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Navn:	Torstein Samuelsen og Casper Sormerud Svendsen

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- ESG Scores and Equity Value: A Study of ESG Premium in the Nordic markets -

Master Thesis of

Casper S. Svendsen

Msc. Sustainable Finance

Torstein Samuelsen

Msc. Sustainable Finance

Campus:
BI Oslo

Under the supervision of:
Leon Bogdan Stacescu

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Abstract

This study explores the relationship between ESG scores and P/B ratios for Nordic-listed companies. We find indications of differences in average P/B and ESG scores. To explore if ESG drives P/B differences, we develop a panel-regression model with six control variables. We find evidence that assets with an ESG score have a higher P/B ratio ($\beta = 0.0046^{***}$), after controlling for traditional drivers of P/B. This confirms our expectation that investors are willing to pay a premium for ESG performance. Contrary to the literature, further investigation shows that low ESG-scoring companies tend to have a higher price premium than high ESG-scoring companies when accounting for control variables and NAs. We discuss implications and possible explanations for these findings and formulate advice for Nordic firms and Asset managers.

Keywords: ESG, Value, Equity value, ESG and value, Price-to-book ratio, ESG scores, Refinitiv Esg Scores

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Abbreviations:

AUM - Assets under Management

CSR - Corporate social responsibility

E - Environmental pillar (part of the ESG)

ESG - Environmental, Social, and Governance

G - Governance pillar (Part of the ESG)

ROE - Return on equity

S - Social pillar (Part of the ESG)

β - Factor`s coefficient (sensitivity)

WACC- Weighted average cost of capital

tCo2e – Tonnes (t) of carbon dioxide (CO_2) equivalent (e)

EUR – Official European Union currency

HAC – Heteroskedasticity- and autocorrelation-consistent

st.dev – Standard deviation

FCF – Free Cash Flow

1. Introduction

In recent years, the growing evidence of climate change (Bernard et al., 2023) and its consequences have brought Environmental, Social, and Governance (ESG) factors into the spotlight, including within the realm of finance (Fender et al., 2020). Sustainability has become fundamental to firms' core business, and many investors and analysts argue that ESG considerations are relevant for evaluating a company's long-term prospects and equity valuation (Fender et al., 2020; Grini, 2020; Wasberg & Lorentzen, 2019). As Investor preference for ESG has increased rapidly over recent years, so have assets under management deemed sustainable (Hale, 2022; Hartzmark & Sussman, 2019; Figure 2). Asset managers and investors depend on easy-to-access and easy-to-incorporate data. ESG scores have become one of the most used metrics for implementing ESG into investment decisions (Amel-Zadeh & Serafeim, 2018). Our thesis shows that higher ESG-scoring companies do not necessarily have higher valuations and returns. Hence, there may be more appropriate ways to evaluate a company's ESG profile or to generate superior returns in a sustainable investment strategy than relying solely on ESG scores in the investment decision.

We show this by studying differences in price-to-book (P/B) ratio in portfolios sorted by ESG scores for Nordic companies in the period 2018-2021, while also creating robust regressions to explain the differences in P/B. We use P/B ratios because it captures how the market values a company relative to its underlying book values. A higher P/B will therefore capture investor preferences for a particular company. Preferences driven by firm characteristics like higher profitability, risk, or a better ESG profile. Literature suggests that ESG practices should increase the value of a company (Hensisz et al., 2019). Our research question is as follows:

How have ESG scores among Nordic companies affected equity valuation?

Given the natural link between valuation and returns, the link between P/B ratio and returns (Fama & French, 1995), and the link between ESG-performance and returns (Bolton & Kacperczyk, 2021; Chang et al., 2022; Ilhan et al., 2021), we add an additional question to our research:

Do assets with a high ESG score, have lower returns on average?

1.1 Importance of the Thesis and Our Contribution

Our thesis will add to the literature in several ways. Firstly, our contribution lies in undertaking evaluations of P/B ratios in relation to ESG scores, a research area that remains unexplored in the Nordic region. We also contribute to understanding where ESG has impacted valuations, which might contribute to further research or insights. As a result, our thesis would interest both investors and companies, as it provides them with informed perspectives on how an ESG score can affect financial valuations. As finance plays a crucial role in allocating funds in the world economy, a better understanding of how the market is pricing ESG can help asset managers and legislators understand how finance is driving the essential transition to a more sustainable economy. Hence, the topic and question of this thesis are highly relevant to today's society.

1.2 The structure of this paper

In section 2, we review literature related to how a company's ESG profile can affect value. Most literature suggests that ESG should increase value and decrease risk, while only a few indicates the opposite. In addition, we review literature that helps us pick the variables for the regression model (Branch et al., 2005; Fama & French, 1995). In the third section, we outline the methodology and methods for our research and form our hypotheses to be tested. Using Brooks (2019), we conclude that a fixed-effect regression model is the best for our panel data. That allows us to capture heterogeneity across time, companies, and industries. Section four describes the data we use in the thesis and research. We provide summary statistics for all variables (Tables; 1; 10 – 13); given limitations in the amount of ESG scores (Table 1), we focus our research on the period 2018-2022. In addition, we investigate the distributions of the variables (Figure 4) and find it appropriate to exclude outliers in most of our included variables (Figure 5). In section five, we first sort all companies in portfolios by their ESG score and test each portfolio's average P/B against each other (Table 8, Figure 6), finding only a significant difference between the worst and best ESG portfolios. Further, we use our filtered data to run our regressions (Equations 3 – 6); results show that having an ESG score increases P/B (Table 3). However, the score level does not necessarily affect (Tables 4 and 5). We also explore returns for the portfolios sorted by ESG score, where the underperformance of the ESG scoring portfolio supports our hypothesis (Figure 1). Lastly, section 6 concludes our research and provides insights for future research.

2. Related literature

2.1 ESG and Value

Even though the ESG term has been around for several decades, the topic has gained wider attention in recent years, as climate change mitigation efforts are gaining momentum (Bernard et al., 2023). Earlier studies related to ESG were usually linked to companies' CSR efforts, often with conflicting results. As the Sustainable Finance literature has grown, more literature on ESG has become available. Not all studies on ESG use ESG scores to determine the sustainability level of a company, however many do. The literature around these scores is divided. While most suggest that better ESG leads to lower risk, higher prices, and higher value. Others argue it is wasteful spending, and some indicate that ESG is not recognized by the market and hence no particular value pattern exists.

Bolton & Kacperczyk (2021) study the relationship between carbon emissions and cross-sectional stock returns in the period 2005-2017. The paper's main finding is that carbon emissions affect stock returns because high-carbon-emitting companies achieved higher stock returns (i.e., higher risk and lower prices) than lower CO2 emitters. This suggests that carbon-intensive firms are exposed to higher transition risk, and investors do price this carbon risk. They recognize that high CO2 emitting companies will achieve lower ESG scores than lower CO2 emitters. We see this paper as evidence that higher ESG-scoring companies should get higher prices in the market (reflected by higher P/B) and that this ultimately leads to lower risk and expected returns for high ESG-scoring stocks.

A similar study by Ilhan et al. (2022) found that the costs of options protecting the downside tail risk are higher for more carbon-intense companies. They claim this comes from the uncertainty about future government regulations and how these will impact carbon-intense companies' costs and returns. One regulation they mention is increased carbon taxes. To back up their findings, they find that when public attention to climate change increases, so does the cost of downside protection. This increase in risk, and the potential increase in costs for carbon-intense companies, should indeed be reflected in stock prices. Therefore, a lower ESG score should give a lower price to reflect the increased risk and hence a lower P/B than less carbon intense companies.

On the contrary, Choi et al. (2020) investigated the view that markets do not efficiently price ESG information. They found evidence that carbon-intensive firms underperform with respect to lower-emitting firms when climate change is more evident, e.g., when temperatures are higher than normal. They conclude that prices underreact to climate risk in normal times. As such, we might observe that ESG does not affect P/B ratios. This paper is more in line with Pedersen et al. (2021), which suggests that pricing will depend on the type of investors that prevail in the market. More ESG-motivated investors in the market will make high-scoring companies achieve higher prices and, thus, lower expected returns. In contrast, the opposite happens if fewer ESG-aware investors are in the market. Given the recent year's increased investor attention towards ESG (Hale, 2022; Hartzmark & Sussman, 2019), we argue that today's market has ESG-aware investors. As such, we should observe that high ESG-scoring companies have high P/B ratios, and their subsequent returns should be low.

A recent review by Chang et al. (2022) studied the value implications of ESG practices in the Asia-pacific region. Using a Discounting CashFlow (DCF) framework, they found evidence that such practices increase firm value. Specifically, ESG might result in more motivated employees, long-term Growth, increased dividends, and reduced risks and costs. The paper also looks at how ESG affects investment returns, concluding that the ESG-stock returns relation can be positive in the short run due to inefficiencies and preference differences. However, the dominant evidence indicates that more highly rated ESG stocks do not offer higher returns in the long run.

Berg et al. (2022), in the paper "*Aggregate Confusion: The Divergence of ESG Ratings,*" investigate the ESG rating divergence across rating agencies. They found that measurement divergence is the primary driver of ESG rating divergence. They believe researchers should carefully choose the data that underlie future ESG studies and ideally work with raw data. If this is not available, one should examine how the data is generated and be skeptical of data that is not transparent. Given ESG rating divergence, the use of ESG rating in research needs to pay attention to the validity of the data used. The complication of this finding is that it could mean that using ESG scores is not the best approach to assessing the ESG characteristics of a company. Hence, investors prefer doing fundamental analysis or using their preferences for the assessment. If so, ESG scores will have lower explanatory power on valuations than expected.

The paper "*Do Investors Value Sustainability?*" studies investors' attitudes toward sustainability and its impact on investment performance. Results show investors favor sustainability, but high sustainability ratings do not necessarily yield superior fund performance. Utilizing Morningstar's rating system, the research found a marked shift in fund flows after ratings were published. High-rated funds saw about a 4% investment increase, while low-rated funds experienced a 6% outflow, but medium-rated funds saw no significant change (Hartzmark & Sussman, 2019). According to this research, higher demand for high-scoring ESG companies should lead to higher P/B ratios.

Drempetic et al. (2020) claim that larger firms spend more on ESG and achieve higher ESG scores. As we know, these larger firms usually trade at lower, more stable P/B. As such higher ESG could lead to lower P/B ratios. Borokova & Wu (2020) claims something similar when they state that "larger firms exhibit better ESG performance because they have more means by which to invest in sustainability, and therefore improve their scores."

Earlier studies on CSR were also dispersed on the effect on value. Rooted in the famous Friedman doctrine, "*The Social Responsibility Of Business Is to Increase Its Profits*" (Friedman, 1970), many argue that CSR is wasteful spending and as such, value-destroying (Lutz, 2012; Baker, 2010). If these perspectives on ESG are dominant in the market, then we should find that higher ESG scores often lead to lower valuations and P/B ratios. Ferrell et al. (2016) present a more nuanced argument and conclude that CSR can be both value-enhancing and -destroying, depending on company-specific characteristics related to corporate governance.

2.2 Litterature Related to Methodology

2.2.1 Why P/B

In the book "Investments" (Bodie et al., 2014, p. 616), it is stated:

> *"Some view book value as a useful measure of fundamental value and therefore treat the P/B ratio as an indicator of how aggressively the market values the firm."*

Similarly to the paper "*The catering theory of Dividends*" by Baker & Wurgler (2004), who showed that dividend-paying firms could be valued at a premium to non-paying firms in specific periods, we will use price-to-book (P/B) ratios to determine if there is a price premium on companies with high ESG scores in the market, by comparing the P/B ratios of high ESG-scoring companies to those of lower ESG-scoring companies and those with no score at all. While Baker & Wurgler called their finding the "*dividend price premium*", we will call this the "*ESG premium*".

We will use P/B ratios to measure valuation and "demand" for a particular stock. When demand is high, the price of the stock, i.e., valuation, increases while the book value remains the same, resulting in a higher P/B ratio. Prices observed in the market are usually derived from valuation models, which model detailed information about a firm into the future. In comparison, book values tend to be more stable.

A higher valuation is as such often driven by expectations on expected FCF and return on equity, higher future growth prospects, lower risk or other quality characteristics. Or, as we want to investigate: a better ESG profile. Where ESG can both be considered a proxy for long-term financial performance (Hensisz et al., 2019), or just represent a non-financial value that investors appreciate.

2.2.2 Building our model

In the paper "*A Price To Book Model Of Stock Prices*" by Branch et al. (2005), they build a regression model for explaining behavior in P/B ratios over or above the mean P/B in their sample of S&P 500 companies (as it existed in 1979). They first find that the average P/B in 1979 was almost equal to 1, while it in 2000 was nearly

5. They find that a company's P/B varies both in a time series and cross-sectional way.

In their model, variability in PB stems from profitability, measured by Return on Equity (ROE), risk, measured by WACC, and growth (G). The risk-free rate in WACC is equal for all, so it lets us capture risk cross-sectionally. In addition, they also tried to add industry dummies (fixed effects) but found them to provide very little additional explanatory power. They argue that differences in P/B across industries are largely due to differences in industry profitability, risk, and growth, which are captured by the explanatory variables. Given their research, we choose to add these variables to our model. Their findings suggest that we will find a positive relationship between P/B and ROE, WACC, and future growth.

Fama &) also showed that Book-to-Market (B/P) had a negative relation with ROE. Using P/B as we do, that is equivalent to a positive relationship. The paper also mentions that low Book to Market (B/M) stocks (equivalent to high P/B) have a higher future return on capital; they call these growth stocks. Another statement from Fama & French (1995) is that size has much to say on profitability. Small stocks tend to be less profitable than larger ones. For us, this means that size can influence P/B. As such, we add market capitalization (market cap.) to our model, where we expect a positive relationship with P/B, as larger firms can be more profitable. However, as we know that high-growth stocks tend to be small, we could also see a negative market cap.

Our thesis investigates whether ESG scores provide any insight into current valuation. Hence we add ESG scores to the model. Current ESG scores reflect a company's current ESG profile and are not so much future-oriented. However, according to literature, a good ESG profile today can reflect higher future growth or lower risk (Bolton & Kacperczyk, 2021; Hensisz et al., 2019) and should be reflected in a "premium" valuation today. We add current or backward-looking measures to our analysis, such as current market capitalization (Mktcap), how long the company has been listed on the exchange (Age), and the last 12-month Revenue growth. We add these to the equation because of the typical characteristics of P/B ratios. For example, young, new businesses typically have a higher P/B ratio than more mature companies operating in mature industries.

3. Research Methodology/ Theory and hypotheses

Our primary hypothesis is that companies with higher ESG scores will have a higher average Price-to-Book ratio (P/B). If so, it would indicate a price premium for high ESG-scoring stocks. We also expect an upward trend in price premiums for higher-scoring firms leading up to 2021 compared to companies with lower ESG scores.

3.1 Testing for differences in means

To test this hypothesis, we first divide stocks into four different portfolios based on their ESG scores. One portfolio will be made up of companies without ESG scores, i.e., ESG scores equal to zero. The three other portfolios are sorted by the 33rd and 67th percentiles concerning that year's ESG scores. As new ESG scores are published annually, the percentiles and the portfolios are rebalanced annually.

We will then calculate the average P/B ratio in each group and perform a standard univariate **difference in means** test (Rice, 1994, pp. 388–400) using a T-test to determine if there is a significant difference in the average P/B ratio between the groups.

The hypothesis for the different groups is stated as follows:

$$H_0: \mu_1 = \mu_2$$
$$H_A: \mu_1 \neq \mu_2$$

Where μ = Sample means

The test statistic (t):

$$t = \frac{(\mu 1 - \mu 2)}{\sqrt{\left(\frac{S_p^2}{n_1} + \frac{S_p^2}{n_2}\right)}} \tag{1}$$

Where,

$$S_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} \tag{2}$$

Where n1 + n2 – 2 = degrees of freedom, and s_p^2 is the standard deviation of group p (Tests Concerning Differences in Means). The formulas for the "difference in mean test" is taken from the book: Mathematical Statistics and Data Analysis (Rice, 1994, pp. 388–400).

We further divide our sample of companies into their respective industries and perform the same analysis as above. Where we create and rebalance the portfolios within each industry regarding that industry's ESG scores. As such, we can compare companies with “superior” ESG scores compared to peers in the same industry and then test the mean P/B of each portfolio against each other.

In this case, the data support our hypothesis, and we find that the average P/B of companies with higher ESG scores is significantly higher than those with lower ESG scores. This will be an initial indication that ESG scores can positively impact P/B ratios, hence an ESG price premium.

3.2 Regressions and significance testing

The second stage of our research will be to investigate the possibilities of **why** we observe these differences. We do this by running a multivariate fixed effects panel regression with P/B as the dependent variable. The independent, explanatory variables are; ESG score, firm size, measured with the market capitalization (mktcap), Revenue growth, years listed on the exchange (age), Return on Equity (ROE), Weighted Average Cost of Capital (WACC), and future long term growth (Labeled “Growth” in the regression) implied by the market.

Our primary interest lies in the ESG score. We aim to determine if the regression coefficient of the ESG score, also known as the slope coefficient, significantly differs from zero. If our hypothesis holds, this coefficient should also be positive, implying that higher ESG scores generally lead to higher P/B ratios. While the ESG score is our focus, we anticipate that other independent variables also affect the P/B ratio. Confirming this influence would bolster our findings regarding the ESG score. For these other variables, we are primarily concerned with the direction of their effects rather than the exact magnitude of their coefficients.

Our hypothesis for the two measures of growth (Revenue growth and Growth) is that they are positive, as high-growth companies are associated with higher P/B ratios. We expect the Age coefficient to be negative, indicating that younger firms tend to have higher P/Bs. Further, our hypothesis for both ROE and WACC is that they are positive. ROE measures a company’s ability to generate returns on its equity. As such, a company that generates higher returns should have a premium pricing with respect to the ones that generate lower returns. WACC proxies for risk in our model; new businesses will, on average, be considered to have a higher risk, while more mature companies will usually be priced with lower risk. As such, we expect higher risk to be associated with higher P/B ratios. These hypotheses are also in line with the papers discussed in section 2.2.2.

To account for the various forms of heterogeneity in our data, both across time and cross-sectionally, we introduce time-, company-, and industry-specific fixed effects into our regressions. We represent these effects using dummy variables and estimate our models using the Least Squares Dummy Variable (LSDV) approach. This method allows for the intercept of our model to fluctuate over time and across companies or industries, thereby accommodating company/industry-specific effects or common effects that impact all firms uniformly. As a result, our model fits the data more accurately, leading to more reliable interpretations of our regression coefficient results (Brooks, 2019)

Subsequently, we have crafted the following regressions. By providing a detailed and nuanced view of the relationships at play, these models facilitate a robust analysis of the determinants of a company's P/B ratio:

Regressions with ESG scores:
Company and time-fixed effect:

$$\begin{aligned}\frac{P}{B}i,t = {} & \beta_0 + \beta_1 mktcap_{i,t} + \beta_2 esgscore_{i,t} + \beta_3 ygrowth_{i,t} + \beta_4 age_{i,t} + \beta_5 ROE_{i,t} \\ & + \beta_6 WACC_{i,t} + \beta_7 Growth_{i,t} + d_i comp_{cat} + d_i time_{cat} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

Industry and time-fixed effect:

$$\begin{aligned}\frac{P}{B}i,t = {} & \beta_0 + \beta_1 mktcap_{i,t} + \beta_2 esgscore_{i,t} + \beta_3 Revenue\ growth_{i,t} + \beta_4 age_{i,t} \\ & + \beta_5 ROE_{i,t} + \beta_6 WACC_{i,t} + \beta_7 Growth_{i,t} + d_i time_{cat} \\ & + d_i industry_{cat} + \varepsilon_{i,t}\end{aligned} \tag{4}$$

Regressions with separate E, S, and G scores:

Company and time-fixed effect:

$$\frac{P}{B}i,t = \beta_0 + \beta_1 mktcap_{i,t} + \beta_2 E_{i,t} + \beta_3 S_{i,t} + \beta_4 G_{i,t} + \beta_5 Revenue\ growth_{i,t} + \beta_6 age_{i,t} + \beta_7 ROE_{i,t} + \beta_8 WACC_{i,t} + \beta_9 Growth_{i,t} + d_i time_{cat} + d_i industry_{cat} + \varepsilon_{i,t} \quad (5)$$

Industry and time fixed effect:

$$\frac{P}{B}i,t = \beta_0 + \beta_1 mktcap_{i,t} + \beta_2 E_{i,t} + \beta_3 S_{i,t} + \beta_4 G_{i,t} + \beta_5 Revenue\ growth_{i,t} + \beta_6 age_{i,t} + \beta_7 ROE_{i,t} + \beta_8 WACC_{i,t} + \beta_9 Growth_{i,t} + d_i comp_{cat} + d_i time_{cat} + \varepsilon_{i,t} \quad (6)$$

Where:
β = Coefficient estimate
i = Referes to company
t = Referes to time
$\frac{P}{B}i,t$ = Price to book ratio for company (i) at time (t).
mktcap = Market capitalization
Revenue growth = Last 12-month Revenue growth
age = Years listed on an exchange
ROE = Return on Equity
WACC = Weighted Average Cost of Capital
Growth = Expected future long-term growth implied by the market through Gordon's growth
d = dummy variable
Comp cat = Refers to a specific company
Time cat = refers to a specific time; in our case quarter
Industry cat = Refers to a specific industry, by TRBC

We have two possible ways to test for significance in the regression models:

The first is to check for the individual significance of the coefficient. Here we can use a single student T-test (Brooks, 2019). When using R programming, this is done automatically and presented in the results as *, **, or ***, denoting if that coefficient is significant at 10%, 5%, or 1%, respectively.

Single T-test hypothesis:

$$H_0: \beta_x = 0$$

$$H_A: \beta_x \neq 0$$

Where x denotes a given variable.

When testing multiple coefficients for significance at once, we use an F-test. Where a multiple F-test hypothesis is stated as follows:

$$H_0: \beta_1 = 0 \; and \; \beta_2 = 0 \; and \; \beta_3 = 0 \; and \; \beta_4 = 0 \; and \; \beta_5 = 0 \; and \; \beta_6 = 0 \; and \; \beta_7 = 0$$
$$H_A: \beta_1 \neq 0 \; or \; \beta_2 \neq 0 \; or \; \beta_3 \neq 0 \; or \; \beta_4 \neq 0 \; or \; \beta_5 \neq 0 \; or \; \beta_6 \neq 0 \; or \; \beta_7 \neq 0$$

This test is often referred to as the "junk test". If we fail to reject this null hypothesis (H_0), it essentially implies that our model has no predictive or explanatory influence over the dependent variable. As such, we are dependent on rejecting this.

Why do we expect Higher P/B for high ESG companies?

With our academic knowledge in Sustainable Finance, together with the findings or conclusions in several papers (Bolton & Kacperczyk, 2021; Chang et al., 2022; Hensisz et al., 2019). We believe that a better ESG profile should lead to, e.g., higher profitability, cost reduction, and risk reduction. In the previous sections, we have also discussed other ways in which ESG can affect value. All of these affect valuation through a regular discount model, either if you use dividends, Free Cash Flow to the Firm, or equity in the denominator.

If our hypothesis is wrong, it might be because ESG initiatives can be costly, reducing the Free Cash Flows available to shareholders. If investors do not appreciate ESG, then prices should go down in the cases of increased ESG scores, meaning lower P/B ratios for high ESG-scoring companies compared to low-scoring companies. We might also find a case where there is no ESG premium or discount. Hence, ESG does not influence valuations relative to book values or demand.

3.3 Returns

As a final step in our research, we want to take a quick look at the returns for the portfolios created by sorting on ESG scores, as explained in section 3.1. Again, portfolios are rebalanced each period, and given the nature of our data, the size of the portfolios will increase with time. Using quarterly closing prices, we calculate each quarter's stock returns with the simple return equitation:

$$Return_t = \frac{Price_t - Price_{t-1}}{Price_{t-1}} \tag{7}$$

We then calculate a cumulative return over the period by multiplying the returns of the given portfolios together. In finance, we say that returns are compensation for risk. The higher the risk, the stock will be priced lower to compensate the buyer for the higher risk.

As such, if our hypothesis that better ESG scores lead to a higher value (i.e., higher prices), is true. Then, a portfolio containing high ESG-scoring companies will, in fact, experience lower returns than a portfolio containing low ESG-scoring firms. This would be in line with Bolton & Kacperczyk (2021), Chang et al. (2022) and Ilhan et al. (2021). We could, however, see the opposite, or no pattern at all, in some early periods, following the findings of Choi et al. (2020), Pedersen et al. (2021), and that ESG investing only in recent years has been priced in (Figure 2). For instance, we can expect high ESG-scoring companies to have superior returns in late 2020 and 2021, which was a period in which a lot of "green" stocks got high valuations (Myrseth, 2020).

4. Data

In this section, we will describe all the data we have used in the thesis and provide some descriptive statistics to understand better the different inputs in the models and why we chose to filter the data in the way we do.

4.1 Data sample

The dataset used for this research contains quantitative data for 1745 companies listed in Norway, Sweden, Denmark, and Finland. This data was collected from 01.01.2011-31.12.2021 and spans across multiple sectors in the Nordic region. Due to limited data availability, especially for ESG scores (explained in section 4.2.3 in this thesis), we have decided to concentrate our thesis on the years 2018-2022. This is to secure unbiased and robust regressions and analysis.

We have sourced data from Refinitiv (Table 9). Our selection of variables ensures a reliable and accurate understanding of the performance of our data universe. The data we have extracted from Refinitiv includes several parameters such as ESG scores, Price-to-Book (P/B) ratios, Market Capitalization (Market Cap), Prices, revenues, Return on Equity (ROE), Weighted Average Cost of Capital (WACC), along with information about the company's industry, country of exchange, and Initial Public Offering (IPO) data for determining the age of the company. The frequency of the data updates varies, with ESG scores updated annually and P/B ratios, Market Cap, revenues, ROE, Prices, and WACC reported quarterly.

To get an overview of the data, we first looked at the variable's distributions (Figure 4). Finding several outliers, these are excluded to provide more robust conclusions. Figure 5 shows the distributions of the 12 611 observations which are the basis for our regressions after adjusting all variables for outliers or missing data. In addition, we review the correlation matrix (Table 14), and it is evident that there are no significant correlations among the variables under consideration. The correlation patterns observed in the data do not present any unexpected or surprising associations between the variables.

As we proceed with the study, we plan to delve further into the specifics of the dataset. We intend to share in-depth statistics, including the number of companies reporting annually, the distribution of companies across different sectors, and the yearly data trends about each company.

4.2 Refinitiv ESG score methodology

Refinitiv's ESG scoring system offers a data-driven, unbiased evaluation of a company's sustainability across various industries (Refinitiv, 2022). It effectively reduces bias by using empirical data and consistent metrics, ensuring that large and small companies are evaluated fairly.

The scoring process (Figure 3) begins with analyzing 630 distinct data points. From these, 186 metrics are selected that are both comparable and most relevant to each industry. These metrics are then organized into 10 ESG categories, which feed into the three core pillar scores: E, S, and G. The final ESG score culminate these pillar scores (Refinitiv, 2022).

Each pillar score is weighted differently based on the industry. For example, an oil company like Equinor has a higher Environmental weightage of 34.5% due to the industry's significant environmental impact. In contrast, a software company like SimCorp has a lower Environmental weight of 13.9%. The Governance score, however, remains constant across all industries. This tailored approach to scoring reflects the unique impacts and responsibilities of different industries.

4.2.1 Category score

When all available data is collected, the first step in calculating the overall ESG score involves the ESG category score (Figure 3) and the treatment of underlying data points which can be either Boolean or numeric. Answers to Boolean queries are defined as "Yes," "No," or "Null" (Refinitiv, 2022). A default value of 0 is applied when no relevant data is available in the market. A numeric value is, for instance, the total Co2 emissions expressed in tCo2e.

To calculate the ten category scores, a percentile ranking methodology is being adopted. This ranking is based on three factors:

(1) How many companies are worse than this one?
(2) How many companies have the same market valuation?
(3) How many companies have a value at all?

Equation 8 shows how the category score is calculated for all companies (Refinitiv, 2022):

$$Score = \frac{no.of\ companies\ with\ a\ worse\ value\ + \frac{no.of\ comapnies\ with\ the\ same\ value\ included\ the\ current\ one}{2}}{no.of\ companies\ with\ a\ value} \quad (8)$$

To ensure an impartial, objective, and trusted assessment of the category scores, Refinitiv applies a materiality matrix. Refinitiv defines materiality as category weights (Refinitiv, 2022). These weights are being established using an objective data-driven method to assess the proportional relevance of all topics in each industrial group (Refinitiv, 2022). To sum up, the category weight is calculated by dividing the magnitude weight of each category by the total magnitude weights of the relevant industrial group (Refinitiv, 2022), as seen in equation 9:

$$Category\ weight\ of\ an\ industry\ group = \frac{Magnitude\ weight\ of\ a\ category}{Sum\ of\ magnitudes\ of\ all\ categories} \quad (9)$$

The first step to get to the pillar weights is to calculate the sum of category weights. This is done by adding all category weights together, which creates new category weights based on the sum of category weights (Refinitiv, 2022) see Table 7.

4.2.2 ESG scores data

Table 1: Descriptive ESG scores statistics

Year	Mean	Std. Dev.	Highest	Lowest	Companies with ESG scores	Companies listed	Percentage reporting
2011	24,01	10,26	34,42	11,05	5	629	0,79%
2012	53,3	19,05	84,99	9,36	61	648	9,41%
2013	54,01	18,3	86	7,44	113	680	16,62%
2014	54,36	17,71	86,19	7,92	118	756	15,61%
2015	54,78	19,59	89,05	2,97	131	845	15,50%
2016	55,83	18,67	89,66	3,52	136	970	14,02%
2017	56,44	18,76	91,71	2,35	151	1105	13,67%
2018	51,29	19,49	91,83	1,28	257	1212	21,20%
2019	49,36	20,98	91,62	1,59	332	1274	26,06%
2020	44,71	21,57	93,15	1,42	566	1386	40,84%
2021	47,97	20,69	92,24	4	555	1658	33,47%
2022	56,44	19,39	89,79	7,54	163	1734	9,40%

This table provides an overview of the descriptive statistics related to ESG scores for listed companies in Norway, Denmark, Sweden, and Finland, spanning the years 2011 to 2021. A number of metrics are observed, including the mean score, standard deviation, highest and lowest scores, the count of companies with ESG scores, total companies listed, and the proportion of those reporting.

Note: Our dataset, as of 2023, includes data for 1745 companies. This total might appear higher than the actual number of companies listed on 31.12.2021. This is because some companies have been listed after our data collection cutoff in 2021. Therefore, our dataset might include companies that were listed in 2022 or 2023, leading to an increased count in comparison to the 2021 listing.

Table 1 reveals that the data regarding ESG scores is limited. In the early sample years, a small number of companies reported ESG scores, constituting as low as 0.79% of the total in 2011. Nonetheless, in recent years, a considerable surge in reporting has been observed, with a notable spike in 2018 from the previous year. By the end of 2021, 33.47% of the companies were reporting their ESG scores. Given the data's availability and the limited number of companies reporting their ESG scores in the earlier years, we have opted to concentrate our analysis and regression studies on the period from 2018 to the end of 2021. This decision was based on the significant growth in reporting starting in 2018, which led to a more robust dataset for these latter years. We have also decided to exclude 2022 from our research universe. This is mainly because it is only 9,40% of available data on ESG scores.

4.3 TRBC industry codes

Our early research involved collecting diverse industry classification systems, such as NAICS, GICS, TRBC, and NACE codes. After careful consideration, we opted to utilize the TRBC Economic Sector Name as our primary classification system. This decision was driven by the desire to ensure a sufficiently large number of companies within each sector, enabling us to conduct rigorous statistical analyses, such as regressions. Table 2 displays all sector names within our data and the number of companies in each sector.

Table 2: Descriptive statistics TRBC economic sector

TRBC Economic sector name	# of companies
Consumer Non-Cyclicals	94
Consumer Cyclicals	172
Industrials	326
Technology	376
Healthcare	269
Financials	178
Energy	103
Real Estate	102
Utilities	27
Basic Materials	90
Academic & Educational Services	8

This table explains the number of companies in each economic sector. Utilities and academic & educational Services have few observations and are excluded for sector analysis.

4.4 Market capitalization

Reported in EUR and stated in whole numbers, we choose to convert it into millions. This variable represents the aggregate market value of the equity. The market value for each share is computed by multiplying the respective outstanding shares by the latest closing price. All available share types include Default, Free Float, and Outstanding shares. Table 10 shows that the average market cap in the full sample is 2 761 million Euro, where the largest is Equinor with 77 105MEUR. By excluding companies without ESG score the average market cap. increases to 5 428MEUR (Table 11). Clearly, more large-cap firms have ESG scores as the literature suggests (Borokova & Wu, 2020; Drempetic et al., 2020). By further filtering the data with P/B caps on 20 and 10, the average market cap. drops to 5 382MEUR and 4929MEUR, respectively (Table 12, Table 13).

4.5 Price-to-Book values

The price-to-book value per share, or P/B ratio, is collected from Refinitiv and is calculated by dividing the closing price by the book value per share. The book value is calculated by dividing the total equity from the last fiscal period by the current total shares outstanding. The data is reported quarterly. The average P/B in our sample is 4.58, with a standard deviation of 7,02 (Table 10). When ESG scores equal to zero are excluded, the mean P/B is 4.55, and the standard deviation is 6.48 (Table 11). When we further introduce the P/B caps, the average P/B and standard deviation. drops as expected (see Tables 12 and 13).

4.6 Revenue growth

Revenue Growth is formulated by collecting quarterly revenues from Refinitiv expressed in EUR, then calculating the last 12-month revenue growth for each quarter. Equation 10 shows how we have derived the revenue growth, $Revenue_t$ denotes the revenue for the current year (t), and $Revenue_{t-1}$ stands for the revenue in the preceding year (t-1).

This metric indicates the pace at which a company's revenue evolves over time. A positive outcome signifies revenue growth, whereas a negative value suggests a contraction in revenue. The magnitude of this measure demonstrates the extent of the revenue change relative to the previous year's revenue. This methodology for calculating the Yearly Revenue Growth is expected to facilitate a more robust and nuanced understanding of a company.

$$Revenue\ Growth\ Yearly = \frac{Revenue_t - Revenue_{t-1}}{Revenue_{t-1}} \tag{10}$$

The mean revenue growth in our sample is 25.80% (Table 10), which decreases to 20% when excluding no-scoring companies (Table 11). The average drops to 19.45% and 18.36% when introducing P/B caps on 20 and 10, respectively (Table 12, Table 13). As higher growth firms are expected to have higher P/Bs, this is as expected.

4.7 Return on Equity (ROE)

ROE is expressed as a percentage from Refintiv. Hence, we divided it with 100 in our data to get it into decimals. From our sample of 27 920 observations, 57.52% also have an ROE from Refinitiv, where the average ROE is -4.40% in our sample (Table 10). When excluding companies that do not have an ESG score, we are left with 6018 observations, where 88% have ROE, and the average ROE is 8.3% (Table 11). Again, as expected when introducing the P/B caps, the average ROE drops slightly to 7.86% (Table 12) and 6.90% (Table 13). Both standard deviations also drop.

ROE is calculated by dividing net profits by the equity and represents the returns a company is able to generate with their current shareholder equity (or assets/input); as such, a higher ROE is usually considered to be better. ROE measures the current profitability of a company. New and younger firms might have lower ROE ratios as sales and net profits are lower. More mature companies will, on average, have higher and more stable ROEs. When assessing ROE, it is important to keep in mind the differences in revenue, costs, and assets across industries. Where some industries usually achieve higher ROE as they experience higher margins or are less asset-intensive. Knowing that a lot of young firms will have lower profitability, we expect higher ROE firms to have lower P/B, while higher P/B firms will have lower ROE. However, given the results of Branch et al. (2005), which find that younger firms might not have an ROE, they will fall out of the regressions as they are excluded. Hence, we can also expect that companies with higher ROE on average have higher P/B as being more profitable when comparing two companies will lead to higher stock prices.

4.8 WACC

This metric is expressed from Refinitiv as percentages. The Weighted Average Cost of Capital (WACC) has a mean of 6.1% in our sample of companies with 12 611 observations and an st.dev. of 3.6% (table 10). When excluding no-scoring companies, the average WACC increases to 6.4%, while the standard deviation decreases to 2.9% (table 11). WACC seems to be more stable, even when introducing the P/B filters, the average WACC only drops to 6.38% and 6.35% as seen in Tables 12 and 13.

4.9 Growth

The growth variable is a self-calculated measure. Considering the Fama French factor HML which is constructed using book-to-market ratio, the opposite of our P/B ratio. It argues that high book-to-market ratio firms, which is equivalent to a low P/B, called value firms outperform low book-to-market firms, known as growth stocks (Pedersen, 2015, Chapter 9). With this in mind, we know that P/B can be used as a good indication of whether a company is valued for growth or value. As companies with higher growth prospects often are associated with a higher valuation with respect to the P/B ratio. We wanted to include a growth term in our model that would reflect the future growth prospects of the company. Equation 11 is an alteration of the Gordon Growth Model, representing the relationship between the stock's price, the company's profitability, the cost of capital, and the expected growth rate. In a financial context, it often represents a long-term constant Growth rate in dividends, earnings, or other key financial metrics. Using equation 11, derived from the paper "A Price To Book Model Of Stock Prices" (Branch et al., 2005) as a starting point, we can mathematically derive an equation for growth (equation 12).

$$\frac{P}{B} = \frac{ROE - g}{WACC - g} \tag{11}$$

$$g = \frac{(ROE - \frac{P}{B}) * WACC}{1 - \frac{P}{B}} \tag{12}$$

With higher growth, we expect to see a higher P/B ratio. Since we start with the Gordon Growth model, this is a long-term growth implied by the market. We view this derived growth as future growth. Contrary to the annual revenue growth we have calculated, which is backward looking.

The average value for our calculated growth is 6.50%, with a relatively high st.dev. (Table 10). With further filtering, the average growth drops to 1.9% (Table 11), 1,77% (Table 12), and 1,45% (Table 13). Whereas the standard deviation remains relatively high, which makes sense when looking at the max and min values.

4.10 Age

The Age variable is also a calculated variable representing the time a company has been listed on an exchange. To be able to determine a company's age, we have collected IPO dates from Refinitiv and calculated the age of the company in the following way.

$$Age_t = Date_t - IPO_{Date} \tag{13}$$

Table 10 shows that the average Age of the full sample is 16.8 years. This number increase to 22.1 when no scoring companies are excluded (Table 11). This confirms some of our expectations about older firms being more likely to have an ESG score. When introducing the P/B caps, both average age and standard deviation. remains stable at 22 and 25, respectively (Tables 12 and 13).

4.11 Prices and Returns

In order to obtain returns on all companies, we have collected quarterly prices expressed in Dollars and calculated returns using the equation below. Prices are collected from Refinitiv.

$$Return_t = \frac{Return_t - Return_{t-1}}{Return_t} \tag{14}$$

5. Result and analysis

In this section, we present the results of our research. In short, we find that in portfolios sorted by ESG scores, there is a significant difference in average P/B only between the worst and the best ESG-scoring portfolios. We also find evidence that industry might be a determinant factor in explaining if higher ESG scores can give higher or lower P/B.

Our regressions also show that having an ESG score can boost a company's P/B ratio. However, the level of the score might be inversely or even unrelated to value. Lastly, we find that an equal-weighted portfolio of high ESG-scoring companies would have underperformed with respect to a low-scoring portfolio, which indicates a lower risk and higher initial value for high ESG-scoring companies.

5.1 Differences in Mean

Table 8 reports the results from the 'difference in mean' tests for 2018-2022. As section 3 of this report outlines, we start our research by looking at and testing the differences in average P/B ratios in portfolios when sorted by their ESG scores (Figure 6). We find that only the portfolio with low ESG scores and the portfolio with high ESG scores have a structural significant (α=0.05) difference in the average P/B score. These findings go against our main hypothesis of an ESG price premium. That being said, no conclusions can be drawn without controlling for traditional drivers of P/B ratios. A significant difference also exists between the average and worst ESG performers in certain quarters, but this difference is not as consistent throughout time. We do not find a significant difference in mean P/B for the remaining portfolios. We note that a large number of NAs (Table 1) might result in the NO ESG portfolio having firms with a large difference in real ESG performance. Here we argue that the portfolio of companies with no score will contain both companies that actually have great ESG performance, as well as companies with very poor real ESG performance. Comparing the portfolios with these (No-ESG) companies might as such result in inconclusive results. We account for this issue in section 5.3.1.

To test if ESG is truly linked to higher P/B ratios, we test on a panel-regression model with six control variables, as discussed in section 3.2. By filtering out the tendency of young, small, risky, and high-growth companies to have high P/B ratios, we are able to figure out if the ESG price premium, exists in the Nordic market.

5.2 Difference in means test across industries

P/B ratios tend to be industry-specific, where companies operating in mature industries like energy, financials, or utilities tend to have a P/B of around 1.5, while growing industries like technology tend to have higher P/B ratios. We sort our sample according to industry to attempt to adjust for these differences. We find that our sample is too small, and no testing gives no meaningful results.

A graphical analysis of Figure 7 to Figure 15, where we look at individual industries does imply that high ESG-scoring companies, on average, have lower P/B than low ESG scorers in six of nine. In the remaining three industries, high ESG scorers have higher, or the same, average P/B ratios (Figures 7 to 15). An interesting finding is that in industries where customers have strong bargaining power, e.g., consumables, higher ESG-scoring companies have, on average higher P/B than lower-scoring companies (Figures 11, 14, and 15). This notion is consistent with higher revenues for higher ESG-scoring companies in these kinds of industries (Hensisz et al., 2019), which would lead to a value premium.

In industries with less direct contact with end-customers or fewer choices, lower ESG-scoring companies have, on average, higher P/B ratios. Indicating that investors may view ESG spending in these industries as less critical or as “money-wasting” (Lutz, 2012; Baker, 2010), i.e., a higher ESG score will not lead to higher future growth/value and hence no price premium.

Another distinctive trend in the plots is the relatively lower fluctuations of the average P/B for the “Best” ESG scorers in almost all industries. This observation is in line with the paper “The Influence of Firm Size on the ESG Score,” which finds that larger, more mature firms often have more resources to use on both reporting and improving their ESG practices, while smaller firms with fewer resources must direct all their profits towards continuing operations (Borokova & Wu, 2020; Drempetic et al., 2020). As such, the higher ESG-scoring companies might be the more mature/big players in their respective industries. As discussed earlier, these companies tend to have lower and more stable P/B. Therefore, we once again stress the importance of accounting for traditional drivers of P/B ratios. Drivers such as company size, growth, and/or age.

Concluding the ‘mean difference’ tests for our sample, we see some trends and significance that stocks sorted by ESG scores do have different P/B on average. We therefore continue our research to investigate whether these differences genuinely stem from the difference in ESG score or if it comes from one of the other drivers of P/B ratios.

5.3 Regression results

This sub-section presents the results from all the regressions we have performed. The Augmented Dickey-Fuller (ADF) test tests all variables for unit roots. Looking at the correlation matrix (Table 14), we can exclude the possibility of Multicollinearity. All regressions are performed using Newey-West heteroscedastic and autocorrelation consistent standard errors (HACs).

Before performing the regression analyses, we decided to cleanse the data. This involves examining the distribution of various variables to identify any potential anomalies (Figures 4 and 5). Notably, we find that the Revenue Growth, Return on Equity (ROE), and Growth variables have outliers that would skew the regression outcomes. To mitigate this issue and ensure the integrity of our results, we apply a bounding restriction to both ROE and Growth, limiting their range between -5 and 5. As for Revenue Growth, we use a broader bounding restriction from -10 to 10. This variable shows a distribution more naturally inclined towards these values, hence the rationale for permitting a wider range.

5.3.1 Regressions including ESG scores equal to zero (full sample)

In summary, the ESG score only shows the expected outcome in 2 of 6 regressions; note that these two are the most important concerning caps and exclusions. They indicate that having an ESG score leads to higher P/B ratios, which is in accordance with our hypothesis and with papers (Bolton & Kacperczyk, 2021; Chang et al., 2022; Hensisz et al., 2019). As expected, WACC is positive in all six regressions, and as such, the most robust result as of now, indicating that higher risk leads to higher P/B’s, in accordance with Branch et al. (2005). We also find solid results for the Age and growth coefficients, which aligns with Drempetic et al. (2020) and

Fama & French (1995). Of the two regressions, the most expected results come when controlling for heterogeneity across industries, using time- and industry-fixed effects. This is an interesting result as multiples, such as P/B, tend to be very industry specific. A more detailed elaboration about each regression is provided below.

We start with running the regressions, equations (3) and (4), using HACs with four lags. For the first two regressions, we put a P/B cap of 150 to exclude extreme outliers in the data. Companies with ESG scores equal to zero are included in these regressions, that is, companies that do not have an ESG score in the Refinitiv database. This allows us to check if having an ESG score influences price-to-book ratios for a company. The company must have all variables available to be included in the regressions. By excluding observations that do not have one or more variables available, our observations go from 27 920 to 13 164. Table 5 summarizes the regression results for the different regressions we run with this dataset.

Using company- and time-fixed effects (Table 3, regression 1), Achieving a relatively good R-squared of 0.6332 and a small F-stat p-value, the model seems reasonable at first glance. ESG score is negative and insignificant. As such, it does not seem that ESG influences the P/B ratio; this result could stem from the low user-friendliness of ESG scores, as described by Berg et al. (2022), or following the reasoning of Choi et al. (2020) ESG might not affect value making scores less usable in predicting value.

The Age coefficient is both positive and significant at the 10% level. Contrary to what we expected, it is positive. The finding suggests that older firms have higher P/B ratios. WACC is positive and significant at the 1% level. As it is expressed in decimals, a 1% higher WACC is associated with a 0.1589 higher P/B. This result is as expected as WACC proxies for risk; a higher risk would be associated with younger, less mature firms who often have higher P/B (Branch et al., 2005). The growth coefficient is significant at the 1% level and negative. Companies with higher growth opportunities are known to have higher P/B. As such, we expected this to be positive (Fama & French, 1995). The ROE coefficient is insignificant for this regression.

As P/B ratios are sensitive to industry, we further investigate this by running a regression using industry and time as fixed effects (Table 3, regression 2), accounting for heterogeneity across time and industry. Remarking that R-squared drops a lot, the F-stat p-value is still small; hence we cannot jointly reject the model. The ESG score now becomes significant at the 10% level. The ESG coefficient is negative, suggesting that a higher ESG score leads to a lower P/B. It also aligns with the trends in most of the plots (Figures 7 to 15), as discussed above. However, as we hypothesize that a higher ESG score should yield higher P/B, it goes against what we expected and against the findings of Bolton & Kacperczyk (2021) and Ilhan et al. (2021). So far, ESG scores can have explanatory power on P/B when accounting for heterogeneity across industries.

The market cap. coefficient is now significant at the 5% level; however, contrary to the expected result, it is positive. Indicating that companies with higher market caps have higher P/B, which is the opposite of what is typical behavior for the P/B ratio. The positive coefficient could, however, be justified as young firms fall out of the sample when we cleanse the data. The annual revenue growth factor is now significant (5%) and, as expected, positive. The Age coefficient is still significant, now at the 1% level. The coefficient goes from positive to negative, which is what we expect. As we have stated earlier in our thesis, younger firms usually have a higher P/B as they are often priced for growth and often have lower book values. WACC is still significant and positive, as we expect it to be. The coefficient for the Growth variable is still significant (5%) and negative. ROE is still insignificant.

Given that the results from the first two regressions did not precisely fit our beliefs in how ESG scores and many of the other variables should behave when explaining P/B ratios. We created two sub-samples by excluding stocks with a certain level of P/B. One sub-sample has a P/B cap of 20, and one has a P/B cap of 10. This reduces the overall observations from 12611 to 12207 and 11149, respectively. As the samples are not reduced by much, this effectively removes outliers that could affect the regression results.
We then run the exact same two regressions with the new sub-samples. Regression results are displayed in Table 3, where regression number 3 and 4 uses the P/B cap of 20 and regression number 5 and 6 uses a P/B cap of 10.

With a P/B cap of 20, the company- and time-fixed effect regression (Table 3, regression 3) coefficients do not change much. ESG score is still insignificant and does not seem to influence P/B. WACC and growth are still significant at a 1% level. Both have the same sign as before the cap. However, the coefficients and standard errors are smaller. We interpret this as an effective removal of outliers. As before, the WACC is positive, as expected. In contrast, the growth is negative, which is still unexpected. All other variables are insignificant in this regression, meaning that the Age coefficient goes from significant to insignificant.

Running the industry and time effect regression with a P/B cap of 20, we also find similar results from the previous regression without the cap. Market cap., revenue growth, age, and WACC are now significant at the 1% level. All significant variables also have the same sign as before, so the interpretation is the same as above. ESG score and growth both become insignificant, while ROE stays insignificant. The R-squared and adjusted R-squared increases relative to the regressions with a P/B cap of 150 for both regressions.

Lastly, we run the two regressions using the data that has a P/B cap of 10. Again, both R-squared measures increase for both regressions, indicating a better fit of the model. Interestingly, for the company- and time-fixed effect regression (regression 5), the ESG score now becomes significant at the 5% level, and the coefficient is positive. The model now suggests that a higher ESG score could lead to a higher P/B ratio, which aligns with our hypothesis and expectations. This also aligns with many of the papers discussed in Section 2 (Bolton & Kacperczyk, 2021; Chang et al., 2022; Hensisz et al., 2019; Ilhan et al., 2021). WACC is still significant and positive, which again is as expected as higher risk should yield a higher P/B (Branch et al., 2005).

The most interesting results come when accounting for the heterogeneity across industries and time with a P/B of 10 (regression 6, Table 3). The ESG score coefficient is also here significant (1%) and positive, which again is a step in confirming our hypothesis. Both growth measures are significant, Revenue growth at 1% and Growth at 10%, both are also positive, which is what we expect. WACC is still significant (5%) and positive, and Age is again significant (1%) and negative, both as expected and with the same interpretation as before.

All these findings are in accordance with the papers (Bolton & Kacperczyk, 2021; Branch et al., 2005; Chang et al., 2022; Hensisz et al., 2019). Market cap. is still significant (5%) and again positive.

Table 3: Panel regressions including ESG scores equal to zero

This table reports summary results for the regressions outlined in section 3, equations 3 and 4, using a dataset where all observations are included, also the ones that do not have a ESG score (ESG score = 0). Nr. of bbservations in the dataset is 12611. We filter the data more by setting caps on P/B ratios, the header denotes what dataset is used. The data considered for this study ranges from January 2018 to December 2021.

	Data: PB<150		**Filtered Data: PB<20**		**Filtered data2: PB<10**	
Regression nr.:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Market Cap.	**0.000003**	**0.00001****	**0.000002**	**0.00001*****	**0.000002**	**0.000007****
	(0.000002)	(0.000004)	(0.000002)	(0.000003)	(0.000001)	(0.000003)
ESG Score	**-0.0038**	**-0.0075***	**0.0039**	**0.0017**	**0.0040****	**0.0046*****
	(0.0049)	(0.0032)	(0.0023)	(0.0020)	(0.0014)	(0.0013)
Revenue Growth $_{t-1}$	**0.0939**	**0.2450****	**0.0461**	**0.1900*****	**0.0227**	**0.1261*****
	(0.0690)	(0.0868)	(0.0322)	(0.0438)	(0.0177)	(0.0279)
Age	**29.7589***	**-0.0227*****	**6.9343**	**-0.0153*****	**-1.0153**	**-0.0101*****
	(12.8650)	(0.0036)	(6.1093)	(0.0025)	(3.6691)	(0.0019)
ROE	**-0.2787**	**-0.4141**	**-0.0994**	**0.1659**	**0.1487**	**0.1834**
	(0.3949)	(0.4055)	(0.1463)	(0.1585)	(0.0930)	(0.0990)
WACC	**15.8911*****	**10.6012****	**6.7444*****	**6.1603*****	**4.3582*****	**3.5957****
	(3.4578)	(3.6110)	(1.5214)	(1.7557)	(1.0293)	(1.1258)
Growth	**-0.2479*****	**-0.2018****	**-0.1142*****	**-0.0134**	**-0.0320**	**0.0602***
	(0.0498)	(0.0749)	(0.0280)	(0.0436)	(0.0184)	(0.0287)
R-squared	0.6332	0.1225	0.7690	0.1918	0.7967	0.2109
Adj R-squared	0.5985	0.1203	0.7464	0.1896	0.7757	0.2086
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Company fixed effect	Yes	No	Yes	No	Yes	No
Industry fixed effect	No	Yes	No	Yes	No	Yes
# of observations	12 611		12 207		11 149	
F-stat p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Note: Coefficient estimates are displayed in bold, where, *** ,** and * denote the statistical significance level of 1%, 5% and 10%, respectively. Standard errors are provided in parentheses.

5.3.2 Regressions excluding ESG scores equal to zero

To sum up, we focus on the results from the regressions with P/B caps, as these regressions effectively exclude outliers. Many of the estimated coefficients also have the expected outcome in these regressions. For instance, growth, age, ROE, and WACC are all as expected according to the literature (Branch et al., 2005; Drempetic et al., 2020; Fama & French, 1995). ESG score only becomes significant when accounting for heterogeneity across industries (Table 4, regressions 2, 4, and 6) and not across companies (regression. 1, 3, and 5). The ESG score coefficient is also negative in all cases, indicating that among companies with an ESG score, the lower-scoring companies obtain higher P/B. This evidence goes against our hypothesis and is more in line with Ferrell et al. (2016) or Berg et al. (2022). More details about each regression are provided below.

Knowing that all companies in a perfect world would and should have a reported ESG score, we know that the companies that fall in the "no score" category could make the regression biased, given the amount of no-score companies it could impact the estimates, especially considering the ESG score. Therefore, we choose to "clean" up the data by excluding companies with zero ESG scores, then run the same regressions (equations 3 and 4) using HACs with four lags. By excluding these zero ESG scores, our sample goes from 12 611 observations to 5 697. In addition, we also here create the two subsamples with a P/B cap of 20 and 10, reducing the observations to 5 530 and 5 107, respectively. The regression results for these data sets are summarized in Table 4. The exclusion gives us an insight into the differences between companies with an ESG score. Hence, a positive ESG coefficient would indicate that having a higher ESG score among companies with ESG scores leads to a higher P/B ratio.

Running the regression with company- and time-fixed effects, using the P/B cap of 150 (Table 4, regressions 1). All variables, but WACC is insignificant. WACC is significant at the 5% level and is positive, as with the regressions, including ESG scores of zero. As such, the evidence that a higher WACC, i.e., risk, leads to higher P/B ratios, grows stronger, still in line with our hypothesis and literature (Branch et al., 2005; Ilhan et al., 2021). Changing company- with industry-fixed effects (Table 4, regression 2), we see some similarities in the results from the previous regressions (Table 3, regressions 2, 4, and 6). Market cap. is significant (10%) and positive. ESG score is significant (10%) and negative, the same as in Table 3 regression 2. Hence, there is evidence that ESG scores might affect valuations measured by P/B. However, in the opposite direction than expected, more in line with the view of Friedman (1970) and Ferrell et al. (2016) that ESG can destroy firm value. Revenue growth is significant (5%) and positive, as expected. Age is significant (10%) and negative, also as expected. What is new from the results in Table 3 is that WACC and growth are now insignificant; however, both are positive, as expected. While ROE now is significant at a 10% level. The ROE coefficient is positive, this result is as expected as companies with higher ROE would trade at higher prices and, as such higher P/B ratios than similar companies with lower ROE (Branch et al., 2005).

The two following regressions (3 and 4, Table 4) are run with a P/B cap of 20. With company- and time-fixed effects (regression. 3), Revenue growth and ROE are positive and significant at 10% or better. Both have the expected direction for their coefficients, as higher growth and higher ROE should yield higher P/B ratios (Branch et al., 2005; Fama & French, 1995). Even though R-squared and adjusted R-squared has increased, none of the other variable estimates are statistically significant for the regression. However, we cannot jointly reject the coefficients.

Running the time- and industry-fixed effect regression (Table 4, regression. 4) market cap., ESG score, Revenue growth, Age, Growth, and ROE are all individually significant at 10% or better. Given the large number of significant estimates in this regression, we focus more on this. As with the previous regression, ROE and revenue growth are both positive and thus in line with our hypothesis. The Growth coefficient is also positive, as expected, indicating that higher growth and current ROE yield a higher P/B ratio; these results align with the results of Fama & French (1995) and Branch et al. (2005). The age coefficient is negative and in line with our expectations that younger firms usually are priced with higher P/B ratios (Fama & French, 1995). The market cap. is also positive and hence counterintuitive when thinking of the P/B ratio properties. Usually, younger firms priced for growth achieve higher P/B's, as the other significant variables imply in our model. We expected younger firms to have a lower market cap. than big/mature firms and hence a negative coefficient. It could, however, be justified as the sample contains some companies that can have both a high market cap and be priced for future growth and hence have larger P/B. In addition, given that we exclude companies that do not have a score, we also exclude many small-cap firms. Considering the findings of Drempetic et al. (2020), we could see that higher market cap. leads to higher P/B.

Looking at the regressions with P/B capped at 10. The company fixed effect model (Table 4, regression 5) obtained significance for the market cap., Revenue growth, ROE, and WACC, at the 10% level. All the mentioned are also positive and as expected. Growth and age are individually insignificant. Nevertheless, they have the expected sign/direction of their coefficients. Lastly, the ESG score is insignificant and negative. This result indicates that ESG scores do not affect valuations in our data and thus go against both our hypotheses. The result does, however, fit the story of Berg et al. (2022), i.e., given the huge divergence in ESG score measures, it is hard to use them. It also fits the findings of Choi et al. (2020) of an underreaction for ESG.

The last regression, with excluded ESG scores equal to zero and a P/B cap of 10, is the industry fixed effect regression (Table 4, regression 6). Here again, we achieve some exciting results. All the coefficient estimates are now significant at the 10% level. In addition, all variables except the ESG score have a coefficient that aligns with our hypothesis. The ESG score is negative and aligns more with the papers of Friedman (1970) and in the right conditions with Pedersen et al. (2021) or Ferrell et al. (2016). What is positive is that we find evidence that ESG scores impact P/B and, thus, valuations. Both of our growth measures are positive, confirming both academic books and our hypothesis that higher growth firms should achieve higher P/B (Fama & French, 1995; Pedersen, 2015, Chapter 9). WACC is positive, this result is as expected as WACC proxies for risk. A higher risk would be associated with younger, less mature firms that often have higher P/B (Branch et al., 2005). This argument also confirms the negative Age coefficient. ROE is positive, as expected. The market cap. coefficient is positive as well. Hence our interpretation above remains strong. Given the negative ESG coefficient but positive market cap., we cannot rely on the findings of Drempetic et al. (2020).

Table 4: Panel regressions excluding zeros.

This table reports summary results for the regressions outlined in section 3, ref equations 3 and 4, using a dataset where we exclude all companies that do not have an ESG score (ESG score = 0). By excluding these companies, our observations go from 12 611 to 5697. We also filter the data more by setting caps on P/B ratios. The header denotes what dataset is used. The data considered for this study ranges from January 2018 to December 2021.

	Data: PB<150		**Filtered Data: PB<20**		**Filtered data2: PB<10**	
Regression nr:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Market Cap.	**0.000004**	**0.000017***	**0.000002**	**0.00001***	**0.00001***	**0.000009***
	(0.000005)	(0.000006)	(0.000004)	(0.000004)	(0.000004)	(0.000003)
ESG Score	**-0.0184**	**-0.0578***	**-0.0113**	**-0.0211***	**-0.0025**	**-0.0065***
	(0.0123)	(0.0099)	(0.0064)	(0.0042)	(0.0041)	(0.0027)
Revenue Growth $_{t-1}$	**0.1538**	**0.6456****	**0.1125***	**0.3725***	**0.0708***	**0.2778***
	(0.1148)	(0.2016)	(0.0524)	(0.0886)	(0.0314)	(0.0642)
Age	**10.6529**	**-0.0093***	**9.0676**	**-0.0066***	**-5.1040**	**-0.0044***
	(12.1187)	(0.0037)	(6.6616)	(0.0028)	(4.5602)	(0.0021)
ROE	**-0.1219**	**4.8258***	**0.9934****	**3.0039***	**0.7665***	**1.4508***
	(1.2552)	(1.2717)	(0.3311)	(0.5146)	(0.2069)	(0.2945)
WACC	**13.4514****	**7.6426**	**5.1201**	**5.0310**	**5.5193***	**4.9026***
	(4.2682)	(5.8421)	(2.6166)	(3.3409)	(1.3357)	(2.1421)
Growth	**-0.1078**	**0.1515**	**-0.0171**	**0.1719****	**0.0100**	**0.1490***
	(0.1028)	(0.1015)	(0.0322)	(0.0641)	(0.0220)	(0.0431)
R-squared	0.7911	0.1513	0.8509	0.2534	0.8492	0.2132
Adj R-squared	0.7699	0.1466	0.8350	0.2491	0.8324	0.2083
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Company fixed effect	Yes	No	Yes	No	Yes	No
Industry fixed effect	No	Yes	No	Yes	No	Yes
# of observations	5 697		5 530		5 107	
F-stat p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Note: Coefficient estimates are displayed in bold, where, *** ,** and * denote the statistical significance level of 1%, 5% and 10%, respectively. Standard errors are provided in parentheses.

5.3.3 Regressions with separate E, S, and G scores

We repeat the same model but run it on E, S, and G individual ratings. The sample for this model is slightly smaller due to poorer data quality for these individual ESG pillar scores. Once more, P/B ratios are restricted at 150, 20, and 10. The observations in the data are now 2438, 2369, and 2166 respectively. Results from regressions are summarized in Table 5.

G is significant when we run company- and time-fixed regression and a P/B cap on 20. However, it is insignificant for all other regressions. This result goes against our hypothesis; however, it could be argued that the result is expected as we believe that larger, more mature firms have more resources to deal with governance and governance issues. While a startup will typically focus more on operations and less on for instance governance measures. Hence, higher governance is associated with lower P/B.

We do not find any strong evidence for E, S, or G explaining P/B in this model. The six control variables still explain the P/B ratio well. We do not see that the market has any preference for E, S, and G.

This result may come from the smaller sample of these individual scores. Investors care about diversification, leading them to use the aggregate ESG score for sample size purposes. There might be a lack of awareness of individual E, S, and G scores, and as such, they are not demanded by the market in the same way as ESG scores are.

For robustness purposes, we emphasize the significance of the six control variables confirming that our model is robust and strong.

Table 5: Panel regressions separated E, S & G (Excluding zeros)

This table reports summary results for the regressions outlined in section 3.2, equations 5 and 6, using a dataset where we exclude all companies that do not have a E or S or G score. By excluding these companies our observations go from 13 067 to just 2 348. We also filter the data more by setting caps on P/B ratios, the header denotes what dataset is used. The data considered for this study ranges from January 2018 to December 2021. Exclusion criteria: do not have all. E, S and G scores

	Data: PB<150		Filtered Data: PB<20		Filtered Data 2: PB<10	
Regression nr:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Market Cap.	**-0.000004***	**0.000012****	**-0.000006*****	**0.00001*****	**0.00002***	**0.00001****
	(0.000002)	(0.000005)	(0.000002)	(0.000003)	(0.000013)	(0.000005)
E-Score	**0.0138**	**0.0047**	**0.0014**	**0.0004**	**0.0020**	**-0.0008**
	(0.0344)	(0.0114)	(0.0136)	(0.0071)	(0.0069)	(0.0043)
S-Score	**-0.0333***	**-0.0350*****	**-0.0015**	**-0.0095**	**-0.0047**	**-0.0073**
	(0.0191)	(0.0135)	(0.0102)	(0.0086)	(0.0072)	(0.0053)
G- Score	**-0.0223**	**-0.0263****	**-0.0224****	**-0.0110**	**-0.0067**	**0.0052**
	(0.0201)	(0.0132)	(0.0094)	(0.0068)	(0.0074)	(0.0039)
Revenue Growth $_{t-1}$	**0.0281**	**0.9962*****	**0.0303**	**0.2909****	**0.0250**	**0.2016****
	(0.1060)	(0.3722)	(0.0650)	(0.1217)	(0.0478)	(0.0936)
Age	**-1.0774**	**-0.0133****	**-0.4178**	**-0.0087****	**0.4849*****	**-0.0076*****
	(0.9358)	(0.0057)	(0.5263)	(0.0041)	(0.0749)	(0.0026)
ROE	**2.4131*****	**5.7297*****	**1.1496*****	**2.3364*****	**0.6320***	**0.7439***
	(0.7426)	(1.3849)	(0.4054)	(0.7247)	(0.3268)	(0.4443)
WACC	**14.4949*****	**4.6777**	**9.2295*****	**7.4823**	**7.4478*****	**4.7626***
	(4.8435)	(7.9066)	(3.1240)	(4.9201)	(1.8328)	(2.6073)
Growth	**-0.0512**	**0.3159****	**-0.0784***	**0.2627*****	**-0.0738***	**0.2226*****
	(0.0537)	(0.1433)	(0.0458)	(0.0984)	(0.0408)	(0.0746)
R-squared	0.8700	0.1869	0.8951	0.2069	0.8916	0.2143
Adj R-squared	0.8372	0.1754	0.8683	0.1954	0.8628	0.2017
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Company fixed effect	Yes	No	Yes	No	Yes	No
Industry fixed effect	No	Yes	No	Yes	No	Yes
# of observations	*2438*		*2369*		*2166*	
F-stat p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Note: Coefficient estimates are displayed in bold, where, *** ,** and * denote the statistical significance level of 1%, 5% and 10%, respectively. Standard errors are provided in parentheses. The data considered for this study ranges from January 2018 to December 2021.

5.4 Robustness testing

Earlier in this section, we introduced various caps for the P/B ratio in our statistical models. This process helps us validate the consistency of our findings. By altering the caps of the P/B ratio and checking if our results remain stable, we argue that this is a form of robustness testing. To further test our initial results, we carried out cross-sectional regressions on an annual basis. This means we compared and analyzed the P/B ratios of different companies in the same year instead of looking at changes over time. To test for robustness, we compare these results with our initial regression findings to see if they align. As shown in Table 6, when we run the regressions for each year separately, the results align well with our initial findings. This suggests our results are consistent and not likely due to chance.

Table 6: Separated year regressions, including ESG scores equal to zero

This table shows results run year by year with company and industry fixed effects, there is a P/B cap on 20.

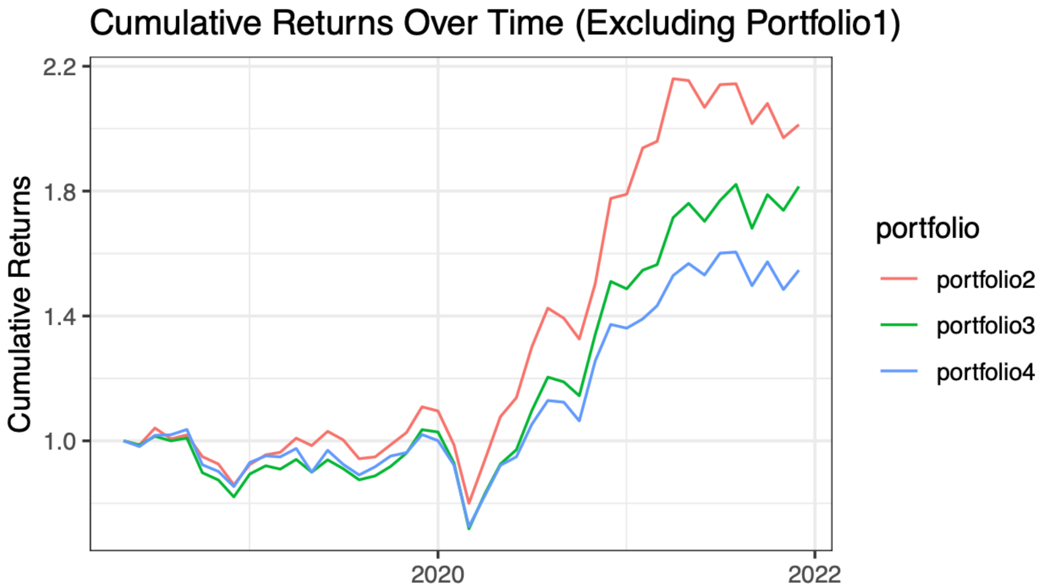
Year	2018	2018	2019	2019	2020	2020	2021	2021
Market Cap.	0.00013***	0.000026**	0.000018**	0.000021**	0.0000026	0.000018**	0.000005**	0.000007***
	(0.00004)	(0.000012)	(0.000008)	(0.0000092)	(0.000007)	(0.000009)	(0.0000026)	(0.0000023)
Esg score	**0.1278*** **	**0.0031**	**0.0301*** **	**0.0052**	**-0.1058*** **	**-0.0013**	**0.0835*** **	**-0.0011**
	(0.0150)	(0.0033)	(0.0099)	(0.0032)	(0.0142)	(0.0034)	(0.0130)	(0.0033)
Revenue Growth $_{t-1}$	**0.0301**	**0.1576***	**0.0276**	**0.1451**	**0.0977** **	**0.2859*** **	**0.0405**	**0.1683** **
	(0.0548)	(0.0909)	(0.0481)	(0.1018)	(0.0463)	(0.0750)	(0.0602)	(0.0694)
Age	**-0.2530*** **	**-0.0179*** **	**0.4732*** **	**-0.0150*** **	**1.6683*** **	**-0.0130*** **	**-0.2503** **	**-0.0168*** **
	(0.0836)	(0.0037)	(0.1042)	(0.0039)	(0.1082)	(0.0042)	(0.1039)	(0.0048)
ROE	**0.2615**	**0.4728**	**0.0600**	**-0.0458**	**-0.5935**	**0.0785**	**-0.2982**	**0.2098**
	(0.2691)	(0.2999)	(0.2589)	(0.2547)	(0.3752)	(0.2558)	(0.3889)	(0.2663)
WACC	**-3.6599**	**4.6438***	**5.1832**	**3.4437**	**5.2321*** **	**1.5261**	**-0.6056**	**10.5545*** **
	(3.0835)	(2.4968)	(3.2115)	(2.8550)	(1.6828)	(3.0114)	(3.7159)	(3.2516)
Growth	**-0.0748*** **	**0.0191**	**-0.0630***	**0.0560**	**-0.0406**	**0.0865**	**-0.1695*** **	**-0.2109** **
	(0.0261)	(0.0702)	(0.0349)	(0.0729)	(0.0324)	(0.0784)	(0.0431)	(0.1020)
R-squared	0.9219	0.1860	0.9012	0.1889	0.9024	0.1881	0.9001	0.1773
Adj R-squared	0.8917	0.1809	0.8628	0.1841	0.8633	0.1836	0.8599	0.1733
Company fixed effect	Yes	No	Yes	No	Yes	No	Yes	No
Industry fixed effect	No	Yes	No	Yes	No	Yes	No	Yes
# of observations	2730		2856		3134		3487	
F-stat p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Note: Coefficient estimates are displayed in bold, where, ***,**, and * denote the statistical significance level of 1%, 5%, and 10%, respectively. Standard errors are provided in parentheses. The data considered for this study ranges from January 2018 to December 2021, where we do not exclude ESG scores that are equal to zero. This approach provides us with a comprehensive pool of 12,207 observations across these years. Since we analyze each year separately in these tests, there's no need to adjust for the impact of specific years or time periods.

5.5 ESG Portfolio Returns

In the interest of further research, we decided to look at returns for the different portfolios we created for section 5.1.

Figure 1: Cumulative Return on ESG Portfolios



The graph shows the cumulative return on 1$ invested in an equal-weighted portfolio sorted on ESG scores from 2018-2021

Where portfolio 2 consist of stocks with the lowest 33% ESG scores
Portfolio 4 is the top 33% ESG scoring companies.
Portfolio 3 is in the middle 33%, i.e., the average performers.
Portfolio 1 contained companies without ESG scores, we exclude this portfolio.

In Figure 1, we see that an equal-weighted portfolio with the worst ESG performers (portfolio 2) would outperform an equal-weighted portfolio with the best ESG performers (portfolio 4) for our period. Considering the risk/return theory, this aligns with our hypothesis of high ESG-scoring companies achieving a price premium. A higher price would mean a lower expected return. This result is also in line with several research papers. E.g., Bolton & Kacperczyk (2021) found higher returns for high carbon-intense companies, Chang et al (2022) stated that most evidence suggests that higher ESG would lead to lower returns; however, in the short run, could be positive returns. Another explanation for the return pattern we see is to look at the properties of large firms. For instance, Drempetic et al. (2020) found that larger firms have more resources to spend on for instance ESG and hence achieve higher scores. As such, it could be that the returns just display a typical large cap. portfolio pattern and the reasoning of Choi et al. (2020) of no specific return pattern for ESG exists given an underreaction.

6. Conclusion

This thesis shows that assets with an ESG score have a higher P/B ratio (β = 0.0046***), after controlling for traditional drivers of P/B. This confirms our expectation that investors are willing to pay a premium for ESG performance. Furthermore, we also find that a factor investment strategy solely based on ESG scores has lower returns. This means that our findings confirm and support the links between P/B ratios, ESG, and returns as described in the existing literature. These findings confirm our second hypothesis and are consistent with our main hypothesis.

We construct a model to explain P/B ratios using concepts from Branch et al. (2005) and Fama and French (1995), and methods by Brooks (2019). Here we account for traditional drivers of P/B, such as ROE, WACC, Revenue Growth, and growth. Following Drempetic et al. (2020), we also include market capitalization and Age. As expected, these six control variables explain P/B well. After controlling for these drivers, we find evidence that ESG scores link to a higher P/B ratio for companies listed on exchanges in the Nordic region between 2018 and 2022. These findings align with Hensisz et al. (2019), who argue that ESG creates value in top-line growth, cost reductions, and three other ways. The findings also support Chang et al.(2022),Bolton & Kacperczyk (2021), and Ilhan et al. (2021), who find that ESG increases value through long-term growth and reduced risk.

When excluding companies without ESG scores (NAs), we also find evidence that a lower, rather than higher ESG score leads to a higher P/B ratio. This finding is surprising and goes against our hypothesis. However, this finding might be explained with arguments from Bolton & Kacperczyk (2021) and Ilhan et al. (2021). Where the argument might be that investors view ESG reporting as a sign of quality, but that "excessive" ESG spending might be seen as wasteful mission drift (Ferrell et al., 2016). We do not find a preference for E, S, and G scores separately.

The returns on portfolios sorted by ESG score show that a high ESG scoring portfolio would underperform a low ESG scoring portfolio which confirms our hypothesis. This finding aligns well with the theory of lower risk, lower returns and with existing literature that finds that factors related to lower ESG scores are associated with higher returns given the higher risk (Bolton & Kacperczyk (2021); Ilhan et al. (2021)).

Overall, we conclude that the market values ESG. Where the widely discussed untrustworthiness of ESG ratings (Berg et al., 2022) does not hinder investors from viewing ESG ratings as a signal for lower risk or better cashflow potential. In addition, do we see that a very high ESG rating is not necessarily valued by the market. We explain this finding with a Friedmannian view and argue that the market suspects wasteful ESG spending and mission drift for assets with very high ESG performance. From these conclusions, we derive the following recommendations for Nordic firms and asset managers:

Advice for Nordic firms:

- The market values ESG as firms with an ESG rating appear to have a higher share price, compared to comparable firms without a rating. This means that the cost of getting an ESG rating might justify itself.
- The market does not value ultra-high ESG scores. This should warn firms to avoid ESG-optimizing strategies and policies that could be regarded as wasteful-spending or mission drift.

Advice for asset managers:

- Investors have a clear preference for ESG performance. This means that sustainability-linked funds, ESG-focused investments, and communication of ESG policy might be valuable and increase AUM.
- Following the market's preference for ESG. Asset managers might argue that this pricing proves that ESG has a financial value. This can either mean that ESG performance increases the financial bottom line, or that investors value ESG performance as a part of their shareholder welfare, without requiring ESG performance to have a financial benefit.
- The relation between the P/B ratio and ESG ratings might disappear over time as mandatory ESG reporting weakens the "signal" that the choice to voluntarily report ESG performance resembles today. This might result in a shift in preference where assets with a mid-range ESG performance might be most preferred by investors.

6.1 Research Limitation and Direction of future research

A considerable limitation in our thesis is the limited amount of ESG scores available on Nordic companies. Tables 4 and 5 show that our sample goes from 12611 to 5697 observations when excluding companies without ESG scores. As all companies have an ESG profile, they should also have an ESG score. However, reporting requirements on ESG still need to be impoved. In addition, considering that there are primarily large firms that report on ESG, or have enough resources to increase their scores (Borokova & Wu, 2020; Drempetic et al., 2020), we might lose a lot of valuable data input in our models. This is also a huge drawback for investors looking to diversify their portfolios. Therefore, we propose future research when reporting requirements become stricter and the ESG data is more comprehensive. We do also propose rating agencies look into their requirements and develop less strict reporting requirements for smaller firms such that the size gap is reduced.

Future research could also be done using the same data but different models. For instance, a model taking the difference from the mean for each variable. Another similar approach is the difference in difference model, where one could check if a change in one or more of the explanatory variables, e.g., ESG score, can explain a change in P/B ratios. This could also help determine if it is worthwhile for companies to work on improving ESG scores or not.

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8. Appendices

Tables

Table 7: Category and pillar weights Example (Refinitiv, 2022)

Pillar	Category	Category weights	Sum of category weights
E	Emissions	15%	44%
	Resource use	15%	
	innovation	13%	
S	Community	9%	31%
	Human Rights	5%	
	Product resposnibility	4%	
	Workforce	13%	
G	Shareholders	5%	26%
	CSR strategy	3%	
	Management	17%	

Example directly from Refinitiv ESG score methodology

Table 8: *Results difference in Mean test*

$$H_0: \mu_1 = \mu_2$$

Rejection rule: |Test statistic| > Critical value

Test Statistic Calculation: The test statistic is computed following the procedure outlined in Equation 1. This value is then compared against the critical value, determined based on a 5% level of significance.

The table presents the conclusions drawn from the hypothesis tests conducted for each group comparison. The null hypothesis (H_0) is either rejected or not rejected, indicating whether there is a significant difference in the average P/B ratio between the groups.

Date	NO ESG vs. High ESG	Low ESG vs. High ESG	Medium ESG vs. High ESG	Medium ESG vs. Low ESG
31/03/2018	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
30/06/2018	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
30/09/2018	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
31/12/2018	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
31/03/2019	Do not reject H_0	Do not reject H_0	Do not reject H_0	Do not reject H_0
30/06/2019	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
30/09/2019	Do not reject H_0	Do not reject H_0	Do not reject H_0	Do not reject H_0
31/12/2019	Do not reject H_0	Do not reject H_0	Do not reject H_0	Do not reject H_0
31/03/2020	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
30/06/2020	Do not reject H_0	Reject H_0	Do not reject H_0	Reject H_0
30/09/2020	Do not reject H_0	Reject H_0	Do not reject H_0	Reject H_0
31/12/2020	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
31/03/2021	Do not reject H_0	Reject H_0	Do not reject H_0	Reject H_0
30/06/2021	Do not reject H_0	Do not reject H_0	Do not reject H_0	Do not reject H_0

30/09/2021	Do not reject H_0	Reject H_0	Do not reject H_0	Do not reject H_0
31/12/2021	Do not reject H_0	Do not reject H_0	Do not reject H_0	Do not reject H_0

The table provided shows the results of the hypothesis tests conducted for different groups based on their ESG scores.

The groups are defined as follows:

- *"NO ESG" refers to companies without ESG scores.*
- *"Low ESG" refers to companies with the worst ESG scores, belonging to the lower percentile portfolio.*
- *"Medium ESG" refers to companies with average ESG scores, belonging to the medium percentile portfolio.*
- *"High ESG" refers to companies with the best ESG scores, belonging to the high percentile portfolio.*

Table 9: Data sources

Variable	**Source**
ESG SCORE	Refintiv
E-Score	Refintiv
S-Score	Refintiv
G- Score	Refintiv
P/B	Refintiv
Market Capitalization	Refintiv
Revenue	Refintiv
Revenue Growth $_{t-1}$	Calculated
IPO date	Refintiv
Age	Calculated
TRBC Economic Sector	Refintiv
ROE	Refintiv
WACC	Refintiv
Growth	Calculated
ROE	Refinitiv
Prices	Refinitiv
Returns	Calculated
Country of Exchange	Refinitiv

This table provides an overview of where the data used in this Thesis have been collected from. Our main source is Refinitiv. Read more about each variable in section 4.

Table 10: Summary statistics including ESG scores = zero

This table contains summary statistics for data used in this Thesis regressions. The sample is from Q1 2018 to Q4 2021. Companies that do not have one or more of the variables available are excluded. Number of observations for each variable = 12 611

Variable	Mean	St.dev	Max	Min	Unit
Price-to-book (P/B) ratios	4,58	7,02	134,72	0,0046	Ratio
Market capitalization	2761	20253	77105	0,00007	MEUR
Revenue growth	25,8%	92,3%	992,8%	-527,4%	Percentage
Return on Equity	-4,4%	49,6%	454,1%	-497,0%	Percentage
WACC	6,1%	3,6%	56,1%	-29,8%	Percentage
Growth	6,5%	68,1%	494,3%	-497,0%	Percentage
Age	16,80	19,63	116,88	0,1	Years

Table 11: Summary statistics excluding ESG = zero

This table contains summary statistics for data used in this Thesis regressions. The sample is from Q1 2018 to Q4 2021. Companies that do not have one or more of the variables available are excluded. Companies that do not have a ESG score are excluded. Number of observations for each variable = 5 697.

Variable	Mean	St.dev	Max	Min	Unit
Price-to-book (P/B) ratios	4,55	6,48	95,71	0,0397	Ratio
Market capitalization	5428,0	25881	77104,66	0,0589	MEUR
Revenue growth	20,0%	67,9%	977,8%	-351,6%	Percentage
Return on Equity	8,3%	29,6%	208,4%	-330,1%	Percentage
WACC	6,4%	2,9%	22,8%	-3,5%	Percentage
Growth	1,9%	54,2%	494,3%	-493,0%	Percentage
Age	22,09	24,752	116,88	0,25	Years

Table 12: Summary statistics excluding ESG = zero and P/B < 20

This table contains summary statistics for data used in this Thesis regressions. The sample is from Q1 2018 to Q4 2021. Companies that do not have one or more of the variables available are excluded. Companies that do not have a ESG score are excluded. Number of observations for each variable = 5 530.

Variable	Mean	St.dev	Max	Min	Unit
Price-to-book (P/B) ratios	3,71	3,63	19,96	0,04	Ratio
Market capitalization	5382,54	25861,95	77104,66	0,06	MEUR
Revenue growth	19,45%	67,46%	977,80%	-351,55%	Percentage
Return on Equity	7,86%	28,21%	138,24%	-330,11%	Percentage
WACC	6,38%	2,86%	22,81%	-3,51%	Percentage
Growth	1,77%	54,97%	494,25%	-493,04%	Percentage
Age	22,35	25,00	116,88	0,25	Years

Table 13: Summary statistics excluding ESG = zero and P/B < 10

This table contains summary statistics for data used in this Thesis regressions. The sample is from Q1 2018 to Q4 2021. Companies that do not have one or more of the variables available are excluded. Companies that do not have a ESG score are excluded. Number of observations for each variable = 5 107.

Variable	Mean	St.dev	Max	Min	Unit
Price-to-book (P/B) ratios	2,89	2,21	9,98	0,04	ratio
Market capitalization	4929,04	20135,56	77104,66	0,06	MEUR
Revenue growth	18,36%	67,03%	977,80%	-351,55%	Percentage
Return on Equity	6,90%	27,05%	138,24%	-330,11%	Percentage
WACC	6,35%	2,82%	22,81%	-3,51%	Percentage
Growth	1,45%	57,18%	494,25%	-493,04%	Percentage
Age	22,84	25,42	116,88	0,25	Years

Table 14: Correlation Matrix of our variables used in regressions

	P/B	Market Cap.	ESG Score	E	S	G	Revenue Growth $_{t-1}$	age	ROE	WACC	Growth
P/B	1	0,0017	0,0056	0,0031	0,0042	0,0044	0,0002	-0,0005	0,0040	0,0179	0,0001
Market Cap.		1	0,1614	0,0889	0,0933	0,0962	-0,0016	0,1564	0,0089	-0,0079	-0,0006
ESG Score			1	0,5455	0,5557	0,5332	-0,0093	0,3564	0,0356	0,0530	0,0045
E				1	0,9210	0,8510	-0,0049	0,1868	0,0179	0,0360	0,0021
S					1	0,9073	-0,0054	0,1694	0,0190	0,0494	0,0029
G						1	-0,0055	0,1549	0,0177	0,0718	0,0035
Revenue Growth $_{t-1}$							1	-0,0092	-0,0006	-0,0029	0,0001
age								1	0,0257	0,0013	0,0007
ROE									1	-0,0157	-0,0020
WACC										1	0,0135
Growth											1

Note: This correlation matrix is from our data after excluding NA´s, and is calculated based on 13164 observations.

Figures:

Figure 2: Growth of US sustainable funds and assets (Morningstar, 2022)

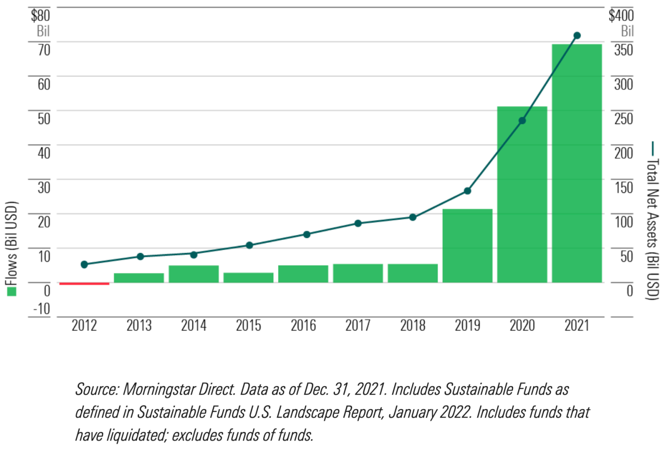


Figure 3: Refintiv ESG methodology (Refinitiv, 2022)

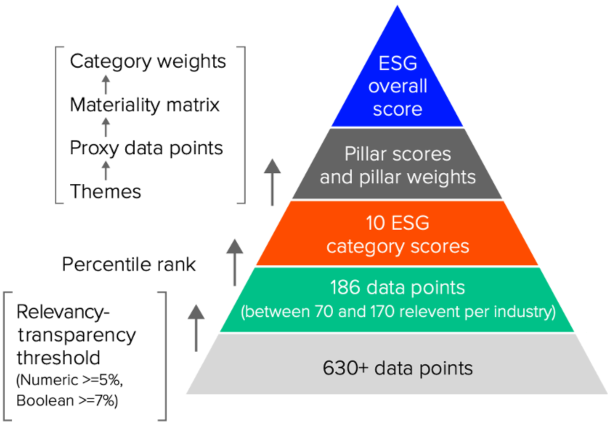


Figure 4: Distribution of collected data from Refinitiv:

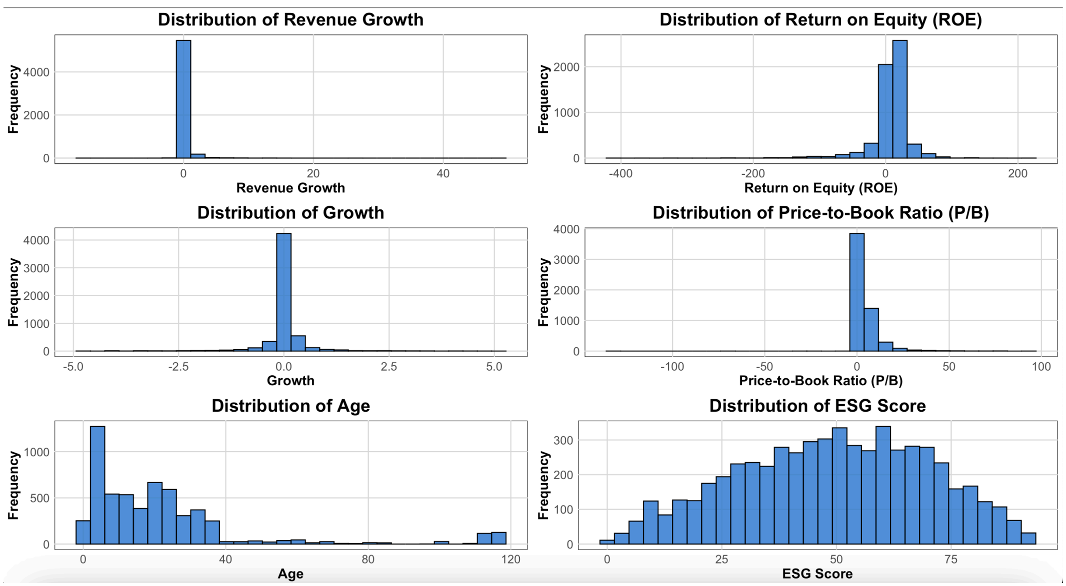


Figure 5: Distribution of data used in our analysis

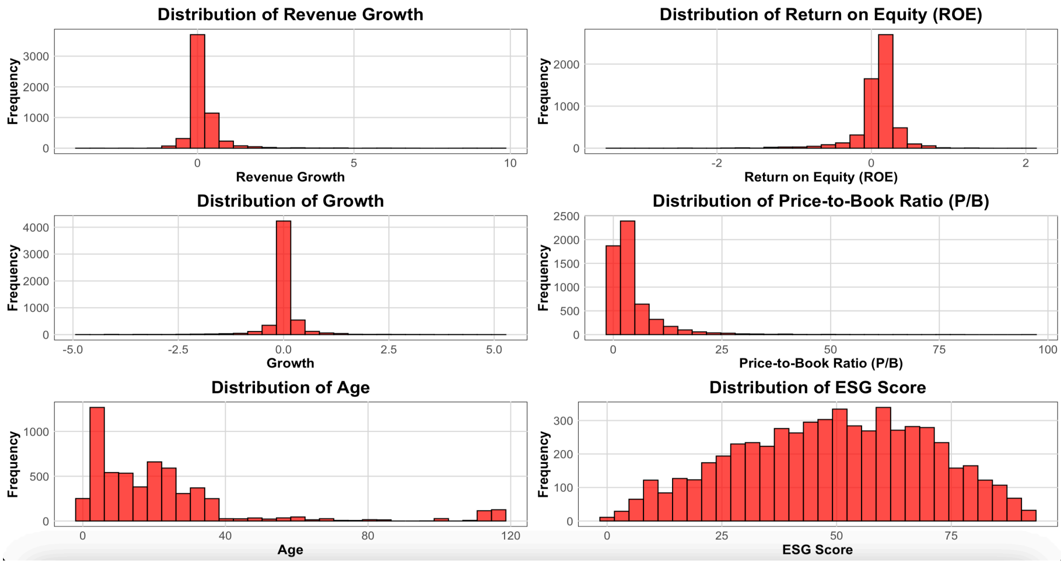
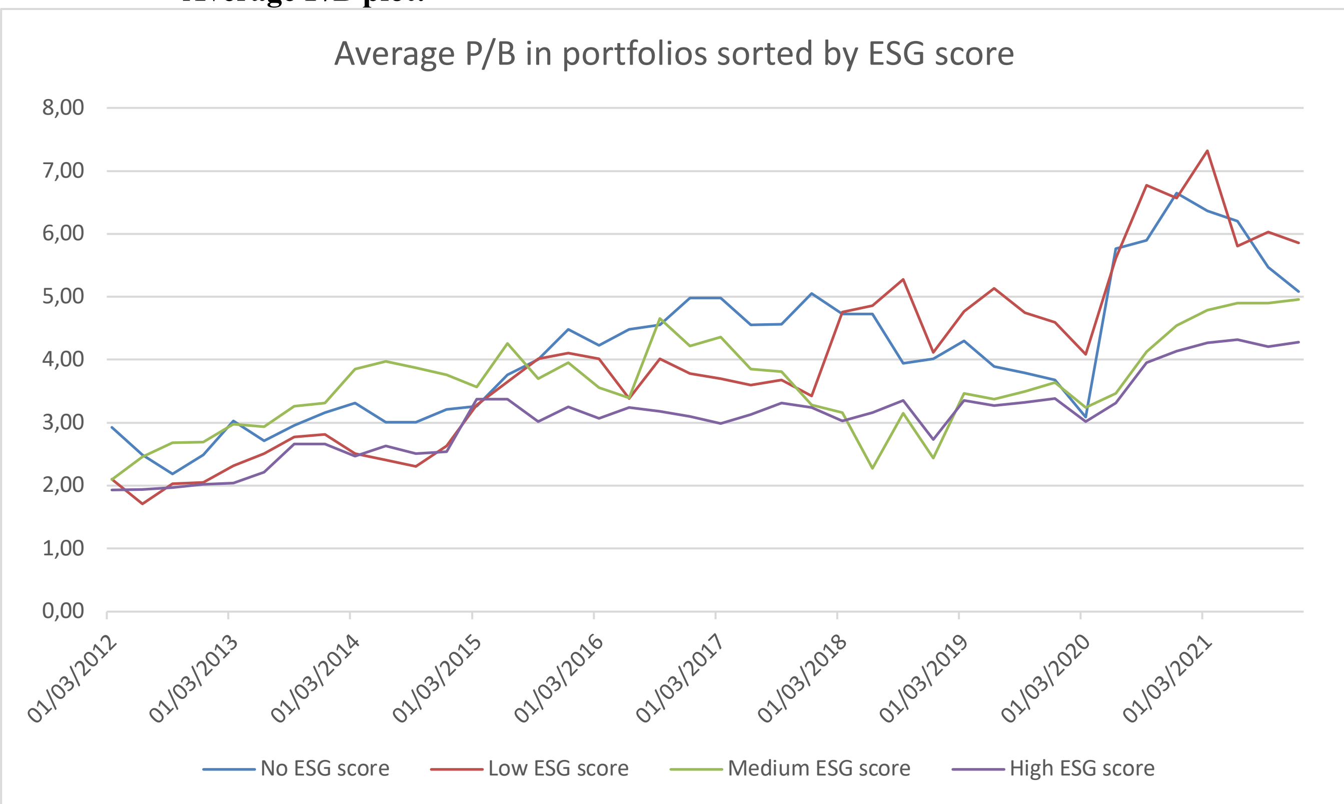


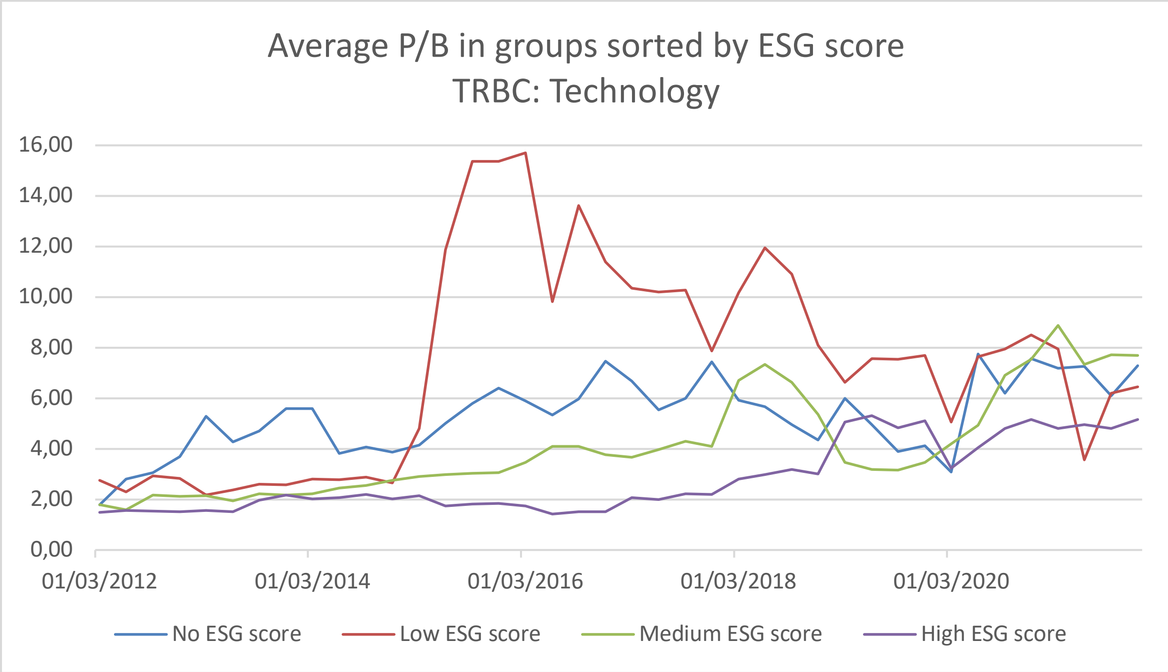
Figure 6: Plots showing P/B averages sorted on ESG score

Average P/B plot:



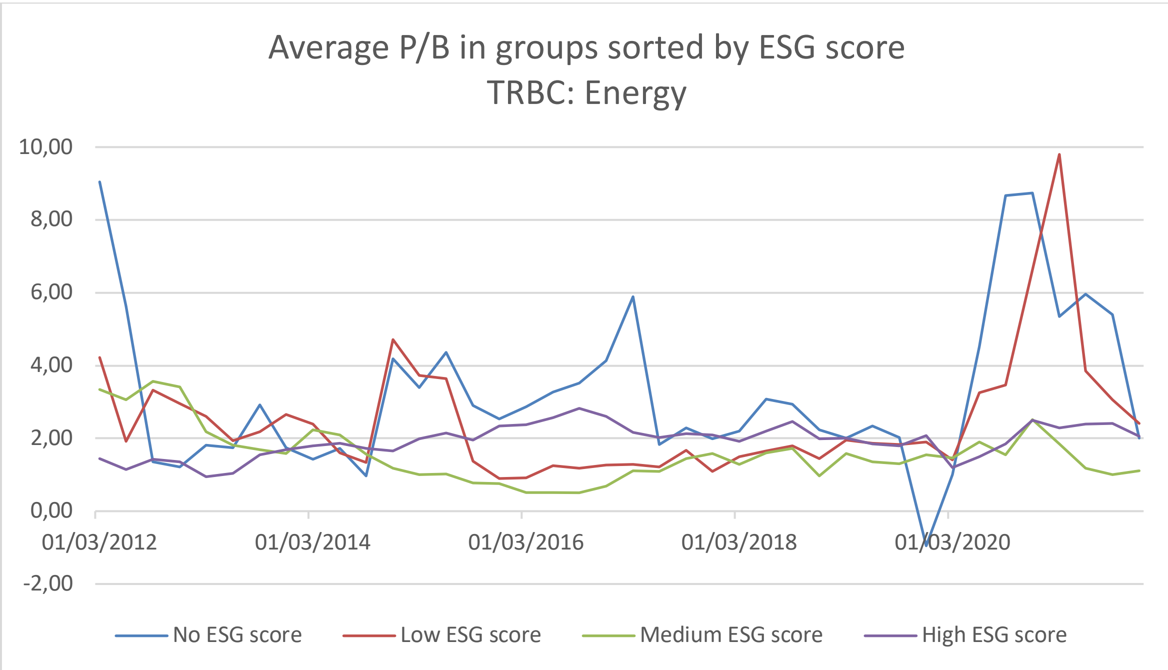
Obs. (2012) = 621, where 60 have ESG score. 561 in No score, And 20 firms in each ESG portfolio.
Obs. (2021) = 1494, where 555 have ESG score. 940 in the no score, 185 in each ESG portfolio.

Figure 7: Average P/B (Technology)



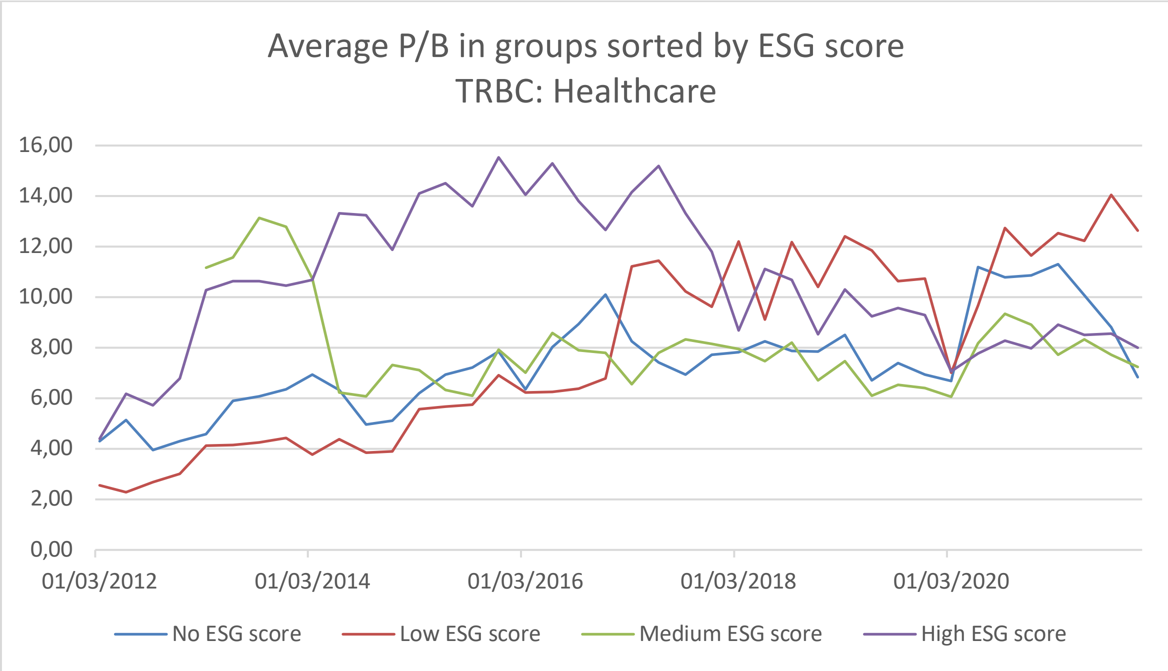
Obs. (2012) = 95, where 9 have ESG scores.
Obs. (2021) = 300, where 104 have ESG scores.

Figure 8: Average P/B (Energy)



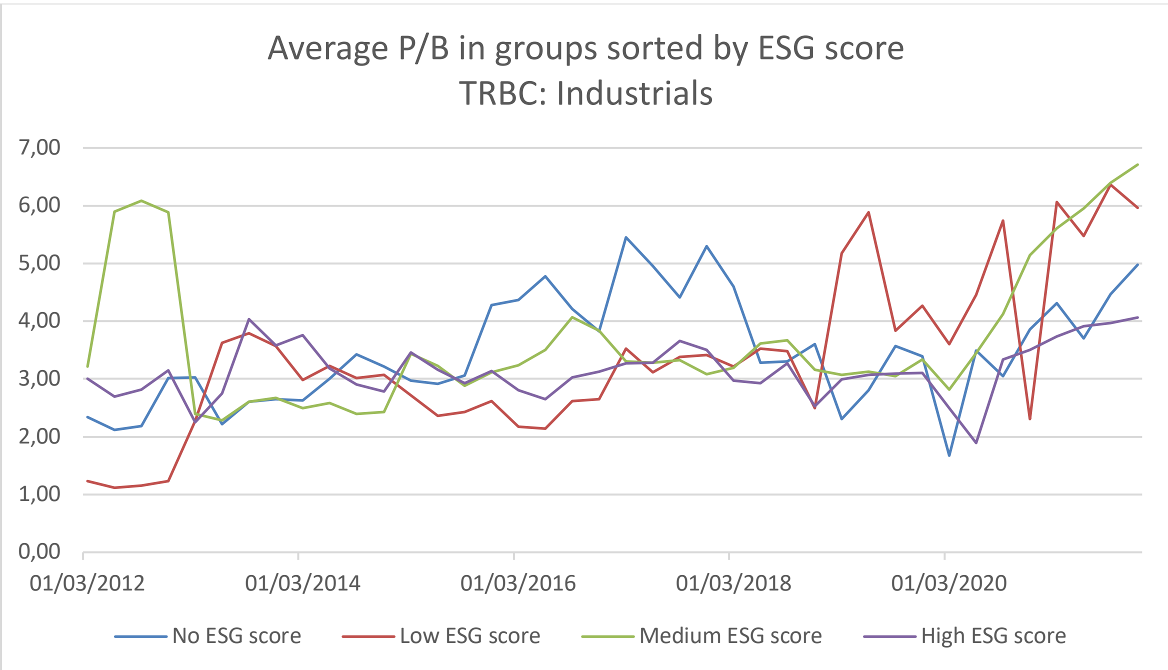
Obs. (2012)=48, where 6 have ESG scores.
Obs. (2021)=87, where 32 have ESG scores.

Figure 9: Average P/B (Healthcare)



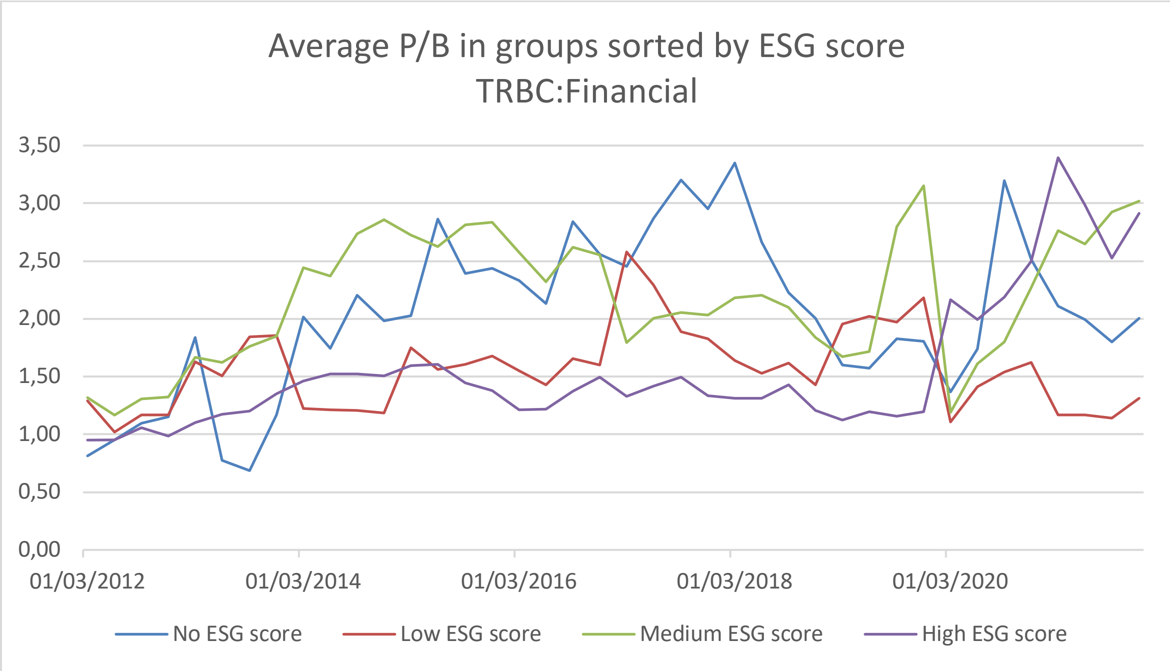
Obs. (2012) = 64, where 2 have ESG scores.
Obs. (2021) = 239, where 74 have ESG scores.

Figure 10: Average P/B (Industrials)



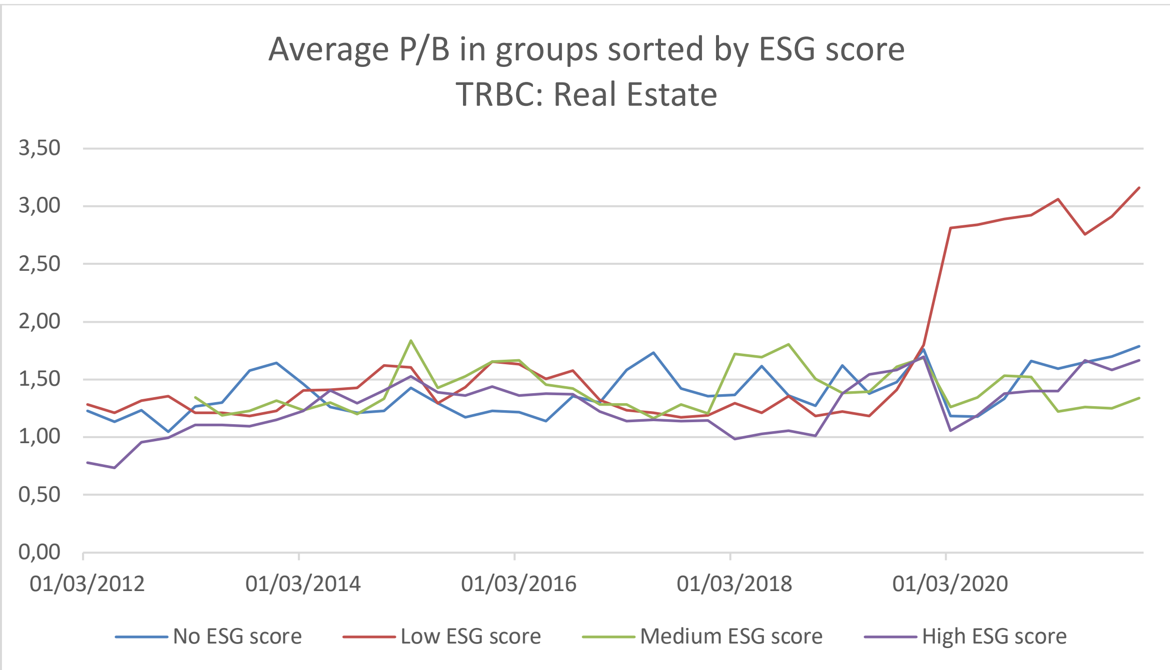
Obs. (2012) = 138, where 11 have ESG scores.
Obs. (2021) = 274, where 120 have ESG scores.

Figure 11: Average P/B (Financial)



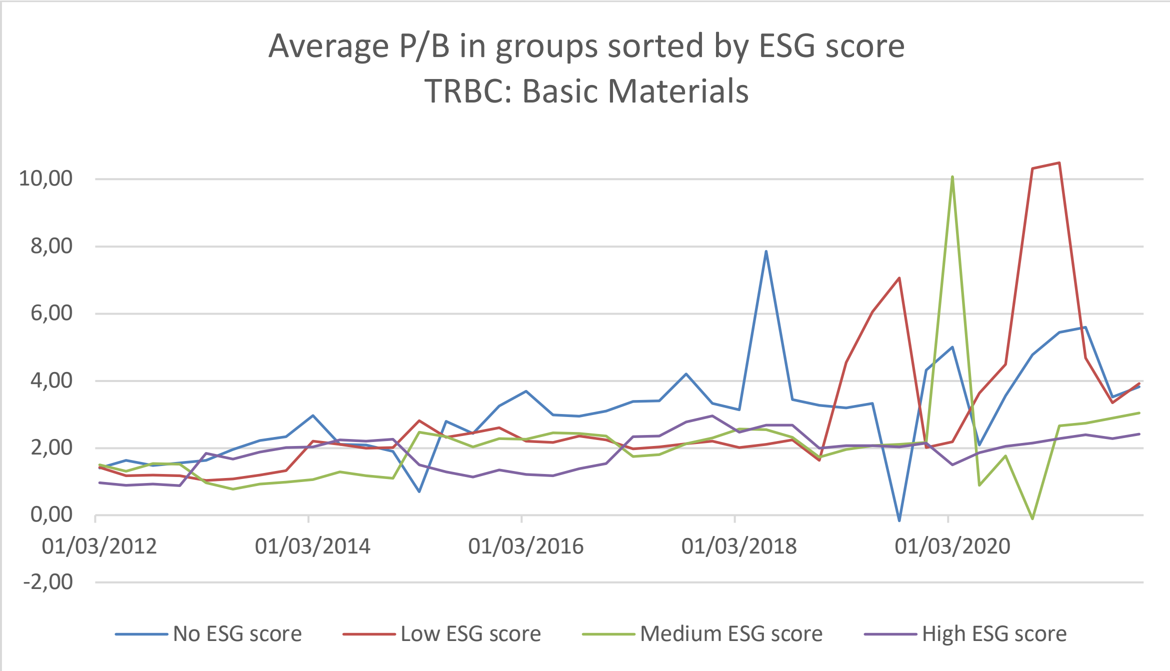
Obs. (2012) = 80, where 12 have ESG scores.
Obs. (2021) = 150, where 47 have ESG scores.

Figure 12: Average P/B (Real Estate)



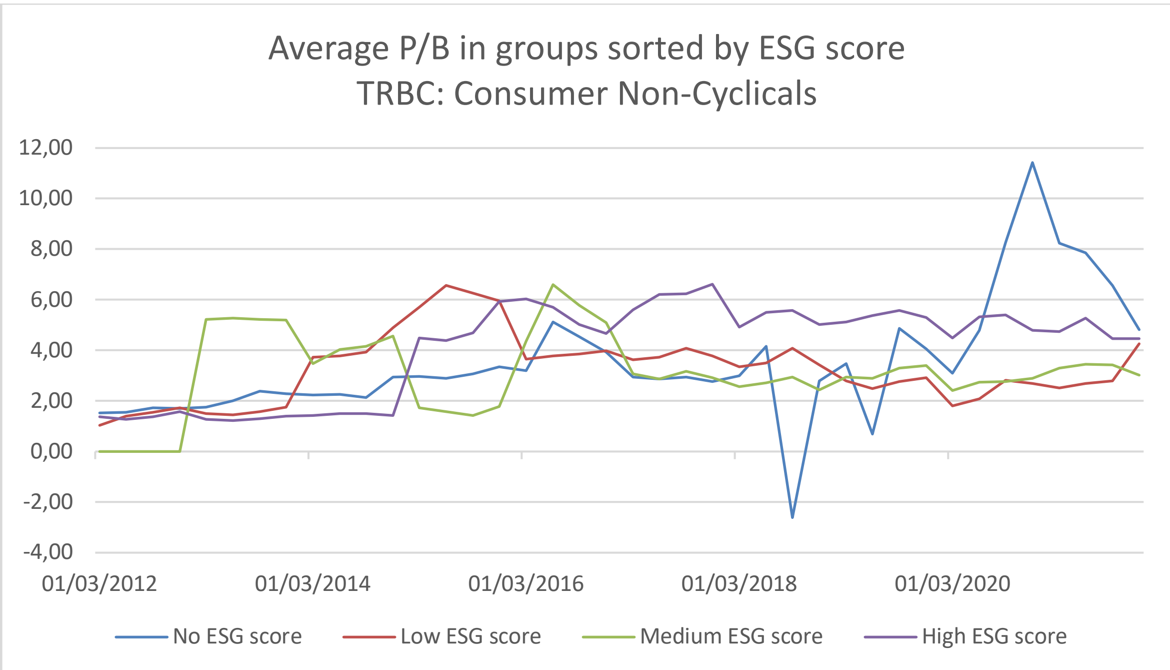
Obs. (2012) = 37, where 2 have ESG scores.
Obs. (2021) = 85, where 30 have ESG scores.

Figure 13: Average P/B (Basic Materials)



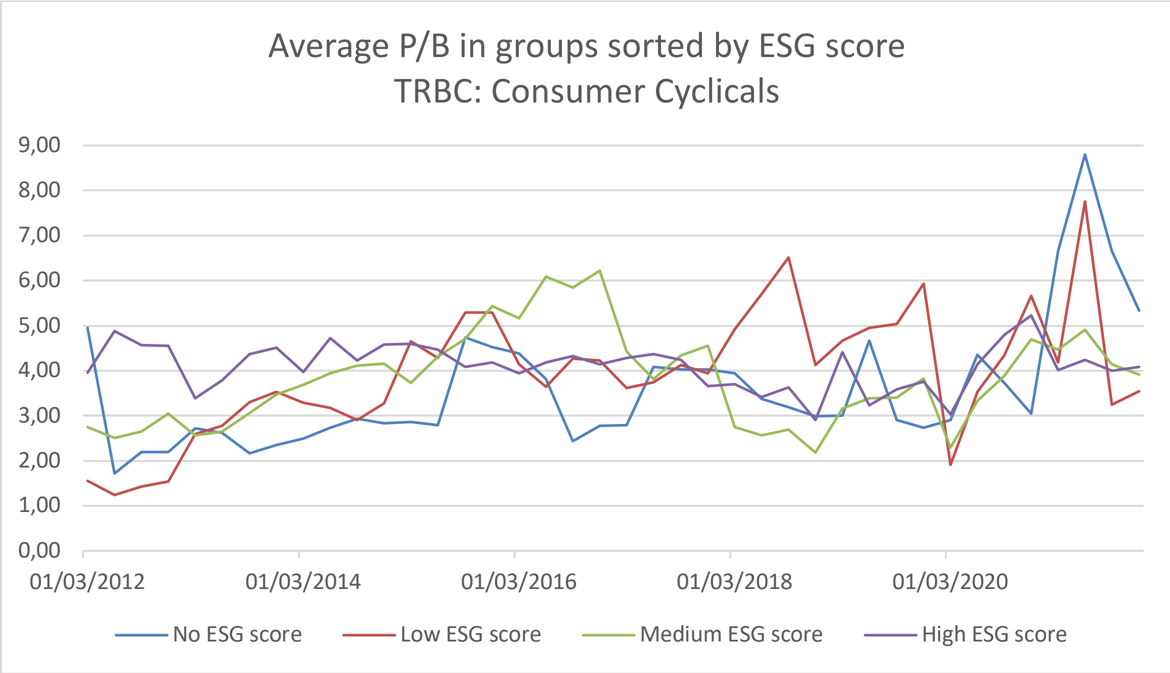
Obs. (2012) = 44, where 7 have ESG scores.
Obs. (2021) = 80, where 45 have ESG scores.

Figure 14: Average P/B (Consumer Non-Cyclicals)



Obs. (2012) = 37, whereas 2 has ESG score.
Obs. (2021) = 80 where 30 have ESG score.

Figure 15: Average P/B (Consumer Cyclicals)



Obs. (2012) = 76, whereas 9 has ESG score.
Obs. (2021) = 152 where 66 have ESG score.