LUND UNIVERSITY

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The Impact of ESG on Financial Performance

Master's Thesis in Financial Economics

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Abstract

In recent years, the focus on environmental, social and governance (ESG) factors has grown substantially from investors and the society overall. This successive switch to more sustainable practices has created a new interesting conversation regarding the impact of ESG on companies' financial performances. This study will deep dive into this new problem statement, investigating the role of ESG both from a firm's perspective and an investor's perspective.

This study included 61 companies acting on the Swedish market between the years 2014-2021. To investigate the impact of ESG on financial performance from a firm's perspective two different regression models were created. All the data for the regression analysis was collected from the Bloomberg database. In the portfolio construction the same companies were used as included in the regression analysis. Two different portfolios were created taking ESG-rating into consideration. The daily Sharpe Ratios were then calculated based on the year 2022 and compared to the market index OMXS30 to see if the portfolios could possibly outperform the market. The stock prices for the portfolio construction were collected through Excel and Yahoo Finance.

The results from this study showed a neutral relationship between ESG and financial performance from a firm's perspective, both in the ROA model and the ROE model. For the portfolios the first one based on the year 2021 performed better than the market index in absolute terms comparing the Sharpe Ratios, but where the difference was not significant. The second portfolio based on the years 2014-2021 performed worse than the market index in absolute terms comparing the Sharpe Ratios.

The conclusion can therefore be drawn, that based on the data sample used in this study there is no significant relationship between ESG-rating and financial performance on the Swedish market from a firm's perspective. The first constructed portfolio did benefit the investor by performing slightly better than the market during 2022 in terms of Sharpe Ratio, however since it was not statistically significantly better than the market portfolio OMXS30 it can not be said that this will be the case in the future. The second portfolio had a lower daily Sharpe Ratio than the market.

Keywords: *Corporate Social Responsibility (CSR); Environmental, Social, Governance (ESG); ESG-rating; Return On Asset (ROA); Return On Equity (ROE); Ordinary Least Squares (OLS); Modern Portfolio Theory (MPT); Sharpe Ratio; Bloomberg; Sweden*

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Contents

1. Introduction

In recent years, the focus on environmental, social and governance (ESG) factors has grown substantially from investors and the society overall. This successive switch to more sustainable practices has created a new interesting conversation regarding the impact of ESG on companies' financial performances. This study will deep dive into this new problem statement, investigating the role of ESG both from a firm's perspective and an investor's perspective.

As sustainability becomes increasingly important the pressure increases for firms to modernize their business practices to meet the needs and expectations from investors and costumers. Taking ESG factors into consideration might not only generate a greater understanding of the focus on sustainability within the business model and address possible weaknesses. It could also advance a firm's success, for instance from a financial perspective. ESG can be seen as a framework to get a better overview of a company's business model, and a way to rate companies in terms of Corporate Social Responsiblity (CSR).

Taking ESG into consideration when deciding which companies to include in a portfolio has become a growing strategy. The investment attitude is progressively changing and more focus is being put towards sustainability requirements. Including ESG as a factor in the portfolio construction to make even smarter decisions can place the investor in a more stable long term position and be beneficial both from a financial perspective and a social perspective. Needless to say, different investors have different preferences and value different factors unequally. Investing sustainably could be a matter of goodwill, an ethical or moral factor for a shareholder. On the other side of the coin, placing more focus towards sustainable labour can be beneficial for a firm as well. By showing for costumers and investors that sustainability is highly valued within its business practices, the interest and respect could increase from shareholders and make the company build a more competitive position in the long run.

The purpose of this thesis is to investigate the impact of ESG on the financial performance indicators Return on Asset (ROA) and Return on Equity (ROE), as well as on portfolio performance. This captures both a firm's and an investor's perspective. The first part will be examined through a regression model and the second part through portfolio construction taking ESG-rating into consideration. Firstly, this gives deeper insight into how these two perspectives interact. Secondly this opens for the possibility to analyse the impact of ESG in both cases separately. In turn, this provides valuable insights regarding the importance of sustainability today, to help making better and more well constructed decisions and investments for people in the future.

The data for the regression analysis was collected through the Bloomberg database. The stock prices for the portfolio construction was collected in Excel and Yahoo Finance. To analyse the impact of ESG on ROA and ROE two different panel data regression models were created by the help of data and variables collected from Bloomberg. ROA and ROE were used as the dependent variables in the two regression models. ESG was used as the independent variable together with relevant control variables to complete the regression models. The significance of the ESG variable in these models was then examined. The time span was between 2014 and 2021, investigating the Swedish market. For the portfolio constructions 10 companies were selected from 10 different sectors having the highest ESG-rating sector wise. The available companies were the ones used in the regression analysis. The choice of companies in the first portfolio was based on the ESG-ratings in 2021, and in the second one on the average ESG rating between 2014 and 2021. The portfolio perfomances were investigated in 2022 and compared to the market index OMXS30 through the risk-adjusted performance measure Sharpe Ratio.

The result showed a neutral relationship between ESG and both ROA and ROE. In addition, the first constructed portfolio had a higher daily Sharpe Ratio during 2022 than the market index, the second portfolio had a lower value. None of the portfolios performed statistically significantly better than the market in 2022.

From a theoretical perspective, this study contributes with understanding the relationship between ESG and financial performance. There are already a wide range of similar studies within this area, but not as many focusing on the Swedish market, and even fewer looking at these two perspectives simultaneously. From a practical perspective, this study can act as guidance and help for companies in their business models, and for investors in their decision making.

1.1 Outline

Section 1 includes an introduction to the subject together with the purpose of this study and a summary of the methodology and results. In Section 2, Literature Review, various previous studies within this area will be presented and summarized. In Section 3, Theoretical Framework, theory regarding CSR, ESG, Regression Analysis and Portfolio Construction will be presented. Section 4, Methodology, contains the approach and methodology of this study. Section 5, Data, presents the data collection and processing. Furthermore, this chapter includes analyses of the data and the most important data is presented. Section 6, Final Regression Models, includes an analysis and presentation of the final regression models. In Section 7 the results are presented and discussed. Section 8 includes the conclusions, contributions, limitations and ideas for future research. Section 9 includes all the references and Section 10 all the appendices.

2. Literature Review

2.1 Previous Research

Numerous previous studies have been made regarding green finance, both concerning the correlation between sustainability and financial performance and green portfolio construction. However, none is exactly alike. The studies can differ in choice of country, time gap, regression model or variables included. In this part some of these previous analyses will be presented and concluded. The purpose is to get a better understanding of the area which makes it easier to create an appropriate regression model. Since the variables used in the models, the model types and the results vary among the different studies a presentation of some of these will help to get a better overview and to be able to regularly compare the results in this project with previous similar articles. There are not a large number of studies made specifically looking at the Swedish market, therefore the studies presented will be focusing on similar analyses but in different countries around the world. As mentioned previously, a complex problem which will be seen after going through the articles below is that financial performance can be explained in different ways. Simultaneously, there is an incredibly large amount of possible combinations of variables to use together with the ESG rating in the regression analysis to explain the financial performance measure. The data can be collected from different sources having dissimilar methods to calculate each variable as well.

2.1.1 Does ESG performance have an impact on financial performance? Evidence from Germany. Velte, P. (2017)

Velte, P. (2017) looked at the relationship between ESG rating and financial performance on the German market. A correlation analysis together with a regression analysis were made for companies between 2010 and 2014. ROA and Tobin's Q were used as measurements for financial performance. The ESG rating was collected from Thompson Reuters Database. As control variables RnD expenses, BETA to account for the systematic risk and total debt to total assets as a measurement for unsystematic risk were used. The natural logarithm of a firm's size in terms of total assets were used to include the size of the company. In addition, a dummy variable for industry was used to capture differences between industries. The regression analysis showed a positive relationship between ROA and ESG, and no relationship between Tobin's Q and ESG.

2.1.2 Revisiting the impact of ESG on financial performance of FTSE350 UK firms: Static and dynamic panel data analysis. Ahmad et al. (2021)

Ahmad et al. (2021) focused on the UK market between 2002 and 2018. They used Market Value (MV) and Earnings Per Share (EPS) as the dependent variables. The different sustainability measurements including ESG score were used together with company size as independent variables. Effective tax rate, capital expenditure to sales, total revenues and leverage were used as control variables. A dynamic panel data regression model was used, and the relationship between ESG and MV respectively ESP turned out to be positive in both cases. The data was collected from Thompson Reuters Database.

2.1.3 Corporate social responsibility governance, outcomes, and financial performance. Wang & Sarkis (2017)

Wang & Sarkis (2017) examined the relationship between CSR and financial performance for companies in the US between 2009 and 2013. The ESG-ratings were collected from the Bloomberg database. The dependent variables were ROA and Tobin's Q. The independent variables were the three pillars of ESG-rating. The control variables were chosen as the company's size, leverage, liquidity and growth regarding change of sales in percentage between one year and another. Wang & Sarkis (2017) found that CSR governance was marginally significant, the environmental pillar significant and the social pillar significant when including them separately in the model. CSR Governance then turned out to be insignificant when introducing the environmental pillar as well as the social pillar respectively in the model. The significance of the environmental and social pillar did not change.

2.1.4 Environmental, Social and Governance (ESG) Scores and Financial Performance of Multilatinas: Moderating Effects of Geographic International Diversification and Financial Slack. Duque-Grisales & Aguilera-Caracuel (2021)

This article stands out in comparison to the other articles. Here the connection between ESG and financial performance was once again examined but this time in Latin America. The time span was between 2011 and 2015 and the data was collected using Thompson Reuters database. The result showed a negative connection between ESG-rating and financial performance. However, this was still in line with the hypothesis of the study. As a consequence of government corruptions in Latin America, stakeholders does not value the sustainability factors equally important as in other parts of the world. Simultaneously, investing in CSR costs money which in turn has a negative direct effect on the financial performance for a company. This might be a reason for the negative relationship. ROA was used as the dependent variable. The independent variables used was the overall ESG score, and the three pillars separately. The data regarding ESG was collected from Thompson Reuters Database. The logarithm of sales was used to account for firm size and leverage was used as control variables.

2.1.5 ESG integration: value, growth and momentum. Kaiser, L. (2020)

This article had more of an investor's perspective. Kaiser (2020) looked at the integration of ESG for investors into their portfolios. The time span was between 2002 and 2015. It turned out to show a positive correlation between ESG level and risk-adjusted performance. This means that based on the data used and results made in this article, the risk-adjusted performance for an investor's portfolio could be improved by increasing the over all ESG level of the portfolio. The study was based on the US and European market. The ESG data was collected from Thompson Reuters Database.

2.1.6 Sustainable investments in the Norwegian stock market. Fiskerstrand et al. (2020)

Fiskerstrand et al. (2020) examined the relation between ESG-rating and financial performance in Norway between 2009 and 2018. The Dow Jones Sustainability Index (DJSI) was used to get the ESG-ratings of the companies. A portfolio construction using regression analysis was made showing no significant connection between ESG score and financial performance. By studying the impact of ESG in portfolio construction this article analysed the relationship between ESG and financial performance more from an investors perspective.

2.1.7 ESG factors and risk-adjusted performance: a new quantitative model. Ashwin Kumar et al. (2016)

In this article the focus was on looking at ESG-rating in relation to stock volatility. The DJSI was used to collect information about ESG-score. The time span was between 2014 and 2015 focusing on the US market. The findings were positive showing not only that investing in highly ESG-rated companies reduces volatility, but also that these investments can yield a higher return.

2.1.8 Does it pay to be sustainable? Looking inside the black box of the relationship between sustainability performance and financial performance. Hussain et al. (2018)

Once again the relation between sustainability and financial performance was examined. This time the authors focused on the US market between 2007 and 2011. ROA, ROE and Tobin's Q were used as dependent variables. The independent variables in the regression model examining the relationship between ESG disclosure and financial performance were chosen as the three pillars in ESG-rating. As control variables the logarithm of the size of the company as total assets was used together with capital expenditure to total assets, RD expenditure to total assets, growth in sales by each year and debt to equity. A dummy variable was also used taking the value one if the sector is sensitive to environmental factors, and zero otherwise. The model used was a panel regression model. The ESG-ratings were collected from Bloomberg. The result showed that all of the pillars of ESG were insignificant and did hence not have a significant relationship to financial performance.

2.1.9 ESG impact on performance of US S&P 500-listed firms. Alareeni & Hamdan. (2020)

Alareeni & Hamdan (2020) investigated the relation between ESG rating and financial performance on the US market. They used ROA, ROE and Tobin's Q as measures for financial performance. The sample period was between 2009 and 2018. A panel regression model was used to examine the connection. The results showed a positive relation between financial performance and ESG-score. However, separating the pillars in ESG showed a rather unpredictable result. For example, the environmental pillar and CSR disclosure had a negative impact on both ROA and ROE, but were still positively related with Tobin's Q. In other words, the environmental factor and the CSR disclosure had a positive impact on a firm's market-based measure, but negative on the accounting-based measures.

The data was collected from Bloomberg. The size of the firm, leverage, growth in terms of total assets and asset turnover were used as control variables. Asset turnover was calculated as net sales to total assets.

2.1.10 ESG and financial performance: aggregated evidence from more than 2000 empirical studies. Friede et al. (2015)

Before the end of this chapter one more article will be presented. Friede et al. (2015) made an aggregated analysis on previous research about ESG and financial performance. More than 2000 studies made from all over the world were included to come up with a generalized result. In more than 50 percent of these previous studies the relationship between ESG and financial performance was positive.

2.2 Summarized result

Table 1 below includes a summary of all the articles to get a good overview of the analyses and results.

Table 1: Authors, time span, source for ESG rating, financial performance measurements, the market analysed and the impact of the sustainability measurement on financial performance for the articles presented in this part of the project.

Study	**Time Span**	**ESG measurements**	**Financial Performance**	**Market**	**Result**
Velte, P. (2017)	2010-2014	Thompson Reuters	ROA, Tobin's Q	Germany	Positive, Neutral
Ahmad et al. (2021)	2002-2018	Thompson Reuters	MV, EPS	UK	Positive
Wang & Sarkis (2017)	2009-2013	Bloomberg	ROA, Tobin's Q	US	Positive
Duque-G & Aguilera-C (2021)	2011-2015	Thompson Reuters	ROA	Latin America	Negative
Kaiser, L. (2020)	2002-2015	Thompson Reuters	Risk-Adj perf.	US, Europe	Positive
Fiskerstrand et al. (2020)	2009-2018	DJSI	Sharpe-ratio	Norway	Neutral
Ashwin Kumar et al. (2016)	2014-2015	DJSI	Volatility, Return	US	Positive, Positive
Hussain et al. (2018)	2007-2011	Bloomberg	ROA, ROE, Tobin's Q	US	Neutral
Alareeni & Hamdan. (2020)	2009-2018	Bloomberg	ROA, ROE, Tobin's Q	US	Positive

3. Theoretical Framework

3.1 Corporate Social Responsibility

As sustainability becomes increasingly important in normal day life it is important for companies to keep up. Corporate social responsibility (CSR) can be seen as a business model to get a better insight of a firm's work towards sustainability (Jin & Lee, 2019). Not only is it important for the company itself, but also for investors, costumers and the public to understand how the business relates to sustainability issues. Establishing CSR is a way of showing for the stakeholders that sustainability is something valuable, and truly something crucial for a business to survive in the long run and stay competitive. Simultaneously, it often creates a better climate in the workplace for the employees. However, CSR does not always come with positive consequences. Even though it is often shown that implementing CSR is positively related to the performance and reputation of a company, a commitment towards sustainable acting costs. An abrupt commitment towards CSR might not work for everyone, and could lead to worse financial performance due to increased costs. Moreover, a mediocre commitment towards CSR with the ulterior motive to increase sales by looking good could also lead to a setback from the stakeholders.

3.2 Environmental, Social and Governance

Environmental, social and governance(ESG) is closely related to CSR. It can be explained as a framework for people to invest responsibly, being more aware about environmental, social and governance factors (Li et al., 2021). Whereas CSR is commonly established by a firm itself, ESG could for instance be a tool for investors in their decision making and an assisting instrument to include to invest more responsibly. Furthermore, ESG could also give the firm a better overview. For example to see how well the sustainability factor in the business model works in practice, or to understand the firm's focus on sustainability and long term value creation. Ever since the ESG concept was introduced it has been helpful in creating different evaluation systems and indices to rate companies in terms of sustainability. Each pillar plays a crucial part, and many studies analyses them separately.

3.2.1 ESG-Rating

There are several databases rating companies according to the three pillars environmental, social and governance. However, each source follow different frameworks and companies get rated in different ways based on how the rating system is built. A commonly used system is based on a rating between 0 and 100 where 100 is the best possible outcome and 0 is the worst. Two well known databases having this system is "Thompson Reuters" and "Bloomberg". Bloomberg's original system was based on 72 different indicators and has since then been regularly developed and more indicators have been added along the way (Wang & Sarkis, 2017). Environmental indicators can for example refer to emissions or waste, social indicators to equality, human rights and health. The governance pillar refers to a firm's implementation of CSR, more from the boards perspective. A company receives three separate ratings based on each pillar in ESG. A company hence gets one environmental score, one social score and one governance score. These can then be combined all together to get the ESG-rating by calculating the average score.

3.3 Financial Measurements

Performance has a comprehensive meaning and companies grow and develop in different ways depending on the business life cycle and at what stage the companies find themselves in. This aggravates the possibility to give an equitable assessment among different companies' regarding financial performance. Furthermore, financial performance measures can be divided into accounting-based measures and market-based measures. The accounting-based instruments measure the financial performance from a firm's perspective. The market-based instruments measure the financial performance more from an investor's perspective. Looking at previous research and the studies presented in the Literature Review, two commonly used accounting-based measures are ROA and ROE. A common market-based measure is Tobin's Q.

3.3.1 Return On Asset

ROA is one of the most commonly used measures when speaking about a firm's financial performance. ROA can be explained as measuring a firm's profitability in relation to its total assets and can in general be calculated as

$$ROA_{i,t} = \frac{NetIncome_{i,t}}{TotalAssets_{i,t}}, \tag{1}$$

for firm i at time t (Alareeni & Hamdan, 2020). Since the net income is divided by total assets representing the size of the firm, it makes it possible to use ROA to compare companies of different sizes.

3.3.2 Return On Equity

ROE is another measure commonly used to represent financial performance. Apart from ROA this measurement instead describes a firm's profitability in relation to its total equity and is generally calculated as

$$ROE_{i,t} = \frac{NetIncome_{i,t}}{TotalEquity_{i,t}}, \tag{2}$$

for firm i at time t (Alareeni & Hamdan, 2020). Since the denominator is a measure that can be connected to the firm's size, it is possible to use ROE as a financial measure to compare companies of different sizes.

3.4 Regression Analysis

Linear regression is used when the relationship between the dependent variable and the independent variables looks to be linear. This is the most commonly used model together with the multiple linear model. Nonlinear regression is usually more relevant to more complex data sets. The simple linear regression can be modelled as

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \tag{3}$$

having only one independent variable (Studenmund, 2013, p.12). β_0 represents the intercept of the model, and β_1 the slope and can be interpreted as the increase in y when x increases by one unit. The error term represented by ϵ includes all the information that is not explained by the independent variable to clarify that the model is not perfect. Furthermore, after fitting a line to the regression the residual for one observation represents the distance between the data point and the fitted line (Studenmund, 2013, p.16). The multiple linear regression having at least two independent variables can for instance be modelled as

$$y_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + ... + \beta_n x_{n,i} + \epsilon_i, \tag{4}$$

where n is the amount of independent variables used (Studenmund, 2013, p.14). Each beta corresponding to one independent variable can no longer be explained as the slope. The interpretation for β_i is instead the increase in y when x_i increases by one unit, keeping the other variables fixed.

To be able to perform the regression analysis data needs to be gathered for all the variables within the same time aspect. Important to have in mind throughout regression analysis is that even though there seems to be a relationship between a dependent variable and an independent variable, that might not be the case in reality. In fact, the variables can be completely independent of each other but just follow the same pattern in time. However, performing the regression analysis in an appropriate software package will yield estimates for all the coefficients and the intercept based on the gathered data. Since multiple linear regression is the most relevant model for this project, the process of estimating the parameters will only be written out for this model. The parameters get estimated by minimizing the sum of the squared residuals (RSS) as shown in (5) (Studenmund, 2013, p.50).

$$RSS = \sum_{i=1}^{m} (y_i - \hat{\beta_0} - \hat{\beta_1} x_{1,i} - \hat{\beta_2} x_{2,i} - ... - \hat{\beta_n} x_{n,i})^2, \tag{5}$$

for n independent variables and m different observations. $\hat{\beta_0}$ is the estimated value for β_0 and so forth.

3.4.1 Dummy variables

Sometimes it is interesting to separate the regression into sub-samples based on some underlying fact. This can be done by introducing a dummy variable to the regression model. This variable usually takes the value either zero or one based on some indicator (Studenmund, 2013, p.14). This indicator can for example be if the data comes from a city or not, whether the observation comes from a specific industry, or simply gender. This makes it possible to compare the data set for potential differences depending on the different values the dummy variable can take. The interesting part with these variables is that adding a dummy variable creates different intercepts for the model based on the different values it can take. This dissimilarity in the intercept is what explains the difference between the groups.

3.4.2 Hypothesis testing

Hypothesis testing is a way of connecting the sample to the real world. Hypothesis testing makes it possible to draw conclusions about the theory being discussed. Although it is nearly impossible to say whether a specific hypothesis is correct or not with a 100 percent certainty, it is possible to reject or keep certain hypotheses concerning a model at a given significance level (Studenmund, 2013, p.128). This generates a better understanding of how well the model describes the real world. Rejecting a hypothesis at a given significance level means that it is seemingly unexpected for this hypothesis to be true (Studenmund, 2013, p.128).

Firstly, a hypothesis has to be formulated before estimating the model. This hypothesis can then be separated into the null hypothesis and the alternative hypothesis. The null hypothesis, defined as H_0 includes what is aimed to be tested, and usually represents the result that is not expected (Studenmund, 2013, p.128). On the contrary, the alternative hypothesis, defined as H_A, includes the result that is expected to occur (Studenmund, 2013, p.129). For instance, if the variable x_1 is expected to be significant in the model then the null hypothesis can be formulated as:

$$H_0 : \beta_1 = 0, \tag{6}$$

and the alternative hypothesis as:

$$H_A : \beta_1 \neq 0, \tag{7}$$

where β_1 is the coefficient in front of x_1. This represents a two-sided test where the β can be assigned both positive and negative values. One-sided tests can also be performed in a similar way and can for example be formulated as:

$$\begin{aligned} H_0 &: \beta_1 \leq 0, \\ H_A &: \beta_1 > 0, \end{aligned} \tag{8}$$

if the β is expected to have a positive sign. Important to know is that accepting a null hypothesis can not be done, it is just not rejected (Studenmund, 2013, p.129). Since hypotheses can only be rejected or not rejected at certain significance levels, there is still a risk of drawing wrong conclusions. There are two types of errors when it comes to hypothesis testing (Studenmund, 2013, p. 130). The first error, the Type I error, is made when a true null hypothesis is rejected. The second error, the Type II error, is made when a false null hypothesis is not rejected. See Figure 1 for clarification. The probability of making a Type I error is equal to the level of significance of the test, often referred to as α (Wooldridge, 2012, p.779). The power of a test is the probability of correctly rejecting the null hypothesis and is the same as the probability of not making a Type II error.

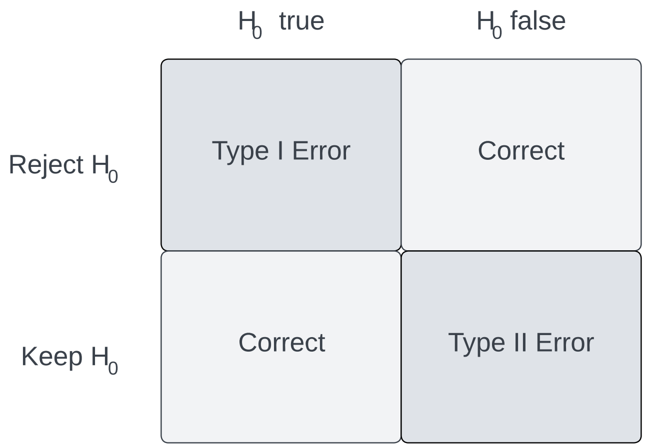


Figure 1: The four possibilities in hypothesis testing.

When the model is assesed it is important to analyse the significance of each variable. Two common tests for this is the t-test and the F-test (Studenmund, 2013, p.134). The t-test is used to test the significance of each variable separately, and the F-test for several variables simultaneously. For the t-test the t-statistic gets calculated in order to draw conclusions about the significance. The t-statistic for coefficient β_i is calculated as:

$$t_i = \frac{\hat{\beta}_i - \beta_{H_0}}{SE(\hat{\beta_i})}, \tag{9}$$

where β_{H_0} is the value the coefficient is assigned in the null hypothesis and SE represents the standard error (Studenmund, 2013, p.135). If the null hypothesis includes a sign other than an equality, then β_{H_0} gets assigned the value closest to the limit (Studenmund, 2013, p.135). The value of β_{H_0} in this study according to the null hypothesis above is therefore zero. The calculated t-statistic is then compared to a critical t-value which is based on degrees of freedom, level of significance and whether the test is one- or two-sided (Studenmund, 2013, p.136). The degrees of freedom is defined as the difference between the number of observations and the number of estimated coefficients. On a given level of significance the null hypothesis is rejected if the critical value is smaller than the t-statistic, in absolute terms.

An alternative to the t-test is to use the p-value often calculated by the regression program itself. The value lies between zero and one. If the p-value is lower than the level of significance then the null hypothesis can be rejected, given that the sign of the estimated $\hat{\beta}_i$ matches the alternative hypothesis (Studenmund, 2013, p.141). If the level of significance for example is five percent and the p-value turns out to be 0.01, then the null hypothesis can be rejected at the given significance level.

Important to know is the difference between one-sided and two-sided hypothesis tests. Two-sided tests occur when the null hypothesis only contains an equality sign. The null hypothesis can then be rejected when the estimated value is significantly different from the value in the null hypothesis, regardless of the sign (Studenmund, 2013, p.148). A one sided-test occurs when a coefficient is expected to be significantly different from a specific value, in a certain direction. The p-values calculated in regression programs are usually based on a two-sided test, and if the test is one-sided as in this study this has to be corrected for by dividing it in half (Studenmund, 2013, p.142).

3.5 Ordinary Least Squares

Ordinary least squares(OLS) is a well known method within regression (Studenmund, 2013, p.37). It is used to estimate the coefficients in the regression model. Since the parameters are unknown from the beginning, estimating these coefficients is rarely perfect and usually generates errors between the estimated parameters and the real, observed values. The residual is defined as the difference between the estimated and the observed value of y, and the error term is defined as the difference between the expected value and the observed value of y (Studenmund, 2013, p.16). See (10) and (11) below and Figure 2 for a demonstration of a residual where res_i is the same as $\hat{\epsilon_i}$.

$$\hat{\epsilon_i} = Y_i - \hat{Y_i} \tag{10}$$

$$\epsilon_i = Y_i - E(Y_i|X_i) \tag{11}$$

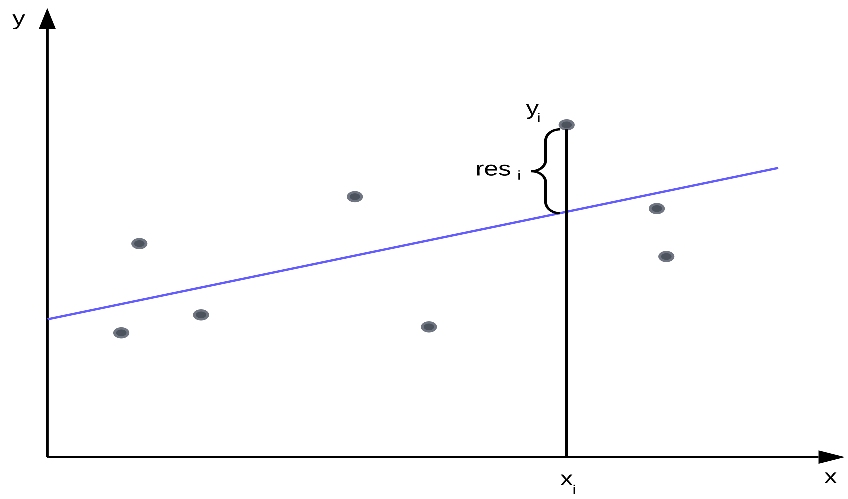


Figure 2: Demonstration of a residual in regression analysis by including some data points and a fitted line.

The residual can be seen as the estimated error term. One intention with the regression is to make these errors as small as possible, and there are hence different techniques to minimize the errors. The OLS technique behind the minimization has already been described in this chapter regarding multiple linear regression, where the sum of the squared residuals are minimized. The reason behind squaring all the residuals is that some are negative and some positive. Not squaring the residuals could therefore make the plus signs and minus signs cancel out and make the model look superior than to what really is the case. One way to measure the goodness of the fit of the estimated regression line is to calculate the value of R^2. R^2 is defined as

$$R^2 = 1 - \frac{RSS}{TSS}, \tag{12}$$

where RSS is the sum of the squared residuals and TSS represents the total sum of squares as a sum of RSS and sum of the squared errors (ESS) (Wooldridge, 2012, p.38). The value of R^2 is always between 0 and 1 where 1 represents a perfect fit and all the data points will then lie on the estimated line. A problem with R^2 is that the value can only increase and not decrease by adding more variables to the regression model (Wooldridge, 2012, p.80). A measure that compensates for this problem is the adjusted R^2 and can be defined as

$$adjR^2 = 1 - \frac{\frac{RSS}{n-k-1}}{\frac{TSS}{n-1}}, \tag{13}$$

where n is the number of observations and k is the number of independent variables (Wooldridge, 2012, p.202). Noticeable is that the fraction now gets a larger value when adding another variable than the fraction for the R^2 because RSS gets divided by a smaller value. This consequently makes the overall adjusted R^2 value smaller than R^2 when adding more variables to the model.

Furthermore, an estimator is said to be unbiased if the expected value of the estimated parameter is equal to the true value. Unbiasedness is important in regression analysis for the results to be correct, since the estimators then are closer to the true value. (Wooldridge, 2012, p.107) Another important term is consistency referring to that as the sample size increases the estimates approach the true values (Studenmund, 2013, p.111). Lastly, if an estimate is unbiased having the minimum possible variance the estimate is efficient (Studenmund, 2013, p.111). If the estimates are unbiased, consistent and efficient then no other possible linear estimator can perform better than OLS (Studenmund, 2013, p.111).

3.6 The Assumptions for OLS

For the OLS estimation to be comparatively better than any other estimator, the conditions presented in Table 2 need to be fulfilled (Studenmund, 2013, p.98):

Table 2: The seven assumptions for Ordinary Least Squares to work correctly and be comparatively better than any other estimator.

The Assumptions for Ordinary Least Squares
1. "The model is linear, correctly specified and has an additive error term"
2. "The error term has a zero population mean"
3. "All explanatory variables are uncorrelated with the error term"
4. "Observations of the error term are uncorrelated with each other"
5. "The error term has a constant variance"
6. "No explanatory variable is a perfect linear function of any other explanatory variable(s)"
7. "The error term is normally distributed"

3.6.1 Assumption 1

Linearity is a key pillar to be able to estimate the regression model with OLS. For the estimation to work the model in this case needs to be linear in parameters, and not necessarily linear in variables (Studenmund, 2013, p.98). A linear model denotes a linear relationship between the independent variable and the dependent variable. If a non-linear variable needs to be included in a linear model this variable can be transformed to fit the requirement. If an independent variable for example is of logarithmic form, it can be reassigned as $x_i^* = log(x_i)$ and then included in the model as usual (Studenmund, 2013, p.99). Linearity can be tested by creating scatter plots between the independent variables separately and the dependent variable. These scatter plots show the relationship between the dependent variable and each independent variable. It is then possible to see if the relationship looks linear or not, and if not then hopefully a variable transformation could be a solution.

That a model is correctly specified can be indicated by several different factors (Studenmund, 2013, p.99). Firstly a correctly specified model needs to be of correct functional form which in this case is linear. If the relationship between the independent variables and the dependent variable show signs of being non-linear, then perhaps variables of other functional forms should be added to the model and the estimation using OLS then no longer works, unless these variables gets transformed to fit the regression model. Secondly, a correctly specified model means that there are no redundant nor omitted variables. A redundant variable is a variable that is included in the model explaining the same thing as another variable included (Studenmund, 2013, p.276). An omitted variable is a variable that is not included, but in fact should be for the model to be correctly specified (Studenmund, 2013, p.178). Having a redundant variable in the regression model does not make the estimated coefficients biased, but it increases their variances (Studenmund, 2013, p.186). This causes problems for the hypothesis testing by decreasing the t-values. Additionally the value of the adjusted R^2 can decrease as well. An omitted variable can on the other hand cause bias among the estimated coefficients, but at the same time decrease the variances (Studenmund, 2013, p.181). Bias caused by omitted variables is often referred to as specification bias since the model is misspecified (Studenmund, 2013, p.178). A substantial problem with omitted variables in a regression model is that it is hard to observe (Studenmund, 2013, p.183). A careful consideration of what variables to include before creating the regression model is therefore necessary.

3.6.2 Assumption 2

The error term can be seen as a random variable. Drawing an observation from the error term can therefore be seen as drawing an observation from a random sample. The distribution of the error term is hence assumed to have the expected value of zero. However, this might not always be the case for the regression model. A smaller sample size could for example generate an expected value for the error term further away from zero and will proceed towards to zero as the sample size increases. One way to compensate for a mean value different from zero is by subtracting the error term with its mean and add it to the constant instead. This changes the intercept of the model but makes the specific condition fulfilled. (Studenmund, 2013, p.100)

3.6.3 Assumption 3

If there would be correlation between an independent variable and the error term then some of the variability in the dependent variable that should only be explained by the error term, might get explained by some independent variable instead. For example, a consequence of positive correlation between an explanatory variable and the error term could be that the value of the estimated coefficient in front of the explanatory variable gets inappropriately high. Violations of this assumption is most commonly caused by omitted variables. The error term explains variations that can not be explained by the other explanatory variables in the model, for example from variables that is not included. If there exists a correlation between a variable that is not included and an explanatory variable, then there will in turn exist a correlation between the error term and this explanatory variable too. The assumption is then violated. (Studenmund, 2013, p.101).

3.6.4 Assumption 4

This is often referred to as zero auto-correlation and means that all the observations belonging to the error term are independent of one another (Studenmund, 2013, p.101):

$$Corr(\epsilon_i, \epsilon_j) = 0, i \neq j \tag{14}$$

Independency refers to that the next outcome is not based on previous observations. However, autocorrelation does not usually entail bias in the estimated coefficients, but the variances will be larger and the estimated standard errors will be biased (Studenmund, 2013, p.331). Consequently, hypothesis testing is no longer reliable. Autocorrelation can be separated into pure and impure autocorrelation. Pure autocorrelation refers to autocorrelation in an otherwise correctly defined model (Studenmund, 2013, p.323). Then the distribution of the error term is the reason for the autocorrelation (Studenmund, 2013, p.325). Impure autocorrelation refers to autocorrelation caused by the model being incorrectly defined. An incorrectly defined model can for instance be caused by omitted variables which in turn cause bias in the estimated coefficients. Hence, impure autocorrelation can cause bias in the estimated coefficients, but not pure autocorrelation (Studenmund, 2013, p.331). There are several tests for auto-correlation and one example will be described below.

The following regression model is at disposal:

$$y_t = \beta_1 + \beta_2 x_{2,t} + \beta_3 x_{3,t} + ... + \beta_k x_{k,t} + \epsilon_t, \tag{15}$$

where all the x's are assumed to be exogenous and the process to be stationary. Assume the error term is behaving as an AR(k) process, that is:

$$\epsilon_t = \theta + \phi_1 \epsilon_{t-1} + ... + \phi_n \epsilon_{t-k} + \gamma_t, \tag{16}$$

where γ_t is a white noise process. If all the ϕ's are equal to zero, then there is no auto-correlation in the model. However, since ϵ_t is unknown the residuals will be used instead. The regression model presented in (15) is then estimated, and an auxiliary regression model for the residuals is thereafter estimated:

$$e_t = \phi_1 e_{t-1} + ... + \phi_n e_{t-k} + \alpha_1 + \alpha_2 x_{2,t} + \alpha_3 x_{3,t} + ... + \alpha_k x_{k,t} + \gamma_t, \quad (17)$$

where e_t are the residuals from (15). It can then be shown that under the null hypothesis which says that there is no auto-correlation in the model, then the R^2 of the model is chi-squared distributed according to:

$$(n-k)R^2 \sim \chi_k^2 \quad (18)$$

(Uyanto, S.S., 2020).

3.6.5 Assumption 5

For this assumption to hold then the observations drawn from the error term need to have the same distribution (Studenmund, 2013, p.101). Another word for the error term to have constant and stable variance is homoskedasticity, and if the variance is not constant it is called heteroskedasticity. Heteroskedasticity causes inefficiency by making the variance of the estimated coefficients unnecessarily large (Dougherty, 2011, Heteroscedasticity, p.3). Another problem with heteroskedasticity is that the calculated standard errors for the coefficients are based on homoskedasticity, and if this is no longer the case then the standard errors will be incorrect (Dougherty, 2011, Heteroskedasticity, p.3). As a consequence the hypothesis testing becomes harder to perform since it is no longer possible to perform the t test nor the F test. For example, the t test that was presented before is divided by the standard error. If the standard error is incorrectly large as a result of heteroskedasticity the t statistic gets incorrectly small causing misleading information about the significance of the estimated parameters (Dougherty, 2011, Heteroskedasticity, p.3). However, important to have in mind is that heteroskedasticity itself does not cause bias for the estimators, and so the coefficients can still be correctly estimated but with incorrect standard errors and variances (Dougherty, 2011, Heteroskedasticity, p.3). Instead it causes inefficiency since there now could be other unbiased estimators with smaller variances. Heteroscedasticity is shown in Figure 3 below.

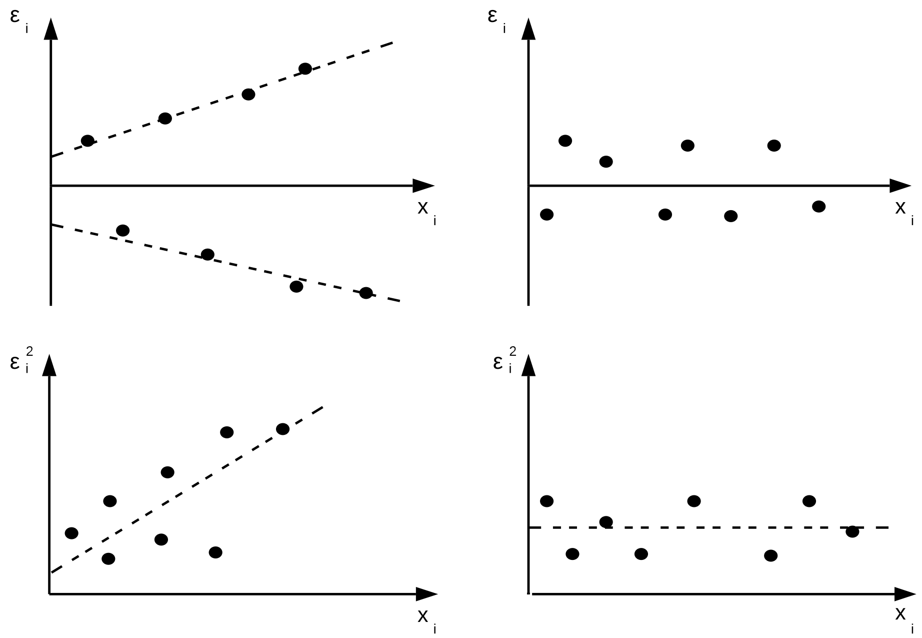


Figure 3: Demonstration of heteroscedasticity to the left and homoscedasticity to the right.

One way to handle heteroskedasticity is to use robust standard errors which for example is a built in function in some regression programs. The standard calculation behind the variance for all the estimated βs is:

$$Var(\hat{\beta}) = (X^T X)^{-1} X^T \Omega X (X^T X)^{-1}, \tag{19}$$

where Ω is a diagonal matrix storing σ^2 which is the variance of the error term (Ford, C., 2020). The principle behind estimating the robust standard errors is to replace the middle term $X^T \Omega X$ with another formula to account for possible variations in the variance of the error term. This formula can be of different kind depending on which method is being used (Ford, C., 2020). In R there is a method known as "HC0" which corresponds to the White's estimator. This simply replaces the diagonal elements in Ω with the estimated residuals instead, since it is assumed in (19) that the variance of the error terms is constant, which might not be the case.

3.6.6 Assumption 6

Perfect collinearity is when an independent variable is an exact linear combination of another variable. Perfect multicollinearity is when an independent variable is an exact linear combination of at least two other independent variables. (Studenmund, 2013, p.103) This means that these variables follow the same pattern and the only thing separating them from one another is possibly the size. If perfect multicollinearity exists then the OLS estimation fails. OLS will not be able to estimate the coeffiecients for the variables being perfectly correlated (Studenmund, 2013, p.103). The reason behind this is that when estimating one independent variable you keep all the other independent variables unchanged. If the variable being estimated is perfectly correlated with another one, then this other variable will change as the variable being estimated changes (Studenmund, 2013, p.263). The solution to perfect multicollinearity is to remove one of the perfectly correlated variables from the model.

Imperfect multicollinearity occurs when at least two independent variables are highly correlated, but not perfectly. Imperfect multicollinearity still keeps the estimated coefficients unbiased, but with incorrectly large standard errors and thus variances as well (Studenmund, 2013, p.266). This again makes the statistics misleading and it could be easier to perform a type II error if the t value for instance is inappropriately small. Furthermore, the value of R^2 tends to be suspiciously high even though there could be many coefficients showing no significant impact in the regression model (Studenmund, 2013, p.266). Multicollinearity could therefore be checked for by either running a correlation matrix between the variables or by looking at the value of R^2 and compare it to the significance of the variables.

A good start to detect possible multicollinearity is by running a correlation matrix between all the explanatory variables. This visualizes how each variable correlates with each other variable, separately. However, if the model includes more than two explanatory variables, high multicollinearity can also occur if several variables together explains another variable (Studenmund, 2013, p.272). This means that if the model is of a multiple linear form, it would be preferable to test for multicollinearity even further than just through a correlation matrix. This is often done by looking at the variance inflation factors (VIFs) through a VIF-test. When performing a VIF-test, a regression model having each explanatory variable as dependent variable and the rest kept as explanatory is created separately (Studenmund, 2013, p.273). This makes it possible to see to which extent one variable is explained by the other variables. If the following model is about to be tested:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \epsilon, \tag{20}$$

then a new regression model is created for each explanatory variable, for x_1 this is

$$x_1 = \gamma_1 + \gamma_2 x_2 + ... + \gamma_n x_n + v \tag{21}$$

By then looking at the R^2 for the model the level of multicollinearity regarding this specific variable is easily seen. The VIF-value for this specific variable, VIF_i, is calculated as:

$$VIF_i = \frac{1}{1 - R_i^2}, \tag{22}$$

where a high R_i^2 yields a high VIF-value. The calculated value for each variable should be below five to avoid problems with multicollinearity, but a value below ten is usually enough too (Studenmund, 2013, p. 274, Wooldridge, 2012, p.98).

3.6.7 Assumption 7

This assumption is connected to assumption two regarding the distribution of the error term. This assumption is not a required condition for the OLS estimation to work, but faciliates the hypothesis testing (Studenmund, 2013, p.105). The reason for this is that the t- and F-statistics can only be truly accepted if the error term follows a normal distribution. However, since this assumption does not have the same influence on the regression analysis as the other ones, less focus will be put on it.

3.6.8 Summary Of The Assumptions

The assumptions stated above belong to different levels of importance for the regression analysis to work correctly. Some are necessary for the coefficients to be correctly estimated, some are necessary for the hypothesis testing to work correctly and some can improve the result, but are not necessarily important. For the estimations to work correctly a linear relationship between the independent and the dependent variables is required. Furthermore, the model needs to be specified in a correct way, and there should be no perfect multicollinearity in the model. Additionally, to be able to perform tests on the estimated coefficients the variances and standard errors needs to be correctly specified as well. Then zero autocorrelation together with homoscedasticity and either low or zero multicollinearity is necessary.

3.6.9 Panel Data Regression

Time series regression is regression based on one single unit over several time periods (Studenmund, 2013, p.15). This could for example be looking at the financial performance for a company based on some independent variables over a few different years. On the other hand, cross-sectional regression is regression based on several different units over one period in time (Studenmund, 2013, p.21). This could for example be looking at the financial performance based on some independent variables for several different companies within different sectors over the same year. Combining time series regression and cross-sectional regression is called panel data regression which is what will be used throughout this study (Studenmund, 2013, p.364).

Estimating a panel data model through OLS is called Pooled OLS where the model can be defined as:

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t,1} + ... + \beta_k x_{i,t,k} + \epsilon_{i,t}, \tag{23}$$

where i represents the units the regression is based on and t represents time. In this case i represents each firm and t represents each year. If exogeneity holds then the estimations are unbiased and consistent, and if homoscedasticity holds together with zero autocorrelation then the estimations are efficient as well.

3.7 Portfolio Theory

The principle behind modern portfolio theory (MPT) is to construct a portfolio of assets having the highest possible expected return and the lowest possible risk (Elton & Gruber, 1997). Markowitz, an economist from America, is usually seen as the father of MPT and introduced the concept in the 1950s (Elton & Gruber, 1997). A fundamental fragment in this concept is that the covariance between assets affects the overall variance of the portfolio. In other words, constructing a portfolio only focusing on the assets' individual variances is not beneficial since they might still have high correlation. This in turn increases the variance and risk of the portfolio.

The resulting variance of a portfolio is built on the individual variances together with how these assets correlate with each other (Elton & Gruber, 1997). A portfolio with maximized expected return at a given level of risk belongs to the efficient frontier. The efficient frontier includes portfolios with the highest possible expected return for different levels of risks, where an investor can choose the most suitable portfolio based on its level of risk-aversion.

Constructing a portfolio with assets having low correlation between each other is called diversifying and reduces the unsystematic risk of the portfolio (Elton & Gruber, 1997). Diversification can be based on several different factors such as industry, region or country. The unsystematic risk is firm specific and therefore possible to reduce through diversification. Systematic risk on the other hand is market based and can therefore not be reduced in the same manner.

The efficient market hypothesis (EMH) is an important keystone behind the portfolio theory. It states that the prices move in the pattern of a random walk, which means that all available information affects the prices instantly, and the price movement tomorrow will hence not be influenced by the news or information today, but only by the events tomorrow (Malkiel, B. G., 2003). It is therefore impossible to predict the movement in the future since it is independent of the past, and the movement is said to be random. Furthermore, all available information is reflected in the price, which means that there is no possibility for arbitrage.

3.8 Sharpe Ratio

The performance of a portfolio can be measured in different ways, and a standard way is to divide the excess return of the portfolio with the standard deviation of the portfolio. This is called the Sharpe Ratio and can be written as:

$$SR_{p,t} = \frac{R_{p,t} - R_{f,t}}{\sigma_{p,t}}, \tag{24}$$

where $SR_{p,t}$ is the Sharpe Ratio for portfolio p over the time period t, $R_{p,t}$

is the average return for portfolio p over the time t, $R_{f,t}$ is the risk free rate over the time t and $\sigma_{p,t}$ represents the standard deviation for portfolio p over the time t (Jobson & Korkie, 1981). Looking at (24) Sharpe Ratio can be interpreted as a measure for risk-adjusted return, as the excess return is divided by the standard deviation. The Sharpe Ratio is hence not only used to compare returns between different investments, but includes risk as well to generate a more fair comparison, since the average investor is risk-averse.

To be able to calculate the daily Sharpe Ratio for a portfolio having access to daily share prices, firstly the daily returns for each asset have to be calculated. The mean daily return is then calculated for each asset and then multiplied by the weight. The weight for an asset represents the fraction of the portfolio that is being represented by the asset. The sum of all of these mean returns multiplied by the weights represents the average daily portfolio return. This return is then subtracted by the daily risk free rate to get the average daily portfolio excess return.

To calculate the standard deviation for the portfolio the covariance matrix between the asset returns is firstly calculated. The standard deviation is then given by the following matrix multiplication:

$$\sigma_{p,t} = \sqrt{\mathbf{w}^T C \mathbf{w}}, \tag{25}$$

where w is the weight vector, and C represents the covariance matrix between the asset returns. The Sharpe Ratio of a portfolio is often compared to a benchmark, which in Sweden for example can be given by the market index OMXS30. To be able to make an equitable comparison, a statistical test can be performed to see whether the two portfolios are significantly different from each other or not.

The hypotheses are formulated as the following:

$$\begin{aligned} H_0 &: SR_1 = SR_2, \\ H_A &: SR_1 \neq SR_2 \end{aligned} \tag{26}$$

which is then reformulated as:

$$SR_{1,2} = ER_1\sigma_2 - ER_2\sigma_1, \tag{27}$$

where ER_1 is the excess return for portfolio 1, and σ_1 is the standard deviation for portfolio 1. This can not be formulated as a t-test but a Z-test being asymptotically normally distributed (Jobson & Korkie, 1981). The Z-value for $S\hat{R}_{1,2}$ is calculated as:

$$Z(SR_{1,2}) = \frac{S\hat{R}_{1,2}}{\sqrt{\theta}} \sim N(0,1), \tag{28}$$

where θ is calculated as:

$$\theta = \frac{1}{T}(2\sigma_1^2\sigma_2^2 - 2\sigma_1\sigma_2\sigma_{1,2} + 0,5ER_1^2\sigma_2^2 + \\ 0,5ER_2^2\sigma_1^2 - \frac{ER_1ER_2}{2\sigma_1\sigma_2}(\sigma_{1,2}^2 + \sigma_1^2\sigma_2^2)), \tag{29}$$

where T is the number of time periods, $\sigma_{1,2}$ is the covariance between the two portfolios (Jobson & Korkie, 1981).

One criticism with modern portfolio theory as well as the Sharpe-Ratio is that it is based on normally distributed returns, which does not always have to be the case (Malkiel, B. G., 2003). It is therefore important to have this in mind throughout the analysis.

3.9 Risk Free Rate

The risk free rate is the return obtained by investing in a risk free asset, and the risk for the investment is hence zero. However, in reality there is no such thing as a completely risk free asset, but the risk is minimal and very close to zero. A risk free asset could for example be a treasury bill, or a government bond.

To convert the rate between two different units in time the calculation is:

$$r_2 = (1 + r_1)^{1/t} - 1, \tag{30}$$

where t represents the sum of the time units in r_2 that adds up to represent the time unit in r_1.

For example, transforming a monthly rate to a daily rate is done through:

$$r_d = (1 + r_m)^{1/30} - 1, \tag{31}$$

where one month is usually represented by 30 days.

4. Methodology

4.1 Sample Selection

There are plenty of studies within this area, examining both the relationship between ESG and financial performance and the relationship between sustainability and investing. However, the supply of such analyses regarding the Swedish market is still limited. It therefore seemed both reasonable and interesting to focus on the Swedish market in this study. The sample selection used was therefore companies acting on the Swedish market. The time span for the regression analysis was selected as a result of how far back in time Swedish companies were ESG-rated in the data base and source that was used to collect the data. Since the portfolios were based on the collected ESG-ratings, they were tested after the time span of the regression analysis to be able to include the latest ESG-ratings.

4.2 Hypotheses

The majority of previous similar studies have shown a positive relationship between the sustainability variable/-s and financial performance. This can for example be seen in the previous Literature Review. Based on these results the two hypotheses regarding the regression analysis for this study will be:

(I) ESG has a significant positive impact on ROA for a firm on the Swedish listed market.
(II) ESG has a significant positive impact on ROE for a firm on the Swedish listed market.

Assigning ESG-rating the variable x_1 gives the following null and alternative hypotheses regarding both ROA and ROE:

$$\begin{aligned} H_0 &: \beta_1 \leq 0, \\ H_A &: \beta_1 > 0 \end{aligned} \tag{32}$$

For the portfolio construction, previous research has shown that both risk and return can be improved by investing in more sustainable companies (Kaiser, L., 2020, Ashwin Kumar et al., 2016). Using the available companies the hypothesis regarding the portfolio construction will therefore be:

(III) Constructing a portfolio with the highest ESG-rated companies sector wise, one from each sector, will perform better than the market index.

The null and alternative hypotheses are formulated as:

$$\begin{aligned} H_0 &: SR_{Constructed} \leq SR_{OMXS30}, \\ H_A &: SR_{Constructed} > SR_{OMXS30}, \end{aligned} \tag{33}$$

where these are daily Sharpe Ratios during 2022.

4.3 Variables for the Regression Analysis

4.3.1 Dependent Variables

One main goal with a regression model is to try to explain the outcome and movement of the dependent variable using the independent variables together with the control variables. In this study the relationship between financial performance and sustainability is examined having financial performance as the dependent variable. The variables ROA and ROE have been chosen to represent financial performance in this study, and the focus will therefore be towards accounting-based financial performance and not market-based financial performance. ROA and ROE are frequently used instruments to represent financial performance for a company. For example looking at the articles presented in the Literature Review. These variables were collected from Bloomberg and thus not calculated manually. In the Bloomberg database, ROA and ROE are calculated as:

ROA for Financials, Banks, Industrials, Utilities and Reits:

$$ROA = \frac{Trailing\ 12M\ Net\ Income}{Average\ Total\ Assets} * 100 \tag{34}$$

ROA for Insurance companies:

$$ROA = \frac{Trailing\ 12M\ Net\ Income + Trailing\ 12M\ Policyholders'\ surplus}{Average\ Total\ Assets} * 100 \tag{35}$$

$$ROE = \frac{Net\ Income\ available\ for\ common\ shareholders}{Average\ Total\ Common\ Equity} * 100 \tag{36}$$

These variables were then divided by 100 since the calculations above are in percentage. The average values are calculated by taking the average of the first and last value during the specific year.

4.3.2 Independent Variables

Since ESG rating is the variable representing sustainability in this study this is the only independent variable that will be used. The ESG rating is collected from Bloomberg. An example of the indicators used in Bloomberg's rating system in 2010 is presented in Figure 4 below.

Panel A: Environmental Performance				
Direct CO2 Emissions	Indirect CO2 Emissions	Total CO2 Emissions	CO2 Intensity	Total GHG Emissions
Travel Emissions	Nitrogen Oxide Emissions	Sulfur Dioxide Emissions	VOC Emissions	Carbon Monoxide Emissions
Methane Emission	Total Energy Consumptions	Renewable Energy Use	Water Consumption	%water Recycled
Discharges to Water	Hazardous Waste	Total Waste	Waste Recycled	Paper Consumption
Paper Recycled	Fuel Used	ODS Eissions	Particulate Emissions	Raw Materials Used
Number of Spills	Nuclear % of Total Energy	Solar % of Total Energy	Phones Recycled	Number of Environmental Fines
ISO 14001 Certified Sites	Energy Efficiency Policy	Emissions Reduction Initiatives	Environmental Supply Chain Management	Green Building Policy
Waste Reduction Policy	Sustainable Packaging	Environmental Quality Management	Waste Per unit of Production	Amount of Spills
Environmental Awards Received	CO2 Intensity per Sales	New Products – Climate Changes	Sulphur Oxide Emissions	Electricity Used
Waste Water	Gas Flaring	%recycled Materials	GHG Scope 1	GHG Scope 2
GHG Scope 3				
Panel B: Social Performance				
Number of Employees CSR	Employee Turnover %	% Employees Unionized	% Women in Management	% Women in Workforce
% Minorities in Management	% Minorities in Workforce	Workforce Accidents	Lost Time from Accidents	Fatalities – Contractors
Fatalities – Employees	Fatalities – Total	Community Spending	Investments in Sustainability	Health and Safety Policy
Equal Opportunity	Human Rights Policy	Number of Awards Received	Political Donations	Training Policy
Business Ethics Policy	Number of Sites			
Panel C: CSR governance				
Size of Board	Number of Independent Directors	Board Duration (Years)	Number of Board Meetings	Board Meeting Attendance %
Fair Remuneration Policy	Climate Change Policy	GRI Criteria Compliance	Verification Type	Percent Disclosure
% Sites Certified	Environmental Accounting Cost	SRI Assets Under Management	Biodiversity Policy	UN Global Compact Signatory
Employee Average Age	% Disabled in Workforce	Lost Time Incident Rate	Employee CSR Training Cost	Board Average Age
Board Age Limit	CEO Duality	Assurance Auditor	Audit Committee Meetings	

Figure 4: The environmental, social and governance indicators from Bloomberg's system in 2010 that was included when calculating each pillar in ESG. Source: Wang & Sarkis, 2017.

4.3.3 Control Variables

The decision behind which control variables to include in the regression model was based on previous research. However, exactly which combination of control variables to use have been differing a lot among previous studies and it was therefore hard to decide specifically which to include in this study. After reviewing similar past analyses the decision was made to mainly follow Wang & Sarkis (2017) in terms of control variables as much as possible and add one extra variable that was used in other studies too. Firstly, since the amount of different combinations of variables to include is large picking one article to act as a baseline seemed like a reasonable choice. Furthermore, Wang & Sarkis (2017) also collected the ESG rating from Bloomberg and used ROA as a dependent variable, which is in line with this thesis as well. In addition, Wang & Sarkis (2017) in turn based the choice of variables on similar previous studies. The variables included in the regression model are presented below.

Leverage (LEV). Wang & Sarkis (2017) and a lot of other studies have included a control variable to represent the unsystematic risk, which is approximately calculated as debt divided by assets. Wang & Sarkis (2017) included a variable calculated as total debt to total assets. This is often referred to as a companies leverage. Leverage can be expressed as the proportion of a companies assets that is financed by debt. The reason behind including this variable is that a company's financial risk can increase with a higher leverage which in turn can decrease the financial performance for the company (Wang & Sarkis, 2017). Leverage can be calculated in some different ways, and since the program used in Bloomberg did not have total debt available, leverage was here instead calculated as:

$$LEV = \frac{Long\ term\ debt}{Total\ Assets}, \tag{37}$$

which is just another way of representing the variable leverage (Hall, T. W., 2012).

Liquidity (LIQ). The next control variable is liquidity. This variable is reasonable to include in the regression model since a higher liquidity can decrease the risk of the company which in turn can increase the financial performance (Wang & Sarkis, 2017). Liquidity is here calculated as:

$$LIQ = \frac{Current\ Total\ Assets}{Current\ Total\ Liabilities}, \tag{38}$$

which is a very common way of representing this variable and can for example be seen in Salama et al., (2011).

SIZE. All of the studies analysed have included size as a control variable in some way. The investors' interest in CSR related activities of a company can depend on the size of the firm (Velte, P., 2017). A larger company usually has the possibility to advance in a way that is hard for smaller companies to copy (Velte, P., 2017), which in turn can increase financial performance. Yet, the size of a firm have had a mixed relation to financial performance in previous studies, but have nevertheless seemed to be significant in many cases. Size is often presented in terms of total assets. However, since some of these values are very high and the variation is large, it is more preferable to use the natural logarithm of total assets instead. Size will be included in the model and will be represented as:

$$SIZE = Ln(Total\ Assets) \tag{39}$$

GROWTH. Some studies also include a company's growth in the model. Growth can be calculated in different ways, for example growth in terms of revenue/sales or growth in terms of assets. Wang & Sarkis (2017) did include growth and calculated growth based on the difference in sales between two years. A reason behind including growth as a variable is that a higher growth usually leads to the possibility of making larger investments which in turn can increase the financial performance (Wang & Sarkis, 2017). When gathering data from Bloomberg only revenue was available. The decision was therefore made to both calculate growth based on revenue and growth based on total assets to compare with each other and with previous studies to include the most reasonable growth variable. The two growth variables were here calculated as:

$$GROWTH_{Rev,i} = \frac{Revenue_i - Revenue_{i-1}}{Revenue_{i-1}}, \tag{40}$$

$$GROWTH_{A,i} = \frac{TotalAssets_i - TotalAssets_{i-1}}{TotalAssets_{i-1}}, \tag{41}$$

where i represents the year.

Research and development (RND). The last control variable to be used in this study, apart from the dummy variables, is one representing research and development expenditure. This can be represented in different ways, sometimes as it is (Velte, P., 2017) and sometimes as a fraction, and can for example be divided by total assets(Hussain et al., 2018) or sales (Fatemi et al., 2018). In Bloomberg Equity Screening there was a calculation for research and development expenditure represented as a fraction. This variable was therefore used and was calculated as:

$$RND = \frac{RND\ expenditure}{Net\ Sales} * 100, \tag{42}$$

where net sales here was represented by revenue. This value was thereafter divided by 100 to account for the percentage. One problem with this variable is that there were a lot of missing values, which was encountered in other studies as well (Fatemi et al., 2018). A solution was to assign these missing values a 0 and then create a dummy variable (R.Dd) taking the value 1 if the value was missing and 0 otherwise to still be able to capture the influence on financial performance by the observations that were not missing (Fatemi et al., 2018). The dummy variable then captures possible differences between those companies that acutally spent 0 money on RND and those who were just missing values.

YEAR. A dummy variable for year was created. Including year as a dummy variable could reduce the risk of serial correlation in the model (Wooldridge, 2009, p.354). Furthermore, a dummy variable for year could reduce problems with omitted variables (Studenmund, 2017, p.477). This together with the variable being included in several other studies as well made it a reasonable variable to include here too.

SECTOR. A dummy variable for sector was created to capture differences between the sectors included in the regression analysis. The sectors are defined according to GICS's system and are presented Table 3 below (MSCI, 2023).

Table 3: GICS's Sector Classification.

Index	**Sector**
10	Energy
15	Materials
20	Industrials
25	Consumer Discretionary
30	Consumer Staples
35	Health Care
40	Financials
45	Information Technology
50	Communication Services
55	Utilities
60	Real Estate

4.4 Choice of Companies for the Portfolio Construction and Portfolio Structure

Two different portfolios was constructed and tested against the market index OMXS30. The choice of companies to include in the portfolios were very straight forward. In the first portfolio the company with the highest ESG-rating in each sector based on the last year (2021) was included which resulted in a portfolio with 10 companies. This portfolio was assigned the name ESG-2021. In the second portfolio the companies with the highest average ESG-rating between 2014-2021 in each sector were included, which also ended up with 10 companies in total. This portfolio was assigned the name ESG-Average. All of the available sectors were used to generate as much diversification as possible. Since sector 10 included 0 companies in this study this sector was skipped.

The reason behind choosing one company from each sector instead of just choosing the 10 companies with the highest ESG-rating overall was to utilize the diversification effect as much as possible. However, this is something to consider when analysing the results, since the portfolios do not include the companies with the highest ESG-rating overall. Furthermore, the portfolio was decided to be equal-weighted. Firstly, this gives all of the stocks an equal impact on the performance. Secondly, equal-weighted portfolios have shown to outperform value-weighted portfolios in the past (Malladi & Fabozzi, 2017). In addition, two different portfolios where created to compare and capture possible differences in performance depending on how the ESG-rating is included to construct the portfolios. The time span to calculate the average ESG-ratings for the ESG-Average portfolio is the same time span that was analysed in the regression analysis.

5. Data

5.1 Data Collection and Processing

5.1.1 Data Collection and Processing regarding the Regression Analysis

Two well known data bases calculating and storing data for different firms all over the world are Thompson Reuters and Bloomberg. These two data bases also rate firms in terms of ESG. Both of these are available at the Finance Society "LINC" at Lund University. The data can easily be exported to Excel both from Refinitiv and Bloomberg making it easy to extract data from the databases. Firstly, data was collected from Thompson Reuters. The choice of firms and years was based on when Thompson Reuters started rating companies in terms of ESG and what companies they rated. A lot of other similar studies used programs like "ASSET4", "Worldscope" or "Datastream" to collect all the data. A program easily accessible in Thompson Reuters was called the "Screener". In Screener it was possible to choose data for specific firms over a specific time span which made it very simple to export it all together afterwards. On the other hand, there were lots of missing data making it very hard to come up with a final reasonable data sample to use in this study. As a consequence of that, Bloomberg was explored instead to see if it was more suitable for this study.

Bloomberg has a similar application called "Equity Screening" making it possible to filter the data based on specific preferences. However, in this application only one year was visible at a time and so the data had to be collected for each year separately. Furthermore, since more and more companies are being ESG-rated each year, the sample sizes differed each year. The variable growth is based on a firm's difference in assets between two years. This made it complicated to add more companies along the way. In addition, the second part of the project considered constructing portfolios based on the ESG-rated firms. Adding companies in later years would make their average ESG-rating unfairly calculated in comparison with the other companies. This study therefore analyses the same companies each year throughout the time span, which simply is based on the available companies in 2014. The time span ended with 2021 because not all ESG-ratings had been published or calculated in Bloomberg for 2022.

In Bloomberg Equity Screening the variables leverage, liquidity and growth were not available, and had to be calculated separately.

5.1.2 Data Collection and Processing regarding the Portfolio Construction

The portfolio construction is based on the same data sample as the regression analysis and the same companies are therefore available. Daily share prices for the assets were collected through the function "STOCK HISTORY" in Excel using the closing prices. This ended up with 252 values on daily share closing prices for each asset, except for one company "SANDVIK" where the prices were expressed in dollars with 247 data points. Furthermore, the majority of the stock prices for "BOLIDEN" were not given. The daily share prices for both SANDVIK and BOLIDEN were instead collected using "Yahoo Finance", where all of the values for BOLIDEN were given and the stock for SANDVIK was expressed in the Swedish Krona. Comparing the data points given by Yahoo Finance and Excel, the share price for 2022-01-06 was given in Excel even though the market was closed. The share price was hence the same as the one given on 2022-01-05. The date 2022-01-06 was therefore removed from the sample to generate a more reasonable average daily return for the stocks. The prices where then turned into returns by the follow:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}, \tag{43}$$

The one month risk free rate was collected using the one month treasury bill from Riksbanken (2023). This risk free rate is given on a yearly basis through the arithmetic formula and is therefore transformed as:

$$r_m = \frac{r_y}{12}, \tag{44}$$

where r_m is the monthly risk free rate and r_y the yearly. This rate was then transformed to a daily risk free rate based on (30) in Section 3.9.

5.2 Secondary Data

Important to remember is that Bloomberg and the stock functions in Excel and Yahoo Finance contains secondary data. Some data being stored could therefore be miscalculated and incorrect. Hence, all data gathered in this project might not be fully correct and could influence the result to some extent.

5.3 Missing Data

Another important aspect to consider in this study is that 20 companies had to be removed from the sample due to missing data. The sample size from the beginning consisted of 81 companies. After modifications and removals due to missing data the sample size ended up with 61 companies. This is important to have in mind, and the results might differ in comparison with if all of the companies available in 2014 could have been used in the project.

There seemed to be no systematics in the missing data and should therefore not cause bias in the results. However, the precision in the estimates is still decreased.

5.4 Descriptive Statistics regarding the Regression Analysis

The descriptive statistics of the variables based on the 61 companies are presented in Table 4 below. This helps to get a good overview of the variables, to locate possible problems with the data and to make it easier to compare with other studies within this area. Since this study is mainly based on Wang & Sarkis (2017), the variables will for the most part be compared with that study. The skewness and kurtosis are included to get a better understanding of how normally distributed each variable is. A normally distributed variable has a skewness of 0 and a kurtosis of 3.

Table 4: Descriptive statistics for the variables ROA, ROE, ESG, LEV, LIQ, SIZE, GROWTH and RND. The descriptive statistics include the number of observations, the mean value, the standard deviation, the minimum value, the maximum value, skewness and kurtosis.

Variable	**n**	**Mean**	**Standard Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
ROA	427	0,067	0,133	-0,476	1,275	3,058	29,933
ROE	420	0,154	0,271	-2,422	2,633	0,371	43,150
ESG	427	44,375	9,828	19,070	72,250	0,030	-0,256
LEV	427	0,180	0,138	0	0,801	1,108	1,869
LIQ	427	1,800	3,721	0,023	66,902	14,004	229,761
SIZE	427	23,786	1,570	19,228	26,986	-0,595	-0,021
$GROWTH_R$	425	109,731	1746,469	-6,775	35381,222	19,617	395,216
$GROWTH_A$	427	0,124	0,349	-0,658	3,705	6,601	58,876
RND	427	0,561	4,696	0	57,357	9,547	94,238

Firstly, looking at Table 4 and comparing the two different growth variables, the standard deviation is much higher for the growth variable that is based on revenue. One explanation behind this could be that this variable has some very extreme values making the standard deviation increase and could displace the mean value significantly. According to Bloomberg some companies had an extreme increase in revenue growth between some years which for instance is observed in the maximum value. These values are certainly questionable. Comparing with the growth variable that Wang & Sarkis (2017) included in their study, the growth variable in terms of assets seems to be a better fit for the model and will therefore be chosen in this study.

Looking at the ROA variable this matches the variable used in the study by Wang & Sarkis (2017) as well. The mean and minimum value are nearly the same, but the standard deviation is a bit higher. Comparing the ROE variable with the same variable used in the study Alareeni & Hamdan (2020) one important difference is that they display the values in percentage. Taking this into account the values are very alike, having almost the same mean, standard deviation and minimum value. They also presented both skewness and kurtosis where their values regarding ROE are further away from a normal distribution.

Comparing the ESG variable is a bit harder since Wang & Sarkis (2017) used each pillar separately. However, both Alareeni & Hamdan (2020) and Hussain et al. (2018) collected the ESG-scores from Bloomberg as well and comparing with Alareeni & Hamdan (2020) this study has a larger mean value and a smaller standard deviation. The maximum value is larger in their study and the minimum value smaller. Looking at skewness the one in this study is very close to the value zero, but where the kurtosis differs a bit from the value three. Since the time spans differ between the studies it is hard to tell if the ESG-rating overall seems to be higher in Sweden than in the US, or if it just depends on the time span or the firms included in the study. The leverage variable is not remarkably different from the one included in Wang & Sarkis (2017)'s even though the variables are calculated in two slightly different ways. All of their values being comparable are a bit higher. Looking at the skewness and kurtosis the values are comparatively close to a normal distribution. Further on to the liquidity the mean value at 1,800 is very close to the one in Wang & Sarkis (2017)'s at 1,755 but where the standard deviation in this study is higher. Their minimum value is higher which is expected due to their lower standard deviation. Looking at the maximum value in this study it is very high which for example can explain the higher standard deviation. Both the skewness and kurtosis take high values as well. However, since the mean value is still close to Wang & Sarkis (2017)'s study might have some extreme maximum values as well, and the reason behind the higher standard deviation is most likely therefore the values being more spread out within the minimum and maximum values. The size variable has a mean value more than twice as big, but where the standard deviations still fairly match. Comparing with another study like Velte, P. (2017)'s the mean value is a bit closer, but still quite a big difference. A reason behind the dissimilarity could be the different time spans used, or simply that the companies chosen in this thesis have more total assets. Looking at growth in terms of total assets Alareeni & Hamdan (2020) also included a growth variable with the same calculation. Comparing the statistics the mean value and standard deviation in this study are bigger, but they have a more extreme maximum value. Their mean value is 0,085 with a standard deviation at 0,257. Since they have a more extreme maximum value, the values in this study regarding growth are most likely more spread out due to the higher standard deviation. Last but not least the RND variable was decided to be included in the model. However, since this variable is represented in different ways in previous studies it gets a little bit harder to compare. Velte, P. (2017) used it directly as the intensity in terms of euros, and Hussain et al. (2018) divided the expenditure with the total sales. The calculation behind the RnD variable in this study is fairly similar to Hussain et al. (2018)'s which makes it reasonable to compare it with the variable in their study. They calculated the mean value to 0,030 and does not match the mean calculated to 0,561 in this study. The reason behind the higher mean value in this study probably has to do with the extreme values which might have to be removed to make the results more appropriate.

As mentioned above, the descriptive statistics makes it possible to locate problems with the data. For example, by looking at the standard deviation together with the maximum and minimum value of each variable it is easy to see if a variable includes some extreme values that might affect the model in a negative way, and perhaps should be removed. The growth variable has already been somewhat discussed, and another variable standing out is the liquidity variable with a maximum value of 66,902 and a very high kurtosis. Furthermore, the growth variable based on total assets that was decided to be included in the model also has a high maximum value and kurtosis. This is important to have in mind and will be further analysed in Section 5.5 looking at outliers in the scatter plots. Some sectors in this study had a very few, or even zero, amount of observations which means that credible conclusions will not be possible to draw from these specific sectors in the dummy variable. A rule of thumb is that at least 30 observations is needed to be able to draw valid conclusions (Mason, & Perreault Jr, 1991). The amount of observations within each sector is presented in Table 5 below.

Table 5: The number of observations included in the ROA and ROE models from each of the 11 different sectors classified according to GICS.

Sector	**Observations - ROA model**	**Observations - ROE model**
Energy	0	0
Materials	42	42
Industrials	153	153
Consumer Discretionary	77	77
Consumer Staples	21	21
Health Care	36	36
Financials	12	12
Information Technology	20	20
Communication Services	21	21
Utilities	7	0
Real Estate	28	28

5.5 Scatter Plots

There are two main reasons behind creating scatter plots between the dependent and the independent variable together with the control variables in this project. The first reason is to study the relationship between the variables and to get a good first overview of the data. As mentioned before the relationship between the dependent and independent variable respectively between the dependent variable and the control variables should be linear since the model is of a multilinear form. Furthermore there should not be a perfect linear relationship between some of the control variables or between the independent variable and some control variable. This causes perfect multicollinearity. Apart from studying the relationship between variables the scatter plots also make it possible to locate potential outliers which could disturb the result of the regression analysis.

5.5.1 Linearity

By looking at the relationships between variables through scatter plots it gets easier to see if any variable needs to be modified to fulfill this condition. Looking at the model the variable representing size is already logarithmized which is a very commonly used technique to transform a non-linear relationship into a linear. Every study that has been analysed and included size in its model used the natural logarithm of some value representing the size of the company. The decision was therefore made to transform this variable from the beginning to save time. By looking at the scatter plot matrix in Figure 5 the relationships between the dependent variables and the independent variable together with the control variables look somewhat linear, with some outliers. The decision has been made that all of the relations look linear enough to continue with the regression analysis, with some possible modifications regarding the outliers.

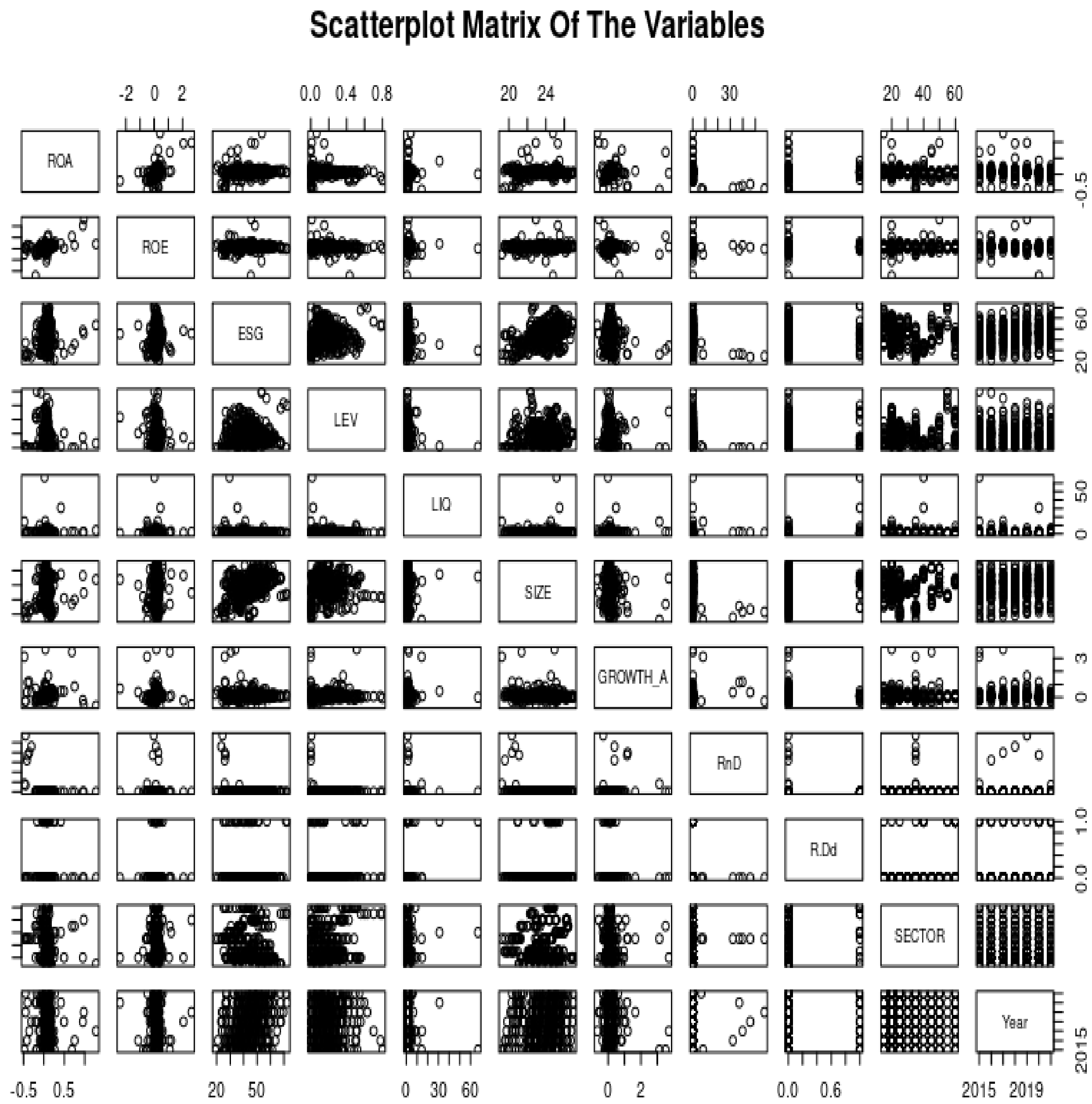


Figure 5: Scatter plot matrix showing the relationship between the dependent variables, the independent variable and the control variables. Starting with ROA, the relationship with ROE is shown in the first box to the right of ROA and the first box below ROA, and so forth.

5.5.2 Outliers

In the part where the descriptive statistics was presented possible outliers could be noticed by looking at the maximum and minimum values of each variable. However, this only presents two possible extreme values, and to be able to see if there exist additional outliers plots between the dependent and independent respectively control variables can be created. The variables LIQ, GROWTH and RND have already been up for discussion, and by looking at the relationship between ROA respectively ROE and these variables, the outliers are easily noticed. Focusing on the LIQ variable two data points are clearly seen as outliers, focusing on the GROWTH variable there seem to be three data points and looking at RND there seem to be five data points. After looking at the data there are two values in the LIQ variable, three values in the GROWTH variable and five values in the RND variable that most likely correspond to these outliers. Both of the extreme values in LIQ corresponds to the company Kinnevik AB-B with the values 30,93 and 66,90 which also is the maximum value for this variable in the descriptive statistics. Regarding GROWTH the first one is for the company Fingerprint Cards AB-B where the growth value was at 349,83 percent. The second one is for the company Hansa Biopharma with a growth value of 312,60 percent. The third one is for Intrum with a growth value of 370,53 percent representing the maximum value in the descriptive statistics. Regarding RND all of the extreme values belong to the same company, namely Hansa Biopharma. The first value is at 32,125, the second one at 39,820, the third at 46,027, the fourth at 57,357 which also is the maximum value, and the last one at 37,251. One possible reason behind why all of these extreme values concerning the variable RND belong to Hansa Biopharma is that their revenue grew with 35381,222 percent between 2015 and 2016. After that growth they perhaps decided to put a lot of money into RnD, which seems reasonable since Hansa Biopharma is a pharmaceutical company.

5.5.3 Transformed Variables

Table 6 below shows the descriptive statistics for the variables LIQ and GROWTH_A before and after modifications. The extreme values presented in the part above was removed to make the variables more reasonable. Comparing the values the mean value and standard deviation have decreased after the modifications for all three variables, and looking at the RND variable the mean value is much closer to the one in Hussian et al. (2018).

Table 6: Descriptive statistics for the variables LIQ, GROWTH and RND before and after modification. The descriptive statistics include the number of observations, the mean value, the standard deviation, the minimum value, the maximum value, skewness and kurtosis. The statistics are based on the same data sample as before but where some outliers are removed according to 5.5.2

Variable	**n**	**Mean**	**Standard Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
LIQ	427	1,800	3,721	0,023	66,902	14,004	229,761
LIQ_{MOD}	425	1,578	1,365	0,023	14,635	5,403	42,063
$GROWTH_{A}$	427	0,124	0,349	-0,658	3,705	6,601	58,876
$GROWTH_{A,MOD}$	424	0,101	0,209	-0,658	1,657	2,406	13,241
RnD	427	0,561	4,696	0	57,357	9,547	94,238
RnD_{MOD}	422	0,064	0,517	0	8,145	14,406	210,409

5.5.4 Multicollinearity

As mentioned in the previous part, multicollinearity can be spotted through scatter plots by looking at relationships between the independent variable and/or the control variables. By looking at the scatter plot matrix in Figure 5 no perfect linear relationship was found between these variables which is positive. However, to further analyze the correlation between the variables a correlation matrix can be created to check if the conclusions drawn from looking at the scatter plot matrix were correct. If the correlation between two variables is higher than 0,8, then this might cause crucial problems for the regression (Studenmund, 2013, p.272). Table 7 below shows a correlation matrix between the variables when ROA is the dependent one, and Table 8 shows the same but when ROE is the dependent variable. Tables presenting the correlation matrices between all the variables including the dummy variables are presented in Appendix 1 and 2. Easily seen below is that the values are far below the critical value, and there should therefore be no problem with multicollinearity based on these correlation matrices. The only comparatively large correlation values in Table 7 and 8 are between SIZE and ESG taking the values 0,418 and 0,467. However, since these values still are considerably smaller than the critical value 0,8, there should not be problems with these correlations either.

Table 7: Correlation matrix for the variables included in the ROA model after the modifications, apart from the dummy variables.

	ROA	ESG	LEV	LIQ	SIZE	GROWTH_A	RND
ROA	1	0.033	-0.194	0.056	-0.028	0.035	-0.232
ESG	0.033	1	0.031	-0.087	0.418	-0.031	-0.063
LEV	-0.194	0.031	1	0.020	0.045	0.075	-0.064
LIQ	0.056	-0.087	0.020	1	-0.089	-0.032	-0.028
SIZE	-0.028	0.418	0.045	-0.089	1	-0.065	-0.130
$GROWTH_A$	0.035	-0.031	0.075	-0.032	-0.065	1	-0.095
RND	-0.232	-0.063	-0.064	-0.028	-0.130	-0.095	1

Table 8: Correlation matrix for the variables included in the ROE model after the modifications, apart from the dummy variables.

	ROE	ESG	LEV	LIQ	SIZE	GROWTH_A	RND
ROE	1	0.049	-0.157	0.010	0.051	-0.114	-0.025
ESG	0.049	1	-0.057	-0.072	0.467	-0.030	-0.061
LEV	-0.157	-0.057	1	0.045	0.103	0.102	-0.064
LIQ	0.010	-0.072	0.045	1	-0.097	-0.033	-0.030
SIZE	0.051	0.467	0.103	-0.097	1	-0.068	-0.133
$GROWTH_A$	-0.114	-0.030	0.102	-0.033	-0.068	1	-0.095
RND	-0.025	-0.061	-0.064	-0.030	-0.133	-0.095	1

5.6 Descriptive Statistics regarding the Portfolio Construction

5.6.1 Companies in the ESG-2021 Portfolio

Looking at Table 9 below Orron Energi has the highest ESG-rating at 71,530. All of the companies have an ESG-rating above 50 except for Kinnevik with a rating of 36,160. All the daily mean returns are negative except for Orron Energi and Hufvudstaden. The majority of companies have a standard deviation of around 0,020 except for Orron with a value more than twice as high.

Table 9: The ESG rating 2021, average daily mean return, weight and standard deviation for the 10 companies in the ESG-2021 portfolio during 2022.

Company	ESG-rating	Avg Return	Weight	Standard Deviation
BOLIDEN	67,340	-0.00074	0.1	0.026
SKF B	60,930	-0.00099	0.1	0.023
ELECTROLUX	59,390	-0.00153	0.1	0.023
AAK	59,920	-0.00028	0.1	0.016
GETINGE B	51,500	-0.00198	0.1	0.027
KINNEVIK B	36,160	-0.00267	0.1	0.032
ERICSSON LM-B	61,490	-0.00170	0.1	0.023
TELE2 B	56,480	-0.00150	0.1	0.017
ORRON ENERGY	71,530	0.00533	0.1	0.048
HUVFVUDSTADEN A	50,800	0.00059	0.1	0.021

5.6.2 Companies in the ESG-Average Portfolio

Looking at Table 10 Boliden has the highest average ESG-rating at 65,611. The ESG-values have all decreased in comparison with the ESG-2021 portfolio. Here there are 5 companies with an ESG-rating below 50. All the daily mean returns are negative except for Orron Energi. The majority of companies have a standard deviation of around 0,020 except for Orron, again with a value more than twice as high.

Table 10: The average ESG rating between 2014-2021, average daily mean return, weight and standard deviation for the 10 companies in the ESG-Average portfolio during 2022.

Company	ESG-rating	Avg Return	Weight	Standard Deviation
BOLIDEN	65,611	-0.00074	0.1	0.026
SANDVIK	60,606	-0.00098	0.1	0.023
THULE GROUP	46,006	-0.00318	0.1	0.023
AAK	56,419	-0.00028	0.1	0.016
GETINGE B	44,177	-0.00200	0.1	0.027
KINNEVIK B	34,698	-0.00267	0.1	0.032
ERICSSON LM-B	56,101	-0.00169	0.1	0.023
TELIA COMPANY	48,577	-0.00104	0.1	0.017
ORRON ENERGY	63,520	0.00533	0.1	0.048
WALLENSTAM B	44,030	-0.00212	0.1	0.021

5.6.3 Comparison between ESG-2021, ESG-Average & OMXS30

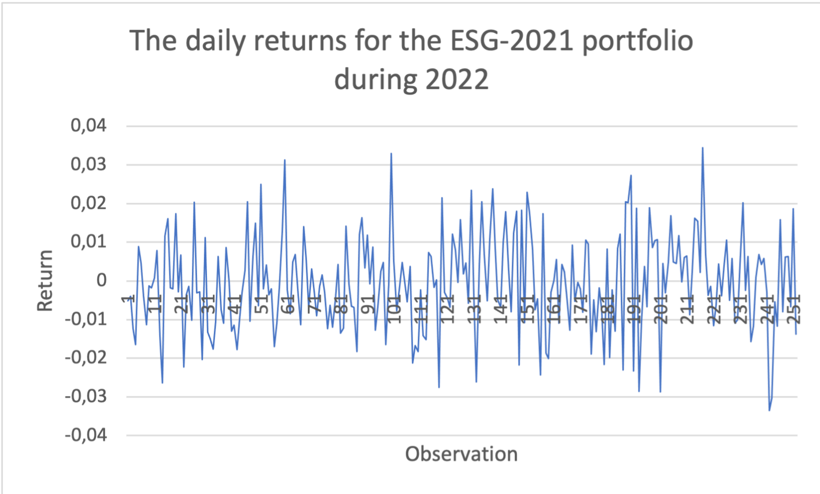
The portfolios daily mean return, daily excess return and standard deviation are presented in Table 11 below. All the daily mean returns are negative, which means that the Sharpe Ratios will be negative as well. The ESG-2021 gives the least negative daily mean return at -0,0005. Afterwards comes OMXS30 with a daily mean return of -0,0006 and lastly ESG-Average at -0,0009. In addition, the ESG-2021 portfolio has the lowest standard deviation, and thereafter comes both ESG-Average and OMXS30 with an almost equal standard deviation.

Table 11: The daily mean return, daily excess return and standard deviation for the ESG-2021 portfolio, ESG-Average portfolio and OMXS30.

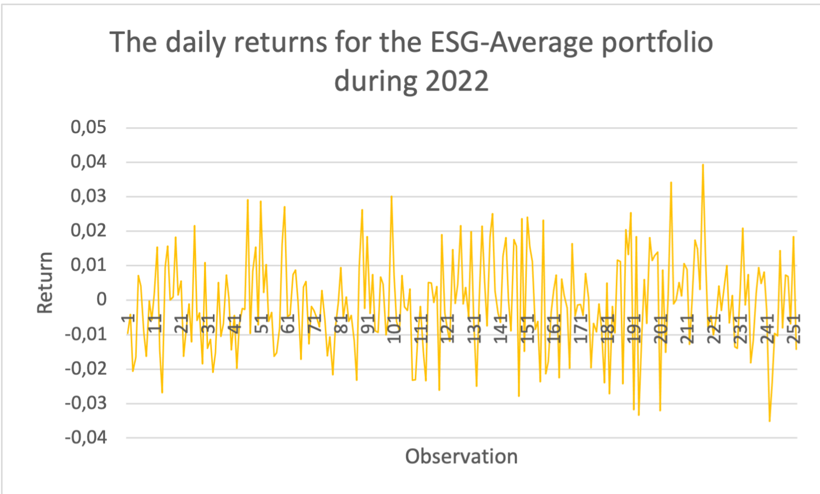
	ESG-2021	**ESG-Average**	**OMXS30**
Daily Mean Return	-0,00055	-0,00094	-0,00062
Daily Excess Return	-0,00064	-0,00103	-0,00072
Standard Deviation	0,01245	0,01362	0,01363

5.6.4 Graph over Returns

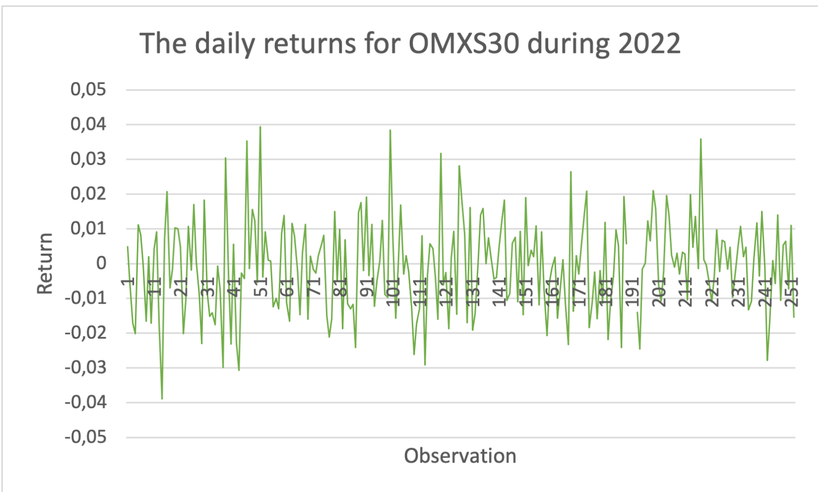
Figure 6 below demonstrates the movement for the three different portfolios daily return over 2022. Noticeable is that all of the returns move around zero, looking to move like random walks according to theory in Section 3.7. In addition, the returns for the ESG-Average portfolio are looking to fluctuate the most.



(a) ESG-2021



(b) ESG-Average



(c) OMXS30

Figure 6: Plots of daily returns for the different portfolios during 2022.

6. Final Regression Models

As mentioned before, the control variables used in this study is based on previous studies, mainly from the project written by Wang & Sarkis (2017). Two other variables were thereafter included, the RND and its dummy variable, based on other similar studies and since it seemed reasonable that spending money on research and development would affect the ROA in some manner. Furthermore, the adjusted R-squared is a good instrument to use when analyzing how well the model describes the dependent variable. The R-squared and adjusted R-squared for both models before and after modifications are presented in Table 12. Interesting to see is that both the R-squared and adjusted R-squared decreased for the model regarding ROA after removing the outliers. The expected result was for the values to increase since the outliers most likely contribute to a more unreliable result, which it did for the model regarding ROE. However, the decision was made to carry on with the modified models, even though the R-squared values was higher for the unmodified model regarding ROA. Each insignificant variable was then removed separately to see how the R-squared values would change and to analyse possible bias in the estimations. There were no substantial changes, which for example can be seen in Appendix 8 and 9 where all of the insignificant variables were removed from each model, apart from the dummy variables.

Table 12: The R-squared and adjusted R-squared values for the ROA and ROE model before and after modifications.

	ROA Model	ROE Model
R-squared before mod.	0.229	0.072
R-squared after mod.	0.141	0.087
Adj.R-squared before mod.	0.187	0.023
Adj.R-squared after mod.	0.093	0.038

By looking at the linearity and multicollinearity in the previous part assumptions 1 and 6 are hopefully satisfied, apart from possible omitted variables. To examine the multicollinearity one step further, a VIF test was performed. Looking at the calculated values below in Table 13 and 14 for both models, all VIF-values are below five except for the SECTOR variable in the ROA model, but is still under ten and closer to five than ten. SECTOR having the highest VIF-value is not very surprising either since the variable had the highest correlation values in the correlation matrix. After examining the VIF-values, multicollinearity is hopefully not a problem in these regression models.

Table 13: A VIF-test for the variables in the ROA model. GVIF stands for Generalized Variance Inflation Factor. Df represents the degrees of freedom and the last column represents the adjusted generalized standard error inflation factor.

	GVIF	Df	GVIF^(1/(2*Df))
ESG	2.392	1	1.547
LEV	1.464	1	1.210
LIQ	1.070	1	1.034
SIZE	2.058	1	1.435
GROWTH_A	1.113	1	1.055
RND	1.131	1	1.063
factor(R.Dd)	1.864	1	1.365
factor(SECTOR)	6.498	9	1.110
factor(Year)	1.334	6	1.024

Table 14: A VIF-test for the variables in the ROE model. GVIF stands for Generalized Variance Inflation Factor. Df represents the degrees of freedom and the last column represents the adjusted generalized standard error inflation factor.

	GVIF	Df	GVIF^(1/(2*Df))
ESG	2.227	1	1.492
LEV	1.244	1	1.115
LIQ	1.066	1	1.032
SIZE	2.037	1	1.427
GROWTH_A	1.116	1	1.056
RND	1.131	1	1.063
factor(R.Dd)	1.872	1	1.368
factor(SECTOR)	4.631	8	1.101
factor(Year)	1.318	6	1.023

By including a constant in the regression model assumption 2 is hopefully satisfied as well. Handling omitted variables in this study has already been slightly discussed, for example by carefully choosing the right variables. Assumption 3 regarding correlation between some independent variable and the error term is harder to satisfy, because the problem is mainly caused by omitted variables. For instance, a Ramsay RESET can be performed to check if the chosen variables have the wanted functional form, or if any modifications should be done to avoid misspecification bias (Wooldridge, 2012, p.306). However, a RESET test in the programming language R can not be used on panel data, and the test would then have to be performed each year and could in other words show different results depending on the year. The RESET test was therefore categorized as inappropriate for this study and was not performed.

The next assumption, namely assumption 4, introduces the problem concerning autocorrelation in the model. A Breusch-Godfrey test for autocorrelation with panel data was performed. The default in this function is to check for autocorrelation with the time lag one, which also is the most frequent time lag to cause serial correlation (Studenmund, 2013, p.323). Looking at the values for both models in Table 15 below, there seems to be no problem with serial correlation since the null hypotheses can not be rejected.

Table 15: Breusch-Godfrey test for autocorrelation for the ROA model and the ROE model.

	Chisq	p-value
ROA	0,927	0,336
ROE	1,119	0,290

Assumption five introduces the problem with heteroscedasticity. If there exists heteroscedasticity in the model the calculated standard errors are incorrect. A solution to this is to use robust standard errors, which accounts for the problem. Both models were therefore estimated again but with robust standard errors to compare the results. Assumption seven is not crucial and will consequently not be further investigated in this project.

All of the necessary assumptions have now been taken into account. The assumptions seem to be mostly satisfied, apart from problems with omitted variables and will have to be something to bring into consideration when analysing the results. The final regression models have been created and are presented below.

$$ROA_{i,t} = \beta_0 + \beta_1^{'} ESG_{i,t} + \beta_2^{'} LEV_{i,t} + \beta_3^{'} LIQ_{i,t} + \beta_4^{'} SIZE_{i,t} + \beta_5^{'} GROWTH_{i,t} + \beta_6^{'} RND_{i,t} + Rdd_i + YEAR_i + SECTOR_i + \epsilon_{i,t}, \tag{45}$$

$$ROE_{i,t} = \beta_0 + \beta_1 ESG_{i,t} + \beta_2 LEV_{i,t} + \beta_3 LIQ_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 GROWTH_{i,t} + \beta_6 RND_{i,t} + Rdd_i + YEAR_i + SECTOR_i + \epsilon_{i,t}, \tag{46}$$

7. Results and Discussion

7.1 Results from The Regression Models

Firstly, comparing the results between the models with and without robust standard errors in Table 16 and 17, the estimates do not differ very much for the ROA model. All the insignificant variables stay insignificant and vice verse. The standard errors do change to some extent but still do not change the result significantly. For the ROE model however the significance for GROWTH changes to insignificant at a 1 percent level. Considering that the result changes significantly for the ROE model and that robust standard errors add stability to the model, the decision was made to use the results with robust standard errors in both cases, to avoid problems with heteroscedasticity as much as possible.

Continuing with the regression results for the ROA model the ESG variable turned out to be insignificant. Crucial to remember is that the null hypothesis was one-sided and the p-value should hence be divided by two. However, since the ESG variable was insignificant even at a 10 percent level for the two-sided test, it will still be insignificant at a 5 percent level for the one-sided test. The LEV variable is negatively significant at a 1 percent level. The variables LIQ, SIZE and GROWTH are all insignificant, but RND is negatively significant at a one percent level like the LEV variable. The only significant variables were hence LEV and RND. Looking at the R^2 value it landed at 0.141 which means that the model explains around 14 percent of the reality. The adjusted R^2 landed at 0.093.

Looking at the ROE model the ESG variable turned out to be insignificant here as well. The only variable, apart from the dummy variable, being significant in this model was the LEV variable, with significance at a one percent level. Sector 55 turned out to be significant as well, but since this sector had less than 30 observations sufficiently good conclusions can not be drawn from that result. Looking at the R^2 value it landed at 0.087 which means that the model explains around 9 percent of the reality. The adjusted R^2 landed at 0.038.

Table 16: Regression results for the ROA and ROE model without robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
ESG	0.0005	0.0003
	(0.001)	(0.002)
LEV	-0.184^{***}	-0.375^{***}
	(0.048)	(0.117)
LIQ	0.004	0.005
	(0.005)	(0.011)
SIZE	−0.004	0.007
	(0.005)	(0.012)
GROWTH_A	−0.001	-0.169^{**}
	(0.029)	(0.070)
RND	-0.078^{***}	−0.016
	(0.017)	(0.041)
RND Dummy	Yes	Yes
Year Dummy	Yes	Yes
Sector Dummy	Yes	Yes
Constant	0.195^{*}	−0.005
	(0.105)	(0.249)
Observations	417	410
R^2	0.141	0.087
Adjusted R^2	0.093	0.038
F Statistic	2.949^{***} (df = 22; 394)	1.767^{**} (df = 21; 388)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 17: Regression results for the ROA and ROE model with robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
ESG	0.0005	0.0003
	(0.001)	(0.002)
LEV	-0.184^{***}	-0.375^{***}
	(0.042)	(0.127)
LIQ	0.004	0.005
	(0.005)	(0.011)
SIZE	-0.004	0.007
	(0.005)	(0.011)
GROWTH_A	-0.001	-0.169
	(0.096)	(0.178)
RND	-0.078^{***}	-0.016
	(0.006)	(0.015)
RND Dummy	Yes	Yes
Year Dummy	Yes	Yes
Sector Dummy	Yes	Yes
Constant	0.195^{*}	-0.005
	(0.116)	(0.263)
Note:	*p<0.1; **p<0.05; ***p<0.01	

7.2 Analysis and Discussion Regarding the Regression Models

Firstly, as mentioned in the previous part the ESG variable turned out to be insignificant in both models. Comparing with previous studies in the Literature Review there is a positive relationship between ESG and financial performance in a majority of the cases. However, looking for example at Table 1 in Literature Review, a neutral relationship has been discovered before and was therefore not completely unexpected.

The next variable included in the models was leverage, which has been included in several similar studies before and is expected to influence the financial performance. Since leverage measures the debt ratio, a higher leverage could impair the financial performance of the company. This variable was statistically significant with a negative sign, and according to the variable description the negative sign is very reasonable. Comparing with previous studies, for instance with Wang & Sarkis (2017) the results regarding leverage matches very well. The interpretation of the variable is that a unit increase in leverage decreases the ROA with 0,184, and the ROE with 0,375. This could be thought of as very large numbers looking at the mean of both ROA and ROE in the descriptive statistics, but important to have in mind is that the leverage variable has a mean of 0,180. A unit increase in leverage is therefore a very large change.

Moving on to the next variable, liquidity, it turned out to have a positive relationship with the dependent variable in both cases, but not significantly. Comparing with Wang & Sarkis (2017) that also included this variable, they had a similar result for ROA but where the variable turned out to be significant as well. Comparing the decriptive statistics for the variable the mean is very similar, but where the standard deviation is much higher in this study which could partly explain the insignificance of the variable. Looking at the interpretation of the variable a positive relationship between liquidity and ROA was expected, since a higher liquidity in this case means a higher amount of current assets in relation to the current liabilities. This result matches the models, but since the variable still is insignificant the only conclusion that can be drawn is that the variable had no significant influence in the models.

The next variable included was the variable accounting for the size of the company. The explanation behind it was that a larger company can be harder to imitate and could therefore result in advantages affecting the financial performance in a positive manner. The impact of the variable has nevertheless differed among previous studies. For example, the variable was insignificant in Wang & Sarkis (2017), negatively significant for ROA and neutral for ROE in Hussian et al. (2018) and positively significant with both ROA and ROE in Alareeni & Hamdan (2020). Because of the large variation of the variable impact wise, that the variable turned out to be insignificant in this study was not completely unexpected. Interesting to add is that the interpretation of the variable differs from the rest, since the logarithm is used in the calculation. Looking only at the values for the coefficient to be able to interpret the variable, a one percentage increase in size here negatively changes the ROA by 0,004 and positively changes the ROE by 0,007, but the variable is insignificant in these models and the impact described above can hence not be proved to be statistically correct.

Another variable included in the models was accounting for growth, since a higher growth could increase the possibilities to improve the financial performance. Based on this together with the result in previous studies the coefficient for growth was expected to have a significant positive relationship with both ROA and ROE. For instance, in Wang & Sarkis (2017) the variable was positively significant for ROA, in Hussain et al. (2018), the variable was positively significant for ROA and ROE, and in Alareeni & Hamdan (2020), the variable was positively significant for ROA and neutral for ROE. In this study the variable was neutral in both cases. The growth simply seems to not have the same impact on the Swedish market based on the companies studied. Moreover, the variable can be calculated in different ways. In some studies including Wang & Sarkis (2017) and Hussain et al. (2018) growth is calculated based on revenue/sales and in some studies including Alareeni & Hamdan (2020), it is calculated based on total assets. It is therefore reasonable that the result for growth in this study is closer to Alareeni & Hamdan (2020), which also is the case and both variables turned out to be insignificant for the ROE model.

A variable accounting for research and development expenditure was also included in the model, and a dummy to capture the missing values. Based on theory the assumption was to see a positive relationship between RND and both ROA and ROE. However, looking at the result the variable had a significant negative relationship with both the dependent variables which was very unexpected. Furthermore there seemed to be no bigger difference between the values that was actually zero and those that were missing. The result connected to research and development was contrary to the expectations, and a similar result is for example shown in Hussain et al. (2018), showing a significantly negative relationship at level 0,1 with ROA and level 0,05 with ROE. A possible reason for the unexpected result could be the comparatively small sample consisting of 60 companies. A regression analysis with more companies could perhaps change the result to the more expected. However, the result is not always as expected, and in this sample spending more money on RND appeared to have a negative effect on the financial performance. Looking back at Duque-Grisales & Aguilera-Caracuel (2021) and drawing a related conclusion, spending money on RND could arguably seem reasonable to reduce the financial performance in the short run.

Continuing with another dummy variable, YEAR, that was included because theory states that this variable could reduce problems with serial correlation and omitted variables. The different results for each year is hence not very interesting in this specific article and will not be discussed very much. The result showed no significant differences between the years either compared to the intercept of the models, except for one year. The year 2020 was significantly different at a one percent level lowering the intercept by 0,026. A possible reason for this could be the pandemic.

The year variable was clearly the most discussed variable to include since the result connected to it seemed somewhat irrelevant for this specific study. However, removing the variable from the regression model decreased the R^2 value from 0,141 to 0,119 and the adjusted R^2 value from 0,093 to 0,084 for the ROA model. Applying robust standard errors to this model made the RND variable insignificant and turned the dummy variable for RND negatively significant at a 5 percent level lowering the intercept by 0,023. The negative sign on this variable means that the general ROA level is decreased for those companies having missing data in comparison to those having an actual zero value on the RND variable. Removing the year variable from the ROE model changed the R^2 value from 0,087 to 0,065 and the adjusted R^2 value from 0,038 to 0,029. Applying robust standard errors did not change the significance of the variable. The decrease in the R^2 after removing year is a large change in both models compared to removing other insignificant variables from the regression model.

This together with the purpose of including the year variable presented above made the variable stay in the model.

The last variable included in the models was the dummy variable for each sector to capture eventual differences between these. As mentioned before, some sectors had less than 30 observations and conclusions from these will hence not be drawn. Starting with the ROA model no sector was significantly different from the intercept. In other words, based on the sectors including more than 30 observations there seems to be no significant differences in terms of the level of ROA. For the ROE model sector 50 was significantly different from the intercept, increasing it with 0,158. Sector 50 only had 21 observations for the ROE model and sufficient conclusions can therefore not be drawn, which means that this result does not say very much.

Finally, the R^2-values are far from perfect and the models describe a small portion of the reality. Looking at previous studies the R^2-value often lies between 0,1-0,5 (Wang & Sarkis, 2017, Hussain et al., 2018, Alareeni & Hamdan, 2020). Comparing the values in this study with these previous articles the ROA model lies inside the given interval. The ROE model has a lower R^2-value and the chosen variables seem to describe ROA in a better way than ROE. The low R^2- and adjusted R^2-values could be a consequence of the chosen variables together with that it could very difficult to describe the reality through a regression model, especially measures like financial performance that can depend on a large amount of different factors.

The two hypotheses regarding the regression models were the following:

(I) Higher ESG rating has a significant positive impact on ROA for a firm on the Swedish listed market.
(II) Higher ESG rating has a significant positive impact on ROE for a firm on the Swedish listed market.

After looking at the result both of the hypotheses turned out to be false in this study since the ESG variable turned out to be insignificant in both models. To check for possible bias in the insignificant variables, each insignificant variable was removed from the model to see if the other coefficients changed significantly which did not happen. The estimated models without all the insignificant variables are presented in Appendix 8 and 9. As mentioned earlier, a neutral relationship has been discovered before and is not something new, but the majority of similar studies still show a positive relationship. Possible reasons for the different result could be the lack of data, the different markets and the different models constructed to express the impact of ESG.

There are lots of different possible models to construct such as a pooled OLS, fixed effect model or a random effect model where a pooled OLS was chosen in this case since it seemed to be a good fit. OLS is the best estimator if the assumptions are satisfied, but being 100 percent sure with that is nearly impossible due to problems with omitted variables as an example. Furthermore, the pooled OLS might not be the best fit for this specific problem and another model type might explain the reality in a better way.

The average ESG-rating for companies also clearly differs between countries and it would therefore be very reasonable to think that sustainability is valuated differently between countries. However, the average Swedish company has a comparatively high ESG-rating which then would further strengthen the hypothesis about a positively significant ESG variable. Important to have in mind is that the data sample used only covers a fraction of the Swedish market.

7.3 Results Regarding the Portfolio Construction

Looking at Table 18 the ESG-2021 performed best during 2022 having a Sharpe Ratio of -0,0513. Close behind came OMXS30 with a Sharpe Ratio of -0,0525. Last came the ESG-Average portfolio with a Sharpe Ratio of -0,0755.

Table 18: The calculated daily Sharpe Ratio for the three different portfolios during 2022.

	ESG-2021	**ESG-Average**	**OMXS30**
Sharpe Ratio	-0,0513	-0,0755	-0,0525

The hypothesis regarding the portfolio construction was the following:

Constructing a portfolio with the highest ESG-rated companies in the Swedish listed market sector wise, one from each sector, will perform better than the market index.

This is true in absolute terms comparing the ESG-2021 portfolio with OMXS30, but not for the ESG-Average portfolio. However, to be able to conclude if the difference is significant a test had to be performed according to the theory in Section 3.8. The test statistics are presented in Table 19 below. The null hypothesis can not be rejected at a 5 percent significance level in either of the two cases having a p-value greater than 0,05.

Table 19: The test statistic for the Z-test. Testing if there is a significant difference between the daily Sharpe Ratios of the two portfolios separately compared to the OMXS30 at a 5 percent level. The test is one-sided and the constructed portfolios are expected to perform better than the market index. The test checks if the daily Sharpe Ratio of the two different constructed portfolios are significantly greater than the daily Sharpe Ratio of OMXS30 during 2022 or not.

Null Hypothesis	**P-value**
SR(ESG-2021) $\leq SR(OMXS30)$	0,51
SR(ESG-AVG) $\leq SR(OMXS30)$	0,69

7.4 Analysis and Discussion Regarding the Portfolio Construction

The result above was according to the hypothesis in absolute terms looking at the Sharpe Ratio of the ESG-2021 portfolio, but not for the ESG-Average portfolio with a lower Sharpe Ratio than OMXS30. However, the difference between the ESG-2021 portfolio and OMXS30 was not significant at a 5 percent level. To generate a well diversified portfolio each sector was included. Some of these sectors had a very few companies. Choosing the firm with the highest ESG-rating from these sectors might not have had the same impact on the portfolio in comparison to sectors having a higher supply of companies. For instance, KINNEVIK is being included in both portfolios with an ESG-rating of 36,160 in 2021 and an average ESG rating of 34,698 between the years 2014-2021. These values are low in comparison to the other companies' ESG-values in the portfolios. KINNEVIK was chosen from a sector having two companies in this data sample, and there was in other words almost nothing to compare with. A larger data sample could therefore have generated better and more well constructed results. In addition, it is important to remember that no portfolio was constructed including the companies with highest ESG-rating overall since one aim was to utilize the diversification effect. This approach could have generated another result.

Looking at the sign of the Sharpe Ratios they are all negative, and since all portfolios' daily mean return were negative this was expected as well. 2022 was a tough year financially as a consequence of both the pandemic and the war. With a highly increased inflation and a large decrease in global growth, 2022 turned into a tense year. This could be a substantial reason for the negative values.

7.5 Reliability, Validity and Generalizability

The reliability of a study can be connected to how easy it is to replicate, and if it would generate the same result. This means that it is important to describe every single step, and that the data is regularly described and compared. It would therefore have been beneficial if the result matched previous studies to increase the reliability. The majority of similar studies regarding the regression showed a positive relationship between ESG and financial performance, and here the relationship is neutral. However, since this study is based on the Swedish market which has not been analysed very much in terms of ESG and financial performance, it gets harder to draw reasonable conclusions about the reliability since the result is compared with other countries. Looking at the portfolio construction, previous studies have shown that it is possible to increase the risk-adjusted return by investing in more sustainable companies. Once again this is compared with results based on other countries. These results lies well in line with the result from this study, where the portfolios performed fairly equal to the market index with no significant differences between the Sharpe Ratios. Furthermore, the data is gathered from secondary sources, and all the values and calculations might not be correct which in turn decreases the reliability of the study. The same applies to the portfolio construction where the daily share prices was gathered through Excel and Yahoo Finance, and some values might not be fully correct. Apart from that, the process and data have been described so that the study should be as easily replicated as possible, but still avoiding abundance.

Validity deals with to what extent the study investigates the research question. The two areas that was supposed to be investigated in this study were the impact of sustainability from two different perspectives. Partly from a company's perspective by looking at the financial performance, and partly from an investor's perspective by investing in highly sustainable firms. ESG is a well used and adapted variable to use when measuring sustainability which made it a very reasonable instrument to use. Important to consider is that the choice of variables included in the regression model could influence the effect of ESG as well, for example by creating bias or through omitted variables. Only a part of the market is investigated and is based on the available ESG-rated companies in 2014.

It is beneficial to consider more than the sustainability factor when deciding what companies to invest in. The impact of sustainability in investing was still investigated, but could perhaps have been combined with other factors to create even more trustworthy results and conclusions. The portfolio was undeniably based on sustainable companies, but could still be weak in the long run due to firm or sector specific factors or events. The portfolio construction was also based on one single year, and the validity would increase by including a longer time span.

To what extent can this study be generalized to another article or situation? Since this study is focusing on the Swedish market it is preferable to be generalized to other studies or situations based on Sweden. However, since the supply of these are fairly limited it is in this case normal to compare with similar studies around the world. In addition, this study does not cover the entire Swedish market since the range of companies being ESG-rated in Sweden in 2014 were quite narrow as well.

8. Conclusions

8.1 Conclusion

As sustainability becomes increasingly important it is necessary for companies to adapt and meet the needs and expectations from their costumers and investors. Companies need to act responsible to stay competitive. This creates new possibilities for investors. Using sustainability as a sufficient pillar in the decision making for specific investments might be beneficial and generate better risk adjusted returns. Sustainability can be measured in different ways, where one popular instrument is to use the ESG-rating. The purpose of this study was to look at the impact of ESG from two different perspectives, mainly the impact from a company's perspective and from an investor's perspective. From the company's perspective, the impact of ESG on financial performance was measured by the use of two different accounting based measurements, ROA and ROE. From an investor's perspective two different portfolios were created taking the companies' ESG-ratings in consideration, choosing the companies with the highest rating, one from each sector. One portfolio was created based on the highest ESG-rated firms 2021, and one based on the highest average ESG-rating between 2014 and 2021. These portfolios were then compared to the Swedish market index OMXS30 using the risk-adjusted measurement Sharpe Ratio.

The majority of previous research has shown a positive relationship between sustainability and financial performance. The result in this study does however not match this majority, and instead showed a neutral relationship between ESG and both ROA and ROE. In other words, based on the data sample and the control variables used together with the independent variable ESG, the ESG-rating of the firms did not affect the level of ROA nor ROE. The hypotheses regarding the regression model was therefore incorrect, since the null hypotheses could not be rejected.

The portfolios were created in Excel using the built in function STOCK HISTORY to get access to daily share prices for the stocks. This function was then supplemented by Yahoo Finance in order to get all the data. In the first portfolio, ESG-2021, one company from each sector with the highest ESG-rating in 2021 was included. In the second portfolio, ESG-Average, one company from each sector with the highest average ESG-rating between 2014 and 2021 was included. The portfolios were then tested on the year 2022 to analyse the performance by the use of the risk-adjusted return measurement, the Sharpe Ratio. Based on previous research, for instance shown in Kaiser, L. (2020) and Ashwin Kumar et al. (2016) portfolios were expected to perform well. The ESG-2021 portfolio outperformed the market index in absolute values. However, after calculating after comparing the Sharpe Ratios, the results showed that none of the portfolios performed significantly better than OMXS30 during 2022.

The conclusion can therefore be drawn, that based on the data sample used in this study there is no significant relationship between ESG-rating and financial performance on the Swedish market from a firm's perspective. Constructing the ESG-2021 portfolio did benefit the investor by performing slightly better than the market during 2022 having a higher Sharpe Ratio. However, since the portfolio was not statistically significantly better than the market portfolio

OMXS30 we cannot say that this will be the case in the future.

8.2 Contributions

This study has contributed with a deeper insight regarding the role of ESG on the Swedish market, both from a company's perspective and an investor's perspective. Since the supply of similar studies made on the Swedish market is quite limited this study can hopefully act as guidance and help for further and deeper research concerning the impact of sustainability for Swedish listed firms.

For the regression analysis the result was quite unexpected since the majority of previous studies show a positive relationship between ESG and financial performance. Important to have in mind is that the regression analysis has been compared with regressions based on other countries. However, that the result differs from the majority leastwise puts the problem into perspective. Furthermore, there are not a lot of studies combining the investor's and firm's perspective in the same study based on the same data sample which made this approach more interesting.

Regarding the portfolio construction the selection of companies was completely based on ESG-rating. The portfolios did not outperform the market but were not far behind the index. This could spark further interest for people to invest more sustainable. In addition, this portfolio construction can be something other studies can improve even further, by not only focusing on the ESG-rating, but combining this with other important factors to create even more stable portfolios.

8.3 Limitations

Unobstructed, studies often comes with limitations and this is not an exception. Firstly, the sample size was quite small and covered far from the entire Swedish market which is important to understand. Using more data gives more reliable results. Secondly, perfect regression models are nearly impossible to create, and a big problem usually affecting these are omitted variables. The results are therefore limited to the variables included in the model.

The portfolio construction is only based on one year, covering more years would generate a more authentic result. The Sharpe Ratio was only calculated on a daily basis. Moreover, this study only focused on the Swedish market and the result is hence limited to Sweden. Lastly, the selection of companies in the portfolios were only based on ESG, and did not include any other factors.

8.4 Future Research

An interesting first approach would be to implement a similar study in some years based on a later time span to compare the results. Another interesting approach would be to perform a similar study but dividing the ESG-rating into the three pillars and analyse them separately instead. Additionally, it would be of interest to compare the Swedish market with another Nordic country such as Denmark, Norway or Finland to see if the importance of sustainability seems to differ between the countries. A similar study could also be done using

Thompson Reuters Database to collect the ESG-rating instead, to analyse if the impact of ESG differs depending on which data base the rating comes from. A deeper analysis within the sector or year variable could also be an interesting adjustment to deeper investigate the difference between sectors or the change in impact of ESG over the years. Another interesting approach would be to add companies along the way as more and more companies get ESG-rated each year, and not only look at the same sample of companies each year. Lastly it would be interesting to include a market-based measure to compare with the accounting-based.

Regarding the portfolio construction a similar approach with a longer time span would be interesting to compare the results. A more complex method of choosing companies and still including the ESG-rating could also be an interesting approach to generate more well constructed portfolios. It would also be interesting to compare a portfolio with highly ESG-rated companies and a portfolio including companies with comparatively low ESG-rating.

9. References

Ahmad, N., Mobarek, A., & Roni, N. N. (2021). Revisiting the impact of ESG on financial performance of FTSE350 UK firms: Static and dynamic panel data analysis. *Cogent Business Management*, 8(1), Article: 1900500.

Alareeni, B. A., & Hamdan, A. (2020). ESG impact on performance of US SP 500-listed firms. *Corporate Governance: The International Journal of Business in Society*. 20(7), 1409-1428.

Ashwin Kumar, N. C., Smith, C., Badis, L., Wang, N., Ambrosy, P., & Tavares, R. (2016). ESG factors and risk-adjusted performance: A new quantitative model. *Journal of Sustainable Finance & Investment*, 6(4), 292-300.

Dougherty, C. (2011). *Introduction to Econometrics.* Third edition. New York: Oxford University Press.

Duque-Grisales, E., & Aguilera-Caracuel, J. (2021). Environmental, social and governance (ESG) scores and financial performance of multilatinas: Moderating effects of geographic international diversification and financial slack. *Journal of Business Ethics*, 168(2), 315-334.

Elton, E. J., & Gruber, M. J. (1997). Modern portfolio theory, 1950 to date. *Journal of banking finance*, 21(11-12), 1743-1759.

Fatemi, A., Glaum, M., & Kaiser, S. (2018). ESG performance and firm value: The moderating role of disclosure. *Global finance journal*, 38, 45-64.

Fiskerstrand, S. R., Fjeldavli, S., Leirvik, T., Antoniuk, Y., & Nenadić, O. (2020). Sustainable investments in the Norwegian stock market. *Journal of Sustainable Finance & Investment*, 10(3), 294-310.

Ford, C. (2020). *Understanding Robust Standard Errors.* University of Virginia Library. Available at: https://data.library.virginia.edu/understanding-robust-standard-errors/. [Retrieved 2023-05-18]

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of sustainable finance investment*, 5(4), 210-233.

Hall, T. W. (2012). The collateral channel: Evidence on leverage and asset tangibility. *Journal of Corporate Finance*, 18(3), 570-583.

Hussain, N., Rigoni, U., & Cavezzali, E. (2018). Does it pay to be sustainable? Looking inside the black box of the relationship between sustainability performance and financial performance. *Corporate Social Responsibility and Environmental Management*, 25(6), 1198-1211.

Jin, C. H., & Lee, J. Y. (2019). The halo effect of CSR activity: Types of CSR activity and negative information effects. *Sustainability*, 11(7), 2067.

Jobson, J. D., & Korkie, B. M. (1981). Performance hypothesis testing with the Sharpe and Treynor measures. *Journal of Finance*, 36(4), 889-908.

Kaiser, L. (2020). ESG integration: Value, growth and momentum. *Journal of Asset Management*, 21(1), 32-51.

Li, T. T., Wang, K., Sueyoshi, T., & Wang, D. D. (2021). ESG: Research progress and future prospects. *Sustainability*, 13(21), Article: 11663.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives*, 17(1), 59-82.

Malladi, R., Fabozzi, F. J. (2017). Equal-weighted strategy: Why it outperforms value-weighted strategies? Theory and evidence. *Journal of Asset Management*, 18, 188-208.

Mason, C. H., & Perreault Jr, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of marketing research*, 28(3), 268-280.

MSCI, 2023. *The Global Industry Classification Standard (GICS)*. Available at: https://www.msci.com/our-solutions/indexes/gics. [Retrieved 2023-04-10]

Riksbanken, 2023. *Search interest exchange rates.* Riksbank. Available at: https://www.riksbank.se/en-gb/statistics/search-interest–exchange-rates/. [Retrieved 2023-05-18]

Salama, A., Anderson, K., & Toms, J. S. (2011). Does community and environmental responsibility affect firm risk? Evidence from UK panel data 1994–2006. *Business ethics: a European review*, 20(2), 192-204.

Studenmund, A. H. (2013). *Using Econometrics: A Practical Guide.* 6th edition. Harlow: Pearson Education Limited

Studenmund, A. H. (2017). *Using Econometrics: A Practical Guide.* 7th edition. Harlow: Pearson Education Limited

Uyanto, S. S. (2020). Power comparisons of five most commonly used autocorrelation tests. *Pakistan Journal of Statistics and Operation Research*, 16(1), 119-130.

Velte, P. (2017). Does ESG performance have an impact on financial performance? Evidence from Germany. *Journal of Global Responsibility.* 8(2), 169-178.

Wang, Z., & Sarkis, J. (2017). Corporate social responsibility governance, outcomes, and financial performance. *Journal of cleaner production*, 162, 1607-1616.

Wooldridge, J. M. (2009). *Introductory Econometrics. A Modern Approach.* 4th Edition. Mason, OH: South Western Cengage Learning.

Wooldridge, J. M. (2012). *Introductory Econometrics. A Modern Approach.* 5th Edition. Mason, OH: South Western Cengage Learning.

10. Appendix

Appendix 1. Correlation matrix between all variables in the ROA model

Table 20: Correlation matrix between all the variables in the ROA model.

	ROA	ESG	LEV	LIQ	SIZE	GROWTH_A	RnD	R.Dd	SECTOR	Year
ROA	1	0.033	-0.194	0.056	-0.028	0.035	-0.232	-0.002	-0.085	-0.084
ESG	0.033	1	0.031	-0.087	0.418	-0.031	-0.063	-0.048	-0.145	0.283
LEV	-0.194	0.031	1	0.020	0.045	0.075	-0.064	-0.018	0.203	0.022
LIQ	0.056	-0.087	0.020	1	-0.089	-0.032	-0.028	-0.020	-0.111	-0.027
SIZE	-0.028	0.418	0.045	-0.089	1	-0.065	-0.130	0.061	0.044	0.106
GROWTH_A	0.035	-0.031	0.075	-0.032	-0.065	1	-0.095	-0.026	-0.025	0.031
RnD	-0.232	-0.063	-0.064	-0.028	-0.130	-0.095	1	-0.035	0.046	0.073
R.Dd	-0.002	-0.048	-0.018	-0.020	0.061	-0.026	-0.035	1	0.455	0.036
SECTOR	-0.085	-0.145	0.203	-0.111	0.044	-0.025	0.046	0.455	1	0.006
Year	-0.084	0.283	0.022	-0.027	0.106	0.031	0.073	0.036	0.006	1

Appendix 2. Correlation matrix between all variables in the ROE model

Table 21: Correlation matrix between all the variables in the ROE model.

	ROE	ESG	LEV	LIQ	SIZE	GROWTH_A	RnD	R.Dd	SECTOR	Year
ROE	1	0.048	-0.151	-0.017	0.055	-0.028	-0.033	0.006	0.043	-0.050
ESG	0.048	1	-0.009	-0.120	0.493	-0.144	-0.225	-0.110	-0.243	0.287
LEV	-0.151	-0.009	1	-0.073	0.146	0.036	-0.156	-0.042	0.090	0.060
LIQ	-0.017	-0.120	-0.073	1	0.0001	0.073	0.010	0.225	0.028	-0.064
SIZE	0.055	0.493	0.146	0.0001	1	-0.143	-0.252	0.095	0.054	0.116
GROWTH_A	-0.028	-0.144	0.036	0.073	-0.143	1	0.141	-0.032	0.023	-0.059
RnD	-0.033	-0.225	-0.156	0.010	-0.252	0.141	1	-0.032	0.061	0.006
R.Dd	0.006	-0.110	-0.042	0.225	0.095	-0.032	-0.032	1	0.451	0.010
SECTOR	0.043	-0.243	0.090	0.028	0.054	0.023	0.061	0.451	1	0
Year	-0.050	0.287	0.060	-0.064	0.116	-0.059	0.006	0.010	0	1

Appendix 3. Regression Results for the Dummy Variables without Robust Standard Errors

Table 22: Regression results for the dummy variables included in the ROA and ROE models without using robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
factor(R.Dd)1	−0.011	−0.041
	(0.030)	(0.074)
factor(SECTOR)20	−0.025	0.021
	(0.021)	(0.050)
factor(SECTOR)25	−0.013	0.053
	(0.022)	(0.052)
factor(SECTOR)30	−0.034	0.071
	(0.030)	(0.071)
factor(SECTOR)35	−0.041	−0.030
	(0.029)	(0.068)
factor(SECTOR)40	−0.036	0.017
	(0.045)	(0.107)
factor(SECTOR)45	−0.052*	−0.030
	(0.031)	(0.074)
factor(SECTOR)50	−0.020	0.158**
	(0.031)	(0.074)
factor(SECTOR)55	−0.012	
	(0.055)	
factor(SECTOR)60	0.00004	0.091
	(0.037)	(0.087)
factor(Year)2016	0.017	0.060
	(0.021)	(0.049)
factor(Year)2017	0.024	0.039
	(0.021)	(0.050)
factor(Year)2018	0.018	0.054
	(0.021)	(0.050)
factor(Year)2019	0.028	0.049
	(0.021)	(0.051)
factor(Year)2020	−0.026	−0.066
	(0.021)	(0.050)
factor(Year)2021	−0.007	0.035
	(0.021)	(0.051)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix 4. Regression Results for the Dummy Variables with Robust Standard Errors

Table 23: Regression results for the dummy variables included in the ROA and ROE models using robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
factor(R.Dd)1	−0.011	−0.041
	(0.020)	(0.059)
factor(SECTOR)20	−0.025	0.021
	(0.031)	(0.038)
factor(SECTOR)25	−0.013	0.053
	(0.029)	(0.036)
factor(SECTOR)30	−0.034	0.071
	(0.033)	(0.061)
factor(SECTOR)35	−0.041	−0.030
	(0.029)	(0.045)
factor(SECTOR)40	−0.036	0.017
	(0.042)	(0.087)
factor(SECTOR)45	−0.052	−0.030
	(0.034)	(0.058)
factor(SECTOR)50	−0.020	0.158**
	(0.034)	(0.076)
factor(SECTOR)55	−0.012	
	(0.034)	
factor(SECTOR)60	0.00004	0.091
	(0.034)	(0.061)
factor(Year)2016	0.017	0.060
	(0.011)	(0.042)
factor(Year)2017	0.024	0.039
	(0.021)	(0.027)
factor(Year)2018	0.018	0.054
	(0.022)	(0.047)
factor(Year)2019	0.028	0.049
	(0.027)	(0.068)
factor(Year)2020	−0.026***	−0.066
	(0.010)	(0.052)
factor(Year)2021	−0.007	0.035
	(0.011)	(0.028)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix 5. Regression Results without the variable YEAR and without Robust Standard Errors

Table 24: Regression results for the ROA and ROE models without including the variable YEAR and without using robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
ESG	0.0002	−0.0001
	(0.001)	(0.002)
LEV	−0.196***	−0.405***
	(0.048)	(0.117)
LIQ	0.005	0.007
	(0.005)	(0.011)
SIZE	−0.004	0.008
	(0.005)	(0.012)
GROWTH_A	0.014	−0.123*
	(0.029)	(0.068)
RND	−0.079***	−0.011
	(0.017)	(0.040)
factor(R.Dd)1	Yes	Yes
factor(SECTOR)	Yes	Yes
Constant	0.203*	0.008
	(0.105)	(0.249)
Observations	417	410
R^2	0.119	0.065
Adjusted R^2	0.084	0.029
F Statistic	3.390*** (df = 16; 400)	1.824** (df = 15; 394)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix 6. Regression Results without YEAR and with Robust Standard Errors

Table 25: Regression results for the ROA and ROE models without including the variable YEAR, using robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
ESG	0.0002	−0.0001
	(0.001)	(0.001)
LEV	−0.196***	−0.405***
	(0.043)	(0.132)
LIQ	0.005	0.007
	(0.006)	(0.011)
SIZE	−0.004	0.008
	(0.005)	(0.011)
GROWTH_A	0.014	−0.123
	(0.091)	(0.157)
RND	−0.079***	−0.011
	(0.006)	(0.013)
factor(R.Dd)1	Yes	Yes
factor(SECTOR)	Yes	Yes
Constant	0.203*	0.008
	(0.114)	(0.260)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix 7. Regression Results without SECTOR and without Robust Standard Errors

Table 26: Regression results for the ROA and ROE models without including the variable SECTOR and without using robust standard errors.

	Dependent variable:	
	ROA	ROE
	(1)	(2)
ESG	0.001	0.001
	(0.001)	(0.002)
LEV	−0.174***	−0.307***
	(0.040)	(0.109)
LIQ	0.004	0.001
	(0.004)	(0.011)
SIZE	−0.006	0.008
	(0.004)	(0.010)
GROWTH_A	0.001	−0.178**
	(0.029)	(0.070)
RND	−0.084***	−0.032
	(0.017)	(0.039)
factor(R.Dd)	Yes	Yes
factor(Year)	Yes	Yes
Constant	0.186**	−0.014
	(0.089)	(0.216)
Observations	417	410
R^2	0.130	0.064
Adjusted R^2	0.102	0.033
F Statistic	4.622*** (df = 13; 403)	2.078** (df = 13; 396)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix 8. Regression Results for the ROA model without ESG, LIQ, SIZE, GROWTH and without Robust Standard Errors

Table 27: Regression results for the ROA model without including the variables ESG, LIQ, SIZE, GROWTH and without using robust standard errors.

	Dependent variable:
	ROA
LEV	-0.185^{***}
	(0.047)
RND	-0.077^{***}
	(0.017)
factor(R.Dd)	Yes
factor(SECTOR)	Yes
factor(Year)	Yes
Constant	0.125^{***}
	(0.022)
Observations	417
R^2	0.138
Adjusted R^2	0.099
F Statistic	3.536^{***} (df = 18; 398)
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix 9. Regression Results for the ROE model without ESG, LIQ, SIZE, RND and without Robust Standard Errors

Table 28: Regression results for the ROE model without including the variables ESG, LIQ, SIZE, RND and without using robust standard errors.

	Dependent variable:
	ROE
LEV	-0.355^{***}
	(0.114)
GROWTH_A	-0.170^{**}
	(0.069)
factor(SECTOR)	Yes
factor(Year)	Yes
Constant	0.176^{***}
	(0.053)
Observations	410
R^2	0.084
Adjusted R^2	0.047
F Statistic	2.260^{***} (df = 16; 393)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix 10. All the companies included in the study

Table 29: All the companies included in the study

Column 1	Column 2
AAK AB	NCC AB-B SHS
AFRY AB	NIBE INDUSTRIER AB-B SHS
ALFA LAVAL AB	NOBIA AB
ASSA ABLOY AB-B	NOLATO AB-B SHS
ATLAS COPCO AB-A SHS	OREXO AB
ATRIUM LJUNGBERG AB-B SHS	ORRON ENERGY AB
AXFOOD AB	PEAB AB-CLASS B
BOLIDEN AB	RAYSEARCH LABORATORIES AB
CLOETTA AB-B SHS	ROTTNEROS AB
DOMETIC GROUP AB	SAAB AB-B
DUNI AB	SANDVIK AB
ELECTROLUX AB-B	SAS AB
ELEKTA AB-B SHS	SECURITAS AB-B SHS
ERICSSON LM-B SHS	SKANSKA AB-B SHS
FAGERHULT AB	SKF AB-B SHARES
FENIX OUTDOOR INTERNATIONAL	SKISTAR AB
FINGERPRINT CARDS AB-B	SVENSKA CELLULOSA AB SCA-B
GETINGE AB-B SHS	SWEDISH ORPHAN BIOVITRUM AB
GRANGES AB	TELE2 AB-B SHS
HANSA BIOPHARMA AB	TELIA CO AB
HENNES & MAURITZ AB-B SHS	THULE GROUP AB/THE
HEXAGON AB-B SHS	TRELLEBORG AB-B SHS
HEXPOL AB	VIKING SUPPLY SHIPS AB
HOLMEN AB-B SHARES	VOLVO AB-B SHS
HUFVUDSTADEN AB-A SHS	WALLENSTAM AB-B SHS
HUSQVARNA AB-B SHS	WIHLBORGS FASTIGHETER AB
INTRUM AB	
JM AB	
KINDRED GROUP PLC	
KINNEVIK AB - B	
LINDAB INTERNATIONAL AB	
LOOMIS AB	
LUNDBERGS AB-B SHS	
MEKO AB	
MODERN TIMES GROUP-B SHS	