ERASMUS SCHOOL OF ECONOMICS

MASTER THESIS FINANCIAL ECONOMICS

Analyses of expanding ESG Strategy with Low Beta Tilt

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ABSTRACT

In this thesis we investigate whether adding a low beta tilt to ESG investment strategies can improve performance in the stock market. We find that higher (risk-adjusted) returns can be gained by adding a beta tilt, after considering three different portfolio construction methods to enhance the ESG strategies with a low beta tilt. A low beta tilt can either reduce the variance of the returns or increase the average return, which results in higher risk-adjusted returns.

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1 Introduction

In this thesis, we investigate the effect of combining a beta tilt into an environmental, social and governance (ESG) portfolio strategy framework. ESG has become a popular topic in academic research the last decades.

It started back in the 1960s, where social responsible investing (SRI) took off after Vietnam War protesters demanded that university endowment funds no longer invest in defense contractors. Organisations started to exclude companies from their portfolios that did not meet their moral or ethical values. The movement towards SRI only grew bigger over time. Over 97 trillion US Dollars are currently managed by Principles for Responsible Investment (PRI) signatories (PRI, 2021). But also retail investors have an increasing interest in SRI. Companies such as ING, Robeco even offer specific sustainable investing options for their customers.

Throughout the years, there has been a focus on finding investment strategies that outperform the market. Anomalies such as January effect (Wachtel, 1942), firm size (Banz, 1981), book-to-market value (Fama and French, 1993) , momentum (Jegadeesh and Titman, 1993) have shown to give excess return in the past. Another one of these anomalies, is the low volatility anomaly (Jagannathan and Ma, 2003; Clarke et al., 2006; Baker et al., 2011). It can be observed that in most markets, low volatility stocks have higher risk adjusted returns than high volatility stocks, which contradicts the theory that higher risks must be compensated with higher returns.

Since investors always prefer lower risk ceteris paribus, it might be useful to somehow combine a beta tilt with an ESG investment strategy, which might give higher (risk adjusted) returns while still being socially responsible.

The aim of this paper is to investigate whether a combination of ESG and low beta investment strategies can improve performance. We will look at multiple investment strategies and compare

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results. The portfolios we will be creating are:

- A Benchmark portfolio
- Quintile (20% of total) beta stocks portfolios.
- Quintile ESG stocks portfolios.
- Combining beta tilt into ESG strategies in three ways.

There are many possibilities how to construct combined strategy portfolios. The strategies used are explained in detail in the methodology section.

Questions that will be answered are:

- Do low volatility stocks outperform high volatility stocks in our dataset?
- Do high ESG stocks outperform low ESG stocks in our dataset?
- Can a combination of ESG and low beta strategies improve risk adjusted returns, compared to ESG strategies?

2 Literature Review

Early research on ESG shows mixed results. In the 1970s, a view was that socially aware management likely has the skills to run a more progressive, profitable, company compared to companies with traditional management, creating seemingly attractive investment opportunities. The Dreyfus Third Century fund, is one of the funds that used this view in their investment strategy, instead of focusing on traditional investment criteria. Moskowitz (1972) proposed this view and claimed to have validated it empirically, by comparing returns of indices with companies that he believes had good social responsible credentials.

On the other hand, there was the view that companies being socially responsible would be a disadvantage due to the cost of it. This would result into less return than companies that are not socially responsible, because these companies would not have the extra costs. Vance (1975) uses perceived social responsibility of the leading firms and finds negative correlation between the social responsibility rank and their stock returns. Both papers did have shortcomings, such as small samples and lack of risk adjustment. It did however show the upcoming interest in SRI back then already.

Alexander and Buchholz (1978) rejects both research findings of Moskowitz (1972) and Vance (1975), defending the Efficient Market Hypothesis introduced by Malkiel and Fama

(1970). Alexander and Buchholz (1978) find an insignificant correlation between risk adjusted returns and social responsibility rankings, using the capital asset-pricing model (CAPM) model (Sharpe, 1964). Risk adjusted returns already reflect this social responsibility factor in their returns, implying that the Efficient Market Hypothesis is not rejected.

Further research conclude the same mixed three views as mentioned before. The first view, Hamilton et al. (1993) finds that SRI has no impact on prices. The second view, where SRI is a trade-off, Aupperle et al. (1985) finds that companies that are socially responsible put resources to make that happen, where other companies do not have to. The last view that SRI doesn't have to be at the cost of returns, Cornell and Shapiro (1987), McGuire et al. (1988) and Eichholtz et al. (2012) all have findings in line with that view. More recently, Nagy et al. (2013, 2015) finds that ESG does not have to be at the cost of risk-adjusted returns. Nagy et al. (2013, 2015) find that two of the suggested strategies, ESG tilt and ESG momentum, outperform the global benchmark used in the eight years prior. ESG momentum show the best results, which looks at the change in ESG of a company (Nagy et al., 2015). The main conclusion of Nagy et al. (2015) is that a significant portion of the returns could be indirectly attributed to ESG, while other parts can be explained by a tilt towards mid market cap and low volatility stocks.

Kaiser (2020) also finds that investors can raise their portfolio's ESG level and increase risk-adjusted returns at the same time. The paper focuses on value, growth and momentum, using US and European data. The main finding is that the inclusion of sustainability aspects does not inevitably result in worse performance. If done correctly, the ESG tilt can bring improved risk-adjusted returns characteristics on style and momentum portfolios with higher aggregated sustainability. The style portfolios refer to the Morningstar Style Box Methodology (2008), which was introduced to identify the investment style of a fund.

Low beta strategies are interesting for investors, because they offer higher Sharpe ratios than the market in the past, while lowering the risk of equity portfolios. This low beta strategy first appeared in research papers in the 1970s, when Jensen et al. (1972) show that the CAPM had shortcomings with regards to the risk return relationship. Where the CAPM predicts that higher risk should result into higher returns, Jensen et al. (1972) find that high beta stocks experience much lower returns than what is expected. Fama and French (1992) find that even the Fama French 3-factor model, an expansion of the CAPM model by introducing a factor for value and size, did not support the positive relationship between returns and beta.

Further research confirms that when measuring returns by a risk measure such as beta or standard deviation, low risk portfolios outperform high risk portfolios. Jagannathan and Ma (2003) find that minimum variance portfolio obtain higher returns and lower risk, compared to a value weighted benchmark, using US stock data from 1968 to 1998 . Haugen and Baker (1991) shows similar results, using US stock data from 1972 to 1989. They conclude that cap-weighted stock indices are sub-optimal, due to alternative strategies having similar expected returns with lower volatility. Baker and Haugen (2012) extends that this observation exists in all world-wide equity markets in the time period 1990 to 2011.

With a growing trend towards SRI, it seems worthwhile to investigate whether combining responsible investing and low beta investment strategies can enhance one another. There has not been any research yet on a mixed strategy of low volatility and ESG. The only related finding is that in Nagy et al. (2015) an ESG strategy had a tilt towards low volatility stocks.

3 Data

We use Datastream to get access to primary listed US stocks that have ESG scores, which totals 3069 stocks. Datastream has Thomson Reuters ESG scores. Due to ESG being a relatively new measure, there is not centuries of ESG data available. We focus on the data from 2010 to 2019, after the financial crisis. It is an interesting period to look at, since Fama French factors failed to show excess returns in the time period 2010 to present (e.g. Bender et al. (2018)).

We use monthly total stock returns and collect their monthly betas from Datastream. The monthly total stock returns, known as Total Return Index (symbol "RI" in Datastream), includes dividend in addition to stock price changes. The historical betas (symbol "897E" in Datastream) are obtained by comparing the change in share price to change in index value on a monthly basis over a five-year period. For industry specifications, we obtain North American Industry Classification Codes (NAICS). A more detailed explanation of NAICS codes can be found in Refinativ (2020). Next to financial data, we need data on observed risk premiums. We gather the historical values of Fama and French 5-factor portfolios and 30-day Treasury Bill rates from Kenneth R. French's data library. Lastly we use Yahoo Finance for the S&P 500 Total Return Index data.

We divide stocks into industries by looking at the first four digits of the NAICS, which is in total 29 industries. However, two industries that only contain one stock are excluded, leaving 27 remaining industries. The stock distribution of each industry can be found in the Appendix (Figure A2). Regarding further data cleaning, the decision is made to create one equal dataset for both ESG and beta strategies. Observations that did not have an ESG score or beta at a certain time, are excluded. Lastly, we exclude observations with stock prices lower than $5 to ensure that our results are not driven by extreme price movements in these low priced stocks. Without this restriction, plenty of stocks had over tenfold price movements in a single month. Data analyses would be too heavily affected by these stocks skewing the results.

Observations	Median	Mean	Standard error	Min	Max
172,575	0.01106	0.01139	0.11005	-0.92907	9.24476

Table 1: This table presents descriptive statistics of the monthly arithmetic returns of all 3069 stocks combined. The sample period runs from January 2010 to December 2019. Note that this is not an average and median of cumulative return, nor log returns. For the mean, this is simply adding all 172,575 observations together, and taking the average.

Table 1 shows some descriptive statistics, to give an insight of the data. The 3069 stocks have combined 172,575 observations, where the average of all these 172,575 monthly returns, is approximately 1.14% and a slightly lower median of 1.11%. This shows that more than half of the monthly returns of all stocks are over 1.11%. Note that it does not say anything about cumulative return. A cumulative return plot can be found in Appendix A3. We will go more in dept on returns in Section 5.2.1.

The minimum and maximum return are fairly extreme, with -92.9% and 924.5% return in a month. Investigating the return data further, the density of the monthly returns can be found in Figure 1. As to be expected, most of the data points lie within the (0.5 – 0.5) interval. Table 2 shows that there are only a few outliers, with less than 6 outliers per interval with returns greater than 200%, and zero between 450% and 900% and only one outlier above 900% return.

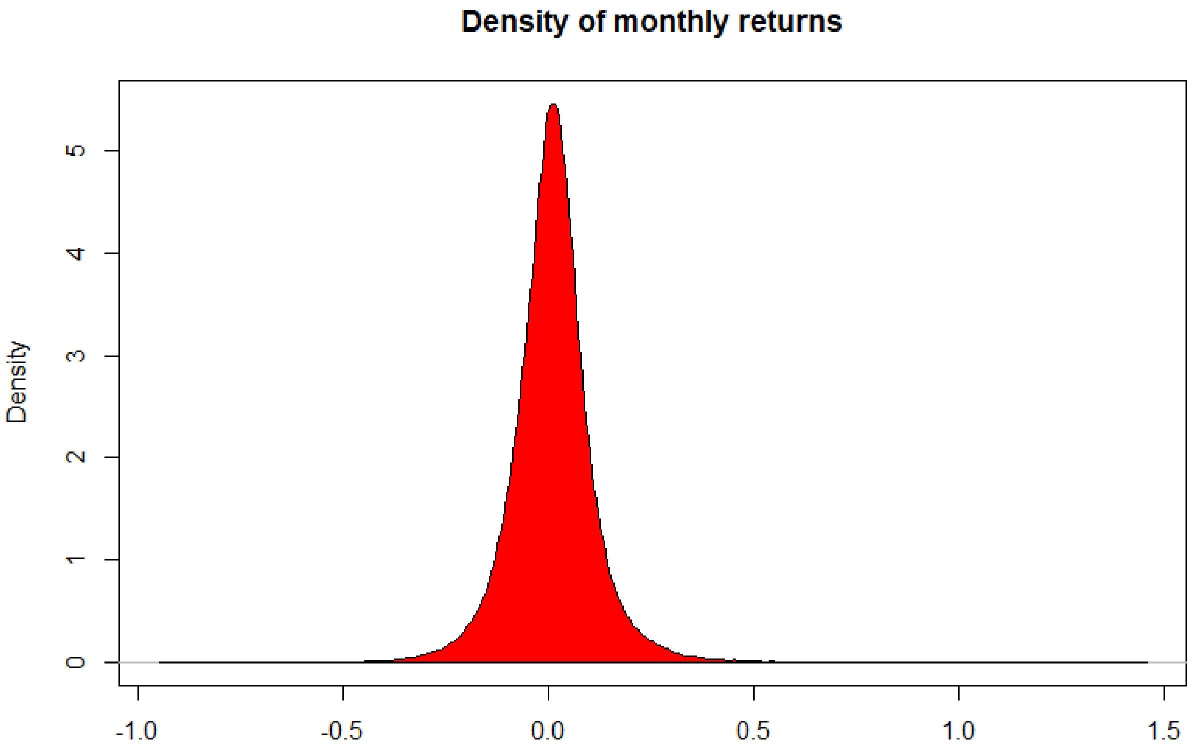

Figure 1: A density plot of all 172,575 observations of monthly stock returns, zoomed in on the (1 – 1.5) interval, due to a very low number of observations above 1.5.

Interval	-1 – -0.5	-0.5 – 0	0 – 0.5	0.5 – 1	1 – 1.5	1.5 – 2	2 – 2.5	2.5 – 3	4 – 4.5	9 – 9.5
N	117	75838	96247	324	27	11	5	2	3	1

Table 2: This table is an addition to Figure 1, presenting the number of stocks that fall in each interval of monthly stock returns.

4 Methodology

4.1 ESG

ESG refers to the three key factors in evaluating the sustainability and associated potential financial performance of a company. The factors are Environmental, Social and Corporate Governance. There are a variety of institutions that offer ESG scores. MSCI, Bloomberg, S&P all have their own way of calculating these scores. Thomson Reuters ESG scores are the ones we use, collected from Datastream.

Thomson Reuters ESG Scores are designed to transparently and objectively measure a company's relative ESG performance, commitment and effectiveness across 10 main themes based on company-reported data. The ESG scores data back to 2002 for approximately 1000 companies from mainly Europe and the US. Today, Thomson Reuters ESG has one of the most comprehensive ESG databases in the industry, with over 7000 companies. There are over 400 ESG measures collected. A subset of 178 most comparable and relevant measures are selected, based on considerations around comparability, data availability, and industry relevance. These 178 then divided into ten main themes, found in Table 3. A more detailed explanation can be found in Appendix A4 and A5 (Thomson Reuter, 2018).

Environmental	Social	Governance
• Resource Use • Emissions • Innovation	• Workforce • Human Rights • Community • Product Responsibility	• Management • Shareholders • CSR Strategy

Table 3: This table presents the 10 Thompson Reuter themes categorized under the Environmental, Social and Governance. Every ESG measure falls under one of these categories.

4.2 Low Beta

The CAPM beta of a stock implies how the returns moves along with the market returns. A beta of one indicates that the stock follows the market, where a beta of zero indicates that market movement has no effect on the stock. With the low beta strategy, an investor targets stocks with the lowest betas. In general, investors aim for low risk. Because low beta stocks are less risky, they are preferred over high beta stocks if both give equal excess returns.

The betas we obtain from Datastream are based on the previous 60 months of price changes, compared to a local index, in our case the S&P 500. The following equation 1 shows how Datastream calculates their historical betas.

$$\beta_{it} = \frac{\sum_{k=t-60}^{t}(x_k - \bar{x}_t)(y_{ik} - \bar{y}_i)}{\sum_{k=t-60}^{t}(x_k - \bar{x}_t)^2} \tag{1}$$

where β_{it} is the monthly beta of stock i at time t, x_k the returns of S&P 500 at time k, $\bar{x}_t$ the average return of the S&P 500 from time $t-60$ to t, y_{ik} the returns of stock i at time k and $\bar{y}_i$

the average return of stock i from time $t - 60$ to t.

4.3 Sharpe Ratio

In the Low beta section, we mention investors ideally want high returns and low risk. Imagine two investment opportunities, where option A has 10% annual return with a standard deviation of 5%, versus option B with also 10% annual return but only a standard deviation of 2%. Investors always prefer opportunity B. Sharpe (1994) developed a ratio where there is a trade-off between returns and its volatility (risk). The formula is as follows:

$$SR = \frac{R_p - rf}{\sigma_p} \tag{2}$$

where R_p is return of a portfolio, σ_p the standard deviation of the portfolio's excess returns, and r_f the risk-free rate.

4.4 Returns

The monthly total return index data of the 3069 stocks collected from Datastream is converted into monthly excess returns (see equation 3). Note that the total return index includes re-invested dividends.

$$r_{it} = \frac{price_{i,t+1}}{price_{it}} - 1 - rf_t \tag{3}$$

where r_{it} is the monthly excess return of stock i on time t, $price_{i,t+1}$ is the total return index of stock i on time $t + 1$ and rf_t the monthly risk-free rate on time t. The risk-free rate used is the 30-day Treasury Bill rates from Kenneth R. French's data library.

Arithmetic returns are used to form portfolios, which is explained in Section 4.6.1. These arithmetic returns are used for the regression analyses. They are then converted into log returns, due to its convenient property of being time additive, to get annual returns of the portfolios.

$$logR_{pt} = \ln(1 + R_{pt} + rf_t) \tag{4}$$

where $logR_{pt}$ is the monthly log return of portfolio p on time t, R_{pt} the arithmetic monthly excess return of portfolio p on time t, and rf_t the monthly risk-free rate on time t.

4.5 OLS Regressions

To investigate our performance, compared to the market and other factors, we use permutations of the Fama French 5-factor model (Fama and French, 2015). The full model is as follows:

$$R_{pt} * 100 = \alpha_p + \beta_1(\beta) + \beta_2(\mathtt{SMB})_t + \beta_3(\mathtt{HML})_t + \beta_4(\mathtt{RMW})_t + \beta_5(\mathtt{CMA})_t + \epsilon_t \tag{5}$$

for all p strategy portfolios, where β, $\mathtt{SMB}_t$, $\mathtt{HML}_i$, $\mathtt{RMW}_t$, $\mathtt{CMA}_t$, are the factors market excess return, size, value, profitability and investment respectively at time t, as retrieved from the Fama and French Library. Note that dropping the $\mathtt{RMW}_t$ and $\mathtt{CMA}_t$ factors yields the three-factor model and further excluding the $\mathtt{SMB}_t$ and $\mathtt{HML}_t$ factors, yields the CAPM. The monthly excess portfolio return R_{pt} is multiplied by 100 for more convenient coefficient interpretation, since all factors are presented in the same way. Note that Fama French uses value weighted portfolios, while our portfolios will be equally weighted. Where small-cap stocks are weighted less in value portfolios, it is trivial that our equally weighted portfolios has a higher weight on small-caps, compared to value weighted portfolios. So we have to be cautious when drawing conclusions. The OLS regressions are purely used to give an idea of how the portfolio moves, compared to the factors and the market.

4.6 Strategies

4.6.1 Portfolio Formation

We use the assumption of no type of transaction costs, taxes and infinitely divisible securities. Assume the data contains n stocks S_i $i \in \{1, 2, \ldots, n\}$ at time t. For every $t \in \{1, 2, \ldots, T\}$, stocks that have r_{it} are sorted on its industries (based on the first 4 digits of the NAICS). In total there are 27 industries. The two industries with one stock are dropped, which leaves a remainder of 25 industries I_i $i \in \{1, 2, \ldots, 25\}$. Per industry, stocks are ranked into quintiles, based on a strategy specific measure. Portfolios $p \in \{1, 2, \ldots, 5\}$ are formed by equally weighting the stocks in each quintile. Portfolios are also rebalanced every month, so that there is consistently an equally weighted portfolio. The industry distributions of the portfolios is equal to the industry distribution of the market. Note that stocks are not value weighted. The number of stocks vary over time t, due to newer companies not being around 10 years ago. If stock i belongs in quintile

1 at time t, $\mathbb{I}_t[x = p]$ will be 1 for portfolio 1, and 0 for all other portfolios. Portfolio returns can be written as

$$R_{pt} = \frac{1}{\mathrm{N}} \sum_{i=1}^{m} \mathbb{I}_t[x = p] r_{it} \qquad , \forall\, t \in \{1, 2, \dots, T\}, p \in \{1, 2, \dots, 5\} \tag{6}$$

where R_{pt} is the return of an equally weighted portfolio p on time t, and m is the total number of stocks with a return on time t, and N is equal to the amount of times $\mathbb{I}_t[x = p]$ is equal to 1 on time t. N is the number of stocks in portfolio p on time t, and R_{pt} is simply the average return of all stocks within the portfolio, due to equal weights.

To get the average portfolio return for a specific quintile, we transform portfolio returns into log returns (see equation 4). We then take the average of the $logR_{pt}$ over $t \in \{1, 2, \dots, T\}$. From here, annual returns are calculated by multiplying the monthly log returns by 12.

$$logR_p = \left(\frac{1}{T} \sum_{t=1}^{T} logR_{pt} \right) * 12 \tag{7}$$

where $logR_p$ is the annual log return of portfolio p, $logR_{pt}$ the log return of portfolio p on time t, and T the total number of months (in our case 120).

The monthly standard deviation of a portfolio is annualized by

$$\sigma_p = \sigma_p^m * \sqrt{12} \tag{8}$$

where σ_p is the annual standard deviation of portfolio p, and σ_p^m the monthly standard deviation of portfolio p calculated with the log returns.

4.6.2 Benchmark

Our benchmark portfolio contains all stocks from all 25 industries, with the same restrictions as used in the strategies. We create an equally weighted portfolio, with monthly rebalancing. Note that Fama French and other indices are value weighted. We will run Fama French regressions on the benchmark portfolio, to give insight how our benchmark compares to the Fama French factors.

4.6.3 ESG Strategy

For the ESG only strategy, we rank stocks within an industry on their ESG scores. We then put stocks into quintile portfolios, calculate the average annual log return, standard deviation and the Sharpe ratio from each quintile portfolio. Note that quintile portfolios have exactly one-fifth of the stocks of each industry.

4.6.4 Beta Strategy

For the beta only strategy, we also stick with the industry distribution from the market portfolio. So instead of ranking the scores on ESG scores, we rank the stocks on their monthly beta, and rank the stocks within its industry and put them in quintile portfolios according their rank.

4.6.5 Strategy 1

The first combined strategy sorts stocks on the weighted score $score\_\mathrm{I}_t$. It is a combination of two components:

$$score\_\mathrm{I}_t = 0.5 \times \frac{rank(\text{ESG score}_t) - 1}{\#\text{stocks in industry}_t - 1} + 0.5 \times \frac{rank(\text{beta}_t) - 1}{\#\text{stocks in industry}_t - 1} \tag{9}$$

Where $rank(\text{ESG score}_t)$ ranks ESG stocks from lowest to highest based on their industry at time t, and $rank(\text{beta}_t)$ ranks stocks from highest to lowest based on its beta at time t. In other words the lowest ESG stock gets value 1, and the highest gets value equal to the total number of ESG stocks on time t within the industry. This is reversed for the beta rank, since low beta is preferred rather than high beta. The *minus one* is required to make the scores run from 0 (lowest) to 1 (highest).

4.6.6 Strategy 2

A different way of obtaining a ESG portfolio with a beta tilt, is inspired from Robeco (2021). They aim for stocks that are 20% better on ESG scores, compared to the industry index. We could simply exclude all stocks that are not 1.2 times the average ESG of an industry at time t. In our case this meant roughly 30% of all data points. We then sort these stocks on their beta, and choose two-thirds with the lowest beta to obtain a portfolio containing 20% of all stocks, similar to our other strategies. Note that this strategy does not guarantee roughly 20% of all stocks in its portfolio on time t. The other strategies are build in a way where there is always 20% of all stocks in its chosen portfolio at all times $t \in \{1, 2, \ldots, T\}$.

4.6.7 Strategy 3

Instead of looking at the average ESG, we could simply only look at the top 40% ESG stocks for the beta tilt ESG portfolio. We then look at the remaining stocks and decide which to pick depending on their betas. First we sort stocks per industry on ESG at time t, pick the top 40% so we are left roughly 40% of all stocks at time t. We then no longer look at ESG, and simply sort the chosen stocks on their beta. Since we want to obtain a portfolio that has roughly 20% of all stocks, we take 50% of the chosen stocks with the lowest beta on times t. Once again we are left with a portfolio that has roughly 20% of all stocks in its portfolio at time t.

5 Results

Results are split up into two parts. First we look into the benchmark portfolio, beta only strategy, and ESG only strategy. Starting with the Fama French regressions, followed by the (risk adjusted) returns. We then look at the the three strategies that have some sort of beta tilt in the ESG strategy and similarly we look at the Fama French regressions and the (risk adjusted) returns.

5.1 Benchmark Portfolios and Factors

5.1.1 Benchmark Portfolio

The monthly returns of the benchmark portfolio, where all 3069 stocks are equally weighted, regressed against the Fama French factors, is shown in table 4. For all computations, we see a highly significant beta coefficient at 99.9% confidence level, with values roughly 1.05 to 1.18, implicating the benchmark portfolio is a little over 1 to 1 correlated with the market movement. The only other factor that has a significant coefficient at 99.9% confidence level, is SMB. Looking at the BP(2) regression results, we see the benchmark portfolio returns regressed against a constant, beta and SMB. The constant alpha is not significant in any regression at 95% confidence level. The R-squared is 0.889, which means that roughly 89% of the variation in returns is explained by the model. The interpretation of the two significant coefficients is:

- If the market on average increases 1%, the benchmark portfolio increases on average approximately 1.051%.
- For every 1% increase on the SMB factor, the benchmark portfolio increases on average approximately 0.524%.

The equally weighted benchmark portfolio has a significant tilt towards small market cap stocks, which explains some of its return. And the significant beta coefficient explains some of its return coming from the market return. The other HML, RMW, CMA factors do not show significant coefficients, which implies there is no significant return explained by exposure to these factors.

	BP(1)	BP(2)	BP(3)	BP(4)	BP(5)	BP(6)
α	-0.021	0.134	0.160	0.143	0.125	0.161
	(0.11)	(0.86)	(1.03)	(0.91)	(0.80)	(1.02)
β	1.177***	1.051***	1.047***	1.048***	1.056***	1.046***
	(24.49)	(24.36)	(24.41)	(23.82)	(24.42)	(23.57)
SMB		0.524***	0.502***	0.513***	0.513***	0.491***
		(7.47)	(7.09)	(6.86)	(7.27)	(6.47)
HML			0.112			0.093
			(1.68)			(1.08)
RMW				-0.048		-0.050
				(0.43)		(0.45)
CMA					0.130	0.044
					(1.25)	(0.33)
Observations	120	120	120	120	120	120
R^2	0.836	0.889	0.891	0.889	0.890	0.892

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: This table presents the estimates of the Fama French regression of the benchmark portfolio average monthly returns against the Fama French factors. The table shows six variations to test for statistically significant coefficients. BP(2) is the 3-factor Fama French regression, and BP(6) is the 5-factor Fama French regression.

5.1.2 Beta Strategy

Table 5 shows the results of the regression on the low beta portfolio of significant 3-factor model factors, in addition to the 3-factor regression results of the complete beta only strategy. In all portfolios, the market and SMB coefficient are significant at 99.9% confidence level. The HML is statistically significant for beta_4 and beta_high at respectively 95% and 99.9% confidence level. The constant alpha is statistically significant in the beta_low and beta_2 portfolio at respectively 99.9% and 95% confidence level. The R-squared 0.862 for beta_low, up to 0.896 for beta_high, which means that roughly 86% of the variation in returns is explained by the model for beta_low, and roughly 90% for beta_high.

The alpha in the beta_low means that on average, the portfolio has approximately 0.470% monthly outperformance, unexplained by the three factors. Annually, this would be approximately 5.8%.

Interesting is the comparison of the coefficients of the strategies within this beta strategy. The beta coefficient is only 0.693 at the low beta strategy, which means that for every 1% the market increases, the beta_low portfolio increases on average approximately 0.693%. Where at higher quintile portfolios, this coefficient increases. At the highest beta portfolio, beta_high, the return of the portfolio increases on average approximately 1.325% for every 1% the market increases. A similar trend can be seen looking at the SMB, where the coefficients rise from 0.605 to 0.880. And lastly, HML increases from portfolio beta_4 to beta_high from 0.191 to 0.264.

The 5-factor regression results can be found in Appendix A1. Only the RMW coefficient appears to be significant at 95% confidence level, which also appears to be negative. In other words, the portfolio appears to have somewhat of a tilt towards weak (low) operating profitability stocks.

	beta_low	beta_2	beta_3	beta_4	beta_high	beta_low
α	0.456***	0.338*	0.134	0.0352	-0.121	0.470***
	(3.47)	(2.31)	(0.82)	(0.20)	(0.59)	(3.59)
β	0.695***	0.879***	0.991***	1.100***	1.325***	0.693***
	(19.12)	(21.76)	(21.83)	(22.20)	(23.32)	(19.06)
SMB	0.617***	0.580***	0.682***	0.766***	0.880***	0.605***
	(10.27)	(8.69)	(9.09)	(9.36)	(9.37)	(10.24)
HML	-0.062	0.072	0.128	0.191*	0.264**	
	(1.09)	(1.15)	(1.82)	(2.49)	(3.00)	
N	120	120	120	120	120	120
R^2	0.864	0.879	0.883	0.888	0.896	0.862

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: This table presents the estimates of the Fama French 3-factor regression of the beta only strategy quintile portfolios, and their average monthly returns. Beta_low is the quintile portfolio with the lowest beta stocks, and beta_high the quintile portfolio with the highest beta stocks. The last column presents the regression of the low beta quintile portfolio on significant factors only.

5.1.3 ESG Strategy

Table 6 shows the results of the 3-factor regression results of the ESG only strategy. In all portfolios, the market and SMB coefficient are significant at 99.9% confidence level, except for the ESG_high portfolio, where SMB is significant at 99% confidence level. The HML coefficient is significant at 95% confidence level in the ESG_high portfolio only. The constant alpha is only significant in the ESG_low portfolio at 95% confidence level. The R-squared 0.880 for ESG_low, up to 0.886 for ESG_high, which means that roughly 88% of the variation in returns is explained by the model for ESG_low, and roughly 89% for ESG_high.

The alpha in the ESG_low means that on average, the portfolio has approximately 0.434% monthly outperformance, unexplained by the three factors. Annually, this would be approximately 5.3%. We see a slight increase in the beta coefficient for higher ESG portfolios from respectively 1.015 to 1.090. Where at the low ESG strategy the beta coefficient is 1.015, which means that for every 1% the market increases, the ESG_low portfolio increases on average approximately 1.015%. Where roughly at every higher ESG portfolio, this coefficient trends slightly upwards. At the highest ESG portfolio, ESG_high, the return of the portfolio increases on average approximately 1.090% for every 1% the market increases. The SMB coefficient shows a decreasing ESG coefficient, from 0.727 to 0.190 and also becoming less significant. And lastly, the HML coefficient for the ESG_high portfolio is 0.164.

The 5-factor regression results can be found in Appendix A1. Neither RMW or CMA have significant coefficients.

	ESG_low	ESG_2	ESG_3	ESG_4	ESG_high	ESG_low
α	0.449**	0.284	0.070	0.070	-0.076	0.434*
	(2.63)	(1.69)	(0.43)	(0.42)	(0.50)	(2.57)
β	1.013***	1.036***	1.027***	1.070***	1.090***	1.015***
	(21.53)	(22.29)	(22.94)	(23.31)	(25.97)	(21.63)
SMB	0.713***	0.628***	0.557***	0.418***	0.190**	0.727***
	(9.18)	(8.18)	(7.53)	(5.52)	(2.74)	(9.53)
HML	0.068	0.072	0.129	0.127	0.164*	
	(0.94)	(1.00)	(1.86)	(1.78)	(2.52)	
N	120	120	120	120	120	120
R^2	0.880	0.880	0.883	0.876	0.886	0.879

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: This table presents the estimates of the Fama French 3-factor regression coefficients of the ESG only strategy quintile portfolios, and their average monthly returns. ESG_low is the quintile portfolio with the lowest ESG stocks, and ESG_high the quintile portfolio with the highest ESG stocks. The last column presents the regression of the low ESG quintile portfolio on significant factors only.

5.2 Returns (1)

5.2.1 Benchmark Portfolio

Table 7 shows the average annual log return of the benchmark portfolio, which is approximately 13.7% with a standard deviation of 0.167. This means that on average, the benchmark portfolio has an annual arithmetic return of approximately 14.7% ($e^{0.137} = 1.147$). As a comparison, the S&P 500 has an annual log return of 13.1% over this period, with a standard deviation of 0.124. This means that on average, the S&P 500 has an annual arithmetic return of approximately 14.0%. The difference can be explained due to the S&P 500 using value weighting, and our benchmark portfolio uses equally weighted stocks which does not have a tilt towards high cap stocks. This could also explains the higher standard deviation our benchmark portfolio has, compared to the S&P 500. The risk adjusted returns, displayed by the Sharpe Ratio, is 0.820 for the benchmark portfolio and 1.061 for the S&P 500.

A cumulative arithmetic return comparison of our benchmark portfolio versus the S&P 500 can be found in the Appendix A3. Here we see a more volatile cumulative return of the benchmark portfolio, compared to the S&P 500. The benchmark portfolio does however outperform the S&P 500 over 10 years in (non risk-adjusted) returns. But it does not outweigh the increase in standard deviation, resulting in lower risk adjusted returns, compared to the S&P 500.

5.2.2 Beta Strategy

Table 7 also shows the average annual log return of the beta only strategy. We observe three trends for increasing beta quintiles:

- The log return decreases from 0.136 to 0.123.
- The standard deviation increases slightly from 0.126 to 0.227.
- The Sharpe Ratio decreases from 1.076 to 0.542.

So we observe a trade-off between Sharpe Ratio (more specifically mainly caused by standard deviation) and beta. For the high beta quintile portfolio it means that the annual arithmetic return is on average approximately 13.1%, with a Sharpe Ratio of 0.542. And for the low beta quintile portfolio the annual arithmetic return is on average approximately 14.6%, with a Sharpe Ratio of 1.076. So a lower return with a higher standard deviation, which in turn creates a lower Sharpe Ratio. The lower standard deviation is to be expected, since the low beta stocks are less volatile then high beta stocks, since it reacts weaker to market movement. But in economic theory, one would expect to gain a compensation in the form of returns, for taking higher risk. But in this case investors get more risk for less returns, A lose-lose situation.

5.2.3 ESG Strategy

Table 7 also shows the average annual log return of the ESG only strategy. We observe three trends for increasing ESG quintiles:

- The log return decreases from 0.166 to 0.116.

- The standard deviation decreases from 0.174 to 0.160.
- The Sharpe Ratio decreases from 0.952 to 0.722.

So we observe a trade-off between returns and ESG. For the high ESG quintile portfolio it means that the annual arithmetic return is on average approximately 12.2%, with a Sharpe Ratio of 0.722. And for the low ESG quintile portfolio the annual arithmetic return is on average approximately 18.0%, with a Sharpe Ratio of 0.952. While the standard deviation decreases slightly for higher ESG quintile portfolios, it does not outweigh the decreasing returns, which results into the difference between Sharpe Ratios. This table shows that the high ESG preference comes with a price, when using equally weighted portfolios.

	ESG					BETA					BM	SP500
	Low	P2	P3	P4	High	Low	P2	P3	P4	High		
$logR_p$	0.166	0.150	0.123	0.129	0.116	0.136	0.140	0.125	0.123	0.123	0.137	0.131
σ_p	0.174	0.172	0.168	0.167	0.160	0.126	0.149	0.171	0.190	0.227	0.167	0.123
SR	0.952	0.870	0.730	0.772	0.722	1.076	0.939	0.733	0.643	0.542	0.820	1.061

Table 7: This table presents the log returns, standard deviation and Sharpe Ratio of the ESG only strategy, beta only strategy, benchmark portfolio and S&P 500. The ESG and beta strategies show all 5 quintile portfolio results.

5.3 ESG Portfolios with Beta Tilt

5.3.1 Strategy 1

Table 8 shows the results of the 3-factor regression of strategy 1. The first 5 columns S1_low to S1_high represent the 5 quintile portfolios. The S1_low represents the low ESG & high beta portfolio, and S1_high represents the high ESG & low beta portfolio. S1_high also has the regression displayed on only significant coefficients, for more accurate coefficient interpretation. For all portfolios we observe a statistically significant beta and SMB coefficient at 99.9% confidence level. The HML coefficient is only statistically significant at 95% for S1_low, S1_2, and S1_3. The constant alpha is only significant for S1_high regression at 95% confidence level. The R-squared 0.892 for S1_low, down to 0.849 for S1_high, which means that roughly 89% of the variation in returns is explained by the model for ESG_low, and roughly 87% for ESG_high.

The alpha in S1_high means that on average, the portfolio has approximately 0.312% monthly outperformance, unexplained by the three factors. Annually, this would be approximately 3.8%. S1_low portfolio has a beta of 1.233, which means that for every 1% the market moves up, the portfolio increases on average approximately 1.233%. The higher the quintile portfolio, the lower the beta coefficient becomes, down to 0.762% for S1_high. The portfolio becomes less correlated to the market, the higher the quintile. Which is in line with the expectation followed by the observed results in the beta only and ESG only strategy (table 5 and 6).

S1_low portfolio has a SMB of 0.771, which means that for every 1% increase in SMB, the portfolio increases on average approximately 0.771%. The higher the quintile portfolio, the lower the SMB coefficient becomes, down to 0.709% for S1_high. The downwards trend means that the portfolio becomes slightly less tilted towards small market cap stocks, for higher quintile portfolios. However, the SMB does reverse the trend from S1_4 to S1_high, becoming larger for S1_high, but ever so slightly.

The HML coefficient is only statistically significant for the first three quintiles at confidence level 95%. It appears to be that the low quintile portfolios are somewhat tilted towards a high book-to-market ratio stocks, where this effect becomes insignificant in higher quintile portfolios.

The regressions, compared to the ESG_high portfolio, show that the alpha becomes significant, the beta decreases, and the SMB increases. Lastly, the HML becomes insignificant. Most important is the beta, that could result into less standard deviation and possibly a higher Sharpe Ratio in the return. The 5-factor regression results can be found in Appendix A1. Neither RMW or CMA has significant coefficients.

	S1_low	S1_2	S1_3	S1_4	S1_high	S1_high	ESG_high
α	0.081	0.130	0.179	0.138	0.316*	0.312*	-0.076
	(0.42)	(0.78)	(1.12)	(0.86)	(2.15)	(2.15)	(0.50)
β	1.233***	1.069***	0.999***	0.931***	0.761***	0.762***	1.092***
	(23.40)	(23.13)	(22.62)	(21.02)	(18.78)	(18.91)	(25.97)
SMB	0.771***	0.709***	0.690***	0.643***	0.709***	0.712***	0.190**
	(8.86)	(9.29)	(9.45)	(8.79)	(10.59)	(10.87)	(2.74)
HML	0.169*	0.178*	0.152*	0.073	0.016		0.164*
	(2.07)	(2.49)	(2.22)	(1.07)	(0.26)		(2.52)
N	120	120	120	120	120	120	120
R^2	0.893	0.894	0.891	0.874	0.865	0.865	0.886

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: This table presents the estimates of the Fama French 3-factor regression of the first strategy. The second S1_high displays the regression on only significant Fama French factors. S1_low is the quintile portfolio with the lowest $score$_I stocks, and S1_high the quintile portfolio with the highest $score$_I stocks.

5.3.2 Strategies 2&3

Table 9 presents the result of the 3-factor regression of strategies 2 and 3. These two strategies are combined in one section due to not having all 5 quintile portfolios. The only portfolios that are created, are comparable with the S1_high quintile portfolio. Both beta and SMB are statistically significant at 99.9% confidence level. The constant alpha and HML are not significant in either regression at 95% confidence level. The R-squared is 0.886 for both strategies, which means that roughly 89% of the variation in returns is explained by the model.

For strategy 2 and 3, the beta coefficients are 1.006 and 0.990 respectively, which means that for every 1% the market moves up, the portfolio increases on average approximately 1.006% and 0.990% respectively. Both are almost perfectly correlated with the market movement, which is higher than strategy 1 (0.762%), and lower than ESG_high (1.092%)

The SMB coefficients for strategy 2 and 3, are 0.561 and 0.528 respectively, which means that for every 1% increase in SMB, the portfolio increases on average approximately 0.561% and 0.528% respectively. Both coefficients are slightly lower than strategy 1 (0.712%), which implies that strategy 2 and 3 are less tilted towards small-cap stocks than strategy 1. But they are both more tilted towards small-cap stocks than ESG_high (0.190%). The HML coefficients become insignificant, similar to strategy 1, while ESG_high has a significant HML coefficient.

	S2	S3	S2	S3	ESG_high
α	0.235	0.252	0.215	0.236	-0.076
	(1.52)	(1.68)	(1.40)	(1.57)	(0.50)
β	1.002***	0.987***	1.006***	0.990***	1.092***
	(23.49)	(23.72)	(23.53)	(23.80)	(25.97)
SMB	0.544***	0.514***	0.561***	0.528***	0.190**
	(7.72)	(7.47)	(8.08)	(7.80)	(2.74)
HML	0.087	0.070			0.164*
	(1.32)	(1.09)			(2.52)
N	120	120	120	120	120
R^2	0.887	0.888	0.886	0.886	0.886

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: This table presents the estimates of the Fama French 3-factor regression of strategy 2 and 3. The second S2 and S3 display the regression on only significant Fama French factors.

5.4 Returns (2)

5.4.1 Strategies 1

Table 10 shows the average annual log return of the quintile portfolios of strategy 1. For S1_low, this is approximately 14.0% with a standard deviation of 0.206. This means that on average, the S1_low portfolio has an annual arithmetic return of approximately 15.0%. We observe that higher quintile portfolios have decreasing trend in log returns, down to approximately 11.8%, which equals an arithmetic return of approximately 12.6%.

The standard deviation however goes down as well, from 0.206 all the way to 0.143, which results in a Sharp Ratio increase from 0.680 to 0.827. The risk adjusted returns are greater for high quintile portfolios, even though the average annual arithmetic return is approximately 2.4% lower on average.

Comparing S1_high and ESG_high, we see the average annual log return is slightly higher (0.002%), while the standard deviation goes down from 0.160 to 0.143. This results in a Sharpe Ratio increase from 0.722 to 0.827.

5.4.2 Strategies 2&3

Table 10 also shows the average annual log return of the portfolios of strategy 2 and 3. For strategy 2, this is approximately 14.1% with a standard deviation of 0.163. This means that on average, the strategy 2 has an annual arithmetic return of approximately 15.2%. It has a Sharpe Ratio of 0.866.

For strategy 3, the average annual log return is approximately 14.2% with a standard deviation of 0.159. This means on average, the strategy 3 has an annual arithmetic return of approximately 15.3%. It has a Sharpe Ratio of 0.895. Due to having a slightly higher return (of 0.1%) and a slightly lower standard deviation (of 0.04), compared to strategy 2, the Sharpe Ratio is slightly better (0.029).

Comparing S2 and S3 to ESG_high, we see the average annual log return is quite a lot higher from 16.0% to respectively 16.3% and 15.9%, while the standard deviation stays almost the same. This results in a Sharpe Ratio increase from 0.722 to respectively 0.866 and 0.895.

	S1_low	S1_2	S1_3	S1_4	S1_high	S2	S3	ESG_high
$log R_p$	0.140	0.134	0.130	0.126	0.118	0.141	0.142	0.116
σ_p	0.206	0.184	0.170	0.159	0.143	0.163	0.159	0.160
SR	0.680	0.726	0.765	0.796	0.827	0.866	0.895	0.722

Table 10: This table presents the log return, standard deviation and Sharpe Ratio of the 3 strategies. Strategy 1 has all quintile portfolios included in the table.

6 Conclusion

The aim of this thesis was to investigate whether a combination of beta tilt in an high ESG strategy can increase risk-adjusted returns. Table 11 summarizes the average log return of the benchmark portfolio, the ESG only portfolio, the beta only portfolio and the portfolios of our 3 strategies.

First off, we found that low volatility portfolios indeed outperform the high volatility portfolios. The high volatility portfolio showed less correlation with the market (beta) in the Fama French regression. The average log returns are almost the same for all portfolios. In line with the Fama French findings, the standard deviation of the low beta portfolio is reduced by almost a factor 2, compared to the high beta portfolio. These differences showed in the Sharpe Ratio that went from 0.542 for the high beta portfolio, to 1.076 for the low beta portfolio.

For the high ESG portfolio we found that it does not outperform the low ESG portfolio. The Fama French regression showed that the low ESG portfolio had a higher tilt towards small market cap stocks than the high ESG portfolio. The average log return of the low ESG portfolio is almost 1.5 times as high as the average log return of the high ESG portfolio. The standard deviation decreases slightly, but that does not compensate the log return reduction. The Sharpe Ratio went from 0.952 in the low ESG portfolio, to 0.722 in the high ESG portfolio. A popular explanation for the observed abnormal returns of sin stocks is that they are systematically underpriced because so many investors avoid them.

All our three strategies ESG strategies with a beta tilt did show an increase in risk-adjusted returns, compared to the ESG only strategy. Where strategy 1 had the lowest log return of 0.118, strategies 2 and 3 had respectively 0.141 and 0.142. The standard deviation of strategy is 1 is 0.143, compared to 0.163 and 0.159. The Sharpe Ratios of strategies 1 2 and 3 are respectively 0.827, 0.866 and 0.895 all outperform the benchmark of 0.711. Depending on investors preferences, one can argue which of the three strategies fits best. Strategy 1 has the advantage of lower risk and higher alpha, whereas strategies 2 and 3 have higher risk and higher returns.

	BM	ESG_high	beta_low	S1	S2	S3
$logR_p$	0.137	0.116	0.136	0.118	0.141	0.142
σ_p	0.167	0.160	0.126	0.143	0.159	0.160
SR	0.820	0.722	1.076	0.827	0.866	0.895

Table 11: This table presents a summary of the relevant average portfolio log return, standard deviation and Sharpe Ratio, to compare our 3 strategies with the benchmark and ESG only and beta only strategies.

In the end, combining ESG and beta strategies is a trade-off between the level of social responsibility and risk adjusted returns. By tilting towards low beta stocks, some high ESG stocks that are in a high ESG only strategy get excluded due to being too volatile. The same goes for the opposite, where low beta stocks get included into the strategy, while having lower ESG than otherwise would be included in a ESG only strategy. However, for strategies 2 and 3 it does add quite some raw average log return, while decreasing the volatility of the portfolio. For strategy 1 the standard deviation decreases, with similar returns as the ESG only strategy. So if you are willing to sacrifice a little on ESG, you can significantly increase your risk adjusted returns if you include a tilt towards low beta stocks, when using equally weighted portfolios.

7 Appendix

7.1 Industry Distribution

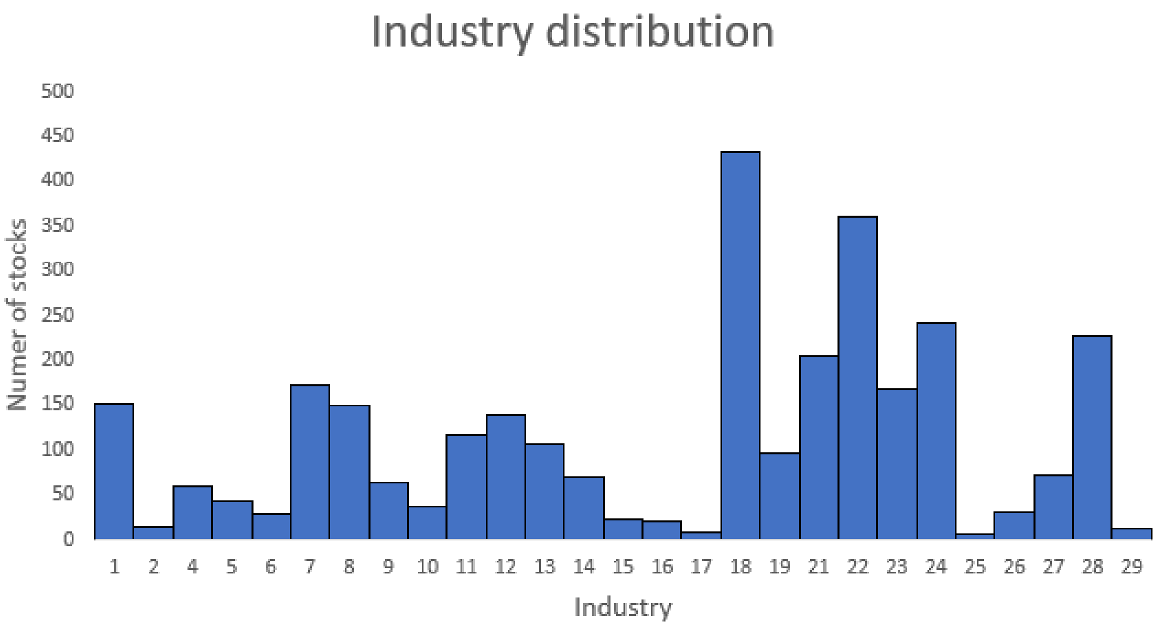

Figure A2: The distribution of stocks in each remaining industry. Note that industry 3 and 20 are excluded due to having only one stock.

7.2 Benchmark Portfolio vs S&P 500

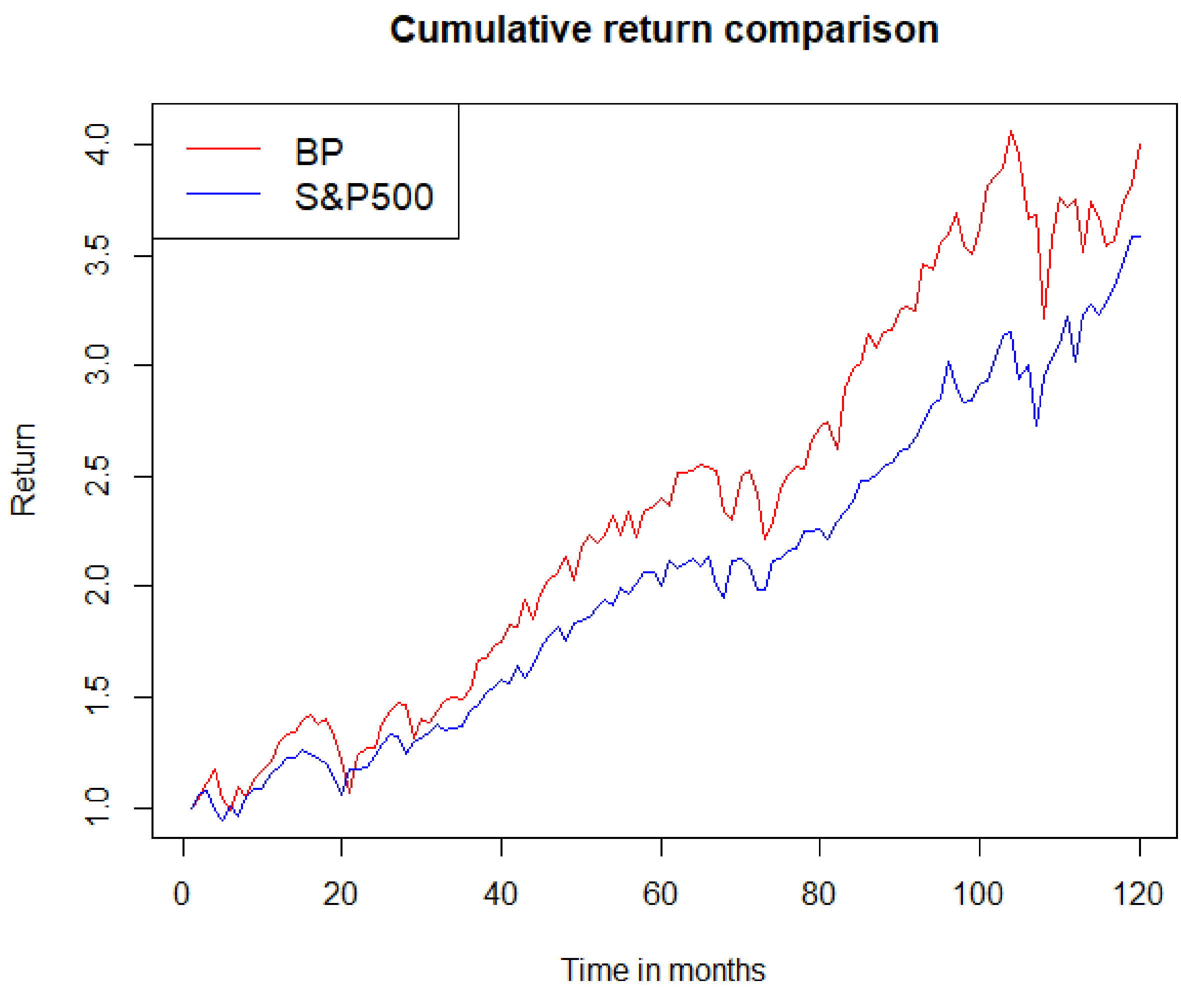

Figure A3: The figure shows both the benchmark portfolio and S&P 500 cumulative returns. The sample period runs from January 2010 to December 2019.

7.3 ESG Methodology

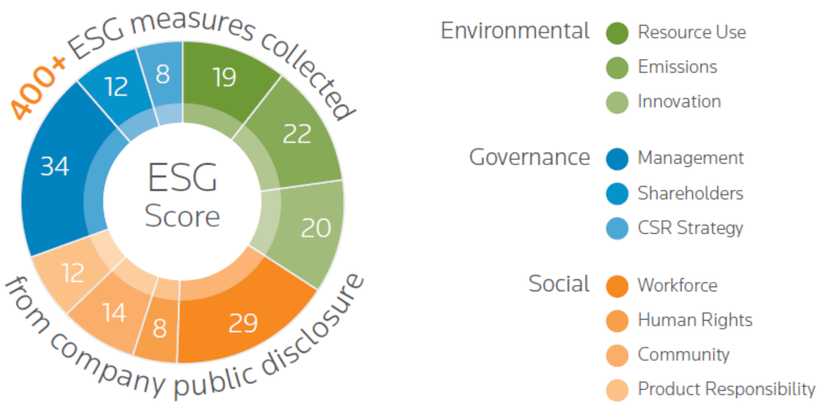

Figure A4: A distribution of the 400 ESG measures collected.

Score	Definition
Resource Use Score	The Resource Use Score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management.
Emissions Score	The Emission Reduction Score measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes.
Innovation Score	The Innovation Score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.
Workforce Score	The Workforce Score measures a company's effectiveness towards job satisfaction, a healthy and safe workplace, maintaining diversity and equal opportunities, and development opportunities for its workforce.
Human Rights Score	The Human Rights score measures a company's effectiveness towards respecting the fundamental human rights conventions.
Community Score	The Community Score measures the company's commitment towards being a good citizen, protecting public health and respecting business ethics.
Product Responsibility Score	The Product Responsibility Score reflects a company's capacity to produce quality goods and services integrating the customer's health and safety, integrity and data privacy.
Management Score	The Management Score measures a company's commitment and effectiveness towards following best practice corporate governance principles.
Shareholders Score	The Shareholders Score measures a company's effectiveness towards equal treatment of shareholders and the use of anti-takeover devices.
CSR Strategy Score	The CSR Strategy Score reflects a company's practices to communicate that it integrates the economic (financial), social and environmental dimensions into its day-to-day decision-making processes.

Figure A5: A brief explanation of each ESG theme.

7.4 5-factor Regression

7.4.1 Beta

	beta_low	beta_2	beta_3	beta_4	beta_high
α	0.452**	0.348*	0.147	0.065	-0.037
	(3.36)	(2.33)	(0.88)	(0.36)	(0.18)
β	0.697***	0.875***	0.986***	1.089***	1.293***
	(18.50)	(20.96)	(21.01)	(21.30)	(22.68)
SMB	0.613***	0.562***	0.664***	0.744***	0.798***
	(9.53)	(7.88)	(8.28)	(8.52)	(8.20)
HML	-0.080	0.062	0.125	0.220*	0.309**
	(1.09)	(0.76)	(1.37)	(2.21)	(2.78)
RMW	-0.018	-0.080	-0.079	-0.100	-0.363*
	(0.19)	(0.76)	(0.67)	(0.78)	(2.53)
CMA	0.044	0.023	0.005	-0.074	-0.121
	(0.39)	(0.18)	(0.03)	(0.48)	(0.70)
N	120	120	120	120	120
R^2	0.864	0.880	0.884	0.889	0.903

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1: This table presents the estimates of the Fama French 5-factor regression of the beta only strategy quintile portfolios, and their average monthly returns. Beta_low is the quintile portfolio with the lowest beta stocks, and beta_high the quintile portfolio with the highest beta stocks.

7.4.2 ESG

	(1) ESG_low	(2) ESG_2	(3) ESG_3	(4) ESG_4	(5) ESG_high
α	0.499**	0.282	0.066	0.048	-0.094
	(2.90)	(1.64)	(0.40)	(0.28)	(0.61)
β	0.994***	1.036***	1.029***	1.077***	1.096***
	(20.70)	(21.54)	(22.18)	(22.74)	(25.32)
SMB	0.670***	0.620***	0.555***	0.420***	0.185*
	(8.17)	(7.54)	(7.00)	(5.19)	(2.50)
HML	0.106	0.0510	0.116	0.0789	0.113
	(1.13)	(0.55)	(1.28)	(0.86)	(1.34)
RMW	-0.193	-0.036	-0.008	0.012	-0.015
	(1.59)	(0.29)	(0.06)	(0.10)	(0.14)
CMA	-0.099	0.051	0.032	0.119	0.126
	(0.68)	(0.35)	(0.23)	(0.83)	(0.96)
N	120	120	120	120	120
R^2	0.883	0.881	0.884	0.877	0.887

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: This table presents the estimates of the Fama French 5-factor regression coefficients of the ESG only strategy quintile portfolios, and their average monthly returns. ESG_low is the quintile portfolio with the lowest ESG stocks, and ESG_high the quintile portfolio with the highest ESG stocks.

7.5 Our 3 Strategies

	S1_low	S1_2	S1_3	S1_4	S1_high	S2	S3	ESG_high
α	0.149	0.174	0.200	0.143	0.302*	0.238	0.250	-0.094
	(0.79)	(1.04)	(1.19)	(0.88)	(2.09)	(1.51)	(1.62)	(0.61)
β	1.202***	1.050***	1.014***	0.927***	0.747***	1.001***	0.988***	1.096***
	(22.91)	(22.37)	(21.60)	(20.40)	(18.52)	(22.66)	(22.93)	(25.32)
SMB	0.705***	0.682***	0.664***	0.649***	0.679***	0.534***	0.509***	0.185*
	(7.87)	(8.51)	(8.27)	(8.36)	(9.85)	(7.08)	(6.91)	(2.50)
HML	0.238*	0.208*	0.145	0.031	0.009	0.075	0.054	0.113
	(2.33)	(2.28)	(1.59)	(0.35)	(0.11)	(0.88)	(0.65)	(1.34)
RMW	-0.242	-0.191	-0.059	-0.083	-0.062	-0.041	-0.020	-0.015
	(1.83)	(1.61)	(0.50)	(0.72)	(0.61)	(0.37)	(0.19)	(0.14)
CMA	-0.178	-0.063	0.057	0.065	-0.005	0.028	0.039	0.126
	(1.12)	(0.44)	(0.41)	(0.47)	(0.04)	(0.21)	(0.30)	(0.96)
N	120	120	120	120	120	120	120	120
R^2	0.900	0.899	0.888	0.877	0.871	0.888	0.888	0.887

t-values in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: This table presents the estimates of the Fama French 5-factor regression of the 3 strategies. S1, S2 and S3 are the three different strategies. S1_low is the quintile portfolio with the lowest *score*_I stocks, and S1_high the quintile portfolio with the highest *score*_I stocks.

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