onwards there is a growing volatility in market returns. In particular, there is a peak in March 2020, which is the period corresponding to the beginning of the Covid-19 pandemic, and a succession of high volatility spikes since April 2022. We can infer that through the pre-processing of data we were able to reduce the volatility of returns in the market but nevertheless not eliminate it.

Proceeding in the same way, we compute the monthly market ESG scores with the following formula

$$\mu_{g,m} = \frac{\sum_{i=1}^{N}(ESGscore_i * MarketCapMonthly_i)}{\sum_{i=1}^{N} MarketCapMonthly_i} \tag{10}$$

where N is the number of stocks considered in the reference year.

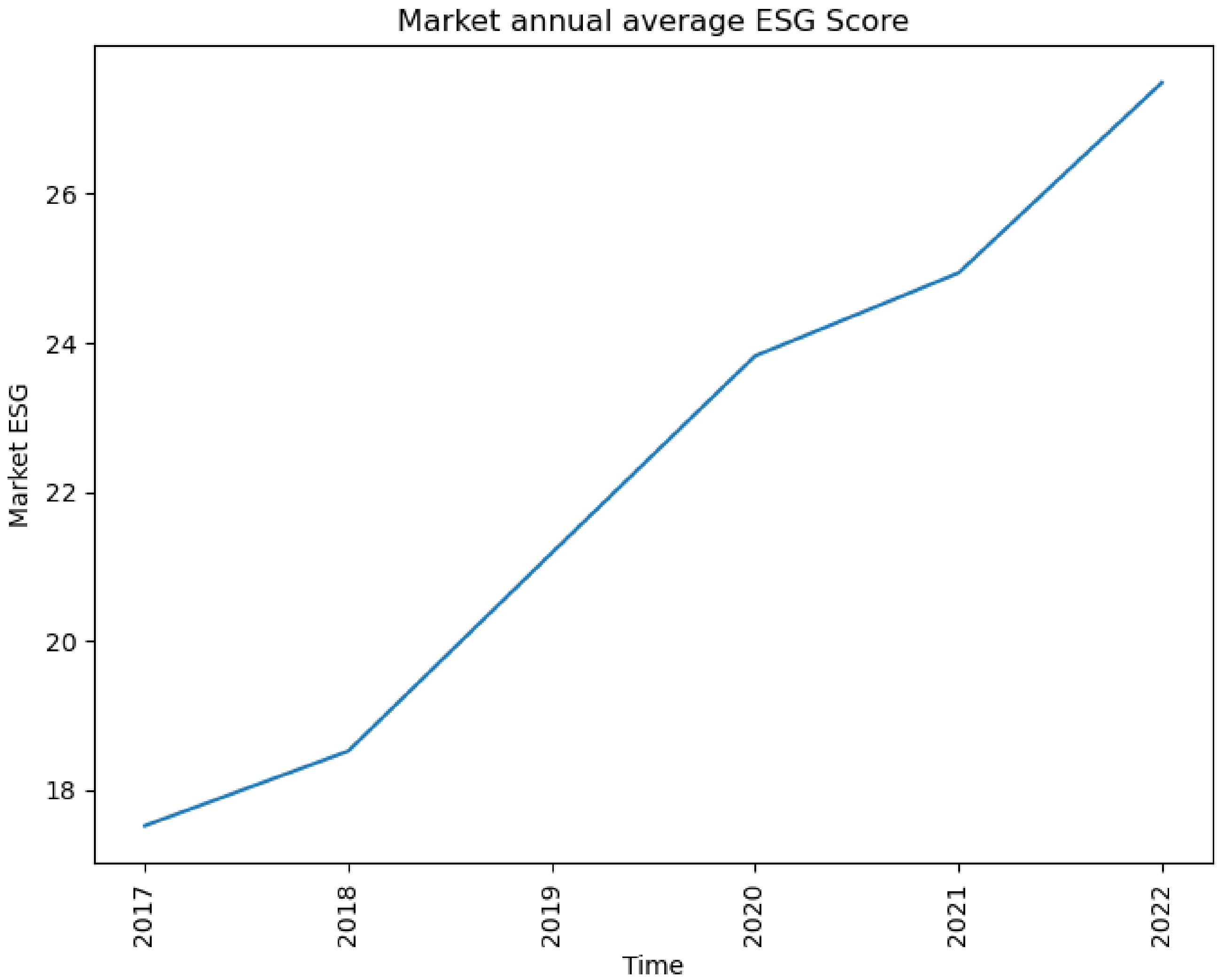


Figure 3: Market annual average ESG score for the reference period (2017-2022).

From Figure 3, we observe that the average annual market ESG score is an increasing function of time, with an increase of about 10 points from 2017 to 2022. This increase in the market ESG score over the years can be due to an increased focus by companies on sustainability issues or even the increase in regulation that impacts many companies in recent years.

We can now perform the estimation of the linear regression model (6). In Table 2, are reported the results of the OLS regression for the 27 portfolios. In all regression analysis the standard errors are corrected for autocorrelation and heteroscedasticity using Newey et al. (1986) [12] robust standard errors. In Appendix B, we report the results for the case of equally weighted data in the computation of the factors.

Table 2: Newey-West adjusted estimates using MarkCap-weighted data for the regression model

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g + \beta_3 \mu_{g,m}$$

Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

(a) α value

		β_2								
		Low			**Medium**			**High**		
		β_3			β_3			β_3		
β_1	**Low**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		63.00*	4.45	2.35	8.11	-2.67	-5.03	-17.68	5.44	20.64*
		β_3			β_3			β_3		
	Medium	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-21.66°	4.16	-1.03	-3.65	-1.79	2.06	0.05	4.67	2.24
		β_3			β_3			β_3		
	High	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-13.16	22.4°	6.51	2.75	0.06	-2.74	-3.97°	27.57	9.78

(b) β_1 value

		β_2								
		Low			**Medium**			**High**		
		β_3			β_3			β_3		
β_1	**Low**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.58***	0.72***	0.59***	0.59***	0.59***	0.66***	0.64***	0.61***	0.55***
		β_3			β_3			β_3		
	Medium	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.98***	1.14***	1.07***	0.96***	1.00***	1.11***	1.02***	0.98***	1.03***
		β_3			β_3			β_3		
	High	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.48***	1.31***	1.35***	1.39***	1.39***	1.32***	1.43***	1.41***	1.46***

(c) β_2 value

		β_2								
		Low			**Medium**			**High**		
		β_3			β_3			β_3		
β_1	**Low**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.82*	-0.02	-0.42°	-0.34	0.16	-0.10	0.85	0.37	1.04**
		β_3			β_3			β_3		
	Medium	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.81**	-0.04	-0.29**	0.35°	-0.09	0.06	0.29*	0.31	0.30
		β_3			β_3			β_3		
	High	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.57*	0.37	-1.05*	0.40°	0.37	0.41	-0.09	1.06	0.53

(d) β_3 value

		β_2								
		Low			**Medium**			**High**		
		β_3			β_3			β_3		
β_1	**Low**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-1.53*	-0.19	0.50°	0.16	-0.05	0.34	-0.48°	-0.28	-0.32
		β_3			β_3			β_3		
	Medium	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.43	-0.20	0.42*	-0.47*	0.13	-0.16	-0.36*	-0.23	0.08
		β_3			β_3			β_3		
	High	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.24	-1.02°	0.95**	-0.51	-0.35	-0.19	0.25	-1.11	-0.11

As expected, the intercept is not statistically significant in the model. Instead, the market factor μ_m turns out to be significant at 0.1% in the model and with a positive impact for every portfolio.

The regression does not show consistent results for all portfolios for the ESG factors in the asset pricing model, μ_g and $\mu_{g,m}$. The result shows that β_2 is significant in portfolios where β_2 is low and β_3 is low or high. We also note 1% significance in the portfolio in the low β_1, high β_2 and high β_3 cluster. Moreover, values found seem not to follow the distribution of the portfolios and nothing can be inferred about the sign of the β_2 coefficient. We find even lower significance in the coefficient associated with market ESG score β_3, which reaches a maximum significance of 1% only in the portfolio identified by high β_1, low β_2, and high β_3. The coefficient values do not seem to follow a precise path, fluctuating around 0, and not allowing inference to be made about the sign of the coefficient.

The results obtained in this first calibration do not to support the model presented by Avramov et al. (2022) [1]. From Table 2, we observe that the positive sign of the market coefficient β_1 is verified in all portfolios but not the sign of ESG coefficients. Indeed, we observe that β_2 does not have a negative sign in all portfolios, as provided in the model (5). In the same way, β_3 does not have a positive sign in all portfolios. This result then is contrary to the assumptions of the model (5).

4.3. Regression analysis with MLE method and LR test

The regression analysis calibrated on the collected data does not yield significant results to support the model presented by Avramov et al. (2022) [1]. In particular, nothing emerges regarding the dependence of coefficient β_3 on β_1 and β_2. Indeed, in model (5) is assumed that the coefficient relating to market ESG score is equal to the product of the coefficient relating to the equilibrium market premium and the coefficient relating to portfolio ESG score. In our model reformulation (6) we assumed $\beta_1 = \beta$, $\beta_2 = -b_M$, $\beta_3 = b_M\beta$ and thus $\beta_3 = -\beta_1\beta_2$. From the results obtained this dependence seems not to be confirmed. For example, in the portfolio with β_1 low, β_2 low and β_3 low we have β_1=0.58, β_2=1.82 and β_3=-1.53. So we observe that $\beta_3 \neq -\beta_1\beta_2$=-1.06.

Therefore, to test this hypothesis, we proceed with the analysis using the maximum likelihood estimation method. For the regression, we use the Log-Likelihood function of the normal distribution, defined as

$$\sum_{i=1}^{N}(\log(\frac{1}{\sqrt{2\pi\sigma^2}}) - \frac{(y_i - h(x_i,\theta))^2}{2\sigma^2}) \tag{11}$$

where $h(x_i,\theta)$ is the estimated value considering the reference model and set of parameters. Then, to test the hypothesis of dependence of parameters, we define two different Log-Likelihood functions with different sets of parameters. We define $L_1(\beta_1,\beta_2,\beta_3)$ for the general model

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g + \beta_3\mu_{g,m} \tag{12}$$

and $L_2(\beta_1,\beta_2,-\beta_1\beta_2)$ for the restricted model

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g - \beta_1\beta_2\mu_{g,m} \tag{13}$$

in which we report the parameter's relation to be tested. For the MLE calibration, we use an optimization algorithm in the family of quasi-Newton methods that approximates the Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS) using a limited amount of computer memory. It is a popular algorithm for parameter estimation in machine learning.

Finally, we perform the likelihood-ratio test on the Log-Likelihood values found, as described in Casella et al. (1999) [8]. This test assesses the goodness of fit of two competing statistical models, specifically one found by maximization over the entire parameter space and another found after imposing some constraint on the parameters. We define Θ_0 as the space of restricted parameters and Θ as the general space of parameters. Therefore we define the following hypothesis test

- H_0: $\theta \in \Theta_0$
- H_1: $\theta \in \Theta$

Then, the likelihood ratio test statistic defined before for the null hypothesis is given by

$$\lambda_{LR} = -2 \ln \frac{\sup_{\theta \in \Theta_0} \mathcal{L}(\theta)}{\sup_{\theta \in \Theta} \mathcal{L}(\theta)} \tag{14}$$

In Table 3, we report the Log-Likelihood values $L_1(\beta_1, \beta_2, \beta_3)$ and $L_2(\beta_1, \beta_2, -\beta_1\beta_2)$, the Likelihood-ratio test found and the significance level in order to reject the null hypothesis H_0 for each portfolio.

Table 3: Log-Likelihood values for each portfolio of the regression model

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g + \beta_3 \mu_{g,m}$$

identified with $L_1(\beta_1, \beta_2, \beta_3)$ and the restricted regression model

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g - \beta_1 \beta_2 \mu_{g,m}$$

identified with $L_2(\beta_1, \beta_2, -\beta_1\beta_2)$.
Likelihood-ratio test on the log-likelihood values found. Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

Portfolio	L_1	L_2	Likelihood-ratio test
1	-183.52	-185.80	4.56*
2	-157.35	-157.71	0.71
3	-166.95	-168.65	3.40°
4	-172.39	-172.45	0.13
5	-155.82	-155.91	0.19
6	-158.42	-159.07	1.29
7	-158.37	-158.49	0.23
8	-152.56	-152.66	0.19
9	-169.65	-172.13	4.95*
10	-188.68	-192.31	7.26*
11	-208.26	-209.56	2.61
12	-144.26	-145.45	2.36
13	-128.69	-131.69	5.98*
14	-114.44	-114.70	0.52
15	-192.62	-192.90	0.56
16	-129.58	-130.45	1.72
17	-152.54	-153.04	1.01
18	-173.47	-175.89	4.84*
19	-204.92	-208.02	6.20*
20	-186.44	-189.85	6.83*
21	-188.11	-189.90	3.58°
22	-180.60	-180.68	0.16
23	-157.68	-158.79	2.21
24	-151.04	-151.51	0.94
25	-183.03	-183.18	0.30
26	-186.70	-190.01	6.61*
27	-196.33	-202.05	11.44*

We note that in only 2 out of 27 portfolios the LR test has a 10% significance level and in 9 out of 27 portfolios has a 5% significance level and we can reject the null hypothesis. The test shows that in the majority of cases the full model and the restricted model fit the data equally well, in accordance with the model presented in the paper. Therefore, we prefer the restricted model because we have no statistical evidence to reject it.

With this analysis, we can also argue that there is no evidence of uncertainty in the model. Indeed, by testing the restricted model, we reject the null hypothesis in only 11 out of 27 cases. Therefore, this supports our idea that there is no uncertainty in the ESG data used.

4.4. Regression on beta coefficients

From the calibration presented in section 4.2, we do not obtain relevant results regarding the sign of the regression coefficients. Indeed, we observe that β_2 does not have a negative sign in all portfolios, as provided in the model (5). In the same way, β_3 does not have a positive sign in all portfolios. In this section, we statistically test whether the dependence of asset returns on portfolio and market ESG score is positive or negative. We perform a cross-section regression as follows

$$\mu_r = \lambda_0 + \lambda_1\beta_1 + \lambda_2\beta_2 + \lambda_3\beta_3 \tag{15}$$

where the β values are from the first stage regression performed in section 4.2. The regression summary statistics are shown in Table 4. In Appendix B, we report the results for the case of equally weighted data in the computation of the factors.

Table 4: Newey-West adjusted cross-sectional regression estimates of the model

$$\mu_r = \lambda_0 + \lambda_1\beta_1 + \lambda_2\beta_2 + \lambda_3\beta_3$$

where the β values are from the first stage regression

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g + \beta_3\mu_{g,m}$$

using MarketCap-weighted data.
Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

λ_0	λ_1	λ_2	λ_3
0.73***	0.61***	-0.04	0.12

As expected the results confirm the positive dependence of returns on market returns at 0.1% level. The results show also a significant level in positive dependence of the intercept but do not provide evidence for the sign of the coefficients related to the sustainability factors. Therefore, it is not possible to confirm the relation in the model. Moreover, the coefficients associated with ESG betas do not appear to be significant in the regression model. Thus, there seems to be no relation between ESG betas and portfolio returns, which therefore does not support the idea of an ESG premium for portfolios.

4.5. Robustness check

As a robustness check, we perform a regression of an extended model which considers other firm characteristics. Specifically, we introduce in the model two factor of the Fama-French 3-factors model (Fama et al. (1993) [10]): SMB, that is the difference between the return of a portfolio of weakly capitalized securities and that of a portfolio of strongly capitalized securities and HML, that is the difference between the return of a portfolio of securities with a strong and a weak book value/market value ratio.

The model presented is as follows

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g + \beta_3\mu_{g,m} + \beta_{SMB}SMB + \beta_{HML}HML \tag{16}$$

where β_1, β_2 and β_3 are the same defined in equation (6), β_{SMB} is the coefficient related to the factor SMB and β_{HML} is the coefficient related to the factor HML. We tabulate the results in Table 5. In Appendix B, we report the results for the case of equally weighted data in the computation of the factors.

Table 5: Extended regression model considering Fama-French factors.

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g + \beta_3 \mu_{g,m} + \beta_{SMB} SMB + \beta_{HML} HML$$

Newey-West adjusted estimates using MarketCap-weighted data. Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

(a) α value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		46.15°	6.37	1.90	8.31	0.63	-4.94	-11.60	4.82	20.93**
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-12.66	-0.08	-0.82	-6.18*	-0.36	1.36	0.27	1.42	0.95
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-8.69	7.07	3.83	-1.38	-0.38	-3.43	-1.59	-14.25	0.92

(b) β_1 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.52***	0.73***	0.61***	0.64***	0.62***	0.69***	0.65***	0.59***	0.50***
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.97***	1.16***	1.07***	0.98***	1.00***	1.12***	1.01***	0.93***	0.94***
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.40***	1.30***	1.34***	1.28***	1.36***	1.31***	1.37***	1.31***	1.33***

(c) β_2 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.32°	0.03	-0.36	-0.37	-0.01	-0.09	0.62	0.32	1.04**
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.53	-0.13	-0.29**	0.45**	-0.06	0.09	0.28*	0.28	0.20
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.38°	0.05	-0.82°	-0.07	0.04	0.43	-0.48	-0.27	0.22

(d) β_3 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-1.11°	-0.27	0.43	0.19	-0.01	0.32	-0.40	-0.24	-0.34*
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.21	-0.01	0.41**	-0.54**	0.04	-0.16	-0.36*	-0.07	0.08
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.16	-0.31	0.81*	0.09	-0.03	-0.17	0.57	0.57	0.10

(e) β_{SMB} value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.67***	-0.07	-0.18°	-0.44***	-0.36***	-0.20*	-0.11	0.14	0.42***
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.22	-0.00	-0.01	-0.15*	-0.03	-0.07	0.07	0.24*	0.68***
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.88***	0.38**	0.11	0.52***	0.20*	0.13	0.40***	0.57***	0.82***

(f) β_{HML} value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.10	0.01	0.03	-0.03	0.09°	-0.09	0.12°	0.04	0.05
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.20°	-0.24*	0.03	-0.12***	0.14***	-0.13	0.02	0.24***	0.15*
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.20	-0.26**	-0.12	0.54***	0.19***	-0.08	0.44***	0.50***	0.47***

As expected the intercept is not significant for almost the entire sample while the β_1 coefficient has 0.1% significance level for all portfolios, consistent with the results found in section 4.2. Regarding the ESG factors, the regression does not show consistent results for all portfolios but is in line with the analysis presented in section 4.2. Indeed, the results show that β_2 is significant in portfolios where β_1 is medium, β_2 is low and β_3 is high. We also note 1% significance in the portfolio in the low β_1, high β_2 and high β_3 cluster. We also find consistency in the coefficient associated with market ESG score β_3, which reaches a maximum significance of 1% only in the portfolio identified by medium β_1, low β_2, and high β_3 and in the portfolio identified by medium β_1, medium β_2 and high β_3. As for the factors associated with the Fama-French model, these exhibit significance within the model, especially in the portfolio cluster with high β_1. Specifically, β_{SMB} seems to be very significant in almost every portfolio. The coefficient β_{HML} largely follows the same significance distribution as β_{SMB}, except in the cluster where β_2 is low.

Overall, we confirm the early results in regression analysis and we have enough robustness in the calibration of the model presented by Avramov et al. (2022) [1].

5. ESG CAPM model excluding ESG market factor

In this section, we present a new model that does not consider the market ESG factor. We construct 9 portfolios based on the β values found in the regression analysis performed on each stock. We fit a linear regression on each portfolio and estimate the coefficients of the model in 5.1. We perform a cross-sectional regression analysis in 5.2 to test the hypotheses of the new model.

The analysis performed in section 4 does not lead to significant results in terms of the sign of the ESG beta and of the ESG premium. In section 4.2 we do not obtain consistent results for market ESG score and portfolio ESG score. Subsequently, in section 4.3, we observe through the likelihood-ratio test that it is possible to confirm a relation between the ESG coefficients in most cases as predicted by the model. However, in section 4.4, we find that instead there is no significance to confirm a relation between ESG betas and portfolio expected returns. Then, we can not claim the dependence on the asset's expected returns from the ESG score of the portfolio and the ESG score of the market.

However, during our analysis, we note that the ESG market score is a linear increasing function of time, as shown in Figure 3. Hence, in the asset pricing model it does not appear to be very informative. Given the results obtained, we wonder whether this factor can alter the calibration of the model and so it would be better not to take it into account. For this reason, we propose a model that does not consider the market ESG score factor

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g \tag{17}$$

where $\beta_1 = \beta$ and $\beta_2 = -b_m$.

In model (17) we propose that the expected excess asset returns depend on the expected market asset returns and the ESG score of the asset. We suppose, as in the previous model, that there is a negative dependence of the expected excess asset returns on the ESG score of the asset. This assumption follows the idea that there is a negative risk premium associated with holding a green asset.

We now follow the same procedure as in the previous section to calibrate and test the assumptions of the proposed model.

5.1. Regression analysis excluding ESG market factor

We perform a calibration of the model (17). The first step is to create the portfolios, which are different from those in the previous section. We perform a first calibration of the regression model (17) on the stocks of the Russell3000 index in the sample in order to estimate β_1 and β_2. We then divide the stocks into 9 portfolios depending on values of β_1 and β_2 found. In particular, for each factor β_1 and β_2, the stocks are divided into three quantiles and then are combined with each other. The result is the construction of 9 different portfolios.

We estimate the new parameters of the model. First, we estimate the return for each portfolio and each month as in (7). During this computation, for every year we consider only the current components of the Russell3000 index with an ESG value during the reference year. Then, we compute the market factor μ_m as in (9) for every month and the portfolios' ESG score for every portfolio as in (8). We calibrate the model on the data. In Table 6, we report the results of the calibration performed with the OLS method. In Appendix B, we report the results obtained in the case of equally weighted data in the computation of the factor.

Table 6: Newey-West adjusted estimates using MarkCap-weighted data for the regression model

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g$$

Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

(a) α value

		β_2		
		Low	**Medium**	**High**
β_1	**Low**	0.46	-0.20	-0.75
	Medium	-2.21	0.92	-0.11
	High	2.99	1.78	-0.05

(b) β_1 value

		β_2		
		Low	**Medium**	**High**
β_1	**Low**	0.64***	0.59***	0.59***
	Medium	1.07***	1.01***	1.00***
	High	1.38***	1.28***	1.44***

(c) β_2 value

		β_2		
		Low	**Medium**	**High**
β_1	**Low**	-0.04	0.02	0.13°
	Medium	0.11	-0.03	0.08**
	High	-0.19	-0.05	0.17***

As expected, the results show that the α coefficient is not significant for any portfolios. Instead the market factor μ_m show a 0.1% significance level and a positive sign in every portfolio.

The results are not as consistent in the case of the ESG portfolio factor μ_g. First, we note that the estimated value of β_2 in the cluster with medium β_1 and low β_2 is greater than the value estimated in the cluster with medium β_1 and medium β_2. In Appendix B, we can observe that this is not the case in the regression performed considering equally weighted data in the computation of the factors. Indeed, this alteration in value in the cluster is due to an extreme ESG score of a stock that has a high market capitalization value and thus a significant weight within the portfolio in the MarketCap-weighted case.

Then, we observe that β_2 is significant in the cluster where β_2 is high, but it does not show a significant level in other clusters. Moreover, the estimated β_2 values fluctuate around zero and do not show a defined sign. We also find that the cases where the coefficient β_2 is significant are those where β_2 is positive. When β_2 is negative, it is never significant. Hence, from our findings, we have no evidence of the negative dependence of the asset pricing returns from the portfolio's ESG score.

5.2. Regression on beta coefficients excluding ESG market factor

The results obtained in the calibration of the regression model without ESG market factor do not give us enough evidence to prefer the latter to Avramov et al. (2022) [1] model. Therefore, we proceed in our analysis, as done in section 4, by performing a cross-sectional regression to investigate the relationship between the portfolio's ESG score beta and the portfolio's expected returns.

We perform the cross-sectional regression

$$\mu_r = \lambda_0 + \lambda_1\beta_1 + \lambda_2\beta_2 \tag{18}$$

where the β values are from the first stage regression model (17) using MarketCap-weighted data excluding ESG market factor. The regression summary statistics are shown in Table 7. In Appendix B, we report the results for the case of equally weighted data in the computation of the factors.

Table 7: Newey-West adjusted cross-sectional regression estimates of the model

$$\mu_r = \lambda_0 + \lambda_1\beta_1 + \lambda_2\beta_2$$

where the β values are from the first stage regression

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g$$

using MarketCap-weighted data.
Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

λ_0	λ_1	λ_2
0.36*	0.37*	-3.19***

As expected the results confirm the positive dependence of portfolio expected returns on market returns at 5% level. We also observe a negative dependence between portfolio expected returns and portfolio ESG beta at 0.1% significance level. We found in section 5.1 that in our sample when the coefficient β_2 is significant then it is also positive. The results shown above, lead us to say that if a stock is positively correlated with its ESG score, then it will have lower average returns than a stock that is negatively correlated or uncorrelated with its ESG score.

The results obtained show that regardless of the ESG score value of some stocks, and thus whether the stock is "green" or "brown," these are subject to a negative ESG premium. This phenomenon can be explained by the fact that in more recent years many investors in the market have used ESG ratings for portfolio choices. This means that many investors rely on the ESG score to invest in a stock, thus influencing its return. This phenomenon is not observable for other stocks.

6. Conclusions

In this thesis, we comprehensively analyzed the implications of market ESG preferences on asset returns and tested whether there is evidence of ESG returns and risk premia. Our results are obtained on a new comprehensive dataset of Russel 3000 stocks.

First, we find no statistical evidence that stock returns depend on uncertainty in the ESG profile of companies. Indeed, we calibrate the model of Avramov et al. (2022) [1] and perform a statistical test to understand whether market data are compatible with the no uncertainty case. In most portfolios, we do not have evidence to reject the null hypothesis of no effect of uncertainty in stock returns (see Table 3). This result reinforces the idea that market players are not affected by a perceived uncertainty in the ratings.

Second, we discuss how in the model of Avramov et al. (2022) [1] with no uncertainty there is no statistical evidence of an ESG risk premium both from the ESG portfolio factor and the ESG market factor (see Table 4). In particular, we perform a cross-sectional regression on the coefficient values estimated in the regression model on the individual portfolios and find no relationship between ESG betas and stock returns. These results have been tested for robustness also considering additional Fama and French factors.

Finally, we estimate a simpler regression model than the one of Avramov et al. (2022) [1] in which the stock returns do not depend on the average market ESG score (17). In this case, the cross-sectional regression shows that stocks are subject to a negative ESG premium (see Table 7). This phenomenon can be explained because, in recent years, many investors have been using ESG ratings in their investment strategies. This means that a lot of investors are now relying on the ESG score when investing in a particular stock, and this, in turn, affects the stock's returns. A possible future development could be to delve into the influence of ESG investment strategies of market investors on asset returns, and then develop an equilibrium model consistent with the regression considered in our analysis.

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A. Appendix A

Summary tables of the 27 portfolios created in section 4.1.

Data	Value
N components 2017	6
N components 2018	38
N components 2019	90
N components 2020	135
N components 2021	105
N components 2022	92
Max return	10.300671
Min return	-10.148983
Mean return	1.386807
Variance return	19.624115
Max ESG Score	-11.75332
Min ESG Score	-19.873968
Mean ESG Score	-15.554958

Table 8: Portfolio 1

Data	Value
N components 2017	18
N components 2018	37
N components 2019	52
N components 2020	60
N components 2021	49
N components 2022	42
Max return	9.836081
Min return	-10.852097
Mean return	1.176487
Variance return	18.839169
Max ESG Score	4.939566
Min ESG Score	-10.555441
Mean ESG Score	-2.724657

Table 9: Portfolio 2

Data	Value
N components 2017	56
N components 2018	58
N components 2019	67
N components 2020	66
N components 2021	62
N components 2022	60
Max return	10.950051
Min return	-7.292741
Mean return	1.271271
Variance return	14.59373
Max ESG Score	34.654243
Min ESG Score	24.435135
Mean ESG Score	30.378336

Table 10: Portfolio 3

Data	Value
N components 2017	19
N components 2018	23
N components 2019	28
N components 2020	32
N components 2021	28
N components 2022	23
Max return	8.919771
Min return	-9.999198
Mean return	1.020771
Variance return	15.983227
Max ESG Score	37.752099
Min ESG Score	30.540302
Mean ESG Score	34.008077

Table 11: Portfolio 4

Data	Value
N components 2017	85
N components 2018	142
N components 2019	179
N components 2020	190
N components 2021	169
N components 2022	154
Max return	9.066738
Min return	-7.997948
Mean return	0.843915
Variance return	12.984982
Max ESG Score	28.154335
Min ESG Score	23.310293
Mean ESG Score	24.9273

Table 12: Portfolio 5

Data	Value
N components 2017	21
N components 2018	40
N components 2019	56
N components 2020	67
N components 2021	58
N components 2022	48
Max return	11.120681
Min return	-7.563441
Mean return	1.44258
Variance return	15.490116
Max ESG Score	31.495297
Min ESG Score	5.382823
Mean ESG Score	19.622879

Table 13: Portfolio 6

Data	Value
N components 2017	24
N components 2018	31
N components 2019	34
N components 2020	35
N components 2021	36
N components 2022	32
Max return	8.982165
Min return	-10.544569
Mean return	0.815646
Variance return	15.635759
Max ESG Score	35.900376
Min ESG Score	31.184116
Mean ESG Score	33.389941

Table 14: Portfolio 7

Data	Value
N components 2017	19
N components 2018	34
N components 2019	47
N components 2020	53
N components 2021	51
N components 2022	38
Max return	9.025795
Min return	-9.867662
Mean return	0.862945
Variance return	13.204245
Max ESG Score	7.955451
Min ESG Score	-2.724113
Mean ESG Score	2.050675

Table 15: Portfolio 8

Data	Value
N components 2017	10
N components 2018	31
N components 2019	92
N components 2020	141
N components 2021	97
N components 2022	88
Max return	13.396602
Min return	-8.555065
Mean return	1.260256
Variance return	14.679779
Max ESG Score	-8.844982
Min ESG Score	-14.94609
Mean ESG Score	-12.331435

Table 16: Portfolio 9

Data	Value
N components 2017	26
N components 2018	61
N components 2019	103
N components 2020	135
N components 2021	135
N components 2022	120
Max return	14.054602
Min return	-15.231434
Mean return	1.362295
Variance return	39.93053
Max ESG Score	-8.990438
Min ESG Score	-20.189328
Mean ESG Score	-15.023985

Table 17: Portfolio 10

Data	Value
N components 2017	21
N components 2018	38
N components 2019	54
N components 2020	57
N components 2021	58
N components 2022	58
Max return	19.95948
Min return	-13.810143
Mean return	1.119408
Variance return	53.327462
Max ESG Score	10.179316
Min ESG Score	-5.74184
Mean ESG Score	1.164582

Table 18: Portfolio 11

Data	Value
N components 2017	60
N components 2018	75
N components 2019	83
N components 2020	85
N components 2021	84
N components 2022	85
Max return	15.155399
Min return	-11.469788
Mean return	1.311424
Variance return	30.702061
Max ESG Score	37.145143
Min ESG Score	20.926721
Mean ESG Score	29.081125

Table 19: Portfolio 12

Data	Value
N components 2017	52
N components 2018	71
N components 2019	78
N components 2020	80
N components 2021	78
N components 2022	73
Max return	11.662221
Min return	-11.672859
Mean return	1.352481
Variance return	26.179385
Max ESG Score	44.534288
Min ESG Score	34.472869
Mean ESG Score	40.127979

Table 20: Portfolio 13

Data	Value
N components 2017	117
N components 2018	167
N components 2019	194
N components 2020	200
N components 2021	197
N components 2022	194
Max return	12.193571
Min return	-13.298786
Mean return	1.180521
Variance return	26.472836
Max ESG Score	18.14085
Min ESG Score	5.25845
Mean ESG Score	12.582004

Table 21: Portfolio 14

Data	Value
N components 2017	20
N components 2018	33
N components 2019	41
N components 2020	46
N components 2021	39
N components 2022	41
Max return	16.221459
Min return	-17.37816
Mean return	1.366795
Variance return	43.209905
Max ESG Score	28.904147
Min ESG Score	13.179162
Mean ESG Score	22.489058

Table 22: Portfolio 15

Data	Value
N components 2017	47
N components 2018	64
N components 2019	75
N components 2020	76
N components 2021	69
N components 2022	67
Max return	13.238665
Min return	-13.80792
Mean return	1.085746
Variance return	29.464245
Max ESG Score	31.23079
Min ESG Score	20.459942
Mean ESG Score	26.825334

Table 23: Portfolio 16

Data	Value
N components 2017	22
N components 2018	39
N components 2019	53
N components 2020	54
N components 2021	51
N components 2022	49
Max return	12.945431
Min return	-19.36148
Mean return	0.966724
Variance return	27.390063
Max ESG Score	6.763043
Min ESG Score	-3.935632
Mean ESG Score	0.256826

Table 24: Portfolio 17

Data	Value
N components 2017	11
N components 2018	44
N components 2019	86
N components 2020	110
N components 2021	99
N components 2022	89
Max return	18.238484
Min return	-12.592659
Mean return	1.210958
Variance return	33.65589
Max ESG Score	-9.173593
Min ESG Score	-15.992245
Mean ESG Score	-13.660532

Table 25: Portfolio 18

Data	Value
N components 2017	17
N components 2018	48
N components 2019	85
N components 2020	115
N components 2021	126
N components 2022	118
Max return	22.576879
Min return	-21.132173
Mean return	2.16787
Variance return	78.048546
Max ESG Score	-6.990551
Min ESG Score	-16.282456
Mean ESG Score	-14.066175

Table 26: Portfolio 19

Data	Value
N components 2017	18
N components 2018	41
N components 2019	51
N components 2020	53
N components 2021	55
N components 2022	56
Max return	21.286786
Min return	-15.600878
Mean return	1.975803
Variance return	57.273753
Max ESG Score	9.99082
Min ESG Score	-8.765038
Mean ESG Score	1.600966

Table 27: Portfolio 20

Data	Value
N components 2017	55
N components 2018	60
N components 2019	72
N components 2020	79
N components 2021	79
N components 2022	79
Max return	19.186726
Min return	-14.316461
Mean return	2.126928
Variance return	57.502447
Max ESG Score	30.972592
Min ESG Score	22.656744
Mean ESG Score	26.095114

Table 28: Portfolio 21

Data	Value
N components 2017	48
N components 2018	77
N components 2019	86
N components 2020	85
N components 2021	88
N components 2022	78
Max return	21.809738
Min return	-23.002311
Mean return	0.674761
Variance return	56.024391
Max ESG Score	29.14737
Min ESG Score	12.157964
Mean ESG Score	18.678338

Table 29: Portfolio 22

Data	Value
N components 2017	74
N components 2018	111
N components 2019	133
N components 2020	139
N components 2021	140
N components 2022	138
Max return	18.189466
Min return	-18.087368
Mean return	1.546574
Variance return	53.305441
Max ESG Score	25.448761
Min ESG Score	14.201115
Mean ESG Score	19.718381

Table 30: Portfolio 23

Data	Value
N components 2017	16
N components 2018	23
N components 2019	36
N components 2020	41
N components 2021	41
N components 2022	41
Max return	15.704453
Min return	-15.572704
Mean return	2.093582
Variance return	47.287275
Max ESG Score	20.678541
Min ESG Score	16.109115
Mean ESG Score	17.860811

Table 31: Portfolio 24

Data	Value
N components 2017	52
N components 2018	75
N components 2019	92
N components 2020	97
N components 2021	98
N components 2022	97
Max return	24.392251
Min return	-20.958717
Mean return	1.409437
Variance return	60.393514
Max ESG Score	29.2745
Min ESG Score	18.10167
Mean ESG Score	23.989997

Table 32: Portfolio 25

Data	Value
N components 2017	22
N components 2018	49
N components 2019	57
N components 2020	61
N components 2021	62
N components 2022	58
Max return	22.942348
Min return	-23.536369
Mean return	1.052174
Variance return	60.564074
Max ESG Score	4.236363
Min ESG Score	-9.494371
Mean ESG Score	-3.560405

Table 33: Portfolio 26

Data	Value
N components 2017	18
N components 2018	65
N components 2019	121
N components 2020	130
N components 2021	140
N components 2022	141
Max return	22.597604
Min return	-24.484505
Mean return	1.775556
Variance return	66.912616
Max ESG Score	-6.974807
Min ESG Score	-18.836133
Mean ESG Score	-14.119626

Table 34: Portfolio 27

B. Appendix B

Table 35: Newey-West adjusted estimates using equally weighted data in the computation of the factors for the regression model

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g + \beta_3\mu_{g,m}$$

Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

(a) α value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		22.77°	-2.19	-1.68	1.25	1.67	-1.09	-3.26°	7.16	16.18**
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		4.75	18.17	-0.60	1.87	10.84°	0.64	-1.76	11.02	10.74
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-6.86	-1.78	-1.66	3.79	1.51	-2.50	-3.00	10.05	24.48

(b) β_1 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.62***	0.63***	0.60***	0.63***	0.65***	0.62***	0.66***	0.69***	0.63***
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.04***	1.04***	1.04***	1.04***	1.04***	1.07***	1.04***	1.04***	1.09***
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.43***	1.39***	1.46***	1.44***	1.39***	1.40***	1.53***	1.51***	1.52***

(c) β_2 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.68	-0.20	-0.20	0.11*	0.15	0.03	0.22*	0.50	1.00***
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.11	0.52	-0.15	0.17	0.44*	0.12	0.32	0.57°	0.80*
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.52	-0.19	-0.18	0.27	0.18	0.08	0.36	0.52°	1.21**

(d) β_3 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.58*	0.06	0.27*	-0.16*	-0.11	0.07	-0.06	-0.32	-0.08
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.31	-0.76	0.14	-0.25	-0.55°	-0.02	-0.18	-0.44	0.01
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.05	0.06	0.22	-0.34	-0.13	0.12°	-0.14	-0.40	-0.30

Table 36: Newey-West adjusted cross-sectional regression estimates of the model

$$\mu_r = \lambda_0 + \lambda_1\beta_1 + \lambda_2\beta_2 + \lambda_3\beta_3$$

where the β values are from the first stage regression

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g + \beta_3\mu_{g,m}$$

using equally weighted data in the computation of the factors.
Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

λ_0	λ_1	λ_2	λ_3
0.46°	0.46°	-0.27°	0.77

Table 37: Extended regression model considering Fama-French factors.

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g + \beta_3 \mu_{g,m} + \beta_{SMB} SMB + \beta_{HML} HML$$

Newey-West adjusted estimates using equally weighted data in the computation of the factors. Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

(a) α value

	β_2: **Low**			β_2: **Medium**			β_2: **High**		
β_1	β_3: **Low**	**Medium**	**High**	β_3: **Low**	**Medium**	**High**	β_3: **Low**	**Medium**	**High**
Low	20.59**	-6.66	-0.37	2.42	1.86	-0.86	-1.25	4.48	16.43**
Medium	2.66	4.87	3.18°	1.86	3.71	1.37	-0.07	3.59	7.74
High	-3.85	-3.10	9.73*	0.98	1.31	-2.02	-4.14°	-0.52	8.55

(b) β_1 value

	β_2: **Low**			β_2: **Medium**			β_2: **High**		
β_1	β_3: **Low**	**Medium**	**High**	β_3: **Low**	**Medium**	**High**	β_3: **Low**	**Medium**	**High**
Low	0.51***	0.59***	0.59***	0.59***	0.63***	0.59***	0.62***	0.62***	0.54***
Medium	0.95***	0.97***	0.99***	0.96***	0.97***	1.00***	0.95***	0.92***	0.96***
High	1.30***	1.31***	1.35***	1.31***	1.30***	1.34***	1.39***	1.36***	1.35***

(c) β_2 value

	β_2: **Low**			β_2: **Medium**			β_2: **High**		
β_1	β_3: **Low**	**Medium**	**High**	β_3: **Low**	**Medium**	**High**	β_3: **Low**	**Medium**	**High**
Low	0.56*	-0.36	-0.30°	0.08	0.06	0.03	0.16	0.25	0.93***
Medium	-0.25	0.03	-0.31*	-0.03	0.11	0.08	0.04	0.16	0.53**
High	-0.43*	-0.28	-0.69**	-0.02	0.02	0.09	-0.08	0.12	0.53

(d) β_3 value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.55***	0.22	0.30*	-0.19**	-0.10°	0.07	-0.09	-0.21	-0.12
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.29°	-0.21	0.13°	-0.12	-0.19	-0.04	-0.06	-0.17	-0.02
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		-0.12	0.12	0.23**	-0.11	-0.08	0.10	0.18	0.00	-0.04

(e) β_{SMB} value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.91***	0.30***	0.07	0.20*	0.10	0.19**	0.24**	0.45***	0.64***
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.75***	0.52***	0.36***	0.44***	0.40***	0.48***	0.53***	0.59***	0.90***
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		1.10***	0.59***	0.66***	0.81***	0.58***	0.49***	0.83***	0.96***	1.02***

(f) β_{HML} value

		β_2								
		Low			**Medium**			**High**		
β_1	**Low**	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.15**	0.02	0.13*	0.15*	0.20***	0.02	0.21**	0.23***	0.19***
	Medium	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.07	0.08	0.33***	0.38***	0.27***	0.18***	0.34***	0.52***	0.39***
	High	β_3			β_3			β_3		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
		0.13*	0.19***	0.49***	0.50***	0.38***	0.07	0.55***	0.53***	0.60***

Table 38: Newey-West adjusted estimates using equally weighted data in the computation of the factors for the regression model

$$\mu_r = \alpha + \beta_1 \mu_m + \beta_2 \mu_g$$

Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

(a) α value

		β_2		
		Low	**Medium**	**High**
β_1	**Low**	0.14	-0.76	0.21
	Medium	-0.98	-0.73°	-0.30
	High	-1.41	-0.73°	0.30

(b) β_1 value

		β_2		
		Low	**Medium**	**High**
β_1	**Low**	0.62***	0.64***	0.67***
	Medium	1.06***	1.04***	1.03***
	High	1.45***	1.41***	1.49***

(c) β_2 value

		β_2		
		Low	**Medium**	**High**
β_1	**Low**	0.04	0.10°	0.22*
	Medium	0.04	0.11	0.13
	High	0.06	0.09	0.21**

Table 39: Newey-West adjusted cross-sectional regression estimates of the model

$$\mu_r = \lambda_0 + \lambda_1\beta_1 + \lambda_2\beta_2$$

where the β values are from the first stage regression

$$\mu_r = \alpha + \beta_1\mu_m + \beta_2\mu_g$$

using equally-weighted data in the computation of the factors.
Values with "°","*","**" and "***" are significant at the 10%, 5%, 1% and 0.1% levels, respectively.

λ_0	λ_1	λ_2
0.61**	0.60**	-5.14***

Abstract in lingua italiana

Questa tesi analizza le implicazioni degli ESG (Environmental, Social, Governance) score e dell'incertezza ESG negli asset returns su un ampio dataset di US stocks. L'analisi non fornisce alcuna evidenza di un impatto dell'incertezza ESG nel mercato negli ultimi anni. Inoltre, il modello proposto da Avramov et al. (2022) [1] che incorpora l'ESG score del singolo stock e l'ESG score di mercato non fornisce risultati statisticamente significativi di un premio ESG. Proponiamo un approccio diverso per integrare l'ESG score nel capital asset pricing model (CAPM). L'analisi conferma che il mercato azionario prezza un premio negativo per il rischio ESG quando trascuriamo l'ESG score non informativo del mercato.

Parole chiave: ESG, CAPM, Investimenti sostenibili, Incertezza ESG