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The Implications of ESG Rating and ESG Uncertainty

Masteroppgave i Økonomi og Administrasjon
Veileder: Thomas Leirvik
Mai 2022

Masteroppgave

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Preface

This thesis is written to fulfill the graduation requirements to the master's degree in Business Administration at NTNU Business School. The thesis is written in the spring of 2022 within the main profile of Financial Investment.

We would like to express our profound gratitude to our supervisor, Thomas Leirvik, for his assistance and encouragement throughout the process. His insight and enthusiasm for our research have been invaluable. We would also like to thank Vu Le Tran for granting us access to ESG and financial data, which was critical for our research.

Heidi Tomtum	Malin M Dahl
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Abstract

In this thesis we investigate ESG rating uncertainty as a supplement to traditional ESG investing analysis. There are only a few research articles on the subject, indicating that this is a relatively new field which requires more research. With the increased demand for ESG investments, we find the consequences of little standardization and regulations in ESG ratings interesting. The fact that investors base investment decisions on ESG ratings, which can be highly subjective and contain biased information, is very different from traditional factors, such as credit ratings, which are highly structured and regulated. Investigating ESG uncertainty alongside ESG ratings will therefore be interesting.

We replicate some of the work of Avramov et al. (2021) by using conditional double-sorted portfolios for raw return, CAPM- and FFC-adjusted return, focusing on the excess return. We investigate both ESG rating and ESG uncertainty, as well as their interaction. As a robustness check, we use a Fama-MacBeth regression in order to evaluate the ESG rating and ESG uncertainty impact on stock returns for companies listed on London Stock Exchange (LSE).

For excess return, our results indicate that ESG rating is positively associated with future performance given a low ESG uncertainty. For the CAPM-alpha we find significant evidence to support that ESG rating is negatively associated with future stock performance when the ESG uncertainty is low. However, as the level of uncertainty increases, this finding is no longer supported. Furthermore, we can confirm that in the univariate portfolio, based on ESG uncertainty, the stocks with low ESG uncertainty will outperform stocks with high uncertainty on LSE. Interestingly, we find in the univariate portfolio, based on ESG rating, that ESG rating can successfully be used to predict stock return.

When performing a robustness check, we can see indications that ESG rating is a significant variable that predicts stock return for the full sample, when ESG uncertainty is absent. Taking ESG uncertainty into account, we discover that ESG ratings can not be used to predict stock returns. This emphasizes the importance of incorporating ESG uncertainty in ESG investment strategies.

Sammendrag

I denne masteroppgaven undersøker vi ESG-rating usikkerhet som et supplement til tradisjonell analyse av ESG-investering. Det er få forskningsartikler som dekker temaet noe som illustrerer at det er et relativt nytt felt med behov for ytterligere undersøkelser. Med økt etterspørsel etter ESG-investering finner vi konsekvensene av lite standardisering og reguleringer i ESG-ratinger interessante. ESG-rating kan være svært subjektivt og skiller seg fra tradisjonelle ratinger, som for eksempel en svært regulert kredittrating. Det vil derfor være interessant å undersøke ESG-usikkerhet sammen med ESG-rating.

Vi replikerer noe av arbeidet til Avramov et al. (2021) ved å bruke betingede dobbelt sorterte porteføljer for avkastning, CAPM- og FFC-justert avkastning, hvor vi fokuserer på meravkastningen. Som en robusthetssjekk bruker vi en Fama-MacBeth-regresjon for å evaluere ESG-usikkerhetens innvirkning på aksjeavkastningen for selskaper notert på London Stock Exchange (LSE).

Gitt en lav ESG-usikkerhet, ser vi tendenser til at ESG-rating er positivt assosiert med fremdtidig avkastning. Ved å undersøke CAPM-alphaen finner vi bevis som støtter at ESG-rating er negativt assosiert med fremtidig aksjeutvikling når ESG-usikkerheten er lav. Da usikkerheten øker, er ikke disse funnene lenger gjeldende. I de univariate porteføljene basert på ESG-usikkerhet, kan vi bekrefte at aksjer med lav usikkerhet utkonkurrerer aksjer med høy usikkerhet. Videre, for de univariate porteføljene basert på ESG-rating, observerer vi at ESG-rating kan predikere aksjeavkastning.

Ved å utføre en robusthetssjekk, ser vi at dersom usikkerhet ikke er tilstede, kan vi bekrefte at ESG-rating predikerer avkastning for hele utvalget. Når usikkerheten tas i betraktning, observerer vi at ESG-rating ikke lenger kan brukes til å predikere aksjeavkastning. Dette understreker viktigheten av å inkludere ESG-usikkerhet i en tradisjonell ESG-investeringsanalyse.

Contents

1 Introduction

In recent decades, the value of an investment is no longer only about the return it generates. An increasing number of investors seek for an investment to have a positive impact on society and the world at large, as well as generating a positive monetary return. In short, "doing well while doing good". Sustainable investing is a strategy where organizations worldwide are adopting the UN's sustainability principles in their business process (United Nations, 2020). Much of this could be attributed to external factors such as increased international and regulatory pressure, as well as societal pressure (Schoenmaker & Schramade, 2019), but it could also be attributed to value-driven strategies. Sustainable investing balances traditional investing with *environmental*, *social*, and *governance* (ESG) related insight to improve long-term outcomes, therefore it can be considered as a part of the investing evolution.

The rising demand for reliable information on how well a firm manages environmental, social, and governance risks and opportunities has resulted in the development of the ESG rating. ESG ratings is one of the most used metrics to measure the sustainable performance of a company. An ESG rating is a quantitative measure of how well a firm performs on the three pillars E, S, and G to better comprehend the external impact of its actions (Varley & Lewis, 2021). A company's external influence can be measured both in absolute terms and in comparison to other companies. Varley and Lewis (2021) identify customers, employees, the debt and equity markets, investors, and asset managers as those who require more precise information on the full impact of their decisions, working conditions, and activities. There are currently about 140 providers of ESG ratings (The Impact Investor, 2022), and each provider decides how much weight each component has in the construction of the final ESG rating. The ratings range from 0 (worst) to 100 (best).

Investors all over the world use ESG ratings as a non-financial criteria in investment decisions, and it is considered one of the biggest developments in financial markets in recent years (Christensen et al., 2021). To exert influence over management, the primary concern for an investor who lacks inside knowledge about corporate values or active ownership, is not whether ESG actions by firms produce value, but whether any such value is adequately recognized by the stock market (Hvidkjær, 2017). He states that the main argument for outperformance of ESG-strategies is that the stock market underreacts to ESG information, and that the value of positive ESG effects are not recognized by the stock market. Another reason for outperformance, as explained by Hvidkjær (2017), is that ESG investing has become more popular over time. As a result, the growing demand for "ESG-stocks" may push the price up, meaning the demand effect may have an impact on the valuation. Certain equities may become undervalued if a large group of investors ignores them (Merton, 1987). This can occur if ESG sensitive investors choose to ignore specific companies that fall outside of their preferred level of ESG rating. Negative screening is a well-known ESG investing strategy in which investors avoid companies with low ESG ratings when constructing a portfolio (Amel-Zadeh & Serafeim, 2017). Furthermore, Markowitz (1959) suggests that excluding entire industries or sectors may affect the risk-return trade-off in a broad portfolio. However, the question is *how* this will affect the optimal risk-return trade-off. Amel-Zadeh and Serafeim (2017) argue that if the undervaluation is permanent, a low price implies a higher dividend/price ratio and, all else being equal, a higher return. There is no benefit to exclusion unless ESG affects prices, and ESG restrictions may not affect the optimal portfolio.

Furthermore, in order to achieve a more sustainable economy, we recognize the need for more transparent ESG data in the financial services industry. In line with the growing demand for accurate information on how well a company is managing E, S, and G risks and opportunities, the number of ESG rating agencies have increased (Gibson et al., 2021). Despite the fact that several companies have emerged in this field, there is no industry standard or framework for producing an ESG rating. As a result, ESG ratings for the same company may differ significantly because each rating agency has its own unique approach for evaluating a firm's ESG exposure and performance (Chapman, 2021). However, this is not solely negative; if every agency is equal, they become less relevant. Similarly, every analyst who values a company, such as Apple, arrives at a value that is not the same as the value arrived at by another analyst. This is due to the fact that different models are used, and different properties are emphasized.

One of the fundamental causes of disagreement, according to Christensen et al. (2021), is that some rating agencies rely significantly on corporate reporting. This enables ESG ratings to be based on metrics that are not specific for the impact of ESG policies. They further underline that the method by which these metrics are employed is confidential and thus not visible to independent researchers. Berg et al. (2021) studies the ESG rating discrepancy and, like Christensen et al. (2021), finds that the ESG data is noisy, causing ESG ratings to be inaccurate.

Even the Commissioner of Securities and Exchange (SEC) Hester M. Peirce has expressed caution about incorporating ESG rating as a determinant in financial decisions. In her Scarlett Letter from 2019, she emphasizes how difficult it is to specify which measures should be included in an ESG rating and criticizes the inconsistencies in the applications of the metrics that are included. "*Even if the rating is not wrong on its own terms, the different ratings available can vary so widely, and provide such bizarre results that it is difficult to see how they can effectively guide investment decisions*", she said, adding that these inconsistencies are important because an increasing number of investors are paying attention to ESG ratings (Peirce, 2019).

Like others, both Berg et al. (2021) and Christensen et al. (2021) try to explain why ESG disagreement exists. Berg et al. (2021) propose a deconstruction of the origins of ESG rating, and uncover three drivers of ESG rating variance by subdividing the ESG ratings of six rating agencies into narrower categories. They first point out that raters employ different sets of attributes; for example, pro bono activities may be included by one rating agency but not by another, this is referred to as scope divergence. Second, they point out that various raters measure the same attributes in different ways, a phenomenon they call measurement divergence. Finally, they draw attention to weight divergence, which occurs when raters assign different weights to distinct attributes while calculating an overall ESG rating. They find that measurement and scope divergence account for the majority of the variances, with weight divergence playing a modest impact. Christensen et al. (2021) investigates the function of transparency as a factor of ESG rating disagreement and discovers that greater disclosure leads to greater disagreement, and highlights that ESG rating is a subjective measure. They also state that the relationship between a company's average ESG rating and ESG rating disagreement is non-linear, implying that the two factors do not have a direct relationship. Interestingly, this research emphasizes the importance of understanding the ESG rating, and more importantly, its implications.

2 Literature

2.1 Literature Review

Estimating a company's future return using ESG performance as a non-financial measure has proven difficult. Multiple studies have looked at the relationship between ESG rating and financial performance. Pedersen et al. (2021) emphasizes the issue of investors having no direction on how to incorporate ESG into portfolio decisions. Moreover, academics and practitioners disagree on whether ESG will help or hurt financial performance.

Bolton and Kacperczyk (2020) question whether carbon emissions are a significant risk for investors who fight climate change, and how this is reflected in stock returns and portfolio holdings. Even after adjusting for business characteristics, they discover that carbon emissions had a significant impact on stock returns, and that a higher stock return is associated with higher emissions as a carbon premium. This means that companies with a low environmental score can be expected to deliver a higher return.

Furthermore, Pedersen et al. (2021) argue in their model that when ESG is set as a neutral return predictor, the implication of high ESG performance as a positive predictor for a stock is weakened. They claim that ESG can become a negative predictor for stock returns if investors change their behavior, and accept returns that are lower if the stock is more responsible, i.e. ESG sensitive investors. Hong and Kacperczyk (2009) state that taking ESG into consideration must lower the expected returns by abstaining from "sin stocks", which are public companies that engage in socially or morally objectionable activities. They investigate the effect of negative screening for sin stocks using stocks from the time period 1926-2006 as a sample, and find that these stocks outperform comparable stocks by 3-4 percent return yearly. The returns are significant at 10 percent level for the standard Fama-French three-factor model. According to Pedersen et al. (2021), a low-score ESG investor demand can therefore be the reason for Hong and Kacperczyk (2009) findings on sin stocks.

Consistent with previous studies (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2020; Pedersen et al., 2021), Luo (2022) find that firms with lower ESG rating earn higher returns than those with higher ESG rating. By examining UK stocks from 2003 to 2020 from Thomson Reuters' database, he find that firms in the low ESG quintile outperform stocks in the high ESG quintile by 0.51 percent per month for value-weighted returns. The ESG premium remains largely significant even after adjusting for the Fama and French (1993) three-factor model and Fama-French Carhart (Carhart, 1997) model. A study by In et al. (2019), finds that a portfolio that consists of long low-carbon-emitting companies and short high-carbon-emitting stocks generate a positive abnormal return.

On the other hand, Gompers et al. (2003) suggests in their study that companies with strong governance yields a positive abnormal return, which is consistent with previous research (Sloan, 1996). Their conclusion holds true for stocks that have a strong social performance (Edmans, 2011), and implies that a firm's social performance is a good predictor of financial results.

Kempf and Osthoff (2007) construct long-short value-weighted portfolios from the S&P500 and Domini 400 Social Index (DS 400) equities. Using data from 1992 to 2004, they discover four-factor significant alphas of roughly 5 percent per year using industry-adjusted ESG ratings. This indicates that firms with a high ESG performance outperform the market on an industry level. However, Borgers et al. (2013) indicate that the ESG outperformance is considerable until 2004, and afterwards it is close to zero and inconsequential. This demonstrates that the effect of ESG can be influenced by the passage of time, or that the ESG premium dilutes as more players engage.

Some of the existing literature shows a contrary relationship between ESG and financial performance, and highlights the complexity of the term ESG. Given that rating agencies are non-transparent about their rating methodologies, it is nearly impossible for an investor to know which ratings can be trusted. Some argue that ESG-strategies are the way to obtain returns exceeding benchmark, in spite of an absence of detailed and globally-agreed definitions about ESG standards (Kynge, 2017). Because of the often contradicting results, a few researchers try to incorporate ESG rating disagreement to investigate whether it has a real impact in terms of market implications.

Gibson et al. (2021) studies the relationship between ESG rating disagreement and stock return in the US amongst six rating agencies with an average correlation of 0.46 and find that stock returns are positively related to ESG-rating disagreement. They therefore advise investors to add a risk premium for the firms with higher ESG rating disagreement. This advice is in line with the risk-return trade-off, which stipulates that the potential return increases as risk increases. This indicates that firms or portfolios with *high* ESG rating disagreement may be considered riskier.

Another recent contribution to the ESG rating uncertainty field is published by Avramov et al. (2021), where the authors studies asset pricing and portfolio implications for companies affected by ESG rating disagreement. They find that in the presence of ESG disagreement the demand for stocks declines, in addition the CAPM-alpha and effective beta rises with ESG rating disagreement. Further, based on a theoretical model to show the interaction between the average ESG rating and ESG uncertainty, they find that stocks with low ESG rating outperforms stocks with high ESG rating only when the ESG disagreement is low. This contradicts the findings by Gibson et al. (2021) and deepens the concerns regarding the inconsistency of ESG ratings by different providers. Finally, Gibson et al. (2021) suggests that the uncertainty that is present with ESG disagreements affects the risk-return trade-off, social impact, and economic welfare.

2.2 Theoretical Framework

Avramov et al. (2021), hereafter ACLT, studies the ESG rating uncertainty, and analyzes the asset pricing and portfolio implications of uncertainty regarding the corporate ESG profile. With a sample of US stocks from 2002 to 2019 they examine the ESG ratings from six well known ESG rating agencies; Asset4 (Refinitv), MSCI KLD, MSCI IVA, Bloomberg, Sustainalytics and RobecoSAM. They create rater-pairs for each firm, with a minimum of to raters for each pair, and calculate the percentile rank. The ESG uncertainty measures the level of disagreement in ESG ratings as the standard deviation of the percentile ranks. Consistent with previous studies on ESG ratings (Chatterji et al., 2016; Amel-Zadeh and Serafeim, 2017; Berg et al., 2021; Gibson et al., 2021), they find an average ESG rating correlation of the percentiles of only 0.48, and an average ESG rating uncertainty of the percentiles of 0.18.

Also, ACLT address how inconsistency in ESG rating can have an impact on a stock's actual performance in the market, and whether institutional ownership influences the investment decision on a particular stock. They find that the ambiguity in the various ESG rating agencies assessments made sustainable investment riskier and reduced investor demand for equities. The authors concluded that "*In the presence of rating uncertainty, investors are less likely to make ESG investments and actively engage in corporate ESG issues. This could increase the cost of capital for green firms and further limit their capacity to make socially responsible investments and generate real social impact*" (Avramov et al., 2021).

In the absence of ESG rating uncertainty, they found that ESG rating is negatively associated with future stock performance, as shown in Preposition 2 from ACLT. This is demonstrated in equation 1:

$$\boldsymbol{\mu}_r = \boldsymbol{\beta}\mu_M - b_M(\boldsymbol{\mu}_g - \boldsymbol{\beta}\mu_{g,M}) \tag{1}$$

where $\mu_M = \gamma_M \sigma_M^2 - b_M \mu_{g,M}$ is the equilibrium market premium, $\sigma_M^2 = \boldsymbol{X}'_M \boldsymbol{\Sigma}_r \boldsymbol{X}_M$ is the market return variance, $\boldsymbol{\beta} = \frac{\boldsymbol{\Sigma}_r \boldsymbol{X}_M}{\sigma_M^2}$ is the N-vector of market beta, $\mu_{g,M} = \boldsymbol{X}'_M \boldsymbol{\mu}_g$ is the aggregate market greenness, $\boldsymbol{X}_M = \sum_{i=1}^{I} w_i \boldsymbol{X}_i$ is the N-vector of aggregate market positions in risky assets, $\gamma_M = \frac{1}{\sum_{i=1}^{I} w_i \gamma_i^{-1}}$ is the aggregate risk aversion and $b_M = \frac{\sum_{i=1}^{I} w_i \gamma_i^{-1} \mathrm{b}_i}{\gamma_M^{-1}}$ is the aggregate brown aversion.

Further, they discuss that those investors who must weigh information of ESG rating and ESG uncertainty when making portfolio decisions, may find the lack of uniformity amongst the ESG rating agencies as a barrier. Due to disagreements on how to collect, measure, and analyze ESG data, this barrier can be both confusing and perplexing. This presumption is based on the findings of Preposition 3 in ACLT, expressed in equation 2 and 3.

$$\boldsymbol{\mu}_r = \boldsymbol{\beta}\mu_M + (\boldsymbol{\beta}_{eff} - \boldsymbol{\beta})\mu_M - b_M(\boldsymbol{\mu}_{g,U} - \boldsymbol{\beta}_{eff}\mu_{g,M,U}) \tag{2}$$

where $\mu_M = \gamma_M \sigma_M^2 - b_M \mu_{g,M,U}$ is the equilibrium market premium, $\boldsymbol{\beta} = \frac{\boldsymbol{\Sigma}_r \boldsymbol{X}_M}{\sigma_M^2}$ is the N-vector of the equilibrium CAPM beta, $\boldsymbol{\beta}_{eff} = \frac{\boldsymbol{\Sigma}_{M,U} \boldsymbol{X}_M}{\sigma_{M,U}^2}$ is the N-vector of effective beta, and $\boldsymbol{\Sigma}_{M,U}^{-1} = \frac{\sum_{i=1}^{I} w_i \gamma_i^{-1} \boldsymbol{\Sigma}_{i,U}^{-1}}{\sum_{i=1}^{I} w_i \gamma_i^{-1}}$ is the inverse of the covariance matrix of ESG-adjusted perceived asset returns, $\boldsymbol{\mu}_{g,U} = \frac{\boldsymbol{B}_M \boldsymbol{\mu}_g}{b_M}$ is the perceived aggregate ESG scores of individual assets, where $\boldsymbol{B}_M = (\sum_{i=1}^{I} w_i \gamma_i^{-1} \boldsymbol{\Sigma}_{i,U}^{-1})^{-1} \sum_{i=1}^{I} w_i \gamma_i^{-1} b_i \boldsymbol{\Sigma}_{i,U}^{-1}$ and $\mu_{g,M,U} = \boldsymbol{X}'_M \boldsymbol{\mu}_{g,U}$ is the perceived aggregate market ESG score.

Preposition 3 explains the equilibrium expected returns with ESG uncertainty. The expected excess return expression in equation 2 modifies the no-uncertainty case in equation 1 by replacing the market beta with the effective beta (see Appendix A). Thus, it is the effective beta that is priced in the cross section of equity returns. ACLT express the expected excess returns as the sum of two components: the first reflects the exposure to the market factor, while the second is a nonzero alpha that stands for (1) nonpecuniary benefits from ESG investing and (2) an additional risk premium attributable to ESG uncertainty.

When controlling for ESG uncertainty and the effective beta, they expect a fixed return gap between the brown and green stocks, as a result of the asset demand diminishing the nonpecuniary benefits from ESG investing:

$$\mu_{r,brown} - \mu_{r,green} = \frac{2\mathrm{w}_{ESG}\mathrm{b}_{ESG}\mu_g}{1 + (1 - \mathrm{w}_{ESG})(\mathrm{b}_{ESG}^2 \frac{\sigma_g^2}{\sigma_r^2} + 2\mathrm{b}_{ESG}\frac{\sigma_{rg}}{\sigma_r^2})} \tag{3}$$

Definitions of $\mu_{r,brown}$ and $\mu_{r,green}$ are shown in Appendix A.

ACLT claims that ESG uncertainty can nontrivially interact with the ESG-performance relation (equation 2) and further highlights the importance of rating uncertainty as a meaningful asset pricing implication, i.e the negative ESG-alpha only exists among stocks with low rating uncertainty.

Based on these interesting, and relevant findings, we want to investigate whether the findings from ACLT can be applied in a different market. In November 2021, the Government of the United Kingdom published *"Greening Finance: A Roadmap to Sustainable Investing"* (HM Government, 2021), expressing their concern that different ESG rating agencies may not be comparable due to a lack of transparency and regulations. They propose a roadmap towards a framework that includes standards for ESG rating agencies to make the ratings comparable, as well as standards for corporations, asset managers, and investment products on how they consider ESG-related matters.

We thought it would be interesting to take a closer look at the companies in this market, because of the UK's unique approach to the growing concern around sustainable finance. We limit our selection to companies listed on the London Stock Exchange in the time period 2007-2020. As a result, we address the following research question:

Do the findings from Avramov et al. (2021) apply for stocks listed on London Stock Exchange, in terms of market implications of ESG rating disagreement?

To answer the research question, we base our thesis on the same methodology as ACLT, in order to make our results comparable. To begin, we focus on risk adjusted return using CAPM. This one-period asset pricing model assumes risk-averse investors with diversified portfolios and prevents individual portfolio risks from being captured. Further, CAPM assumes no transaction costs or taxes, and that all securities are easily accessible. In addition to free financing, this model follows the market efficiency theory's assumption that all information is available for all market participants. Mathematically, the formula for CAPM is given as:

$$E(R_{it}) = \alpha_i + R_{ft} + \beta_t \times (R_{mt} - R_{ft}) + \epsilon_{it} \tag{4}$$

Where $E(R_{it})$ is the expected return on asset i, R_{ft} is the risk-free rate and R_{mt} is the expected market return. $R_{mt} - R_{ft}$ represents the expected excess return of the market portfolio over the risk-free rate, also known as the Equity Risk Premium (ERP). β_t expresses the market beta and is calculated by dividing the covariance of assets by the variance of market return. We obtain monthly betas for each company by a 5-year rolling regression.

Further, in response to the strict assumptions from CAPM and sole focus on market risk, Fama and French (1993) developed the three-factor model, which added value and size risk factors to the CAPM model. Based on research from Jegadeesh and Titman (1993), Carhart (1997) added a fourth factor; monthly momentum, to Fama and French (1993). The momentum factor refers to the velocity of price changes in financial instruments and is retrieved by calculating the premium between one-year winners and losers. Carhart (1997) demonstrates that it describes cross-sectional variation of portfolio returns better than the Fama and French (1993) three-factor model.

$$\begin{aligned} R_{it} = \alpha_i + \beta_{MKT} \times (R_{mt} - R_{ft}) + \beta_{SMB} \times SMB_t + \\ \beta_{HML} \times HML_t + \beta_{MOM} \times MOM_t + \epsilon_{it} \end{aligned} \tag{5}$$

Where R_f is the risk-free return, $R_m - R_f$ is the excess market return, SMB_t is the size factor which represents the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, and HML_t is the value factor. HML is the difference between the returns on diversified portfolios of high and low B/M stocks. MOM_t are the returns on value-weighted, zero-investment one-year momentum in stock returns. Additional description of the variables are shown in Appendix C.

In the final section, we use cross sectional regression of Fama-MacBeth. One of the appealing aspects of Fama-MacBeth is that it can be run on unbalanced panel datasets. In a balanced panel, every variable has an observation for every time period, whereas in an unbalanced panel, this is not required. Given that some firms are not publicly listed over the entire period, as well as that we have some missing data for some of the firm characteristics, using a Fama-MacBeth will overcome this weakness. The Fama and Macbeth (1973) regression is a two-step procedure to test how financial or macroeconomic factors describe portfolio or asset return which enables us to see the relationship between risk and expected return. The first step determines the factor exposure for each factor by time-series regression. Each factor's betas will be estimated, then each stock will be regressed against one or more factor time series. The regression is estimated using ordinary least squares.

$$R_{n,t} = \alpha_n + \beta_n \times \boldsymbol{F}_n + \epsilon_{n,t} \tag{6}$$

For each cross-sectional observation, the second step in Fama-MacBeth regression involves regressing return on the estimated factor loadings from the first step. This is accomplished by performing T cross-sectional regressions of the returns on N beta estimates.

$$R_{i,T} = \gamma_T + \gamma_{T,n} \times \beta_{i,n} + \epsilon_{i,T} \quad (7)$$

The dependent variable, excess return, is the firm's monthly excess return. *ESG rating*, *Low ESG Uncertainty* and the cross-linked variable *ESG* $\times$ *Low ESG Uncertainty* is the explanatory variables of most interest.

The control variables in our Fama-MacBeth regression are firm specific, and include market capitalization, gross profit, six-month momentum, investment and leverage. The model equation is shown in Table 6. Market capitalization refers to the total value of a company's shares and is calculated by multiplying share price with shares outstanding. Gross profit refers to a company's profits earned after subtracting the costs of producing and distributing its products. Six-month momentum factor is the momentum which is calculated as the cumulative return from month m-6 to m-1. Investment and leverage simply refers to a company's investment and leverage values.

Lastly, we use Newey-West standard errors to avoid the consequences of pure first-order serial correlation in time-series data. Without changing the coefficients, this correction will adjust the OLS estimates of the standard error to the coefficient. This makes sense, because if serial correlation does not cause bias in the coefficients but affects the standard errors, we expect a change in the standard errors to the coefficients rather than a change in the coefficients (Studenmund, 2016).

3 Research Design

3.1 Data selection and descriptive statistics

By collecting ESG data from three different ESG rating agencies; Arabesque, TruValue and Refintiv, we construct rater-pairs which consist of one individual company with an ESG rating from at least two different rating agencies.

Furthermore, we retrieve both firm and market specific factors. From the AQR Data Library we retrieve the market-specific monthly Fama-French three factors (Fama & French, 1993). FactSet provides firm-specific factors such as market capitalization, book-to-market value, gross profit, investment, and leverage. Their firm-specific data is reported daily.

When merging all datasets, we extract the data as the last day of each month, to create monthly data, and for each company, we calculate the six-month momentum factor and the 5-year rolling beta.

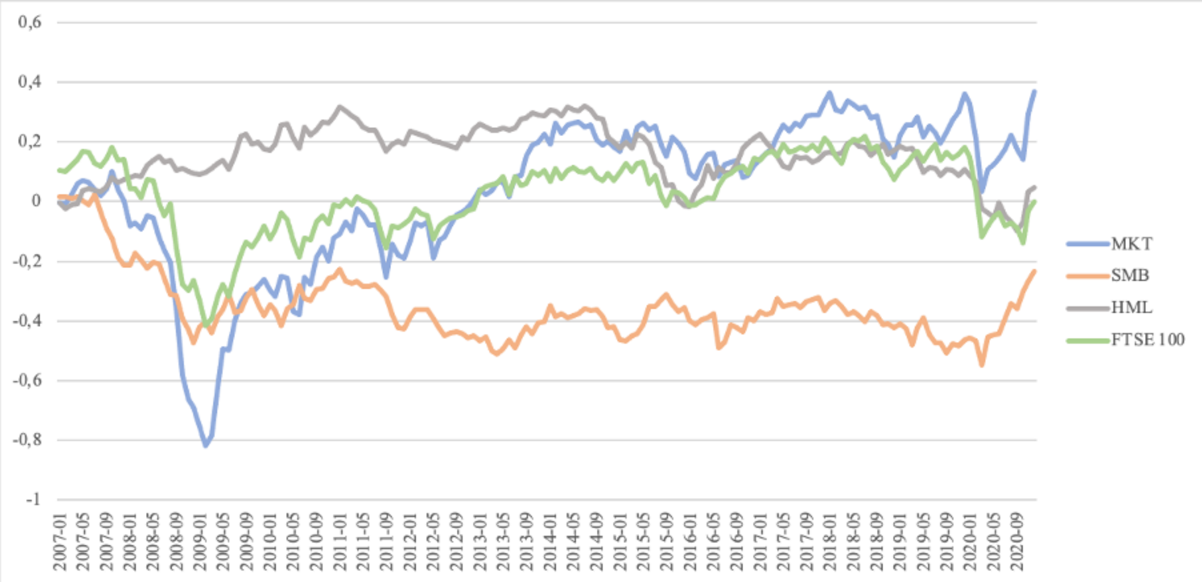

Figure 1: Market factors. This figure plots the historical monthly returns of market factor, size factor, book-to-market factor and FTSE 100 (in %) in the time period 2007-2020.

Arabesque is an ESG rating agency that claims to process 150 million data points each day to provide ESG ratings for over 7,000 companies worldwide. They specialize in advising and data solutions by combining big data with environmental, social, and governance criteria to analyze the performance and long-term viability of businesses worldwide. Their S-Ray solution uses machine learning models to assess a company's performance and long-term viability, as well as stock selection strategies to customize portfolios to a wide range of investor ESG preferences (Arabesque, 2022). From Arabesque, we retrieve 1,963,049 daily ESG ratings from 2003 to 2022 for 678 unique companies.

TruValue Labs is a subsidiary of FactSet, a data and software solutions company, that collects daily data on the most significant positive and negative ESG events. Their machine learning algorithms take individual events from over 100,000 different sources and associate them with a company and at least one of the Sustainable Accounting Standards Board's categories. The data used in their algorithms is not based on information from the companies themselves. TruValue claims to make these events more transparent by summarizing the most influential news pieces and providing qualitative and quantitative statistics on each event (TruValue, 2022). We retrieve 2,254,807 daily ESG ratings for 1,034 different firms from TruValue between 2007 and 2022.

Refinitiv, unlike the other two ESG rating agencies, collects information from ESG specialists. It is formerly known as the Thomson Reuter Database, and its ESG ratings are based on publicly available sources, such as company websites, annual reports, and corporate social responsibility reports (Refinitiv, 2022). We retrieve 2,646 annual ESG ratings from 189 different companies from Refinitv from 2007 to 2020.

3.1.1 Data Collection

To build the database for further study, we obtain ESG ratings for firms listed on London Stock Exchange from the three agencies. The ESG rating agencies assign an ESG rating from 0-100 based on the pillars E, S, and G, with a rating closer to 100 signifying a better ESG performance. From Arabesque and TruValue we extract the last daily observation of each month to obtain monthly observations. Since Refintiv provides annual ESG data and most ratings change infrequently within a year (Gibson et al., 2021), we argue that it makes sense to simply use the respective annual ESG data as monthly.

To create a joint database for all three agencies, we set a constraint on a minimum of two rating agencies for each company in the overlapping time period. This constraint gives us a database of monthly ESG data for 460 unique companies from 2007-2020.

	N	1st Qu.	Median	Mean	3rd Qu.	StdDev
ESG Rating						
TruValue	45,646	46.99	55.35	54.97	63.38	12.42
Arabesque	45,646	49.63	55.18	54.64	59.97	7.43
Refinitiv	6,828	43.45	56.23	57.00	71.82	18.27

Table 1: Table 1 describes the monthly ESG data in the joint database.

From Table 1, we observe that TruValue and Arabesque have more observations (45,646) than Refintiv (6,828). This illustrates that Refinitiv provides a smaller database for LSE stocks, compared to TruValue and Arabesque. We require each firm to have a rating from a minimum of two rating providers, making our sample consist of 45,646 monthly firm level observations. While TruValue and Arabesque tend to issue overall ratings of 55 points, Refintiv provides some higher ratings with an average of 57 points. These trends are especially obvious in the third quartile, where Refintiv ESG-ratings are higher with a score of 71.82. In comparison, TruValue and Arabesque have a third quartile of 63.38 and 59.97. Furthermore, Refintiv has the most variation with a standard deviation of 18.24, whereas Arabesque has the lowest variation with a standard deviation of 7.43.

3.2 Portfolio Construction

For each year, we construct rater-pairs for all unique companies. These rater-pairs are made up of one individual company with an ESG rating from two or three ESG rating agencies, for example, Tesco PLC has three rater-pairs because all providers obtain an ESG rating, whereas Rightmove PLC only has one rater-pair because Arabesque and TruValue are the only ones to provide an ESG rating.

To range the ESG ratings and calculate the uncertainty between the rater pairs, we use percentiles to obtain a comparable scale. For each rater pair-year, we sort all stocks covered by a minimum of two agencies, and calculate the percentile rank. Then, for each stock, we compute the pairwise rating uncertainty, as the absolute difference in ESG rating percentiles for each rater-pair, and divide it by the root of two. The ESG uncertainty is then the standard deviation of the disagreement between ESG rating agencies.

Specifically, let $r_{j,t,A}$ and $r_{j,t,B}$ denote the ESG percentile rank for stock j in year t from the raters A and B. The pairwise rating uncertainty is calculated as

$$\frac{|r_{j,t,A} - r_{j,t,B}|}{\sqrt{2}} \tag{8}$$

As an example; a company that is rated by two rating agencies at the 32nd and 62nd percentiles will generate a rating uncertainty of 0.21.

	Panel A: Pairwise ESG rating correlation			Panel B: Pairwise ESG rating uncertainty		
	TruValue	Arabesque	Refinitiv	TruValue	Arabesque	Refinitiv
TruValue	-	0.021	0.117	-	0.219	0.243
Arabesque	0.021	-	0.121	0.219	-	0.193
Refinitiv	0.117	0.121	-	0.243	0.193	-

Table 2: Table 2 illustrates the pairwise correlation and rating uncertainty for the percentiles. In Panel A, we report the correlation in the percentile ranks for each rater pair-year and then average them over time. In Panel B, we report the average ESG rating uncertainty for each rater pair. The pairwise rating uncertainty for each stock is calculated as the standard deviation of the ranks provided by the two raters in the pair. Finally, we compute and average the ESG rating uncertainty across all stocks for each rater pair-year.

From Panel A in Table 2, we observe that even with small differences in the average ESG-ratings across the agencies, as seen in Table 1, we find a consistently low correlation between the percentiles. Between TruValue and Refinitiv we find a correlation of 11.70 percent and 12.10 percent between Arabesque and Refinitiv. The correlation between TruValue and Arabesque reports only 2.10 percent. In accordance with previous studies (Avramov et al., 2021; Gibson et al., 2021), we were expecting a low correlation, nevertheless we found correlations at this level noteworthy, which indicates higher uncertainty for stocks on LSE. Furthermore, in Panel B we observe an average ESG rating uncertainty of the percentiles of 0.22. At the percentile level, an average ESG rating uncertainty around 0.20 is considered high, and substantiates our low correlation.

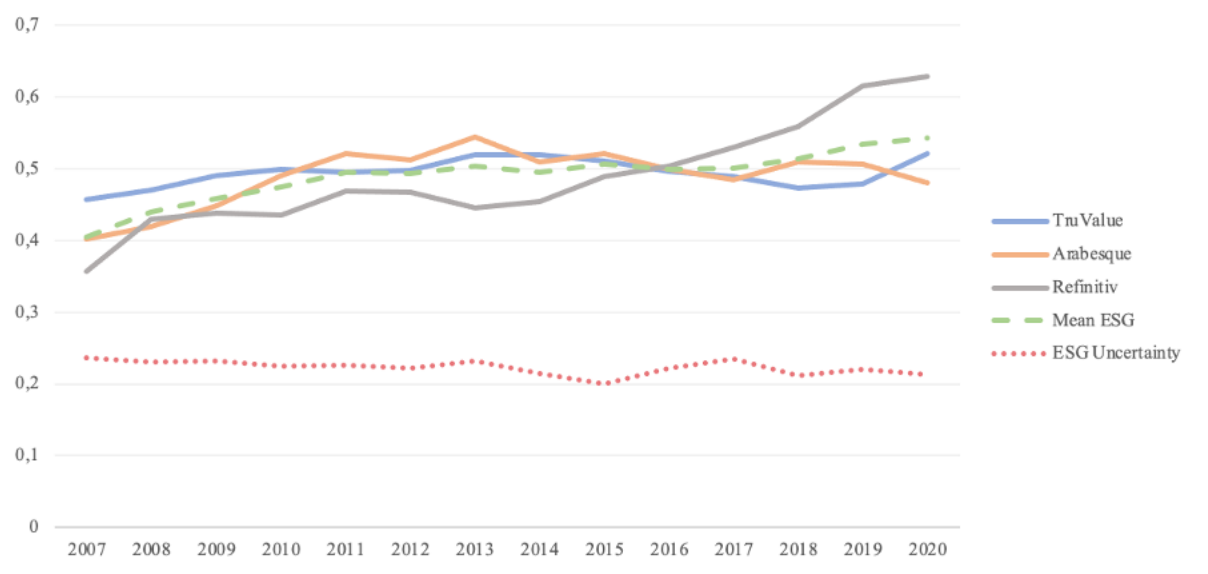

Figure 2: Figure 2 shows the percentiles (y-axis) of market ESG rating acquired from each data provider over time, as well as the mean ESG rating uncertainty across the data providers.

Compared to Arabesque and TruValue, Refinitiv has the lowest ESG percentile rating in 2007 and the highest rating in 2020, indicating a greater change in the mean ESG percentile ratings. Furthermore, we can see that percentile ESG uncertainty has decreased from 2007 to 2020, but the changes are minor.

To make the analysis comparable to ACLT, we create double-sorted portfolios. A double-sort approach makes sense because the correlation is low, as shown in Panel A in Table 2. Sorting procedures are commonly used to identify and investigate relationships between expected returns and asset class characteristics. To test for and establish cross-sectional relationships between expected asset returns and asset characteristics, the portfolio sorting approach has become widely used and is one of the dominant approaches in empirical finance. In recent years, the literature informally recognized sorting into portfolios as a nonparametric alternative to enforcing linearity on the relationship between returns and characteristics (Cochrane, 2011; Fama and French, 2017; Cattaneo et al., 2020).

3.2.1 Independent double-sorted portfolios

To create annual independent single-sorted portfolios, we divide the companies into quintiles based on their mean percentile rank at the end of each year. The quintiles range from *low* to *high*, based on both ESG rating and uncertainty. In addition, the portfolios are rebalanced annually to allow us to capture the change in ESG rating and ESG uncertainty over time. For ESG rating, stocks in the high portfolio are referred to as *green*, while stocks in the low portfolio are referred to as *brown*.

Panel A: Rating Quintiles					
	Low	2	3	4	High
Mean	0.684	0.876	0.862	0.994	0.943
Std	6.489	5.868	5.746	5.212	4.874
Min	-31.500	-23.911	-24.384	-23.864	-22.438
Max	32.485	28.021	27.169	22.951	16.789
Sharpe ratio	0.340	0.500	0.501	0.650	0.654

Panel B: Uncertainty Quintiles					
	Low	2	3	4	High
Mean	0.899	0.639	0.910	0.925	0.976
Std	5.532	5.837	5.671	5.207	5.982
Min	-24.838	-28.737	-28.441	-20.489	-24.132
Max	21.302	24.287	25.000	22.276	32.468
Sharpe ratio	0.546	0.349	0.540	0.600	0.554

Table 3: Table 3 shows descriptive statistics of monthly average returns of the ESG-rating portfolios in Panel A and ESG uncertainty portfolios in Panel B. The Sharpe ratio is calculated as the annual excess return divided by the annual standard deviation, expressed as: $SR = \frac{(1+r)^{12}-1}{\sigma\sqrt{12}}$, where r is referred to as the excess return.

According to Panel A in Table 3, all five portfolios yield a positive monthly average return. Moving from low to high ESG rating, we see tendencies to an increased average return, similar to Gibson et al. (2021) and In et al. (2019). The low and high portfolio has an average monthly return of 0.68 and 0.94 percent. This implies that companies with high ESG rating earn 0.26 percent more per month in average return than the companies with low ESG rating. Portfolios in the higher quintiles (*high* and *4*) have a standard deviation of 4.87 and 5.21 percent, resulting in a Sharpe ratio of 0.65 for both portfolios. Interestingly this indicates that these portfolios deliver the best performance. However, it will be interesting to see if this relation holds true when ESG uncertainty is factored into subsequent analysis. We observe that green stocks tend to outperform brown stocks, given monthly average return and Sharpe ratio. This contradicts previous findings on the subject, such as In et al. (2019).

From Panel B in Table 3, all five portfolios yield a positive monthly average return. We observe that firms with higher ESG rating uncertainty have a higher average monthly return. Stock returns appear to be positively related to ESG rating uncertainty, implying that firms with higher uncertainty face a risk premium. Interestingly, this implies that ESG uncertainty may be recognized in the market. On the other hand, we observe a fairly similar standard deviation of 5.53 and 5.98 for the low and high portfolios, resulting in an equal Sharpe ratio of 0.55. This indicates that as ESG uncertainty increases, there is no difference in risk-adjusted performance.

We create independent double-sorted portfolios by combining the single-sorted portfolios. For each year, we sort all companies into their associated portfolio, given the percentile ESG rating and uncertainty rank. In this case, both ESG rating and uncertainty are sorted independently at the same time into quintiles, by their respective percentile rank. As a result, we have two quintile portfolios (from *low* to *high*) that are sorted independently of one another, and it gives a total of 25 (5x5) portfolios for the entire 14-year period.

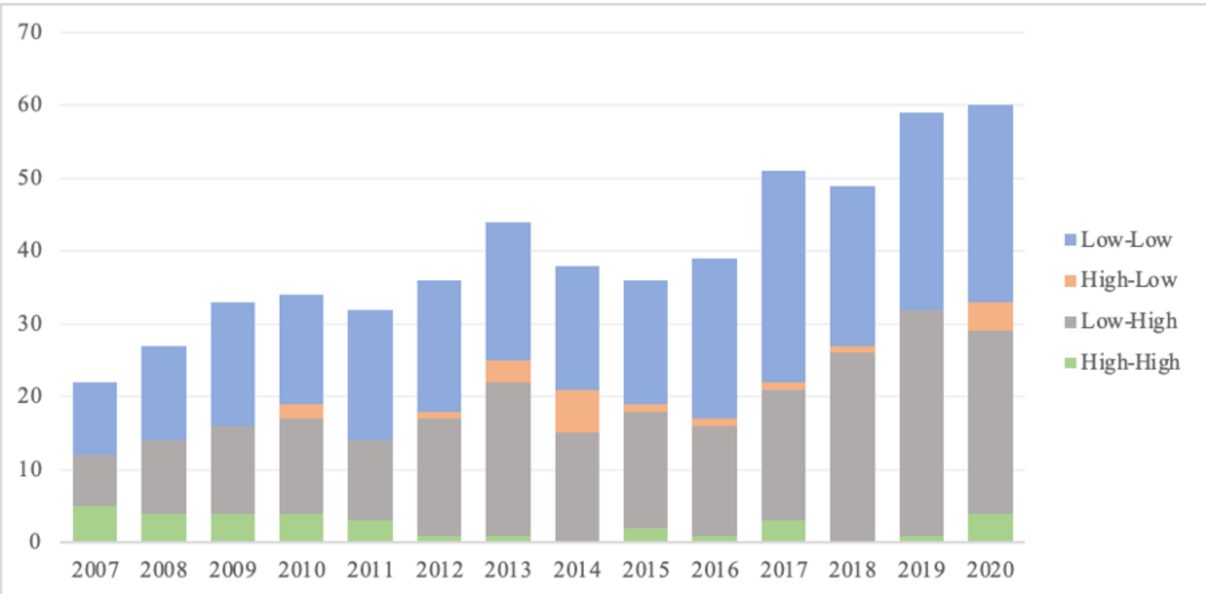

Figure 3: Figure 3 plots the distribution of the unique companies in the independent double-sorted extreme portfolios, for the time period 2007-2020. To clarify, portfolio *High-Low* are the companies with a *high* ESG uncertainty and *low* ESG rating.

Illustrating the change in the number of companies in the extreme portfolios from figure 3, we note a variety across the time period. As a result of an independent double portfolio-sort strategy, we discover that some portfolios don't have any companies in certain years. The portfolio of *High-Low* has zero companies in the years 2007-2009, 2011, and 2019. This may lead to misinterpretations in subsequent analysis, making it difficult to capture the true relation between ESG rating, ESG uncertainty, and stock returns.

3.2.2 Conditional double-sorted portfolios

Conditional sorts solve the empty portfolio problem by construction; first sorting by uncertainty, and then by rating within each uncertainty-based portfolio. ACLT argues that a conditional sort gives better control for rating uncertainty. In an unconditional sort, the order of the sort does not matter, while in the conditional sort, the factor that is sorted first has a much greater influence on predicted returns. Each year, stocks are now divided into quintiles, based on the uncertainty of their ESG rating using the same method applied in independent double sorts. Stocks are further sorted into quintiles based on their ESG ratings within each ESG rating uncertainty group, to generate the 25 (5x5) portfolios.

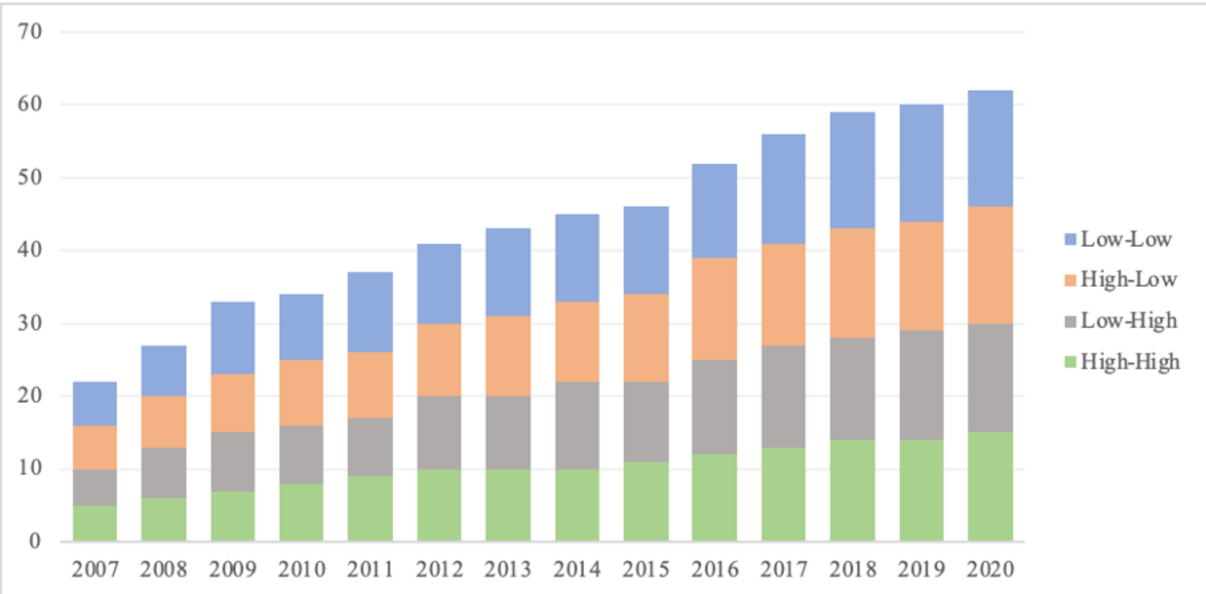

Figure 4: Figure 4 plots the distribution of the unique companies in the conditional double-sorted extreme portfolios, for the time period 2007-2020. To clarify, portfolio *High-Low* are the companies with a *high* ESG uncertainty and *low* ESG rating.

From Figure 4, we now observe an even distribution of companies in the extreme portfolios. This strengthens our future analysis and makes it directly comparable to the results from ACLT.

4 Empirical Results

In this section we will display and discuss the results of the conditional double sorted portfolios of raw returns in Panel A as well as the risk-adjusted CAPM returns in Panel B, and Fama-French Carhart returns, in Panel C (shown in Appendix B). Panel A, B and C report the regression alphas. We also discuss the results of our robustness check, using Fama-MacBeth regression, as mentioned in section 2.2.

First, we will discuss the overall trends that are observable between stock returns and the two sorted factors. We examine the tables for systematic patterns in monthly return as portfolio characteristics change both vertically and horizontally. There are several noteworthy trends between the monthly returns and the two sorted factors. The ESG rating uncertainty effect, observed from Table 3, is still noticeable for the conditional double sorted portfolios. Panel A and Panel C display a somewhat systematic increase in monthly return as we move from low uncertainty to high uncertainty, given that the ESG rating is in the bottom quintiles. This is in line with the risk-biased hypothesis, and it indicates that a higher ESG rating disagreement should result in higher future stock returns. Firms with a higher level of disagreement in ESG ratings are considered riskier, and investors must be compensated for the additional risk they take by investing in high-disagreement stocks. From Table 3, we observe that green stocks, i.e stocks with ESG rating in the top quintiles, have a greater Sharpe ratio and marginally higher average monthly return compared to the lower quintiles. When taking ESG rating uncertainty into consideration, this trend is also notable in Panel A and Panel C, when ESG rating uncertainty is in the bottom quintiles.

ESG rating	Panel A: Return ESG uncertainty					
	Low	2	3	4	High	All
Low	1.015 *	0.108	0.721	1.052 **	0.884	0.659
	(1.78)	(0.19)	(1.29)	(2.15)	(1.48)	(1.32)
2	0.348	0.757	0.797	0.873 *	1.003 *	0.798 *
	(0.65)	(1.27)	(1.44)	(1.91)	(1.68)	(1.76)
3	0.933 *	0.667	1.045 **	0.809 *	1.015 **	0.834 *
	(1.92)	(1.31)	(2.40)	(1.79)	(2.35)	(1.88)
4	0.734 *	0.603	0.762 *	0.889 **	0.761	0.944 **
	(1.65)	(1.34)	(1.82)	(2.14)	(1.30)	(2.35)
High	1.273 ***	0.910 **	1.115 ***	0.976 **	0.801 *	0.918 **
	(3.32)	(2.19)	(2.65)	(2.39)	(1.88)	(2.44)
LMH-R	-0.258	-0.803 **	-0.395	0.075	0.082	-0.259
	(-0.63)	(-2.15)	(1.09)	(0.25)	(0.21)	(-1.16)

ESG rating	ESG uncertainty					
	Low	2	3	4	High	HML-U
All	0.852 **	0.601	0.887 **	0.913 **	0.884 *	0.032
	(2.00)	(1.33)	(2.05)	(2.28)	(1.91)	(0.17)

Table 4: Table 4 reports the alphas of the time-series average of monthly returns for the conditional double sorted portfolios and the zero-investment (long-short) ESG rating strategies. Panel A reports the predicted raw return, as well as the long-short strategy (LMH-R) of going long (short) the low (high) ESG rating stocks. HML-U is referred to as the zero investment strategy of going long (short) the high (low) ESG uncertainty stocks. Newey-west adjusted t-statistics are shown in brackets for each portfolio where numbers with "*", "**", and "***" are significant at the 10%, 5% and 1% levels, respectively.

Panel A

There are several findings worth noting. We observe that the long-short portfolio given a low ESG rating uncertainty is negative at -0.26 percent per month. This indicates that ESG rating is positively associated with future performance among stocks with low rating uncertainty. However, this relationship is only significant for the second lowest quintile, and we observe tendencies for green stocks to outperform brown at lower levels of rating uncertainty. The tendencies of green stocks outperforming brown are consistent with the findings presented by In et al. (2019) on stock returns given their level of carbon emission.

On the other hand, ACLT discover a negative association between ESG rating and future performance for the stocks with low rating uncertainty. We find that Preposition 3 (equation 2 and 3) does not hold for stocks listed on LSE. Investors can confidently state that a company is *green*, given a low ESG uncertainty. This can indicate that sustainable transformation is more profitable in the UK compared to the US, reflecting pecuniary benefits from holding green assets. We can argue that the trend from Panel A in Table 3 remains valid and suggests that investors trading on LSE are ESG sensitive, as they still require a risk premium to hold green stocks.

In the case of higher ESG uncertainty, the long-short portfolio (LMH-R) turns positive, indicating that the positive return predictability of ESG ratings no longer holds for the remaining firms. It even turns negative for the stocks with higher ESG uncertainty. With increased uncertainty, investors trading on the LSE may no longer trust the given ESG rating and, as a result, prefer brown stocks. This suggests that disagreements between rating agencies can have a significant impact on a traditional ESG investing strategy, and highlight the importance of ESG uncertainty. Interestingly, this tilts the relation in equation 3, where brown stocks outperform green, opposite of what we would expect from Preposition 3. ESG uncertainty weakens the positive ESG-performance relationship, emphasizing the importance of rating uncertainty in terms of asset pricing implications. However, due to the lack of significance in the LMH-R portfolios, we are unable to confirm these findings. This can be explained by our small sample size, as we investigate only 460 of the nearly 2,000 companies listed on the LSE, accounting for roughly 20 percent of the total and might not be a representative sample. With a larger sample size, we may be able to confirm our findings and discover differences in how investors handle ESG uncertainty between the LSE and US market.

From the univariate portfolio sort based on ESG ratings, we note an insignificant long-short portfolio for the full sample (column "All"), indicating weak return predictability of the overall ESG rating on LSE. This is an interesting finding and consistent with previous research (Avramov et al., 2021; Pedersen et al., 2021), as it demonstrates that ESG rating has little influence on long-term performance. The overall ESG rating notes a negative alpha of the long-short portfolio of -0.26 percent per month. Different findings in overall ESG rating are interesting, even with insignificant findings, because it illustrates the contrary evidence in existing literature. As shown when investigating different ESG proxies as a return predictor (Gompers et al., 2003; Hong and Kacperczyk, 2009; Edmans, 2011; Bolton and Kacperczyk, 2020).

The lack of consistency across ESG rating agencies may be a barrier for investors who must weigh information on ESG ratings against uncertainty when making portfolio decisions. Because the UK government has invested time and resources in beginning the process of defining an ESG framework (HM Government, 2021), it shows that the government recognizes that today's ESG rating is a cause for concern. Improving ESG data quality may lead to a more accurate understanding of how ESG ratings affect financial performance. Our findings indicate that uncertainty is a vital issue in the UK, and that implementing a framework may eventually diminish the uncertainty.

Furthermore, we observe how rating uncertainty is in play at market level (row "All"). Investigating the HML-U, we look at the difference in excess return between the high and low uncertainty portfolios. We find a marginal and insignificant positive alpha of 0.03 percent. This implies that stocks on LSE with high ESG uncertainty will outperform those with low uncertainty at the market level. Due to a lack of significance, we can not confirm that the stocks listed on LSE follow this assumption, where the asset alpha increases with ESG uncertainty. Regardless, our results indicate that a company's ESG uncertainty is adequately recognized by the market.

	Panel B: CAPM-adjusted return					
ESG rating	ESG uncertainty					
	Low	2	3	4	High	All
Low	1.064 *	0.577	0.456	0.524	0.372	0.568
	(1.95)	(1.52)	(1.13)	(1.52)	(1.20)	(1.50)
2	0.422	0.390	0.478	0.461	0.548	0.514
	(1.22)	(1.18)	(1.18)	(1.16)	(1.25)	(1.37)
3	0.488	0.323	0.496	0.434	0.382	0.411
	(1.23)	(0.98)	(1.39)	(1.3)	(1.21)	(1.17)
4	0.453	0.603	0.413	0.434	0.464	0.397
	(1.14)	(1.34)	(1.21)	(1.38)	(1.17)	(1.17)
High	0.479	0.442	0.450	0.501	0.279	0.426
	(1.32)	(1.20)	(1.61)	(1.37)	(0.82)	(1.22)
LMH-R	0.585 **	0.135 **	0.006	0.023	0.093	0.142 **
	(2.03)	(2.43)	(0.04)	(0.20)	(0.57)	(2.38)
ESG rating	ESG uncertainty					
	Low	2	3	4	High	HML-U
All	0.502	0.390	0.462	0.469	0.434	-0.068 **
	(1.33)	(1.09)	(1.30)	(1.41)	(1.19)	(-2.16)

Table 5: Table 5 reports the alphas of the time-series average of monthly returns for the conditional double sorted portfolios and the zero-investment (long-short) ESG rating strategies. Panel B reports the predicted CAPM-adjusted return, as well as the long-short strategy (LMH-R) of going long (short) the low (high) ESG rating stocks. HML-U is referred to as the zero investment strategy of going long (short) the high (low) ESG uncertainty stocks. Newey-west adjusted t-statistics are shown in brackets for each portfolio where numbers with "*", "**", and "***" are significant at the 10%, 5% and 1% levels, respectively.

Panel B and C

Adjusting for market risk exposure, we observe that the long-short portfolio (LMH-R) for low ESG uncertainty yields a significant positive CAPM-alpha of 0.58 percent per month. Given a low ESG uncertainty, stocks on LSE are negatively associated with future stock performance, in line with equation 3, where brown stocks outperform green. In this portfolio, we observe contrary results from Panel A in Table 4 indicating that there is market risk affecting stock performance for LSE.

However, when uncertainty rises to a higher level, brown stocks continue to outperform green. Preposition 3 (equation 3) demonstrates that when uncertainty reaches a certain level, this relation tilts and green stocks outperform brown. We observe that the negative relation between ESG rating and stock performance remains at higher levels of uncertainty, indicating that ESG uncertainty does not weaken the negative ESG-performance relation. This could imply that investors trading on LSE have low trust in the ESG rating, because they prefer brown stock regardless of the level of uncertainty, as it appears that the asset demand of ESG-sensitive investors do not diminish. This is supported by the fact that the UK government was one of the first to implement a proper ESG roadmap (HM Government, 2021).

The FFC-adjusted return (from Appendix B) is negative for the LMH-R portfolio given that ESG uncertainty is at a lower level, which indicates that ESG rating is positively associated with stock performance when the uncertainty is low. Similar tendencies can be seen in Panel A (Table 4). The inconsistency in Panels B (Table 5) and C (Appendix B) when adjusting for market risk can be attributed to our small sample size.

From the univariate portfolio based on ESG rating (column "All") in Panel B, we now see a positive and significant LMH-R portfolio of 0.14 percent for the full sample. Like Luo (2022), we find that in the absence of ESG uncertainty, brown stocks outperform green. For the stocks listed on LSE, we find that ESG rating can successfully be used to predict stock returns when adjusted for market risk exposure. From Panel A and B, we observe two contrary tendencies on LSE. In some ways, this is not a surprising result given the wide range of findings in the existing literature. Consequently, this may weaken the credibility of the ESG ratings. However, the differences in findings when adjusting for risk exposure can also be explained by our sample size.

The HML-U from the univariate portfolio (row "All"), based on ESG uncertainty, is statistically significant with a monthly CAPM-alpha of -0.07 percent. Indicating that stocks with low uncertainty outperforms stocks with higher uncertainty. In contrast to the US market, we find that at market level, investors do not require a risk premium for holding stocks with high uncertainty. This finding lends credence to the argument that LSE investors may lack fundamental trust in ESG ratings because the market does not respond when uncertainty rises. It is possible that investors are looking beyond the ESG rating, because they do not have access to multiple ratings and it is time consuming to obtain this information. Moreover, our findings are now inconsistent with the risk-biased hypothesis (Gibson et al., 2021), where stocks within the upper quintile of ESG uncertainty are considered riskier than stocks in the lower quintile of ESG uncertainty. This suggests that the stocks on LSE do not require a risk premium when the uncertainty increases. According to Preposition 3 (equation 2), in the presence of ESG uncertainty, investors on LSE are less likely to engage in corporate ESG issues.

Collectively, in Panel A, we find a positive association between ESG rating and future stock performance, indicating that green stocks tend to outperform brown, given a low uncertainty. When performing a Fama-MacBeth regression as a robustness check, we would therefore expect the cross-linked variable *ESG* $\times$ *Low ESG Uncertainty* to be positive. For the CAPM-alpha, given a low uncertainty, the ESG rating is negatively associated with future stock performance, indicating that brown stocks outperform green stocks. We should therefore expect to see a negative ESG-performance relation when the ESG uncertainty is low.

	Excess return				CAPM-adjusted return			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ESG	-0.001	-0.001 **	-0.002	-0.002 **	-0.005 *	-0.002 *	0.001	-0.002
	(-1.34)	(-2.17)	(-1.47)	(-2.25)	(-1.75)	(-1.72)	(0.01)	(-1.30)
ESG x Low ESG Uncertainty			0.002	-0.001			0.004	-0.002
			(0.99)	(-1.33)			(0.86)	(-1.03)
Low ESG Uncertainty			-0.072	-0.051			-0.232	0.071
			(-1.02)	(-1.10)			(-0.85)	(1.05)
Log(Market Cap)	-0.301	0.010 **	-0.032	0.020 **	0.004	0.010	0.006 *	0.005
	(-1.51)	(1.99)	(-1.32)	(2.01)	(1.30)	(1.61)	(1.73)	(1.51)
Log(BM)	-0.038 *	-0.023	-0.060 **	-0.020	0.002	0.001	0.003	0.001
	(-1.80)	(-1.2)	(-2.20)	(-1.1)	(0.48)	(0.31)	(0.83)	(0.59)
6M Momentum	0.019	0.028	0.036	-0.001	-0.003	0.003	0.005	-0.002
	(0.30)	(1.48)	(0.84)	(-0.01)	(-1.47)	(0.95)	(0.64)	(0.38)
Gross Profit		0.002		0.017		-0.001		0.004 *
		(0.12)		(1.03)		(-0.01)		(1.75)
Investment		-0.004		-0.002		0.002		0.001
		(-1.09)		(-0.98)		(1.38)		(0.18)
Leverage		-0.004		-0.003		-0.003		-0.001
		(-0.28)		(-0.20)		(-0.48)		(-0.76)
Constant	0.149	0.037	0.174 *	0.028	0.013 *	-0.004	-0.016 *	-0.023
	(1.62)	(1.29)	(1.73)	(1.30)	(1.84)	(-0.43)	(-1.79)	(-0.23)
Obs	3,537	3,117	3,547	3,117	1,657	1,447	1,657	1,447
R-Squared	0.043	0.062	0.058	0.067	0.051	0.069	0.059	0.061

Table 6: This table illustrates the regression results where, Model 1 to 4 is referring to the excess returns and model 5 to 8 is the CAPM-adjusted returns. Newey-West t-statistics is shown in brackets, and numbers with "*", "**", "***" are significant on 10%, 5% and 1%, respectively. The following Fama and MacBeth (1973) regression model on stock level is presented as: $r_{i,m} = \alpha_0 + \beta_1 ESG_{i,m-1} + \beta_2 ESG_{i,m-1} \times Low\,ESG\,uncertainty_{i,m-1} + \beta_3 Low\,ESG\,uncertainty_{i,m-1} + \boldsymbol{\beta}_i \boldsymbol{F}_{i,m-1} + \epsilon_{i,m}$ where $r_{i,m}$ refers to the excess return (models 1 to 4) or CAPM-adjusted return (models 5 to 8) of stock i in month m. $ESG_{i,m-1}$ refers to the lagged ESG rating, $Low\,ESG\,uncertainty_{i,m-1}$ refers to a dummy variable that takes the value of one if the uncertainty is in the bottom quintile across all stocks in that month and zero otherwise. The vector $\boldsymbol{F}$ is firm-specific control variables such as Log(Market Cap), Log(BM), 6M momentum, Gross profit, Investment and Leverage. Additional description of variables are shown in Appendix C.

Robustness check

From Model 3, we observe that the coefficient of β_2 is as expected. The model reads a positive association in the cross-linked variable *ESG* $\times$ *Low ESG uncertainty*. However, this association is not significant. Hence, we can not confirm our finding in Panel A from Table 4. Furthermore, in Model 4, we observe a negative association in the coefficient β_2, which is contrary to our expectations. The change in sign indicates that firm-specific variables influence this coefficient. We observe contrary results that ESG uncertainty is an insignificant asset implication. From Panel A in Table 4, we find an insignificant alpha of -0.26 percent for the LMH-R portfolio from the univariate portfolio based on ESG ratings. This is supported by Model 1 & 3 in FMB, which finds that ESG rating fails to predict stock returns for the full sample, indicating that the overall ESG rating has weak return predictability, which is consistent with previous studies (Avramov et al., 2021; Pedersen et al., 2021). However, in Model 2 & 4, we observe a significant negative association between ESG rating and excess return. This finding highlights the problem of using ESG rating to predict stock performance, as shown in existing studies (Berg et al., 2021; Christensen et al., 2021).

When adjusting for market risk exposure (MKT) in Model 5 to 8, we find the same contrary results for β_2, as in Model 1 to 4. We note that the sign of the coefficient in Model 7 is not as expected based on Panel B in Table 5. Furthermore, the relationship loses significance as we move from portfolio to firm level. Including firm-specific factors, we see a shift in sign, implying that firm characteristics have an impact on the relation between ESG rating and low uncertainty. This can be explained by some factors may have a direct impact on the ESG rating. In Model 8, we find, as expected, a negative ESG-performance relationship when ESG uncertainty is low. The coefficient, however, is insignificant, with a Newey-West adjusted t-value of -1.03. As a result, we can neither confirm nor deny that our findings support ACLT's findings for stocks on LSE.

From Panel B in Table 5, we discover a significant and positive CAPM-alpha for the LMH-R portfolio of 0.14 percent for the univariate portfolio. As a result, we discover evidence that ESG ratings can successfully predict stock returns. The FMB regression supports this finding that in the absence of uncertainty, ESG rating (β_1) can successfully predict stock return. The negative association found in Panel B Table 5, is also present in Models 5 and 6 in FMB, meaning brown stocks outperform green. However, adding ESG uncertainty (β_2), this relation is no longer significant. This highlights the fact that ESG uncertainty is a factor of importance. Thus, ESG can non-trivially interact with the association between ESG rating and stock return.

Despite the fact that our findings do not indicate that ESG uncertainty affects stock returns, due to insignificant variables, it will have a practical impact for investors looking to make green investments. Our findings support growing concerns about the inconsistency of ESG information disclosure and ratings provided by different rating agencies. The lack of clear policies for sustainability reporting and standards of rating methodology makes it harder for investors to tell the true color of a company. This can help explain why previous ESG investing research yielded such disparate results. The UK's new sustainable reporting policies (HM Government, 2021), may help mitigate ESG uncertainty so that ESG investing can lead to greater sustainable impact. For now, the importance of ESG uncertainty in future ESG investing research papers can not be overstated. This is emphasized by the fact that the ESG rating is significant when we exclude uncertainty, but is no longer significant when we include uncertainty.

5 Conclusion

We investigate whether the findings of Avramov et al. (2021) apply to companies listed on the London Stock Exchange by constructing 25 (5x5) portfolios for raw returns, CAPM- and FFC-adjusted returns. As a robustness check, we use a Fama-MacBeth regression to assess the impact of ESG rating disagreement on stock returns.

In contrast to ACLT, we find that ESG rating is positively associated with future performance when the uncertainty is low in the conditional double-sorted portfolios for raw-returns. This relation is weakened by an increase in ESG uncertainty, which causes Proposition 3 to tilt. When we adjust for market risk exposures (CAPM), we find, like ACLT, significant evidence to support Proposition 3 (equation 2 and 3) that ESG rating is negatively associated with future stock performance when uncertainty is low. However, as the level of uncertainty increases, this finding is no longer supported.

In the absence of ESG uncertainty, we find that brown stocks outperform green in the LMH-R portfolio, for the CAPM-alpha. Furthermore, we discover that ESG rating can be used to successfully predict stock return for stocks listed on the LSE. In contrast to ACLT, we find that stocks with low uncertainty outperform stocks with high uncertainty in the HML-U portfolio. In the US, investors require a risk premium for holding stocks with high uncertainty, but this does not hold true for stocks listed on LSE.

We confirm, using the Fama-MacBeth robustness check, that ESG ratings, like previous studies, are too subjective to predict stock return. We can not confirm that brown stocks outperform green on LSE, but we have a strong indication due to significant, negative associations in Model 2, 4, 5 & 6. Interestingly, when we include ESG uncertainty in models 1, 3, 7, & 8, the ESG rating is no longer a significant factor and highlights the importance of including uncertainty.

Given a low uncertainty, the cross-linked variable *ESG* $\times$ *Low ESG Uncertainty* we can neither confirm nor deny the findings from ACLT of a negative ESG performance relationship. More importantly, we can not confirm our portfolio sort findings and therefore we are unable to find supporting evidence for equation 2 and 3 on LSE, after accounting for rating uncertainty.

Finally, like ACLT, we confirm that ESG uncertainty is an important factor to include when studying the relation between ESG rating and stock return because of contrary results in the models in FMB. Our findings support the previous research argument (Berg et al., 2021; Christensen et al., 2021; Peirce, 2019) that clear guidelines for methodology and transparency in reporting of non-financial data should be required due to differing responses to the ESG and stock performance relationship. The ESG rating varies depending on which rating agency is used, making it nearly impossible to determine whether a company is truly green without taking the uncertainty into account.

Our study, however, has several limitations. First, it is unclear whether and how our results hold in larger cross-sections of stocks. Second, we had very limited access to ESG data and thus only three ESG rating agencies, which may limit the power of our results. We would therefore recommend increasing the number of ESG rating agencies in future research to make the results more comparable to ACLT. Lastly, in future studies on ESG rating and stock return, we see a need to include ESG rating disagreement as an important explanatory factor.

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A Appendix 1

$$\boldsymbol{\beta}_{eff} = \frac{\sigma_M^2}{\sigma_{M,U}^2}\boldsymbol{\beta} + \frac{b^2\sigma_{g,M}^2}{\sigma_{M,U}^2}\boldsymbol{\beta}_g + \frac{2b\sigma_{rg,M}}{\sigma_{M,U}^2}\boldsymbol{\beta}_{rg}$$

$$\mu_{r,green} = \frac{\beta_{green}\gamma\sigma_M^2(1 + b_{ESG}^2 - \frac{\sigma_{g,green}^2}{\sigma_r^2} + 2b_{ESG}\frac{\sigma_{rg,green}}{\sigma_r^2}) - \mathrm{w}_{ESG}b_{ESG}\mu_g}{1 + (1 - \mathrm{w}_{ESG}(b_{ESG}^2\frac{\sigma_{g,green}^2}{\sigma_r^2} + 2b_{ESG}\frac{\sigma_{rg,green}}{\sigma_r^2})}$$

$$\mu_{r,brown} = \frac{\beta_{brown}\gamma\sigma_M^2(1 + b_{ESG}^2 - \frac{\sigma_{g,brown}^2}{\sigma_r^2} + 2b_{ESG}\frac{\sigma_{rg,brown}}{\sigma_r^2}) - \mathrm{w}_{ESG}b_{ESG}\mu_g}{1 + (1 - \mathrm{w}_{ESG})(b_{ESG}^2\frac{\sigma_{g,brown}^2}{\sigma_r^2} + 2b_{ESG}\frac{\sigma_{rg,brown}}{\sigma_r^2})}$$

B Appendix 2

	Panel C: FFC-adjusted return					
ESG rating	ESG uncertainty					
	Low	2	3	4	High	All
Low	1.082 **	0.346	1.097 **	1.169 ***	1.141 ***	0.911 ***
	(2.58)	(0.84)	(2.59)	(3.70)	(2.55)	(3.29)
2	0.626 *	1.096 **	1.180 **	0.780 **	1.569 ***	0.969 ***
	(1.02)	(2.19)	(2.50)	(2.57)	(3.02)	(3.74)
3	1.112 ***	0.706 *	1.073 ***	0.962 ***	0.822 **	0.972 ***
	(3.39)	(1.91)	(3.99)	(3.34)	(2.52)	(3.92)
4	0.764 ***	0.606 *	0.666 **	0.861 ***	1.136 **	1.004 ***
	(2.81)	(1.97)	(2.14)	(3.33)	(2.39)	(4.54)
High	1.268 ***	0.788 *	1.040 ***	1.069 ***	0.801 **	0.884 ***
	(4.82)	(2.82)	(3.89)	(3.85)	(2.52)	(4.01)
LMH-R	-0.187	-0.443	0.057	0.100	0.340	0.026
	(-0.46)	(-1.10)	(0.14)	(0.32)	(0.82)	(0.12)
ESG rating	ESG uncertainty					
	Low	2	3	4	High	HML-U
All	0.962 ***	0.705 ***	1.016 ***	0.964 ***	1.082 ***	0.12
	(4.43)	(2.77)	(4.07)	(4.72)	(3.63)	(0.56)

Table 7: Table 7 reports the alphas of the time-series average of monthly returns for the conditional double sorted portfolios and the zero-investment (long-short) ESG rating strategies. Panel C reports the predicted FFC-return, as well as the long-short strategy (LMH-R) of going long (short) the low (high) ESG rating stocks. HML-U is referred to as the zero investment strategy of going long (short) the high (low) ESG uncertainty stocks. Newey-west adjusted t-statistics are shown in brackets for each portfolio where numbers with "*", "**", and "***" are significant at the 10%, 5% and 1% levels, respectively.

C Appendix 3

Table 8: Description of variables used in this Study

Variables	**Definition and source**
Main variables	
ESG rating	ESG ratings from three agencies: Arabesque, TruValue and Refinitiv. For each year, we sort all stocks covered by a minimum of two agencies, and calculated the percentile rank for each stock-rater pair. The pairwise average rating is then computed for each stock as the average rank across the two raters in the pair. The firm-level ESG rating is calculated as the average pairwise rank of all rater pairs.
ESG uncertainty	For each rater pair-year, we sort all stocks covered by a minimum of two agencies and calculate the percentile rank. Then, for each stock, we compute the pairwise rating uncertainty as the absolute difference in ESG-rating percentiles for each rater-pair and divided by the root of two. The ESG-uncertainty is then the standard deviation of the disagreement between ESG-rating agencies. The firm-level ESG uncertainty is calculated as the average pairwise rating uncertainty across all rater pairs.
ESG^{ALL}	For each year, we sort all stocks covered by each rater and calculate the percentile rank for each stock. The firm-level ESG rating is calculated as the average pairwise rank of all rater pairs.
ESG uncertainty^{ALL}	For each year, we sort all stocks covered by each rater and calculate the percentile rank for each stock. The firm-level ESG rating is calculated as the standard deviation of the ranks of all rater pairs.
Firm characteristics	
Log(Market Cap)	Log (Market Cap) is the logarithm of the market capitalization and refers to the total value of a firm's shares. Market capitalization is calculated by multiplying share price with shares outstanding.

Variables	**Definition and source**
Log(BM)	Log(BM) is the logarithm of the book-to-market ratio for a firm and is calculated as the book value of equity divided by market capitalization at the end of each year.
6M Momentum	Six-month momentum factor is the momentum and is calculated as the cumulative return from month m-6 to m-1.
Gross Profit	Gross profit refers to a firm's profits earned after subtracting the costs of producing and distributing its products.
Investment	Investment refers to the firm's investment value.
Leverage	Leverage refers to the firms leverage value.
Market characteristics	
SMB	The size factos SMB is the average return on the three small portfolios minus the average return on the three big portfolios: SMB = 1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth).
HML	The value factor HML follows Fama French (1992, 1993 and 1996). HML is the average return on the two value portfolios minus the average return on the two growth portfolios: HML = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).
MOM	The momentum factor MOM is the average return on the two high return portfolios minus the average return on the two low return portfolios: MOM = 1/2 (Small High + Big High) - 1/2 (Small Low + Big Low).

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