CAN YOU TURN THE TRADE-OFF INTO A WIN-WIN SITUATION?

A STUDY ON IMPLICATIONS OF INCORPORATING ESG’S INFORMATIVE VALUE INTO PORTFOLIO MANAGEMENT

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Bachelor Thesis

Stockholm School of Economics

2022

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Abstract

Using data on Nasdaq Nordic stocks between 2016-2020, the thesis empirically analyzes how information about Environmental, Social, and Governance efforts derive implications for portfolio management. Our results reveal that ESG has no predictive value for firm fundamentals, except the social pillar proxied as local community impact assessment. Furthermore, the study can not conclude that market participants value information about a firm's sustainable efforts. Moreover, the factor model analysis reports that our proxies for ESG and Governance efforts have individual explanatory value for stock returns which can be integrated into predictions to attain a more realistic estimate. Finally, the thesis discusses if ESG's informative value can be exploited in portfolio construction. Through the construction of an ESG efficient frontier, we visualize the implications of ESG inclusion and discuss if the trade-off between a performing and sustainable portfolio can be diminished. We relate the results to research in the area of Sustainable Responsible Investment and conclude that our findings partly contradict those of previous empirical analysis. The discussion hence covers what contributing insights our study conveys.

Keywords

ESG, Sustainable Responsible Investing, Portfolio Management, Nasdaq Nordic

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Acknowledgements

We would like to direct our sincere gratitude towards Marieke Bos for valuable guidance and support, Rickard Sandberg for insightful advice, and MSCI ESG Research LLC for providing ESG-scoring data.

Bachelor Thesis
Bachelor Program in Business Economics
Stockholm School of Economics

1. Introduction

A firm's ability to incorporate Environmental, Social, and Governance efforts has received substantial attention over the past decade, and sustainable prosperity is now a relevant factor for corporate success. Simultaneously, there is an ongoing trend among investors to integrate ESG in investment evaluation and sustainable investments have grown by 15% between 2018 and 2020 (Global Sustainable Investment Alliance, 2021). The monumental shift toward sustainable portfolio management and the spiraling strive amongst investors to consider ESG factors in financial analysis has motivated this thesis to disclose how ESG investing interplays with portfolio performance. Previous literature suggests that sustainable investments come at the cost of stock return (Hong and Kacperczyk 2009, Taylor, Stambaugh and Pastor 2019). Despite the proposed trade-off between stock performance and sustainability, investors find little guidance in approaching it. This thesis explores the possibility of incorporating sustainability into portfolio construction to investigate if the alleged trade-off remains when an investor utilizes information about ESG's informative value.

Hence, our two research questions can be formulated as follows;

i. Do ESG characteristics have an explanatory value of future firm fundamentals?

ii. Can ESG awareness diminish the trade-off between portfolio performance and sustainability inclusion?

Our thesis will partly replicate and extend the empirical framework presented in Responsible investing: The ESG-efficient frontier (Pedersen, Fitzgibbons, and Pomorski, 2021). To study how ESG can be integrated into portfolio management, we analyze elements of stock performance on Nasdaq Nordic over the period 2016-2020. We proxy each pillar in ESG as a metric that aims to represent investor estimation of sustainability. Firstly, an analysis of the relation between ESG-proxy and future firm profitability is conducted to investigate whether sustainability predicts firm fundamentals. Secondly, taking the Efficient Market Hypothesis (Fama, 1970) into account, we further investigate if the ESG-proxies are incorporated in stock price or if their potential predictive value can be exploited in portfolio management. Thirdly, we explore if there are abnormal excess returns associated with each ESG-proxy to evaluate if a sustainable approach in portfolio management outperforms traditional prediction models. Lastly, the thesis studies if each ESG-proxy generates a factor return to conclude how information about sustainability efforts can be used in the valuation process to achieve a more realistic prediction.

Our thesis documents the following empirical findings. The results do not report statistical predictive value for firm fundamentals of our chosen proxies, except for the S-proxy that exhibits positive relation with Return on Net Operating Assets on a 10% significance level. Furthermore, the study reveals that all ESG-proxies, except the Governance, lack significant relation with stock valuation. Our G-proxy exhibits a negative relation with valuation on a 5 % significance level, suggesting that information about our estimated proxy is not incorporated into stock price. The result further discloses a positive abnormal excess return for the ESG-proxy, implying that a return premium can be attributed to stocks with a high ESG score to derive a better prediction. Moreover, a negative abnormal excess return is identified for the G-proxy, indicating that a return discount can be applied to good governance stocks to enhance predictions. The proxies for the Environmental and Social pillar report no significant alpha and hence have no predictive value of returns. In a visualization of how the above discussed results impact the incorporation of sustainability into portfolio management, we derive the ESG-efficient frontier plotting Sharpe ratio against portfolio ESG. A perceived and realized frontier is constructed for both the ESG aware and unaware investor, anticipating the implication of utilizing ESG's informative value. Lastly, observing the ESG efficient frontier, we discuss the possibility of diminishing the trade-off.

Our thesis contributes to the literature on numerous matters. Since Pedersen et al.'s (2021) framework of ESG-efficient frontier was recently published, a replication alone, to anchor their results, contributes to the research area of Sustainable Responsible Investing. Using the framework on companies listed on Nasdaq Nordics, the thesis will anticipate if the mitigated trade-off studied by Pedersen et al. (2021) is achievable in other market settings than the US stock market.

A visualization of the cost and benefit of SRI is valuable for an investor with existing motivation for sustainable investments since it enables a more well-founded decision based on preferred portfolio ESG score relative to risk-adjusted return. Furthermore, the study is valuable for an investor that currently ignores sustainable investment due to the general perception that the trade-off between performance and ESG is definitive and cannot be impacted. Previous research studies Sustainable Responsible Investments by analyzing the past and lacks guidance on how an investor can approach the incorporation of ESG in investment decisions to impact future outcomes. Raising the awareness of how ESG-factors' informative value of firm fundamentals, derived from the past, can be exploited in portfolio construction to potentially diminish the trade-off, the thesis strives to increase financial incentives to invest sustainably.

Pedersen, et al. (2021) uses ESG-proxies to estimate how the average investor determines a firm's level of sustainability. Each proxy quantifies sustainability efforts by identifying one metric and is not comprehensive in describing a company's total level of ESG. Therefore, it is relevant to study additional ESG-proxies to make the conclusions more exhaustive. Since our thesis analyzes different ESG-proxies using the same framework, we will provide a valuable extension.

The rest of our paper is structured as follows. Section 2 describes the most relevant findings in previous empirical studies, inducing our hypothesis stated in section 3. Section 4-5 describes our data and methodology applied. Section 6-7 reports on our empirical results and discusses how they relate to previous literature. Section 8 provides concluding remarks and suggestions for future research.

1.2 Definitions

1.2.1 ESG awareness:

ESG awareness is defined as the knowledge about how Environmental, Social and Governance efforts can create financial opportunities, both each factor respectively and combined (Pedersen et al., 2021). Previous studies sort investors based on the level of motivation to invest sustainably. The ESG motivated investors are suggested to evaluate investment decisions based on a preferred sustainability level, while unmotivated investors assess risk and return, ignoring ESG. This thesis introduces the distinction between an ESG aware investor and an ESG unaware investor, recognizing that investors exploit information about sustainability differently when predicting risk and return.

ESG aware investor (A-investor)
An ESG aware investor incorporates ESG's explanatory value of firm fundamentals on stock performance in portfolio management decisions.

ESG unaware investor (U-investor)
The unaware investor does not regard ESG-characteristics as decisive for firm fundamentals or returns. Hence, the U-investor will neglect information on a firm's sustainable efforts and solely rely on traditional procedures in portfolio management.

2. Literature review

We incorporate the following two areas of research as a baseline for our contribution; Studies that consider how ESG affects firm value and those covering how ESG affects portfolio performance.

Previous research acknowledges that sustainability efforts correlate with firm fundamentals. In a study on how Corporate Social Responsibility affects shareholder value, Ferrell et al. find a positive relation between CSR and firm value (Ferrell, Liang, et al. 2016). Likewise, Friede, Busch and Bassen observe comparable results when they perform an aggregated analysis on evidence from 25 previous empirical studies. They conclude that 90% of the studies find a nonnegative correlation and the majority a positive relationship between ESG and Corporate Financial Performance (Friede, Busch and Bassen, 2015). This consensus is of interest to our thesis since it signals that sustainable commitments can be valuable information when predicting a firm's financial performance.

In order to answer the research questions, it is crucial to analyze the impact of ESG factors on stock returns. In the article The price of sin: The effect of social norms on markets (Hong and Kacperczyk, 2009) provide evidence that Sin stocks (companies involved in producing alcohol, tobacco, and gaming) experience higher returns than otherwise comparable stocks. They argue the existence of a sustainability norm among investors impacting their behavior and investment evaluation. As a result, the market demand is biased towards stocks with a high ESG profile. Hence, the return of stocks that contradict the norms, such as sin-stocks, increase in comparison (Hong and Kacperczyk 2009). Compliantly, Taylor et al. conclude that green assets demonstrate lower expected returns due to the high demand for these stocks. (Taylor, Stambaugh, et al., 2019)

Hence, previous research agrees that ESG-factors may decrease stock performance due to the biased market demand toward sustainable stocks. They conclude that potential return is neglected if investments are made with an ESG constraint. This consensus suggests the existence of a trade-off between a sustainable and performing portfolio but overlook the possibility of reducing it. The thoroughness of this trade-off will be unfolded in our thesis to explore if it can be mitigated.

Kempf and Osthoff provide broadening insights since they conclude that using ESG-ratings in valuation is beneficial for the accuracy of predictions. They empirically show that a portfolio going long stocks with a high socially responsible rating and short those with low experience a statistically significant abnormal return of 8.7% per year when traditional factor models are applied (Kempf and Osthoff 2007). This conclusion suggests that if an investor uses ESG-rating as an additional factor in portfolio construction, the perceived return outperforms traditional market predictions and potentially initiates a more accurate perception of future returns.

What previous research in the area of Sustainable Responsible Investments overseas is how insights about ESG's predictability of firm fundamentals can be exploited in portfolio construction. Existing literature either studies how sustainable effort impacts firm value or stock performance but ignores the interplay between the two conclusions. The study by Kempf and Osthoff proposes that stock return prediction could be more precise if ESG factors are incorporated in investment evaluations (Kempf, Osthoff 2007). Their findings provoke an interest in further investigating how portfolio performance is impacted by adding ESG factors to traditional valuation models.

In the article that this thesis aims to partly replicate, Responsible investing: The ESG-efficient frontier, Pedersen et al. (2021) present a framework that quantifies the performance cost and benefit of including ESG-criteria in portfolio decisions. Similar to previous research, they analyze how ESG affects firm fundamentals and stock performance. However, unlike earlier literature, they further study how investors can exploit ESG's explanatory value in portfolio construction. Hence, they partly approach the abnormal excess return proposed by Kempf and Osthoff (Kempf, Osthoff 2007) and study the implications of absorbing it in valuation.

3. Hypotheses

i. We expect that ESG characteristics predict future firm fundamentals

Friede, Busch, et al. (2015) and Ferrell, Liang, et al. (2016) suggest a positive correlation between firm value and sustainable efforts, proposing that ESG characteristics provide valuable information when predicting future firm performance. Pedersen et al. (2021) report mixed results for the ESG-proxies when testing their predictability of future returns. However, their results indicate a significant positive correlation between ESG and firm fundamentals for most of their examined proxies. Hence, combining the results from previous studies, we expect ESG characteristics to predict firm fundamentals.

Given that the first hypothesis holds, the prospect for sustainable stocks would intuitively increase. However, according to the Efficient Market Hypothesis (Fama, 1970), all pertinent and available information is immediately incorporated into the stock price. Consequently, for the first hypothesis to be valuable for our overall analysis, it is crucial to examine whether ESG characteristics are priced in the market, which the following hypothesis will approach.

ii. We expect that ESG characteristics are priced in the market

Galema, Plantinga and Scholtens (2008) report evidence that stocks with high ESG-score experience a lower book-to-market ratio. This suggests that sustainable stocks are more overpriced than stocks with a low ESG-score. Moreover, Pedersen et al. (2021) report that all ESG factors were priced in the market, except the proxy for Governance efforts. Hence, we predict that ESG characteristics are incorporated into the stock price.

iii. We expect that ESG characteristics do predict returns

Kempf and Osthoff (2007) report that a portfolio constructed on ESG factors experiences a statistically significant abnormal excess return. Moreover, Pedersen et al. (2021) found a significant positive abnormal excess return on a portfolio constructed based on Governance efforts and a negative abnormal excess return for a portfolio constructed based on social efforts. The findings in previous literature hence suggest that if an investor uses ESG in portfolio construction, the return will deviate from the market predictions. Therefore, we predict that ESG characteristics do predict returns.

4. Data

4.1 Panel Data Set

Our sample consists of firms listed on the Nasdaq Nordics between 2016-2020. The inspirational paper, Responsible Investing: The ESG Efficient Frontier (2021), analyzes the S&P 500 index with the incentive to exclude effects from small-cap stocks. Therefore, merely Large Cap Stocks have been considered throughout this paper. There are two dimensions in our data set since we repeatedly observe stock characteristics of our sample. The observations are proxies for ESG and the remaining regression variables for the sample period between 2016 and 2020. Hence, we utilize a panel data set with cross-sectional units observed over time (Wooldridge 2010).

In an ideal data environment, we would adopt a more extended panel to leverage our analysis on more observations. Since our thesis examines the interaction between ESG and portfolio performance, the relevance of our results and applicability of the conclusions would require ESG focus amongst investors to be constant over the extended period. However, the topics of ESG and SRI have recently gained a foothold in financial markets (Global Sustainable Investment Alliance, 2021). Hence, observing a more extended panel could falter our conclusions, given the setting for our analysis.

Due to the listing and delisting of firms, we did not obtain a balanced panel for the sample period (Wooldridge 2010). Hence, the listing and delisting induce an inherent explanation for why the panel is unbalanced, increasing the risk of correlation with idiosyncratic errors. This would imply unobserved aspects that affect the independent variable and potentially lead to biased regression coefficients (Wooldridge 2012). In the optimal data environment, we would analyze a balanced panel with a consistent sample from Nasdaq Nordics Large Cap throughout the whole sample period.

4.2 ESG Proxies

In the optimal data environment, one common agency publishes transparent ESG ratings for all firms according to regulated guidelines. However, there are numerous ESG rating providers publishing divergent scores for the same firms (Livsey, 2022). Due to the ambiguity among ESG ratings, merely considering published scores to estimate investor perception of firm sustainability could induce inconsistent conclusions (Berg, Kölbel and Rigobon 2019). Hence, compliant with the methodology applied by Pedersen, Fitzgibbons, et al. (2021), we use one proxy for each ESG pillar and a weighted rating of all three pillars in the analysis. Since there are several ways to quantify ESG efforts, the following section describes the underlying rationale of our chosen proxies.

4.2.1 ESG-Proxy

To proxy how an investor assesses overall ESG, we use ratings provided by MSCI. MSCI publishes scores for a relatively large share of companies listed on Nasdaq Nordic and is one of the prominent and prolonged ESG-scoring providers (Livsey, 2022). Moreover, the MSCI scores are the same as those used by Pedersen et al. (2021) since the thesis does not aim to examine the ambiguity among ESG scoring providers.

4.2.2 E-Proxy

When assigning the Environmental pillar a quantitative metric, a comprehensive measure disclosing if the company adjusts its business to sustainability goals is desired. OECD presents that CO2 and GHG are commonly used as core metrics of the environmental pillar in ESG (Boffo, Marshall and Patalano, 2020). We hence proxy Environmental efforts as the natural logarithm of Greenhouse Gasses (scope 1 and 2) over Sales, while Pedersen et al (2021) uses Carbon Intensity over Sales. Following the methodology by Pedersen et al. (2021), the ratio is negated in order to assign greener companies a higher score. The GHG emissions are measured in kilotons, and sales are the reported end-year sales, including net income from investments, in millions of euros. The data was collected from Nordic Compass, a database provided by the Swedish House of Finance. The choice to use the natural logarithm on the E ratio derives from a performed skewness test. As shown in Table 13 in the appendix, the result exhibits positive skewness which is adjusted for using the natural logarithm to obtain a normal distribution of the data (Wooldridge, 2012).

4.2.3 S-Proxy

A central aspect of the Social pillar in ESG is how a company engages and interacts with the community surrounding its operations (S&P Global, 2020). Hence, our chosen proxy for Social efforts enclose if a company assesses its impact on local communities. The proxy is intrinsically binary, assigning the stock a value of 1 if it assesses its social impact on local communities and a value of 0 otherwise. The data is obtained from Nordic Compass.

4.2.4 G-Proxy

The Governance pillar aims to represent how well the company governs itself and complies with legislation and requirements from external stakeholders (Henisz and Koller, 2019). The Global Reporting Initiative provides standards for how a firm should disclose its sustainable responsibility. Hence, whether the company is compliant with the GRI standards is an indicator of a responsible company and accountability from the management (Global Reporting, 2022). Therefore our chosen proxy for Governance efforts is GRI compliance. The data is obtained from Nordic Compass, and discloses if the company reports in accordance with GRI guidelines level three or higher. GRI compliance is assigned a value of 1 and deviation from the standards a value of 0, making the proxy binary.

4.3 Regression Variables

4.3.1 Regression on Future Firm Fundamentals

4.3.1.1 Dependent Variables

Following the methodology by Pedersen et al. (2021), Gross Profit over Assets and Return on Net Operating Assets are used as the dependent variables when examining future firm fundamentals. Gross Profit over Assets aims to determine how effectively a company utilizes its assets to generate gross profits. Hence, GPOA is calculated as Gross Profit over total assets (Novy Marx, 2013). The purpose of adopting Return on Net Operating Assets as a financial metric is to capture the firm's operating profitability, excluding the impact of enforced capital structure. By excluding the effect of leverage, one attains a pure metric of profitability based on operational efficiency. Return on Net Operating Assets is calculated as Operating Income over Net Operating Assets[1] (Nissim and Penman, 2001). The financial statement data is obtained from Capital IQ.

$$GPOA_t = \frac{Gross\ Profit_t}{Total\ Assets_{t-1}}$$

$$RNOA_t = \frac{Operating\ Income_t}{Net\ Operating\ Assets_{t-1}}$$

The dependent variables are calculated as above. In the regressions, the metric for subsequent years are used as dependent variables. Hence the adopted dependent variables are $GPOA_{t+1}$ and $RNOA_{t+1}$.

Table 1. Descriptive Statistics Dependent Variable - GPOA(t+1)

Year	N	Mean	SD	Min	Max
All	**899**	**29.16%**	**25.94%**	**-13.08%**	**163.25%**
2016	160	33.92%	29.84%	10.75%	163.25%
2017	180	29.67%	26.56%	-13.08%	139.87%
2018	185	30.81%	26.18%	0.90%	149%
2019	189	26.77%	24.48%	6.78%	142.09%
2020	185	25.33%	22.06%	-5.42%	141.61%

The table reports the descriptive statistics for the dependent variable for each year during the sample period 2016-2020. GPOA is calculated as Gross profit at time (t), over total assets at time (t-1). The dependent variable reported in the table is GPOA at time (t+1) since we use the subsequents years GPOA as the dependent variable in our regressions.

Observable in Table 2 Panel A, the data for Return on Net Operating Assets include outliers in relation to the prevalent dataset. Since Ordinary Least Squares regressions may be sensitive to these data points (Wooldridge, 2012), we decided to remove extreme outliers for RNOA, as visible in Table 2, Panel B. Hence, the data used for Return on Net Operating Assets throughout our analysis are those with removed outliers.

[1] Net Operating Assets is further calculated as Net Working Capital + Goodwill + Other Intangibles + Net Property, Plant & Equipment (Stewart, 1990).

Table 2. Descriptive Statistics Dependent Variable - RNOA(t+1)

Panel A: RNOA(t+1)					
Year	N	Mean	SD	Min	Max
All	**868**	**-172.92%**	**53224.89%**	**-1565531.2%**	**57141.8%**
2016	155	-9.50%	3934%	-41919.46%	22811.23%
2017	173	330.06%	4365.04%	-4755.47%	57141.79%
2018	177	-241.32%	2919.16%	-36473.10%	1094.10%
2019	183	-8477.1%	115734.90%	-1565531.2%	8518.0%
2020	180	208.18%	1754.06%	-458.59%	21326.84%
Panel B: RNOA(t+1) with removed outliers					
Year	N	Mean	SD	Min	Max
All	**756**	**16.20%**	**15.19%**	**-31.98%**	**79.49%**
2016	127	16.59%	13.01%	-31.98%	61.49%
2017	152	16.65%	16.23%	-25.00%	78.38%
2018	156	17.07%	15.80%	-13.00%	73.42%
2019	164	13.87%	15.53%	-28.96%	78.59%
2020	157	16.62%	14.78%	-26.03%	79.49%

The table reports the descriptive statistics for the dependent variable for each year during the sample period 2016-2020. RNOA is calculated as Operating Income at time (t), over Net Operating Assets at time (t-1). Net Operating Assets is calculated as (Net Working Capital + Goodwill + Other Intangibles + Net Property, Plant & Equipment). Panel B shows RNOA(t+1) with removed extreme outliers and is the dependent variable used in the regressions. The dependent variable reported in the table is RNOA at time (t+1) since we use the subsequents years RNOA as the dependent variable in our regressions.

4.3.1.2 Independent Variables

Following the methodology by Pedersen et al. (2021), the control variables used are Market Beta, representing the expected change in the stock price relative to a change in the market (Berk and DeMarzo, 2017), the natural logarithm of the company's Market Capitalization, representing firm size, and the natural logarithm of book-to-price ratio[2]. The book-to-price ratio determines the market's stock valuation, where a high ratio indicates that the stock is undervalued (Berk and DeMarzo, 2017). Additionally, we implement a time dummy in the regressions in order to control for time fixed effects (Gösser and Moshgbar, 2020). Hence, all four regressions for each dependent variable are performed using constant control variables while the ESG proxies are separately integrated as the independent variables targeted to analyze.

Independent variables:

E = The negated greenhouse gas emission ratio

S = Social impact assessment on local communities

G = Reporting in accordance with GRI guidelines

ESG = The ESG score provided by MSCI

Beta = The market beta

Firm size = The natural logarithm of Market Capitalization

Book-to-Price = The natural logarithm book-to-price ratio

Year = A dummy variable for each year

[2] Book-to-price ratio is calculated as ((Total Assets-Total Liabilities)/Market Capitalization), (Berk and DeMarzo, 2017).

Table 3. Descriptive for independent variables - Firm Fundamentals

Variable	N	Mean	SD	Min	Max
E-proxy	742	0.94	2.77	-14.07	14.71
S-proxy	975	0.34	0.47	0	1
G-proxy	975	0.59	0.49	0	1
ESG-proxy	895	5.54	0.87	2	8.6
Beta	895	0.94	0.52	-0.23	3.73
LN(BM)	883	-0.90	0.81	-3.63	1.7
LN(Market Cap)	896	8.44	1.14	5.12	12,00

The table reports the descriptive statistics for the independent variables in the regressions for firm fundamentals. The independent variables; E LN(Negated GHG intensity), S (social impact on local communities), G (GRI compliance), and ESG (MSCI ESG Scores) are the four ESG metrics used in this thesis. The three control variablesare the Market Beta, the natural logarithm of the book-to-market ratio, and the natural logarithm of the Market Capitalization.

4.3.2 Regression on Valuation

4.3.2.1 Dependent Variable

Following the methodology by Pedersen et al. (2021), the natural logarithm of price-to-book ratio is used as the dependent variable for examining if our ESG-proxies are priced in the market. The price-to-book ratio is calculated as firm Market Capitalization divided by the Book Value, where the Book Value is calculated as the Assets minus Liabilities (Berk and DeMarzo, 2017). The data for Market Capitalization, Assets, and Liabilities is obtained from Capital IQ. The dependent variable is calculated as follows;

$$LN(P/B)_t = LN\left(\frac{Market\ Capitalization_t}{Book\ Value_t}\right)$$

Table 4. Descriptive Statistics Dependent Variable - LN(P/B)

Year	N	Mean	SD	Min	Max
All	**883**	**0.90**	**0.81**	**-1.70**	**3.63**
2016	157	0.93	0.76	-0.66	3.24
2017	174	0.94	0.74	-0.49	3.10
2018	181	0.79	0.80	-1.02	3.21
2019	187	0.91	0.80	-0.80	2.86
2020	184	0.93	0.93	-1.70	3.63

The table reports the descriptive statistics for the dependent variable LN(P/B) for each year during the sample period 2016-2020. LN(P/B) is the Natural Logarithm of the price-to-book ratio, calculated as Market Capitalization divided by Book Value (Total Assets minus Total Liabilities).

4.3.2.2 Independent Variables

Following the methodology by Pedersen et al. (2021), the targeted independent variables are our ESG proxies and the control variable is Market Beta. The additional control variables in the above descriptive statistics (Table 5), Market Capitalization and book-to-price ratio have been excluded as they intrinsically are integrated into the dependent regression variable.

Independent variables:

E = The negated greenhouse gas emission ratio

S = Social impact assessment on local communities

G = Reporting in accordance with GRI guidelines

ESG = The ESG score provided by MSCI

Beta = The market beta

Table 5. Descriptive Statistics Independent Variables - Valuation

Variable	N	Mean	Std. Dev.	Min	Max
E-proxy	742	3.80	2.77	-14.07	14.71
S-proxy	975	0.34	0.47	0	1
G-proxy	975	0.59	0.49	0	1
ESG-proxy	895	5.54	0.87	2.00	8.60
Beta	895	0.94	0.52	-0.23	3.73

The table reports the descriptive statistics for the independent variables in the regressions on valuation. The independent variables; E LN(Negated GHG intensity), S (social impact on local communities), G (GRI compliance), and ESG (MSCI ESG Scores) are the four ESG metrics used in this thesis. The control variable is the Market Beta.

4.3.3 Factor Return Regression

4.3.3.1 Dependent Variable

In line with Pedersen et al. (2021), these regressions aim to derive factor returns that can be applied to the expected return formulas applied in the ESG efficient frontier (see Equation 1 and 2). To incorporate the attributable explanatory value of book-to-market and ESG factor in relation to the remaining expected return formula, the dependent variable should express how well the stock performs in addition to equity risk premium. Hence, the dependent variable is realized yearly return, excess to market risk premium;

$$r_{t+1} = r_{realized} - \overline{MKT_t}$$

4.3.3.2 Independent Variables

Following the methodology applied by Pedersen et al. (2021), z-scores for each factor are used to estimate factor exposure. Z-scores are obtained using the following formula:

$$z\ score_x = \frac{X - \bar{X}}{\sigma}$$

Since the regression aims to examine the factor return for each ESG-proxy and book-to-market ratio; the following independent variables are used:

$$BM\ z\ score = z\ score_{Book\ to\ market\ ratio}$$
$$E\ z\ score = z\ score_{E\ proxy}$$
$$S\ z\ score = z\ score_{S\ proxy}$$
$$G\ z\ score = z\ score_{G\ proxy}$$
$$ESG\ z\ score = z\ score_{ESG\ proxy}$$

4.3.4 Factor Model Regressions

4.3.4.1 Dependent Variable

Following the methodology applied by Pedersen et al. (2021), monthly stock returns are used as the dependent variable when analyzing abnormal excess return. Stock returns are obtained using the following formula;

$$r_{i,t+1} = \frac{P_{i,t+1}}{P_{i,t}} - 1$$

where $P_{i,t}$ is the adjusted closing price for stock i at time t. Data on closing pricing have been obtained from Capital IQ.

4.3.4.2 Independent Variables

Following the methodology applied by Pedersen et al. (2021), the independent variables controlled for are market excess return and Fama French Factors (Fama and French, 1993). To proxy the market index, adjusted closing price for OMX Nordic 40 index was collected from Capital IQ. Market returns are calculated using the same formula as for stock returns. To proxy Risk-free rate, Swedish 10 year Government Debt was collected from Capital IQ.

Fama and French (1993), established that there exists a *small firm effect* from which firms with a small Market Capitalization outperform those with a high Market Capitalization and a *value premium*, from which firms with a high book-to-market outperform those with a low ratio. In an extended Fama and French factor model (five-factor), they revealed the existence of a *robustness premium* deriving an excess return for firms with robust operating profitability and an investment *premium* that generates excess return for firms that invest conservatively over those that invest aggressively. The Fama French Factors are collected from Kenneth R. French Dartmouth College Database (2022).

Independent variables:

$r_m - r_f$ = Market excess return

SMB = Factor premium for small firms

HML= Factor premium for value stocks

RMW= Factor premium for robust firms

CMA = Factor premium for conservative investments

5. Methodology

The following section describes the methodology applied to answer our research questions. Since portfolio management incorporates multiple mechanisms, sectional data analyses are crucial to obtain a comprehensive conclusion. Hence, the study is performed on four essential elements of portfolio management and partly replicates the methodology applied in Responsible Investing: The ESG-efficient frontier (2021). The sectional data analyzes yield the conclusion on how each ESG-proxy affects portfolio construction. To answer the second research question, we will investigate what happens when an investor is aware of the potential explanatory value each ESG-proxy has on stock prospects.

5.1 Ordinary Least Square Regressions

5.1.1 Regression on Future Firm Fundamentals

Following the methodology by Pedersen et al. (2021) we perform Pooled Ordinary Least Squares (OLS) regressions, to examine if each ESG-proxy respectively predicts future firm fundamentals. Thus, four Pooled OLS regressions, separately integrating the proxies, are performed on each profitability metric. The attributes of a panel dataset are considered through the clustering of standard errors at firm level. Hence, we control for unobserved firm specific characteristics that may occur when observing the same firm over several years (Wooldridge 2012). To further exclude the influence of time specific market conditions in the estimates, time fixed effects are applied to the Pooled OLS regressions (Wooldridge 2010). The yearly fixed effects are implemented through the usage of time dummies (Wooldridge, 2012). The Pooled Ordinary Least Square Regressions are formulated as following:

$$GPOA_{t+1} = \beta_0 + \beta_1 E_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$
$$GPOA_{t+1} = \beta_0 + \beta_1 S_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$
$$GPOA_{t+1} = \beta_0 + \beta_1 G_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$
$$GPOA_{t+1} = \beta_0 + \beta_1 ESG_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$

$$RNOA_{t+1} = \beta_0 + \beta_1 E_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$
$$RNOA_{t+1} = \beta_0 + \beta_1 S_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$
$$RNOA_{t+1} = \beta_0 + \beta_1 G_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$
$$RNOA_{t+1} = \beta_0 + \beta_1 ESG_t + \beta_2 Beta_t + \beta_3 Firm\ Size_t + \beta_4 Book\ to\ Price_t + \beta_5 year_t + \varepsilon$$

5.1.2 Regression on Valuation

To further examine if ESG characteristics are priced in the market, we perform Pooled OLS regressions with the natural logarithm of the price-to-book ratio as the dependent variable, compliant with Responsible investing: The ESG-efficient frontier (2021). Hence, these regressions aim to investigate how the market values ESG characteristics and if investors are willing to pay a higher price for these stocks. Pooled OLS regressions are performed for each ESG proxy, controlling for the Market Beta. As for the above regressions, standard errors are clustered at the firm level. Hence, the four regressions are formulated as following;

$$LN(P/B) = \beta_0 + \beta_1 E + \beta_2 Beta + \varepsilon$$
$$LN(P/B) = \beta_0 + \beta_1 S + \beta_2 Beta + \varepsilon$$
$$LN(P/B) = \beta_0 + \beta_1 G + \beta_2 Beta + \varepsilon$$
$$LN(P/B) = \beta_0 + \beta_1 ESG + \beta_2 Beta + \varepsilon$$

5.1.3 Factor return Regressions

To study if ESG-proxies can be quantified as indicators of returns, cross sectional Ordinary Least Square Regressions are performed. As described in the data section, realized returns excess to the market in the following year are used as the dependent variable. Compliant with the methodology applied in Responsible investing: The ESG-efficient frontier (2021), book-to-market z-score and z-score for the respective ESG-proxy are used as independent variables to represent the factor exposure. The regression coefficient will hence be interpreted as factor returns.

Compliant with Pedersen et al. (2021), this thesis assumes that an U-investor utilizes that returns are solely driven by valuation, while an A-investor will additionally consider ESG as explanatory for returns. Hence, to distinguish their diverse awareness on what available information to exploit in predictions, separate regressions are performed. The five Cross-sectional regressions are thus formulated as following;

$$r_{t+1}(U\ investor) = \beta_0 + \beta_1 BM\ z\ score_{i,t} + \varepsilon$$
$$r_{t+1}(A\ investor) = \beta_0 + \beta_1 BM\ z\ score_{i,t} + \beta_2 E\ z\ score_{i,t} + \varepsilon$$
$$r_{t+1}(A\ investor) = \beta_0 + \beta_1 BM\ z\ score_{i,t} + \beta_2 S\ z\ score_{i,t} + \varepsilon$$
$$r_{t+1}(A\ investor) = \beta_0 + \beta_1 BM\ z\ score_{i,t} + \beta_2 G\ z\ score_{i,t} + \varepsilon$$
$$r_{t+1}(A\ investor) = \beta_0 + \beta_1 BM\ z\ score_{i,t} + \beta_2 ESG\ z\ score_{i,t} + \varepsilon$$

5.1.4 Underlying assumptions of Ordinary Least Square Regression

The Ordinary Least Square regression assumes that no multicollinearity exists between the independent variables meaning the regression variables are not correlated to one another. Furthermore, the OLS makes an assumption about homoscedasticity implying that the variance among error terms are equal or highly similar for the model. If the regression violates any of the underlying assumptions of Ordinary Least Square Regression, the validity of the results diminishes (Newbold and Carlson, 2012).

To test if the assumption about no multicollinearity holds, a Variance Inflation Factors-test (VIF) is performed. As reported in Table 14-17 in the appendix, no multicollinearity among our regression variables exists since no VIF-value is above 10 (Wooldridge 2012). To further conclude if the dataset is homoscedastic, we perform a Breush-Pagan test. As presented in Table 18-19 in the appendix, the test shows heteroscedasticity for part of the data.

5.1.5 Adjusting for heteroskedasticity

Performing the Breusch-Pagan test, heteroskedasticity is identified in the models which indicates that the usage of Ordinary Least Square Regression may not provide the best linear unbiased estimator (Newbold and Carlson, 2012). Hence, robust standard errors are applied on the OLS regressions to account for heteroscedasticity. Since the Pooled OLS regressions on Valuation are performed with clustered standard errors, the model intrinsically accounts for heteroskedasticity and no further adjustment is required (Newbold and Carlson, 2012).

5.2 Factor Model Regression

To conclude if a sustainable approach in portfolio management induces abnormal excess returns, time-series regressions are performed on three distinguished factor models; Capital Asset Pricing Model, Fama French three-factor Model and Fama French five-factor Model. Following the methodology in Responsible Investing: The ESG-efficient frontier (2021), the abnormal excess return is interpreted as the alpha of each factor model regression.

Each year, our sample is sorted into five portfolios based on quintiles of their ESG-score and E-proxy. For the Governance and Social proxy, only two portfolios are created since the scores are binary. The portfolios are constructed at time t while monthly returns for the following year are observed. Each year, the portfolios are rebalanced to account for development of the firms' sustainability level. For each proxy, an additional portfolio is created that goes long stocks from the highest portfolio and short the ones from the lowest yielding a Good-minus-Bad (GmB) portfolio. The alpha our regression derives is that of the ESG factor mimicking GmB portfolio.

The first regression is derived from the Capital Asset Pricing Model (Berk and DeMarzo, 2017):

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \times (r_{M,t} - r_{f,t}) + \varepsilon$$

Where $(r_{M,t} - r_{f,t})$ represents the monthly market excess return at time t. $r_{i,t} - r_{f,t}$ is the excess return of portfolio i at time t and ε is the residual (error term).

As the purpose is to identify if there exists a factor premium associated with ESG, the derived results will increase in robustness if the influence of already established factor premiums are isolated. Hence, the second regression used is derived from the Fama and French three-factor model (1993):

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \times (r_{M,t} - r_{f,t}) + \beta_{i2} \times SMB_t + \beta_{i3} \times HML_t + \varepsilon$$

To further isolate impacting factors, the third regression is derived from the Fama and French five-factor model (1993):

$$r_{i,t} - r_f = \alpha_i + \beta_i \times (r_{M,t} - r_{f,t}) + \beta_{i2} \times SMB_t + \beta_{i3} \times HML_t + \beta_{i4} \times RMW_t + \beta_{i5} \times CMA_t + \varepsilon$$

5.3 ESG-efficient frontier

To visualize the outcome of the above described data analyses and conclude on the second research question; Can ESG awareness diminish the trade-off between portfolio performance and sustainability inclusion?, the thesis will lastly derive the ESG-efficient frontier.

According to modern portfolio theory, investors are assumed to consider the expected return and risk for their investment sphere before constructing a portfolio that satisfies their mean-variance preferences (Berk and DeMarzo, 2017). We will, in line with Pedersen et. al (2021), consider an extended mean-variance evaluation in which the investor constructs a portfolio based on preferences in risk, return and sustainability.

Following the methodology in Responsible investing**:** The ESG-efficient frontier (2021), the A-investor and U-investor perceive the prospect of each stock differently due to a diverse knowledge and understanding of how Environmental, Social, and Governance factors impact return. The U-investor is assumed to perceive annualized expected return as:

$$E_t^U(r_{i,t+1}) = \overline{MKT_t} + bm_{i,t}\overline{BM_t} \qquad \text{Eq. 1}$$

where, $\overline{MKT_t}$ is the equity risk premium, $bm_{i,t}$ is the cross-sectional z-score of the stock's book-to-market ratio and $\overline{BM_t}$ is the factor return of the book-to-market ratio, derived from the cross sectional factor return regression in Table 10.

An A-investor is assumed perceive annualized expected as;

$$E_t^A(r_{i,t+1}) = \overline{MKT_t} + bm_{i,t}\overline{BM_t} + s_{i,t}\overline{ESG_t} \qquad \text{Eq. 2}$$

where, $s_{i,t}$is the stock's cross-sectional z-score of the proxy for ESG and $\overline{ESG_t}$ is the factor return of the proxy for ESG, derived from the cross sectional factor return regression in Table 10.

Both investors are assumed to choose the portfolio that maximizes Sharpe ratio, calculated as the portfolio expected excess return over portfolio standard deviation (Berk and DeMarzo, 2017). Since the two investors perceive expected return for the individual stock differently, the U-investor and A-investor will choose two different portfolios, allowing for dissimilar Sharpe ratios. To visualize the trade-off between risk adjusted return and portfolio sustainability level, an ESG-efficient frontier is plotted respectively for both investors with Sharpe ratio on the y-axis and ESG level on the x-axis. The frontier reveal portfolios that maximize Sharpe ratio for each level of portfolio ESG preference computed as;

$$ESG_{portfolio} = \Sigma\ (W_i \times ESG_i)$$

The perceived frontier is plotted based on each investor's expectations on portfolio return. A second ESG-efficient frontier is thereafter plotted with realized Sharpe ratios of the portfolios from the perceived frontier for each investor. The realized Sharpe ratio for each portfolio is computed on the basis of annual stock returns.

6. Empirical Analysis

6.1 Do ESG Characteristics Predict Firm Fundamentals?

Table 6 and 7 shows the results of the pooled regressions with yearly fixed effects for our sample. The regressions aim to examine our first hypothesis on whether our ESG-proxies predict future firm fundamentals, estimated by Gross Profit over Assets and Return on Net Operating Assets.

Table 6. Do ESG characteristics predict future firm fundamentals?

Dependent variable	RNOA (t+1)			
	(1)	(2)	(3)	(4)
E-proxy	0.0015			
	(0.66)			
S-proxy		0.0270*		
		(2.11)		
G-proxy			0.0084	
			(0.46)	
ESG-proxy				-0.0182
				(-1.67)
Beta	0.0264*	0.0147	0.0153	0.0174
	(2.36)	(1.14)	(1.16)	(1.24)
LN(BM)	-0.0977***	-0.0864***	-0.0869****	-0.0927***
	(-12.17)	(-6.00)	(-5.72)	(-6.55)
LN(Market Cap)	0.0096	0.0065	0.0077	0.0119
	(1.69)	(0.76)	(0.86)	(1.25)
Constant	-0.0307	0.0018	0.0045	0.0683
Number of observations	574	743	743	686
R-squared	0.241	0.197	0.192	0.208
Adjusted R-squared	0.230	0.188	0.183	0.199
Estimation method	Pooled with time FE	Pooled with time FE	Pooled with time FE	Pooled with time FE

This table reports the regression of future firm fundamentals, measured as Return on Net Operating Assets, on our current ESG proxies. Return on Net Operating Assets is hence measured one year into the future. The four proxies for ESG are E LN(Negated GHG intensity), S (social impact on local communities), G (GRI compliance), and ESG (MSCI ESG Scores). The three control variablesare the Market Beta, the natural logarithm of the book-to-market ratio, and the natural logarithm of the Market Capitalization. The estimation method is a pooled regression with yearly fixed effect.
Robust *t-statistics* are in parantheses and clustered at the firm level.
***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 6 reports the results from the regression using Return on Net Operating Assets as the dependent variable and discloses low significance levels. The only control variable exhibiting significance at a 1% level is the natural logarithm of the book-to-market ratio. Moreover, the regression coefficients for our E, G, and ESG proxies are insignificant, suggesting that they have no predictability of the following years' RNOA. However, the positive coefficient for our S-proxy on a 10% significance level indicates that Social efforts proxied as the social impact on local communities have an explanatory value. Hence, the first hypothesis is rejected for all proxies except for our Social, emphasizing that the analyzed ESG-proxies are not predictors of future firm fundamentals.

Table 7. Do ESG characteristics predict future firm fundamentals?

Dependent variable	GPOA (t+1)			
	(1)	(2)	(3)	(4)
E-proxy	0.0006			
	(0.13)			
S-proxy		0.0317		
		(1.63)		
G-proxy			0.0187	
			(0.74)	
ESG-proxy				0.0217
				(1.04)
Beta	0.0733*	0.0648*	0.0659*	0.0692*
	(2.02)	(2.19)	(2.20)	(2.20)
LN(B/M)	-0.1925***	-0.1970***	-0.1992***	-0.2042***
	(-8.11)	(-9.16)	(-9.08)	(-9.36)
LN(Market Cap)	-0.0233	-0.0251	-0.0246	-0.0290*
	(-1.60)	(-1.90)	(-1.83)	(-2.05)
Constant	0.2973*	0.2852*	0.2884*	0.2118
	(2.23)	(2.51)	(2.53)	(1.29)
Number of observations	668	867	867	803
R-squared	0.335	0.355	0.353	0.373
Adjusted R-square	0.327	0.349	0.347	0.366
Estimation method	Pooled with time FE	Pooled with time FE	Pooled with time FE	Pooled with time FE

This table reports the regression of future firm fundamentals, measured as Gross Profit over Assets, on our current ESG proxies. Gross Profit over Assets is hence measured one year into the future. The four proxies for ESG are E LN(Negated GHG intensity), S (social impact on local communities), G (GRI compliance), and ESG (MSCI ESG Scores). The three control variablesare the Market Beta, the natural logarithm of the book-to-market ratio, and the natural logarithm of the Market Capitalization. The estimation method is a pooled regression with yearly fixed effect.
Robust *t-statistics* are in parantheses and clustered at the firm level.
***p-value<0.01, **p-value<0.05, *p-value<0.1

Compliant with the previously discussed profitability metric, the regression coefficients experience low significance when Gross Profit over Assets is applied as the dependent variable. As observed in Table 6, the natural logarithm of the book-to-market exhibits negative coefficients at a significance level of 1%. The insignificance of regression coefficients for the ESG proxies anchor the rejection of our first hypothesis. We hence conclude that our examined ESG characteristics have no predictability of future firm fundamentals.

Furthermore, the above regressions identify no predictability in our ESG-proxy. These results align with what Pedersen et al. (2021) observe for RNOA. Hence, in consensus with Pedersen et al. (2021), we conclude that information about MSCI ESG-score cannot be exploited in portfolio management to identify prospects in firm operations if the investor uses RNOA to estimate profitability. However, contradictory to our results, Pedersen et al. (2021) found a significant coefficient for MSCI ESG-proxy in the regression on GPOA. Based on their findings, an ESG aware investor can use the ESG-proxy to predict firm profitability, measured as GPOA. However, the same conclusion is not obtained for our sample, and we cannot suggest the exploitation of MSCI ESG score in portfolio management.

Moreover, our S-proxy shows a positive relation to RNOA at a 10% significance level which contradicts the negative relation found by Pedersen et al. (2021). However, their proxy for Social is the sin stock indicator presented by Hong and Kacpercyk (2009). Pedersen et al. (2021) assign companies engaging in sin industries a value of 0 and a value of 1 otherwise. Hence, their results suggest that sin companies are predicted to demonstrate higher Return on Net Operating Assets in the subsequent period than non-sin companies. In comparison, we find that information about if companies assess their social impact on local communities has an explanatory value of RNOA in the following year. Although our findings are different from Pedersen et al. (2021), the analyzed S-proxy target dissimilar aspects of the S pillar in ESG. The proxy employed by Pedersen et al. (2021) focuses on the industry in which the firm is operating, while our examined proxy aims to describe how the firm engages with the society enclosing its operations. Hence, the contradicting results suggest that distinguished elements within the S pillar affect a firm's operating profitability differently.

Compliant with Pedersen et al. (2021), we found no significant predictability in our E- or S-proxy of future Gross Profit over Assets. As previously discussed, we use different proxies for Environmental and Social efforts than those utilized in Responsible investing: The ESG-efficient frontier (2021). Our agreement in results suggests that the absence of relation between future GPOA and the pillar remains, even when Environmental and Social efforts are estimated differently. As part of our contribution, we therefore enhance Pedersen et al.'s (2021) conclusion and extend it with more exhaustive implications about Pillar predictability.

Furthermore, no significance for our E- and G-proxy are observed, when employing RNOA as the dependent variable. Contradictory, Pedersen et al. (2021) found positive coefficients for their E- and G-proxy at a 1% significance level. Pedersen et al. (2021) hence conclude that their adopted proxies for Environmental and Governance predict Return on Net Operating Assets. We observe no predictability, which in contrast to Pedersen et al. (2021) implies that an ESG-aware investor cannot utilize information about our E- and G-proxy to increase performance in portfolio management. As a part of our contribution to the area of research, we cannot anchor the conclusions derived in Responsible investing: The ESG-efficient frontier (2021).

As discussed above, our results are considerably different from the findings in Responsible investing: The ESG-efficient frontier (2021). The contradictory results are partly derived from the usage of different proxies for each ESG pillar but can also be explained by the distinct attributes of our sample. Pedersen et al. (2021) leverage data from a sample period spanning January 1963 to March 2019 for their E-, S-, and G-proxies and from January 2007 to March 2019 for the MSCI ESG scores, while our sample period is limited to 2016-2020. Since the ESG focus among investors has substantially increased (Global Sustainable Investment Alliance, 2021) in recent years, it is reasonable to assume differences in prerequisites for sustainability in the financial market. Additionally, their time-fixed effects are executed on a monthly basis in contrast to our yearly fixed effects. The reason behind our different methodologies is the limitation in availability of monthly data for our proxies.

6.2 Are ESG Characteristics Valued by the Market?

Table 8: Do ESG characteristics exhibit higher valuation?

Dependent variable	LN(P/B)			
	(1)	(2)	(3)	(4)
E-proxy	0.0269			
	(1.26)			
S-proxy		0.0235		
		(0.35)		
G-proxy			-0.294**	
			(-3.18)	
ESG-proxy				0.074
				(1.41)
Beta	-0.4992***	-0.4308***	-0.4385***	-0.4134***
	(-5.44)	(11.65)	(-5.08)	(-4.28)
Constant	1.2664***	1.2924***	1.4824***	0.8884**
	(9.47)	(11.65)	(11.65)	(2.73)
Number of observations	674	875	875	811
R-squared	0.116	0.076	0.107	0.078
Adjusted R-square	0.114	0.074	0.105	0.076
Estimation method	Pooled	Pooled	Pooled	Pooled

This table reports the regression for the valuation ratio (Natural Logarithm of the price-to-book ratio) on each ESG proxy. The four proxies for ESG are E LN(Negated GHG intensity), S (social impact on local communities), G (GRI compliance), and ESG (MSCI ESG Scores). We control for Market Beta in the regression. The estimation method is a pooled regression. Robust *t-statistics* are in parantheses and clustered at the firm level.
***p-value<0.01, **p-value<0.05, *p-value<0.1

The Pooled OLS regression with the natural logarithm of price-to-book ratio as dependent variable aims to determine whether the ESG characteristics are priced in the market. A significant, positive relationship between the proxies for ESG pillars and the price-to-book ratio hence indicates the market's willingness to pay a higher price for sustainable characteristics. Consequently, a negative regression coefficient infers that the implied proxy is not priced in the market and could be exploited by ESG-aware investors if it is a predictor of future firm fundamentals. Furthermore, Table 8 exhibits that the governance proxy has a significant negative coefficient. Interpreting these results, companies that are not GRI compliant exhibit a higher price-to-book ratio than those that are. Hence, the market does not value our estimate for governance efforts, and we can reject the second hypothesis for the G-proxy. However, for the remaining ESG proxies, we find no significant explanatory value of the valuation ratio, implying that we cannot conclude that investors value these ESG characteristics. Hence we have to reject our second hypothesis for all examined proxies.

Our result of a significant, negative coefficient for the G proxy is compliant with the results proposed by Pedersen et al. (2021) for their employed governance proxy. Pedersen et al. (2021) adopted low accruals as a proxy for Governance, with the motivation that accurately governed firms possess conservative accounting principles (Sloan, 19966, Kim et al., 2012). The G-proxy analyzed in our study covers GRI compliance and is, therefore, another way of quantifying well-governed firms. Nevertheless, both proxies depict the G pillar in ESG but in a distinct manner. Hence, our compliant results support the consensus that good governance is a firm characteristic that is not priced in the market. The conclusion indicates that aware investors could gain higher returns on stocks with high G-proxy, under the prerequisite that the governance characteristic is a predictor of future firm fundamentals.

As previously discussed, Pedersen et al. (2021) suggest that their G-proxy is a predictor of future firm fundamentals. Combining the observed predictability with the result that their G-proxy is not priced in the market, they conclude that investors can utilize information about the concerned proxy in investment decisions. In contrast, we found no predictability of future firm fundamentals, implying that we cannot conclude how the negative coefficient for the G-proxy in Table 8 can be used in portfolio construction. Hence, our results cannot fully establish the conclusion derived by Pedersen et al. (2021) that information about G-proxy is valuable to accomplish a well-performing portfolio.

6.3 Do ESG Predict Returns?

Table 9: Do environmental, social and governance efforts predict returns?

	E (low ghg)	S (Asses Social impact)	G (GRI-compliant)	ESG (MSCI)
Panel A: Equal-weighted returns				
CAPM alpha	7.17%	2.45%	-3.2%	12.25%**
	(1.45)	(0.85)	(-1.06)	(2.46)
Three-factor (FF3) alpha	6.81%	3.14%	-3.11%%	10.83%**
	(1.31)	(1.06)	(-0.99)	(2.22)
Five-factor (FF5) alpha	5.27%	3.43%	-4.31%	6.6%
	(0.95)	(1.09)	(-1.33)	(1.34)
Panel B: Value-weighted returns				
CAPM alpha	1.52%	0.66%	-9.86%***	15.37%**
	(0.28)	(0.18)	(-2.87)	(2.58)
Three-factor (FF3) alpha	2.26%	1.32%%	-7.36%**	14.9%**
	(0.40)	(0.34)	(-2.19)	(2.54)
Five-factor (FF5) alpha	0.81%	1.92%	-8.6%**	15.65%**
	(0.13)	(0.46)	(-2.44)	(2.64)

The table reports the performance of good minus bad portfolios for each ESG proxy respectively in the sample period 2016-2021. It reports on the portfolio's one-factor CAPM alpha, three-factor alpha, and five-factor alpha that controls for the FF factors. t-*statistics* are in parentheses

*** p-value <0.01, ** p-value <0.05, * p-value <0.1

To assess if the usage of our ESG-proxies can enhance return predictions, the abnormal excess returns of the Good-minus-Bad portfolios are observed. An abnormal excess return observation indicates that the factor mimicking portfolio outperforms benchmark predictions. Hence, a statistically significant alpha implies that the factor model applied does not perfectly predict returns, which signals that the corresponding ESG-proxy has explanatory value in return predictions. As reported in Table 9, the portfolios constructed based on our Environmental and Social proxy do not experience a significant abnormal excess return. Thus we cannot conclude if they can be used in valuation to predict returns. These results are somewhat contradictory to the ones found by Pedersen et al. (2021). They found a negative alpha for the three-factor model in the value-weighted portfolio for their S-proxy, suggesting that their adopted S-proxy should be incorporated as a return discount in prediction. Furthermore, they find a positive alpha for the portfolio based on their E-proxy when applying the CAPM factor model at a 5% significance level. However, the significance decreases when applying the extended factor models. Fama French has established evidential factors with the predictive value of returns (Fama and French, 1993), that should be considered for a more robust conclusion. Since Pedersen et al.'s (2021) does not observe significant abnormal excess return when applying the

Fama french factor models, their observed CAPM alpha could potentially derive from Fama french factors and not from the applied E-proxy. Therefore, our conclusion that information about environmental efforts does not predict future returns is in line with Pedersen et al. (2021) when isolating previously established explanatory factors.

The factor mimicking portfolio for MSCI ESG-score report on a positive significant alpha when regressed as a Capital Asset Pricing Model for both the equal-weighted and value-weighted portfolio. The positive and significant abnormal excess return remains when further isolating the impact of established alphas in the Fama French Factor models (1993). The results communicate that sustainability proxied as MSCI ESG score can be used as an informative factor in portfolio construction and has an explanatory value of returns. Hence, adding a return premium to the conventional factor models for stocks with a high MSCI ESG score could potentially absorb the abnormal excess return and allow a more realistic prediction. Our finding of a positive abnormal excess return for the MSCI ESG proxy contradicts what Pedersen et al. (2021) establish in their study. They find no significant alpha when applying either factor model to the excess return. Hence they conclude that information about a stock's MSCI ESG-score cannot be used in return predictions to derive more accurate estimates. Since we utilize the same ESG-proxy as in Responsible investing: The ESG-efficient frontier (2021), the contradictory conclusions illuminate that their findings do not apply to our sample. Hence, we contribute with insights that emphasize how distinct market settings provide dissimilar prerequisites for Sustainable Responsible Investing. As previously discussed, we examine a sample period following the monumental shift in ESG relevance on financial markets, while Pedersen et al. (2021) applies a more extended period. Hence, the increased interest in Sustainable Responsible Investing might affect the setting for ESG stocks and generate an enhanced explanatory value for future returns.

The factor mimicking portfolio for sustainability proxied as GRI compliance report significant results for the value-weighted portfolio. As observed in Table 9**,** alpha is consistently negative for all three-factor models indicating that the excess return of a portfolio constructed based on Governance proxy underperforms predictions made by the Capital Asset Pricing Model and Fama French factor model. Hence, the results reveal that an investor can include a return discount attributed to stocks with high governance levels to obtain a more precise estimate. Our results contradict the positive alpha for the G-proxy presented in Pedersen et al. (2021). Hence, there is an ambiguity in whether information spawned from a firm's governance efforts comprises a return premium or discount for predictions. Since our study concludes on a dissimilar G-proxy than in Responsible investing: The ESG-efficient frontier (2021), it contributes with insights that all parts of the Governance pillar cannot be assumed to predict returns in similar manners. Summarily, reviewing the result, we do not reject our third hypothesis for our ESG and Governance proxy but for the Environmental and Social proxy. Hence, we conclude that ESG proxied as GRI compliance and MSCI ESG score do predict returns.

6.4 Quantification of ESG's Predictive Value

The cross-sectional Ordinary Least Squares regressions performed with realized return excess to the market as a dependent variable aims to further unfold the predictability of ESG-proxies. Factor returns quantifies the explanatory value on stock returns attributed to the exposure of book-to-market and ESG-level. Hence, the regression reveals how much of a stock's realized return can be explained by its level of sustainability in relation to valuation.

Table 10: Quantification of ESG-characteristics predictive value

Panel A: 2016					
Dependent variable	Realized Yearly Excess Return (t+1)				
	(1)	(2)	(3)	(4)	(5)
BM Z-Score	0.01487	0.0290	0.0207	0.0155	0.0186
	(0.92)	(1.58)	(1.14)	(0.96)	(1.17)
E Z-Score		-0.0047			
		(-0.25)			
S Z-Score			0.02640		
			(1.22)		
G Z-Score				-0.0266	
				(-1.38)	
ESG Z-Score					0.0481*
					(2.24)
Constant	0.1124***	0.1218***	0.1107***	0.1125***	0.1080***
	(5.97)	(6.28)	(5.82)	(6.00)	(5.67)
Multiple R-squared	0.004	0.014	0.015	0.016	0.045
Adjusted R-square	-0.002	-0.003	0.002	0.004	0.031
Estimation method	OLS	OLS	OLS	OLS	OLS

Panel B: 2017					
Dependent variable	Realized Yearly Excess Return (t+1)				
	(1)	(2)	(3)	(4)	(5)
BM Z-Score	-0.0180	-0.0438*	-0.0165	-0.0150	-0.0171
	(-0.94)	(-2.19)	(-0.87)	(-0.79)	(-0.82)
E Z-Score		0.0155			
		(1.06)			
S Z-Score			(0.0207)		
			(1.15)		
G Z-Score				-0.0334*	
				(-1.99)	
ESG Z-Score					0.0030
					(0.16)
Constant	-0.0417*	-0.0456*	-0.0422*	-0.0416*	-0.0469*
	(-2.44)	(-2.41)	(-2.49)	(-2.46)	(-2.60)
Multiple R-squared	0.006	0.038	0.014	0.027	0.006
Adjusted R-square	0.0005	0.022	0.003	0.016	-0.007
Estimation method	OLS	OLS	OLS	OLS	OLS

Panel C: 2018					
Dependent variable	Realized Yearly Excess Return (t+1)				
	(1)	(2)	(3)	(4)	(5)
BM Z-Score	-0.0316	-0.0346	-0.0318	-0.0283	-0.0369
	(-1.31)	(-1.48)	(-1.32)	(-1.20)	(-1.49)
E Z-Score		0.0001			
		(0.00)			
S Z-Score			0.0032		
			(0.20)		
G Z-Score				-0.0327	
				(-1.43)	
ESG Z-Score					-0.0189
					(-0.65)
Constant	-0.0544*	-0.0826***	-0.0540*	-0.0539*	-0.0685**
	(-2.37)	(-3.71)	-(2.36)	(-2.35)	(-2.87)
Multiple R-squared	0.010	0.017	0.010	0.021	0.015
Adjusted R-square	0.005	0.001	-0.001	0.010	0.003
Estimation method	OLS	OLS	OLS	OLS	OLS

Panel D: 2019					
Dependent variable	Realized Yearly Excess Return (t+1)				
	(1)	(2)	(3)	(4)	(5)
BM Z-Score	-0.1050***	-0.0659*	-0.1053***	-0.0994**	-0.1105**
	(-3.47)	(-2.34)	(-3.50)	(-3.30)	(-3.14)
E Z-Score		-0.0060			
		(-0.15)			
S Z-Score			0.0076		
			(0.29)		
G Z-Score				-0.0544	
				(-1.64)	
ESG Z-Score					0.0067
					(0.18)
Constant	0.1254***	0.0908**	0.1258***	0.1242***	0.1318***
	(3.93)	(2.92)	(3.98)	(3.94)	(3.97)
Multiple R-squared	0.055	0.032	0.055	0.069	0.056
Adjusted R-square	0.050	0.018	0.045	0.059	0.048
Estimation method	OLS	OLS	OLS	OLS	OLS

Panel E: 2020					
Dependent variable	Realized Yearly Excess Return (t+1)				
	(1)	(2)	(3)	(4)	(5)
BM Z-Score	0.0489	0.0402	0.0436	0.0501	0.0586
	(1.55)	(1.33)	(1.35)	(1.49)	(1.25)
E Z-Score		0.0199			
		(0.77)			
S Z-Score			-0.0720***		
			(-3.42)		
G Z-Score				-0.0327	
				(-1.11)	
ESG Z-Score					-0.0262
					(-1.02)
Constant	-0.0760**	-0.0688**	-0.0749**	-0.0753**	-0.0706**
	(-3.15)	(-2.92)	(-3.16)	(-3.12)	(-2.99)
Multiple R-squared	0.021	0.018	0.067	0.030	0.031
Adjusted R-square	0.016	0.006	0.057	0.020	0.019
Estimation method	OLS	OLS	OLS	OLS	OLS

This table reports the regressions for the Factor Returns for the Z-scores for the book-to-market ratio and the four ESG-proxies. The dependent variable is the realized yearly return, excess to market risk premium. The four ESG-proxies are the same as in Table 6. The estimation method is OLS.
Robust *t-statistics* are in parantheses.
***p-value<0.01, **p-value<0.05, *p-value<0.1

The regressions in Table 10 exhibit low significance level for the independent variables which indicates that the quantification of our ESG-proxies' predictive value cannot be obtained for all observations. The exposure of our ESG-proxy reports a positive and significant factor return in 2016 which suggests that a return premium can be attributed to high MSCI ESG-rating. The regressions disclose a negative, significant factor return for our G-proxy in 2016 and for our S-proxy in 2020. These results imply that a factor discount was derived for firms with a high Governance score and Social score for the implied years. In Responsible Investing: The ESG-efficient frontier (2021), the observed factor returns are not reported. Therefore, we cannot derive a comparable discussion for contributing insights.

7. Discussion

Since our thesis aims to reveal the interplay between how ESG affects firm profitability and stock valuation, we have studied the two areas separately but will henceforth disclose the possibility to integrate them. Hence, the following section will firstly discuss the two areas in relation to existing literature and thereafter visualize the implications from incorporating ESG's informative value into portfolio management.

7.1 How do our Findings Relate to Previous Literature?

We rejected our first hypothesis about ESG characteristics' predictability of firm fundamentals for all proxies except the S-proxy. The absence of explanatory value for the profitability metrics are contradictory to the findings by Ferrell, Liang et al. (2016), stating that a positive correlation between CSR and firm value exists. Moreover, Friede, Busch, et al. (2015) presented that the majority of empirical studies find a positive relationship between Corporate Financial Performance and sustainable efforts. Our contradicting results are intrinsically contributing to the literature since they indicate that ESG characteristics are not predictors of firm fundamentals within our sample period. Since Ferrell, Liang et al. (2016) and Friede, Busch, et al. (2015) performed their studies before the monumental shift in relevance of ESG on financial markets, their sample experiences different conditions than ours. To accurately examine how ESG affects the interplay between firm fundamentals and portfolio construction, it is crucial that the concluding implications for portfolio management are derived from prevailing market conditions. While challenging previous research, our thesis hence contributes to the research since it observes the current environment for sustainable investing.

To enable the incorporation of ESG into portfolio management, it is furthermore essential to consider what time frame of Corporate Financial Performance that provides the most efficient information. There is a substantial distinction between our thesis and the empirical papers examining firm's ESG commitment with regards to the time frame of applied profitability metrics. Ferrell, Liang, et al. (2016) and Friede, Busch et al. (2015) have a long-term perspective on firm profitability in their studies since they focus on firm value and Corporate Financial Performance, which are metrics that intrinsically emphasize future value. However, in line with Pedersen et al. (2021), our study aims to determine if ESG characteristics could be employed by an ESG-aware investor whose primary goal is to achieve the highest possible risk-adjusted return while still considering ESG. Since our thesis integrates the conclusions on how ESG relates to CFP with the ones on how ESG affects stock prospects, it is more relevant to apply a shorter time frame on the analyzed metric. It is reasonable to assume that the average investor will rebalance its portfolio on a regular basis and therefore benefits more from insights derived from a shorter perspective. Previous research oversees how the interplay between ESG and Corporate Financial Performance can be exploited in portfolio management since they use a longer time frame on firm characteristics. Through the utilization of a shorter time frame, we more precisely examine the financial incentives to invest sustainably.

Further on, we rejected the second hypothesis stating that we expect ESG characteristics to be priced in the market. Hong, Kacperczyk (2009) and Taylor, Stambaugh et al. (2019), suggests that the increased focus on sustainability among investors has induced higher demand for companies with high ESG levels. Gelema et al. (2008) further reveals that the increased demand has derived premium prices. Hence, rejecting our second hypothesis contradicts previous literature. Moreover, our insignificant coefficients for the E-, S-, and ESG-proxy suggest that we cannot conclude on the relation between ESG and valuation. Thus the results by Hong, Kacperczyk (2009), Taylor, Stambaugh et al. (2019), and Gelema et al. (2008) do not hold for our sample. Hence, we contribute to the literature with the insight that a common relation between how the market values a stock and the stock's ESG is not applicable to all market settings.

As discussed above, our study concludes that information about ESG has little informative value of firm fundamentals in our sample. Therefore we can not suggest that portfolio construction can be enhanced by the utilization of firm fundamentals predictions. However, the integration of ESG into portfolio management can still be attained through information about how ESG predicts stock return. As previously disclosed, our study on factor models concludes that ESG proxied as MSCI ESG-score have predictive value of stock returns, compliant with Kempf and Osthoff (2007). In contrast to Kempf and Osthoff (2007), our study utilizes that ESG can be divided into three pillars and hence considers a more extensive estimate of sustainable efforts. However, as discussed in section 6.3, our results exhibit discrepancy in the proxies' predictive value, which emphasizes the importance of considering each ESG pillar individually. Kempf and Osthoff's (2007) identification of an explanatory value attributed to ESG has provoked the interest to investigate how one can utilize information about ESG in portfolio construction. Hence, our finding that each ESG pillar has different predictive value provides contributing insights that need to be considered in investment decisions which is further discussed in section 7.2

7.2 Incorporation of ESG into Portfolio Management

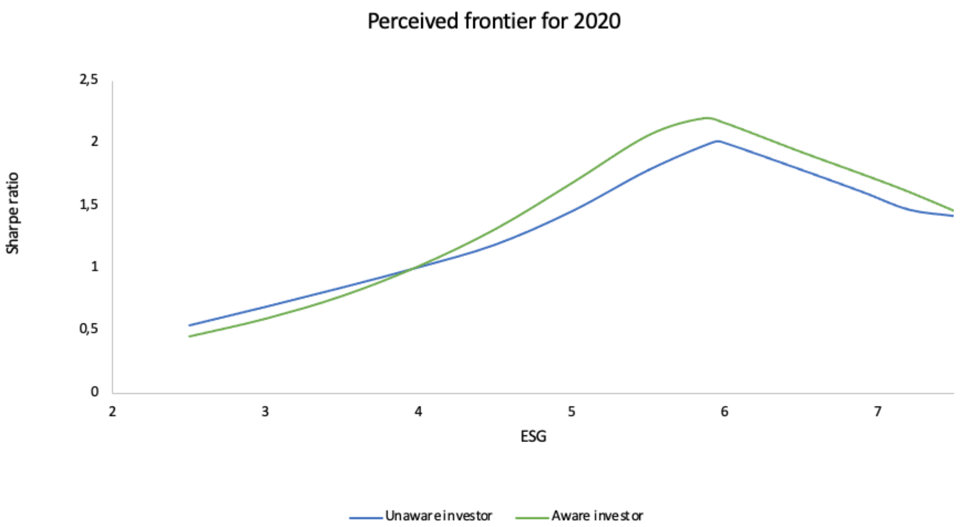
As previously revealed and discussed, ESG has an informative value that can be used as a predictor for future returns to attain a more precise estimate. Hence the conclusion indicates that information about sustainability can be exploited in portfolio construction. Through the factor return regression (Table 10), the predictive value is quantified which enables the integration of ESG information into valuation. The following section will visualize and discuss the implication of utilizing ESG's informative value, as estimated by factor returns, in portfolio construction. Using factors observed in 2019 to forecast returns and construct portfolios for 2020 a distinction between the ESG aware and unaware investor's ability to predict return is derived. We construct the frontiers for our examined ESG- and E-proxy (Table 11 and 12), disregarding the proxies for S- and G since they are binary, resulting in an investment screening where investors either consider or do not consider these stocks in investment decisions. The same analysis has been performed for 2021 but since the two frontiers reveal the same results, the frontiers for 2021 has been included in Table 20 and 21 in the appendix.

Noteworthy is that the ESG efficient frontier does not intend to propose general conclusions applicable for the population, but rather illuminate the interplay between our previously established results. Hence, no statistical analysis is performed and the conclusions discussed can only be assumed to apply for the implied year. Furthermore, the factor returns used in return predictions are not statistically significant as discussed in section 6.4 and do therefore not accurately absorb ESG's informative value. However, since the purpose of the frontiers is to illustrate the implication of using ESG characteristics, the derived results from table 10 will still be used for visualization purposes.

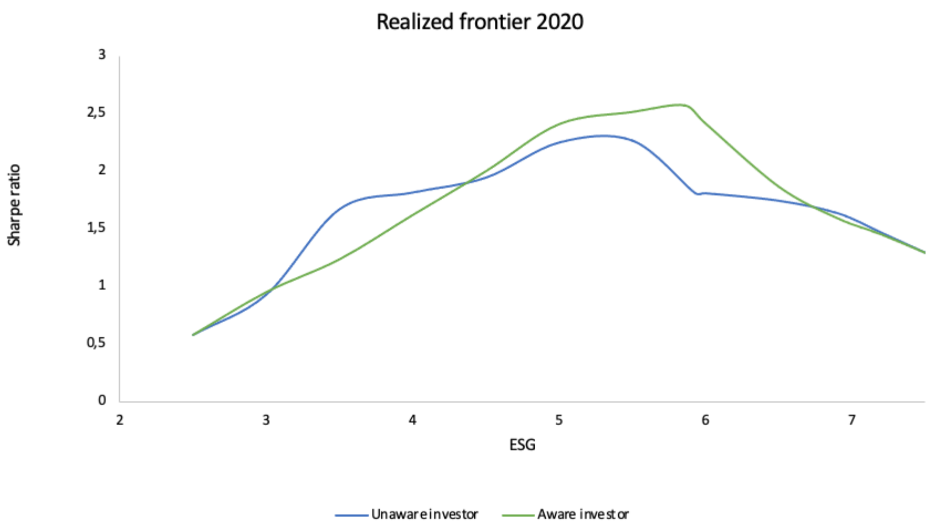
7.2.1 ESG-Efficient Frontier

Table 11: ESG efficient frontiers

Panel A illustrates annualized maximized sharpe ratio for each level of ESG constraint, using ex ante predictions of the two investors.



Panel B illustrates realized sharpe ratio of portfolios from Panel A



Using MSCI ESG scores as a proxy for ESG, we estimate the ESG efficient frontier. Returns predictions are, for the unaware investor driven by valuation and for the aware also driven by the ESG proxy

Table 11, Panel A illustrates the perceived frontier for both the ESG aware and unaware investor. Since the two investors do not utilize the same information in return predictions, they will interpret stock prospects differently. The perceived frontier reveals distinct investment decisions made by the A-investor and U-investor to maximize Sharpe ratio at each level of ESG constraint. The ESG-aware investor incorporates the return premium signaled by MSCI ESG-score derived from Table 9, when predicting future returns. Hence, the A-investor will perceive that Sharpe ratio is maximized in a portfolio with weight bias towards high ESG stocks, which is revealed in the frontier. Using the portfolios constructed to maximize perceived Sharpe ratio at each level of ESG, a realized frontier can be plotted. Table 11, Panel B visualizes the realized Sharpe ratios of each portfolio for both the ESG aware and unaware investor. Comparing the realized frontiers for the two investors, three main conclusions can be derived.

Firstly, the shape of both frontiers reveal that the Sharpe Ratio increases in line with the inclusion of ESG. However this implication is only true up to a certain level of portfolio sustainability. Reviewing the descriptive statistic of MSCI ESG-score for our sample (Table 3), the average ESG score is 5.54. The realized frontier for both investors indicate that the Sharpe ratio experienced a diminishing effect when the portfolios are constrained to a higher ESG score than the sample average. Hence, the result suggests the existence of a trade-off between a performing and sustainable portfolio, compliant with evidence discussed in previous research (Hong and Kacperczyk 2009, Taylor, Stambaugh, et al. 2019).

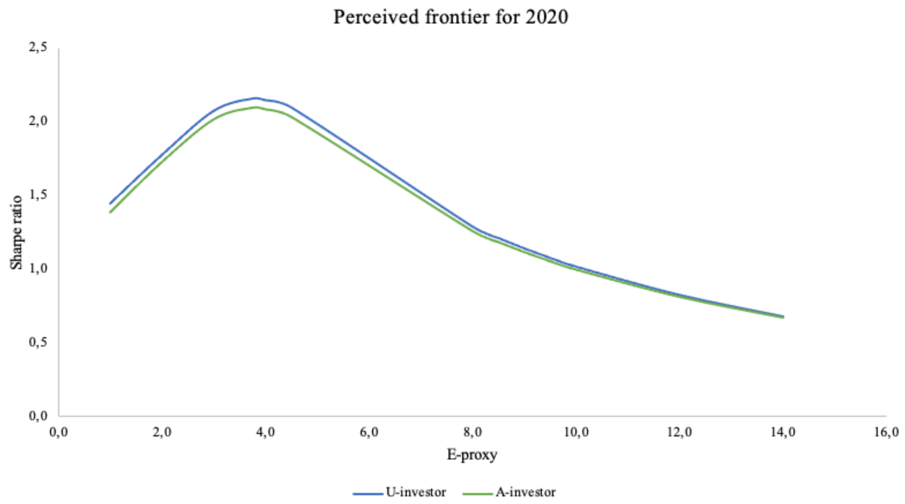
Secondly, the realized frontiers disclose that the portfolios constructed to maximize perceived Sharpe ratio enables the ESG aware investor to obtain higher risk-adjusted return for each level of ESG constraint. This finding agrees with the abnormal excess return observed for the MSCI ESG factor mimicking portfolio in Table 9. Since the ESG aware investor incorporates a return premium for stocks with high ESG score, the predictions aim to absorb the abnormal excess return and allow a more realistic perception of future prospects. The awareness of a return premium derived for high ESG score and the exploitation of this informative value in portfolio construction, enables the A-investor to obtain a higher Sharpe ratio.

Thirdly, the realized frontier reports that an ESG aware investor faces a lower trade-off between increasing the portfolio ESG level and maintaining a high Sharpe ratio. The A-investor maximizes realized Sharpe ratio at portfolio ESG level higher than the U-investor. Increasing the level of ESG-constraint, the A-investor maintains a high Sharpe ratio while the U-investor's diminishes. Hence, an increased ESG portfolio level induces a larger reduction in Sharpe ratio for the U-investor. This implies that an ESG aware investor can reduce the tradeoff between sustainability and portfolio performance, in terms of Sharpe ratio, by exploiting the value itself in investing responsibly.

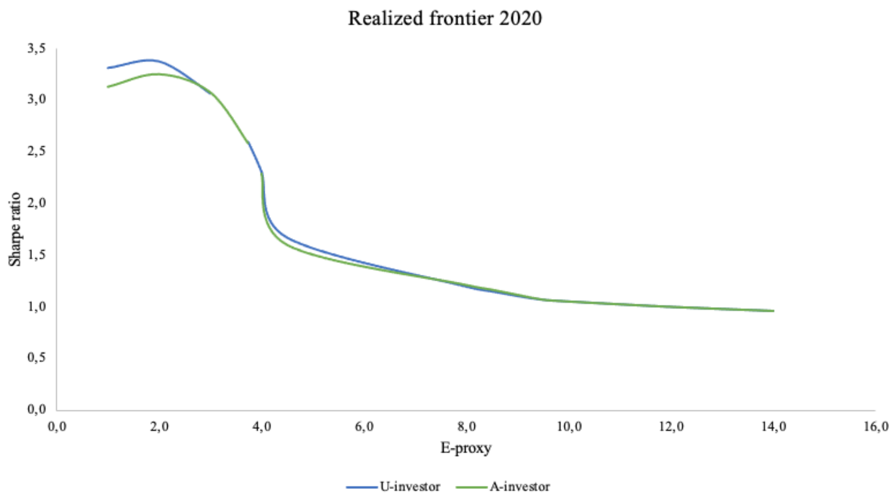
7.2.2 Environmental-Efficient Frontier

Table 12: E efficient frontiers

Panel A illustrates annualized maximized sharpe ratio for each level of environmental constraint, using ex ante predictions of the two investors.



Panel B illustrates realized sharpe ratio of portfolios from Panel A



Using greenhouse gas over sales as a proxy for Environmental efforts, we estimate the E efficient frontier. Returns predictions are, for the unaware investor driven by valuation and for the aware also driven by the E proxy.

Table 12, Panel A illustrates the perceived frontier of maximized Sharpe ratio at each level of portfolio environmental score. The perceived frontiers for the ESG-aware and ESG-unaware investors are almost aligned which suggests that incorporating an additional factor return for the E-proxy does not yield further implications than if the book-to-market ratio were used alone for return predictions. Reviewing the realized frontiers in Table 12, Panel B, they are close to identical for the ESG aware and unaware investors. The alignment of the frontiers implies that the realized Sharpe ratios are homogenous for any given Environmental constraint. The shape of both realized frontiers reveal a trade-off between adding Environmental level to the portfolio and maintaining a Sharpe ratio, similar to what is discussed in previous literature (Hong and Kacperczyk 2009, Taylor, Stambaugh, et al. 2019). Furthemore, since the frontiers are synchronized, the trade-off implied for the A-investor and U-investor is the same.

The observed result further illuminates that information about our Environmental proxy cannot be used to obtain a different portfolio outcome. This implication coherently agrees with the observations derived from Table 9 for our factor model regression. A factor mimicking portfolio based on environmental proxy does not report on significant abnormal excess return. Hence our E-proxy has no predictive value of stock returns which is a potential explanation of the frontiers' similarities. Comparing the insights derived from the ESG- and E-efficient frontier, one can conclude that the tradeoff between a performing and sustainable portfolio can be reduced when information about MSCI ESG-score is exploited, but not through the utilization of our E-proxy. The diverse conclusions further emphasize the importance of considering each pillar of ESG individually in portfolio management to obtain optimized outcomes.

7.3 Limitations

There are considerable limitations in our models and data sample, impeding us from achieving robust results. Ideally, we would like to analyze all and the same companies listed on Nasdaq Nordic Large Cap over the sample period. In that case, we would obtain a balanced panel reducing the risk of idiosyncratic errors correlated with companies falling out of the sample. An alternative approach to using an unbalanced panel would be to exclude companies lacking data over the sample period. However, we decided to include firms with missing data for some years in order not to reduce the sample size too much since too few observations can result in further concerns. (Wooldridge 2012)

Moreover, several conceivable explanations for why our ESG-proxies exhibit low explanatory value exist. We will further present some reasons causing limitations to our results. Since the demand for ESG in investments has substantially increased in recent years (Global Sustainable Investment Alliance, 2021), our short panel may even be too long. The revised ESG focus among investors can affect the awareness and demand for ESG characteristics within the sample period, conceivably causing biases in our results. Furthermore, examining proxies as quantitative metrics for ESG causes subjectivity in the analysis. Although we aimed to analyze comprehensive and distinguishable characteristics, ESG-aware investors will evaluate diverse aspects of a firm's sustainability level. Accordingly, it is not feasible to encounter ESG-proxies as valuable to all ESG aware investors. Hence, the diverse knowledge and importance of our chosen proxies among ESG aware investors is a limitation to our results.

Furthermore, as visible in Table 6 and 7, not all incorporated control variables are significant, implying they are not value added for the validity of the model. In addition, these tables show a relatively low R^2, meaning that the analyzed ESG-proxy in combination with the chosen control variables are not extensive for describing the variation of our dependent variables (Wooldridge 2012). In that sense, replicating Pedersen et al. (2021) through integrating the same control variables is a limitation to our results since there are better fitted models for our examined sample. Moreover, some of our enforced tests for multicollinearity disclose that heteroskedasticity exists among the error terms in our fitted models, see Table 18 and 19 in the appendix. We decided to add robust standard errors for the Factor Return model to account for the heteroskedasticity in the regression. However, applying Whites robust standard errors only affects the t statistics and does not change the regression coefficients (Wooldridge 2012). Thereby, not performing a better fitted regression to account for the heteroskedasticity in our models is also a limitation to our results.

8. Concluding Remarks

8.1 Conclusion

The monumental shift in financial markets to consider ESG as a decisive factor in evaluation has increased the importance of further studying Sustainable Responsible Investing. There is an ongoing discussion on how to mitigate global emerging risks that urges investors to include a sustainability criteria in investment decisions (OECD, 2021). However, the interplay between ESG and portfolio management has previously not been studied from a constructive viewpoint but rather with the motive to establish a correlation. Despite agreeing results in empirical research that investing with an ESG constraint hurts returns, investors find little guidance on how to efficiently incorporate sustainability into portfolio management. Hence, the motivation to invest sustainably is challenged by diminished financial incentives. The increased relevance of ESG has thus provoked this thesis to study if the alleged trade-off between a performing and sustainable portfolio can be diminished. Our study partly replicates Pedersen et al. (2021) and extends it with contributing insights.

In this study we have unfolded the possibility to successfully incorporate information about sustainability into portfolio construction by analyzing three main elements. Firstly we have examined if information about ESG correlates with future firm profitability to answer the research question; Do ESG characteristics have an explanatory value of future firm fundamentals? Our study reports low significance in the relation between analyzed ESG proxies and profitability metrics, except for the Social proxy. Therefore we cannot conclude that ESG characteristics have an explanatory value of firm fundamentals. Hence, our results do not anchor the correlation between sustainable efforts and firm value proposed in previous literature (Ferrell, Liang, et al. 2016, Friede, Busch, et al. 2015).

Since an exhibited predictive value of firm fundamentals does not affect stock return unless the market is unaware of the potential correlation (Fama, 1970) , we furthermore investigated if the ESG-proxies are valued by the market. For the majority of our examined proxies, we did not find any relation with the applied valuation ratio. Hence we can not conclude upon whether the market incorporates information about our ESG-proxies in the stock price. Moreover, for the G-proxy we found a statistically significant negative relation suggesting the examined ESG characteristic predicts lower valuation. Our results are relatively surprising compared to other findings in the field of study. Previous literature suggests that ESG is correlated with firm fundamentals and argues a biased demand towards sustainable stocks (Hong and Kacperczyk 2009, Taylor, Stambaugh, et al. 2019). Hence they conclude that the market imposes a higher valuation for ESG stocks. Our contradictory results are intrinsically contributing to the literature since they emphasize that studies on Sustainable Responsible Investing needs to be reconsidered for each individual market setting. Noteworthy, our study has intrinsic limitations since we replicate statistical models from a paper examining a different data set, suggesting there might be better fitting models and control variables applicable to analyze our data.

Lastly, the integration of sustainability into portfolio management requires knowledge of how ESG can be used in predictions. Hence, we performed factor models regression to identify potential abnormal excess returns. Our study reports that neither our E-proxy or S-proxy have explanatory value of future returns, while the G-proxy has a negative and ESG-proxy a positive predictive value. Hence we conclude that the integration of sustainability into portfolio management can be attained through the usage of a return premium attributed to stocks with a high MSCI ESG score, or by incorporating a return discount assigned to GRI compliant stocks.

To broaden the perspective of investor behavior, we introduce ESG-awareness that represents knowledge of how Environmental, Social and Governance efforts can create financial opportunities. Acknowledging that investors will exploit all information they perceive to be relevant, an aware investor is assumed to absorb ESG's informative value of returns into predictions. Hence, utilizing the value itself in investing sustainably, the aware investor will estimate future return differently. To answer the second research question; Can ESG awareness diminish the trade-off between portfolio performance and sustainability inclusion?, we visualize the distinct portfolio choices of an aware and unaware investor through the construction of a ESG-efficient frontier plotting Sharpe ratio against portfolio ESG. Maximizing ex ante Sharpe ratio at each level of ESG constraint, the perceived frontiers are obtained for both investors. The realized frontiers are thereafter constructed based on the investment decisions visualizing differences in realized Sharpe ratio at each level of ESG inclusion for the two investor types.

Our frontier constructed for sustainability proxied as MSCI ESG-score, visualize that both investors indeed face a trade-off between ESG inclusion and maintenance of a high Sharpe ratio as discussed in previous literature ((Hong and Kacperczyk 2009, Taylor, Stambaugh and Pastor 2019). However a comparison of the two frontiers illuminates that the trade-off is smaller for the ESG aware investor. Hence, we conclude that through the incorporation of ESG's informative value into portfolio construction, the trade-off between portfolio performance and sustainability inclusion can be reduced. Contradictory, the frontiers for our E-proxy disclose that the existing trade-off cannot be reduced through ESG awareness. Instead we conclude that the incorporation of our E-proxy's predictive value of returns, does not yield further implications than if the valuation ratio were used alone for return predictions. The contradictory results for our ESG- and E-frontier further emphasizes the importance of considering each ESG pillar individually in portfolio management.

To conclude, this study finds no explanatory value in ESG of firm fundamentals for our sample, which suggest that an investor cannot utilize information about sustainable efforts to estimate future firm profitability. However, our results suggest that MSCI ESG-rating has predictive value of returns that can be incorporated into portfolio construction to attain a better prediction. Hence, through the exploitation of knowledge about Environmental, Social and Governance efforts affecting stock prospects, an ESG-aware investor can diminish the tradeoff between portfolio MSCI ESG score and Sharpe ratio.

8.2 Future Research

As disclosed in our study, the chosen proxies for E, S and G do not report coherent results for each regression. Compliant with Pedersen et. al (2021) we hence conclude that each pillar of ESG has distinct implications for portfolio management and should be treated individually. We visualize that an ESG-aware investor can diminish the trade-off between a sustainable and performing portfolio, utilizing information about MSCI ESG score but not using our proxy for Environmental Pillar. Consequently there is an interest to further explore how each ESG Pillar affects financial opportunities differently.

The ESG proxies are chosen to capture investor estimates of how a firm performs in each respective pillar. However, as previously discussed, neither our proxies nor the one utilized in

Responsible Investing; ESG-efficient frontier (2021), are exhaustive metrics of the pillars. Since there are investors that may consider additional aspects of sustainability that have not yet been studied it is of interest to further investigate the incorporation of ESG in portfolio management using alternative proxies. Part of our analysis report results that contradicts those by Pedersen et. al (2021) for the same pillar, when the dissimilar proxies are applied, which further emphasized the interest in examining new proxies for ESG.

Lastly, in comparison to previous studies, we apply a current sample period following the monumental shift in Sustainable Responsible Investing. Hence, our partly contradictory results to existing literature suggests that the market environment for ESG investing has changed. We thus recommend that research on the interplay between ESG and portfolio management should be revised continuously.

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Appendix

Table 13: Skewness test for Normal Distribution	
Variable	Skewness
Negated E Score	14.8722
LN(Negated E Score)	-0.1279035

This table shows the results form the Skewness test for the Negated E-proxy and the Natural Logarithm of the Negated E Proxy. The Negated E-proxy data exhibit a Positve Skewness. The LN(Negated E Score) is close to 0 and follows a Normal Distribution.

Table 14: Correlation Matrix LN(Negated E Score)

Variables	1	2	3	4	VIF
(1) Beta	1				1.070556
(2) LN(N. E Score)	-0.07*	1			1.040478
(3) LN(B/M)	0.32***	-0.11***	1		1.053151
(4) LN(Market Cap)	-0.27***	0.00	-0.21***	1	1.091543

This table shows the correlation for the independent variables for the regressions in Table 6 and 7. The test performed is The Pearson Product-Moment Correlation.
***p-value<0.01, **p-value<0.05, * p-value<0.1

Table 15: Correlation Matrix S Score

Variables	1	2	3	4	VIF
(1) Beta	1				1.068238
(2) S Score	-0.03	1			1.104700
(3) LN(B/M)	0.28***	-0.02	1		1.063830
(4) LN(Market Cap)	-0.27***	0.14***	-0.23***	1	1.071654

This table shows the correlation for the independent variables for the regressions in Table 6 and 7. The test performed is The Pearson Product-Moment Correlation.
***p-value<0.01, **p-value<0.05, * p-value<0.1

Table 16: Correlation Matrix G Score

Variables	1	2	3	4	VIF
(1) Beta	1				1.070410
(2) G Score	-0.03	1			1.059250
(3) LN(B/M)	0.28***	0.17***	1		1.093220
(4) LN(Market Cap)	-0.27***	0.14***	-0.23***	1	1.075725

This table shows the correlation for the independent variables for the regressions in Table 6 and 7. The test performed is The Pearson Product-Moment Correlation.
***p-value<0.01, **p-value<0.05, * p-value<0.1

Table 17: Correlation Matrix ESG Score

Variables	1	2	3	4	VIF
(1) Beta	1				1.070556
(2) ESG Score	-0.10***	1			1.040478
(3) LN(B/M)	0.27***	-0.11***	1		1.053151
(4) LN(Market Cap)	-0.29***	0.23***	-0.20***	1	1.091543

This table shows the correlation for the independent variables for the regressions in Table 6 and 7. The test performed is The Pearson Product-Moment Correlation.
***p-value<0.01, **p-value<0.05, * p-value<0.1

Table 18: Heteroscedasticity Results

Dependent Variable	E Score	S Score	G Score	ESG Score
RNOA(t+1)	37.742***	6.5644	13.85*	27.422***
GPOA(t+1)	67.05***	79.804***	81.973***	77.099***
LN(P/B)	27.411***	2.9348	24.309***	8.1733**

The table shows the results from the Breusch-Pagan heteroscedasticity test for the regressions in Table 6, 7, and 8.
Significant results imply rejecting the null hypothesis of homoscedasticity.
***p-value<0.01, **p-value<0.05, *p-value<0.1

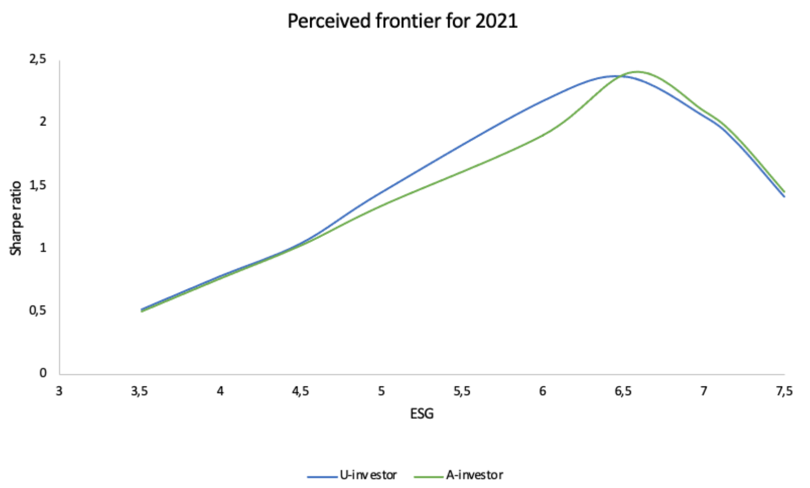
Table 19: Heteroscedasticity Results

Dependent Variable	BM z-score	E z-score	S z-score	G z-score	ESG z-score
Yearly Return 2016	7.545***	4.5044	8.483**	9.3267***	7.5008**
Yearly Return 2017	0.84811	0.011067	4.1928	2.7262	6.4438**
Yearly Return 2018	0.00015773	2.2248	3.068	3.9044	5.7408*
Yearly Return 2019	4.2608**	2.5063	5.8521*	4.5088	5.0545*
Yearly Return 2020	0.059025	0.471	3.8865	10.293*	2.6297

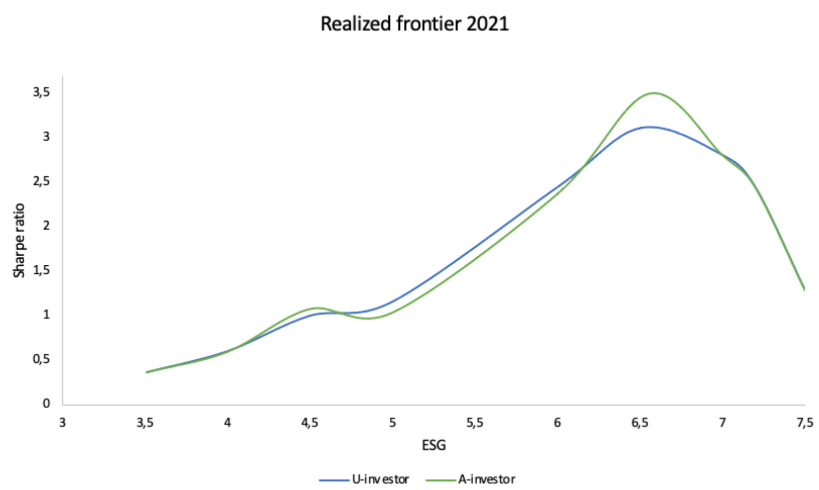
The table shows the results from the Breusch-Pagan heteroscedasticity test for the regressions in Table 10. Significant results imply rejecting the null hypothesis of homoscedasticity.
***p-value<0.01, **p-value<0.05, *p-value<0.1

Table 20: ESG efficient frontiers

Panel A illustrates annualized maximized sharpe ratio for each level of ESG constraint, using ex ante predictions of the two investors.



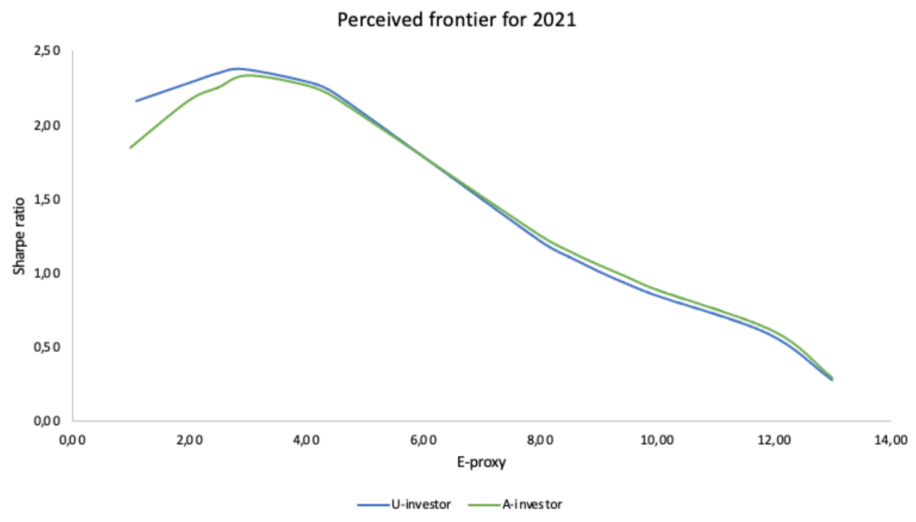
Panel B illustrates realized sharpe ratio of portfolios from Panel A



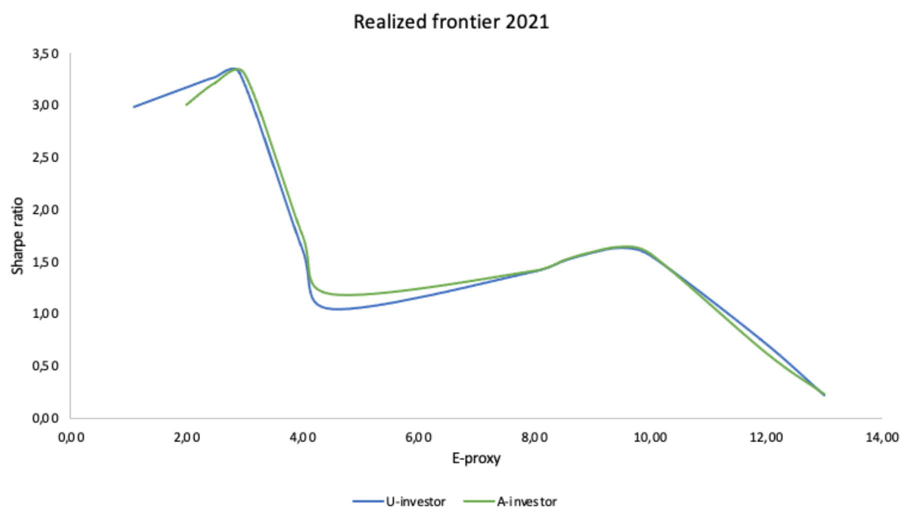
Using MSCI ESG scores as a proxy for ESG, we estimate the ESG efficient frontier. Returns predictions are, for the unaware investor driven by valuation and for the aware also driven by the ESG proxy

Table 21: E efficient frontiers

Panel A illustrates annualized maximized sharpe ratio for each level of environmental constraint, using ex ante predictions of the two investors.



Panel B illustrates realized sharpe ratio of portfolios from Panel A



Using greenhouse gas over sales as a proxy for Environmental efforts, we estimate the E efficient frontier. Returns predictions are, for the unaware investor driven by valuation and for the aware also driven by the E proxy.