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Does ESG-score Impact Stock Price Volatility in the Nordic market? An Empirical Study

Hans Merckoll and Ola Kvarberg

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Abstract

This study analyses in several dimensions the effect of ESG-score on stock price volatility in the Nordic countries during the time period 2010-2019. The effect of ESG-score on stock price volatility has been studied both with ESG-score in aggregate and with each ESG-score pillar separately, namely the E-score, S-score and G-score. This study also analyses industry specific and country specific differences in the effect of ESG-score on stock price volatility in the Nordic countries.

Comprehensive screening in Refinitiv followed by meticulous processing in R-Studio resulted in an unbalanced panel data set. All firms with available ESG-score and necessary financial parameters in Refinitiv as of 01.02.2021 listed on the Nordic exchanges were included in the study. The data sample consists of 259 firms listed on the Norwegian, Swedish, Danish and Finnish exchanges. Through scrutinizing the data sample against the assumptions of the classical OLS model, the random effects model proved to be the best estimator for the regression coefficients.

A causal relationship between ESG-score and stock price volatility has been found in several dimensions in the Nordic countries during the time period 2010-2019. ESG-score and E-score are found to negatively impact stock price volatility, while G-score and S-score failed to demonstrate an impact on stock price volatility. There are also industry specific and country specific differences in the effect of ESG-score on stock price volatility in the Nordic countries. The effect of ESG-score, S-score and G-score is negatively greater in Sweden and positively greater in Norway respectively relative to the other Nordic countries, while the effect of E-score is negatively greater in Denmark relative to the other Nordic countries. The effect of ESG-score is positively greater in industry sector industrial and negatively greater in industry sectors bank and "other". The effect of E-score is positively greater in industry sector industrial and negatively greater in industry sector "other". The effect of S-score is positively greater in industry sector industrial and negatively greater in industry sector "other". The effect of G-score is positively greater in industry sector industrial and negatively greater in industry sectors insurance and "other".

The statistically significant negative relationship between ESG-score and stock price volatility found in the Nordic countries in the time period 2010-2019 may have vast implications, in which investors, businesses, firms and politicians are served, other than ethical reasons, a rationale to implement ESG-measures.

Preface

This study was conducted by Ola Kvarberg and Hans Merckoll as a master's thesis at the University of Stavanger in the spring of 2021.

The study has been both instructive and interesting. Throughout the study, the authors have applied and learned a lot about econometrics, finance, sustainability and programming. These topics are, in the view of the authors, important skills to possess in both the present and the future.

The authors wish to acknowledge the supervisor of this study, Erlendur Ingi Jonsson, for his commitment, great guidance and for the many interesting conversations we have had along the way.

Finally, the authors wish to comment on the topicality of the study. As the awareness of sustainability measures is ever high, the authors have conducted the study using existing literature as of 31.12.2020, even though more recent articles have been used on occasions.

Disposition

Introduction
The introduction will present the background, research questions, research objectives, novelty of the data sample and delimitations of the study.

Analysis of the Nordic market
The analysis of the Nordic market will present a brief analysis of the Nordic market during the time period 2010-2019.

Theoretical framework
The theoretical framework will first thoroughly explore the concepts "ESG" and "stock price volatility". Then, a literature review relevant to the study at hand will be presented.

Data framework
The data framework will present the underlying theory necessary to conduct a regression analysis. This chapter will also provide the framework used in the methodology chapter.

Method
The method will present the methodology used in this study by presenting data sampling, variables, regression equations, hypotheses and data validation.

Descriptive statistics
The descriptive statistics will provide central tendency, variability and a correlation matrix of the data sample.

Empirical results
The empirical results will present the results found in this study. All results will be briefly commented but not discussed before the discussion and analysis chapter.

Discussion and analysis
The discussion and analysis chapter will interpret and discuss the results into a wider context by means of the underlying theory and literature review previously provided. Also, the discussion and analysis chapter discusses the research quality of the study.

Conclusion
The conclusion will present the conclusions made by the authors.

Further work
Further work will present suggestions to further work relevant to the study at hand.

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Abbreviations

Abbreviation		Meaning
ARCH	-	Autoregressive Conditional Heteroskedasticity
ASEAN	-	Association of Southeast Asian Nations
BRIC	-	Brazil, Russia, India and China
CFP	-	Corporate Financial Performance
CPI	-	Consumer Price Index
CSR	-	Corporate Social Responsibility
EBIT	-	Earnings Before Interest and Taxes
EGARCH	-	Exponential Generalized Autoregressive Conditional Heteroskedasticity
E-score	-	ESG-score Pillar Environmental
ESG-score	-	Environmental, Social and Governance score
GARCH	-	Generelized Autoregressive Conditional Heteroskedasticity
GDP	-	Gross Domestic product
GRI	-	Global Reporting Initiative
GSCI	-	The Global Sustainable Competitiveness Index
G-score	-	ESG-score Pillar Governance
OLS	-	Ordinary Least Squares
OMXCB	-	OMX Copenhagen Benchmark Index
OMXHB	-	OMX Helsinki Benchmark Index
OMXICE8	-	OMX Iceland 8
OMXSB	-	OMX Stockholm Benchmark Index
OSEBX	-	Oslo Stock Exchange Benchmark Index
RQ	-	Research Question
SPV	-	Stock Price Volatility
SRI	-	Socially Responsible Investment
SSE	-	Explained Sum of Squared
SSR	-	Sum of Squared Residuals
SST	-	Total Sum of Squares
S&P 500	-	Standard and Poor's 500
S-score	-	ESG-score Pillar Social

Symbols

$\bar{x}$ = Mean
σ^2 = Variance
σ = Standard deviation
y = Dependent variable
x = Independent variable
u = Error term
β = Regression coefficient
ϵ = Residual
R^2 = Coefficient of determination
α = The unobserved effect
Δy = Change in the dependent variable
Δx = Change in the independent variable
Δu = Change in the error term

1. Introduction

The introduction will first present the background for the study, including stating the research questions in which this study is based on. Furthermore, the objectives of the study will be presented. Finally, the novelty of the data sample and delimitations used in this study will be presented.

1.1 Background

Promoting the United Nations Sustainable Development Goals, sustainability-awareness is of increasingly importance. ESG-score, a proxy for sustainability rating, should therefore be a consideration for companies and investors in their endeavors. Therefore, understanding the relationship between ESG-score and its associated stock price volatility (SPV) is crucial to promote and ensure companies and investors willingness to make ESG-aware decisions. Existing research relating ESG-score and stock returns are mostly in the U.S., or on large capitalization firms (Borovkova & Wu, 2020). Also, there is a lack of consensus whether ESG-score and financial performance is related (Revelli & Viviani, 2015). Further research relating ESG-score and financial performance, such as stock returns, dividend policy, SPV and earnings, outside the U.S. may therefore be of great interest to the ESG-aware investor such that the plausible trade off between sustainable investing and risk in the Nordic[1] countries becomes more tangible.

There are several reasons why the interest for researching sustainability is ever high. One prominent reason is because the corporate world has a better understanding of the importance of sustainability, supported by studies that have found companies achieving high scores on sustainability reports are performing better (Kell, 2018). A major study relating the relationship between ESG and corporate financial performance (CFP) has used more than 2000 existing studies over the last four decades, and found that the vast majority of the studies proved a non-negative relationship between ESG and CFP, moreover the majority of the studies were found to have a positive relationship[2] between ESG and CFP. The same study also found that the positive effect of ESG on CFP appears to be independent with time (Friede et al., 2015).

[1]In this study, the term "Nordic countries" is the collective name for the countries: Sweden, Denmark, Norway, Finland and Iceland. States such as Greenland, Faroe Islands and Åland Islands are excluded due to their dependency with the Danish and Finnish economies.

[2]In the review study (Friede et al., 2015), the positive effect is synonym with a beneficial effect.

Implementing sustainability measures has been important in the Nordic countries. The Global Sustainable Competitiveness Index (GSCI) provided by SolAbility demonstrated that Nordic countries excels at achieving high ESG-scores (SolAbility, 2020). A key finding in the GSCI 2020 report is that while the Nordic countries all achieve top rankings on the GSCI 2020, neither the U.S. nor Brazil, Russia, India and China (BRIC) ranks above 30 on the GSCI 2020 (SolAbility, 2020). As a major part of the existing research on sustainability is focusing on the largest economies, researching sustainability in smaller economies, that also excels at achieving high sustainability ratings, may rejuvenate the interest of researching sustainability in several dimensions.

As Harry Markowitz laid the foundation for modern portfolio theory, where the relationship between expected return and market risk was conceptualized (Markowitz, 1959), an immense amount of research on risk and return has been conducted. A significant part of this research has been conducted to explore determinants and drivers for expected return and market risk. Research such as (Artmann et al., 2012), (Haugen & Baker, 1996), (Tarazi & Gallato, 2012) and (Cauchie et al., 2004) studies the determinants and drivers for expected return and (Baskin, 1989), (Schwert, 1989), (Shi et al., 2021), (Sadorsky, 2003) and (Sörensen & Deboi, 2020) studies determinants and drivers for market risk. While firm value and momentum are common determinants in the existing literature for expected return, there is a lack of consensus in the existing literature whether macroeconomic factors like interest rate and exchange rates influences the expected return. Market risk, represented as SPV (Markowitz, 1959, p. 6), has been studied in regard to what level dividend policy, institutional freedom, macroeconomic factors and other performance factors influences SPV across different markets and time periods. However, no tangible relationship between sustainability ratings and market risk, across different markets and time periods, have been made in previous research.

The limited research relating ESG-score and SPV leaves a research gap on the topic of interest. A meta-analysis has shown that there is no clear consensus whether a proper relationship between sustainability performance and financial performance exists (Revelli & Viviani, 2015). Existing research on sustainability performance and SPV is mainly limited to large capitalization firms, or firms listed in the U.S. (Borovkova & Wu, 2020). However, several studies have investigated whether Corporate Social Responsibility (CSR) and ESG serve as determinants of financial performance indicators (Giese et al., 2021), (Aouadi & Marsat, 2018), (V Matos et al., 2020), (Johansson & Fahlén, 2019) and (Benlemlih, 2019). This research has investigated CSR and ESG with financial performance indicators such as dividend yield, earnings, leverage and firm value. Research has also found a strong correlation between sustainability performance and firm size, implying larger firms are more capable of implementing sustainability improving measures (Borovkova & Wu, 2020). Furthermore, research has also found a positive relationship between dividend yield and ESG-score (Johansson & Fahlén, 2019). However, the direct relationship between ESG-score and SPV has not been researched to the same extent. Three studies from the U.S., China and India have been found, all with different conclusions: a positive, a negative and no relationship between ESG-score and SPV respectively (Tasnia et al., 2020)(Broadstock et al., 2021)(Meher et al., 2020). Therefore, this study will attempt to provide a tangible relationship between ESG-score and SPV in the Nordic countries. Following are the research questions to be answered in this study:

- RQ1: What is the relationship between ESG-score and SPV in the Nordic stock market?
- RQ2: What is the relationship between each ESG-score pillar and SPV in the Nordic stock market?
- RQ3: Are there differences in the effect of ESG-score, in aggregate or in pillars, on SPV across the Nordic countries?
- RQ4: Are there differences in the effect of ESG-score, in aggregate or in pillars, on SPV across different industry sectors in the Nordic countries?

As the objectives of this study is to discover in several dimensions the relationship between a firm's ESG-score and SPV in the Nordic countries during the time period 2010-2019, the relationship of a firm's ESG-score and SPV will be studied with the ESG-components in aggregate and with each respective component of the ESG-score, namely the E-score, S-score and G-score. The same methodology, namely using the ESG-components in aggregate and each respective component of the ESG-score, will then be used to study the effect of ESG-score on SPV across the Nordic countries and the industrial sectors. As the importance of sustainability awareness is continually growing, this study will by answering the proposed research questions may provide a tangible relationship of ESG-score and SPV to the ESG-aware stakeholder.

The data sample used in this study is novel as the research questions presented earlier has not previously been answered, and hence the data sample remains unique. The data consists of 259 firms from the Nordic exchanges. All firms are constituents of either the Norwegian, Swedish, Danish or Finnish exchanges. The data sample in this study is constructed as an unbalanced panel data set consisting of all firms listed on the Nordic exchanges with available ESG-score and necessary financial parameters for at least one year in the time period 2010-2019, in Refinitiv as of 09.02.2021. Therefore, the only exclusion of firms is due to lack of ESG-score, the necessary financial parameters and firms not being listed on the Nordic exchanges.

The most prominent delimitation[3] of this study is choosing the time period in which data is collected. Given the fact that firms in more recent years have a greater availability of ESG-scores, a larger percentage of the data sample with available ESG-score for the entire period may have been obtained if the desired time frame of the study was shorter and more recent[4]. However, given several economic recessions affecting the Nordic market in the recent years such as the oil price crash in 2014 and the COVID-19 in 2020, the authors found it necessary to use the entire decade (01.01.2010 - 31.12.2019) to get results not

[3] Delimitations are chosen limitations, made by the authors, such that the study is conducted in a feasible manner.

[4] As a consequence of some firms not being included in the entire time frame of the study due to lack of data, fewer observations of these firms are included, and hence the unbalanced panel data set.

overly affected by such economic crisis. Finally, as there is no uniform ESG-score, another delimitation to this study is using one rating provider rather than another rating provider. Consequently, as ESG-scores vary substantially for the same firms with different rating providers, the conclusions drawn in this study are made entirely with the assumption of Refinitiv's ESG-score being the "true" ESG-score.

The two main concepts of this study, namely ESG-score and SPV, are both common terms in the financial context. ESG is the abbreviated form of Environmental, Social and Governance and serves as a common proxy for the collective concept of sustainability. There are several providers of ESG-score, such as Refinitiv, Sustainalytics and MSCI. The ESG-score is a measure that commonly ranges from 0 to 100 or CCC to AAA, dependent on the rating provider. These rating providers uses different frameworks when creating their respective ESG-scores, such as: fundamental, comprehensive and specialist, and the ESG-scores therefore vary substantially among the various rating providers (Feifei Li, 2020). In this study the provider of ESG-score is Refinitive. SPV, in the financial context, is used to describe fluctuations of economic indicators (Kotze, 2005). However, a distinction between mere volatility and risk is important, as the term risk includes the likelihood of loss (Horcher, 2005). Volatility is usually described by the measures "variance" and "standard deviation". In this study, the measure for volatility is standard deviation, and consequently the term "stock price volatility" is the standard deviation of a firm's stock price return in this study.

2. Analysis of the Nordic market

In this chapter, an analysis of the Nordic market in the time period 2010-2019 is conducted such that an understanding of the development of ESG-measures and market volatility in the Nordic countries during the time period 2010-2020 is obtained.

As a precursor to an analysis of the Nordic market during the time period 2010-2019, a brief reminder of how the Nordic countries stands out from the other industrialized countries will be provided. While the Nordic countries serve as leaders of GDP/capita today, many other industrialized countries were equally or even higher ranking of GDP/capita in the 1950s (Fellmann, 2019). The intriguing part however, is that the Nordic countries have served comprehensive welfare systems, high taxation and experienced a high level of governmental influence on the respective economies (Fellmann, 2019), contrary to many other economic superpowers today. Firms subject to this study were in some parts of the data observations recovering from the financial crisis of 2007-2008, and the fact that the Nordic countries experienced a smaller recession than many other countries[1] (Fellmann, 2019) might serve as an interesting factor in the following analysis of sustainability measures and SPV. Therefore, with this in mind, the development of ESG-measures and SPV in the Nordic market during the time period 2010-2019 may be dependent on the recessions following the financial crisis in 2008 and may be different from the development of ESG-measures and SPV in other parts of the world.

2.1 The Nordic countries

The Nordic countries have small and open economies. Small and open economies are often subject to globalisation, in terms of export and import, and hence vulnerable to international economic fluctuations (Fellmann, 2019). While all Nordic countries have important industries, the available natural resources in each respective country makes the industrial sectors different. Oil, forestry, aquaculture and hydropower are the major industry segments in Norway. Timber production, iron, precision equipment, motor vehicles and processed food are major industry segments in Sweden. While timber and paper production were some of the major industries in Finland, telecommunication and electronics are the major industries in Finland today. Fishing, hydropower and aluminum are the major industry segments in Iceland. Agriculture, food industry, energy and pharmaceutical products are major industry segments in Denmark (Fellmann, 2019). The industry segments of

[1]Note that Iceland suffered an financial crisis in 2008-2011.

Denmark differ from the other Nordic countries in which the natural resources of Denmark provides a different foundation for building industries.

In 2010, the world economy was recovering from the severe financial crisis of 2008. The Nordic economies, except for Iceland, was to a smaller extent impacted by the crisis compared to other European economies (Fellmann, 2019). The Finnish economy experienced a major fall in GDP, using 10 years to recover the GDP to the pre-crisis level. Finland has, however, experienced a strong economic expansion since 2017/2018. Norway, Sweden and Denmark on the other hand, had expanding economies already in 2010 (Ekonomifakta, 2020). However, as the world economy still experienced a recession in 2010 export demand in the Nordic countries suffered. Consequently, Norway and Sweden weakened their currencies to accommodate the lower export demand (Fellmann, 2019). Since 2010, Norway, Sweden, and Denmark have mostly experienced expansions of their economies, with exceptions such as the petroleum price plummet in 2014-2015. In contrast to the other Nordic countries, Iceland suffered severely during and after the financial crisis of 2008 (Fellmann, 2019). Three major banks in Iceland collapsed as earlier expansions into foreign markets combined with major loans made the banking sector vulnerable to a financial crisis. However, the Icelandic economy recovered rapidly after 2011 (Fellmann, 2019).

2.2 Sustainability in the Nordic countries

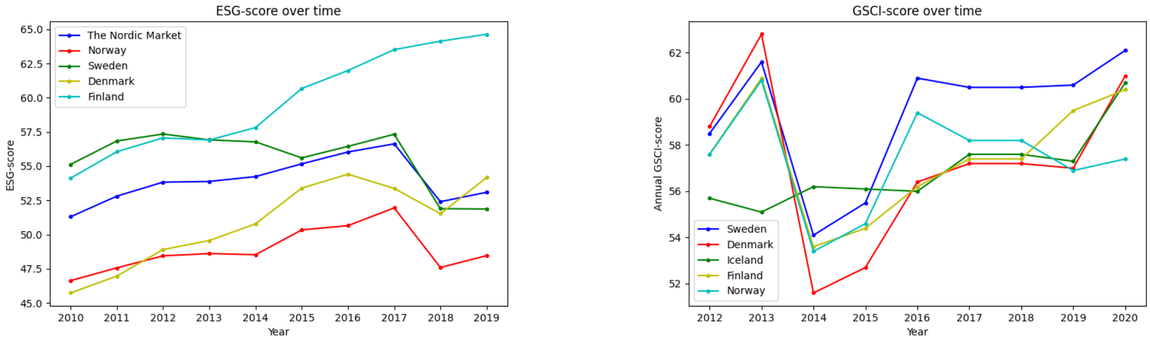
ESG as a term was first used in 2005, and was based on the already existing ideas of Socially Responsible Investment (SRI), even though SRI is mainly focused on ethical criterions such as not investing in the tobacco and weapon industries. Factors important in ESG-investing, contrary to SRI, were assumed to have financial relevance (Kell, 2018). Previous to the era of using the term ESG, measuring to what extent a firm implemented sustainability measures was strenuous. However, with the launch of the Global Reporting Initiative (GRI) in year 2000, more than 80% of major corporations uses the GRI standards in 2018. As research in 2013 found a positive relationship between ESG-reporting and financial performance, ESG-investing experienced a massive growth. This massive growth of ESG-investing is believed to be a consequence of firms with ESG-reporting systems and better transparency performs better financially in the long run (Kell, 2018). In the following, whether these findings applies to the Nordic countries as well will be discovered.

A comparison of the development of ESG-score and GSCI-score is provided in the figure below[2][3]. Figure 2.1 (a) demonstrates a steady, but modest growth of ESG-score. Figure 2.1 (a) also shows a rapid decline of ESG-score in 2017, that starts to rebound in 2018. Figure 2.1 (b) demonstrates a sharp decline in GSCI-score in 2014. Figure 2.1 (b) also shows a flat development of GSCI-score following the decline in 2014, eventually growing in 2019. Therefore, a modest growth of ESG-score with time, and no pattern in the development of GSCI-score with time is illustrated in Figure 2.1. However, Iceland seems not to follow the

[2] The plot was made by the authors of a table provided in the Appendix A.4

[3] As this study used all firms with available ESG-score during the relevant time period, Figure 2.1 (a) is the exact development of ESG-score for the data sample used in this study.

same pattern as the other Nordic countries in the development of GSCI-score.

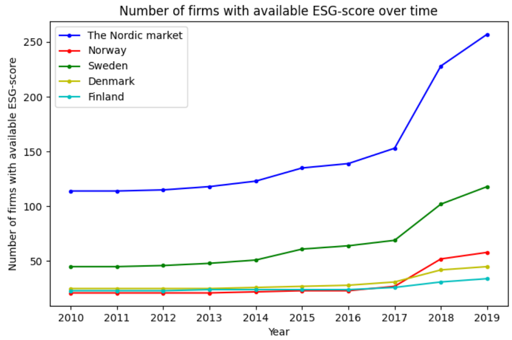


(a) ESG-score over time (b) GSCI-score over time

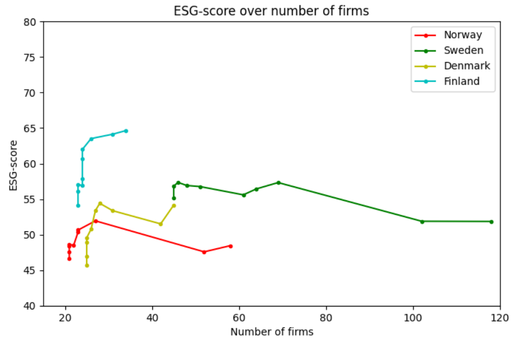
Figure 2.1: Schematic illustration of a comparison between the development of ESG-score and GSCI-score.

In Figure 2.2 (a), the development of firms with available ESG-score in the Refinitiv data base during the time period 2010-2019 is provided. The figure demonstrates by large a minuscule growth from 2010-2017 with the exception of Sweden that experienced a growth in number of firms with available ESG-score in 2014. However, Sweden and Norway both demonstrates a rapid growth in number of firms with available ESG-score in 2017, both nearly doubling the number of firms with available ESG-score from 2017-2019 (69-118 and 27-58 respectively). Denmark and Finland also experienced a substantial, but lesser growth of firms with available ESG-score from 2017-2019. The rapid growth of firms with available ESG-score during 2017-2019 may be explained by existing research, which indicates the growth of firms with available ESG-score is due to the more recent information regarding the value of ESG-reporting (Kell, 2018).

One reason for the rapid decrease in ESG-scores in 2017 might be a consequence of the massive increase in number of firms with available ESG-score at the same time. The rationale for this is that firms just starting to implement ESG-reporting have worse ESG reporting systems than firms with well established ESG reporting systems. In that case a sudden increase in number of firms with ESG-reporting systems might decrease the average score. Also, as ESG-score and firm size was found to be correlated in previous research, the decrease in ESG-scores might be explained as firms just starting with ESG-reporting systems are smaller and newer firms. Figure 2.2 (b) presents the average ESG score of all firms in the study for each respective country when the number of firms increases. There are some indications in the plot that ESG-score decreases as the number of firms increases as Sweden, Norway and Denmark demonstrates a modest but decreasing trend in average ESG-scores when the number of firms increases. However, the evidence of this trend is weak, as average ESG-score in Denmark increases slightly after experiencing a major decrease in average ESG-score with increasing number of firms and Finland only experiencing increasing ESG-scores with increasing number of firms for the entire time period.



(a) Number of firms with available ESG-score



(b) ESG-score over number of firms

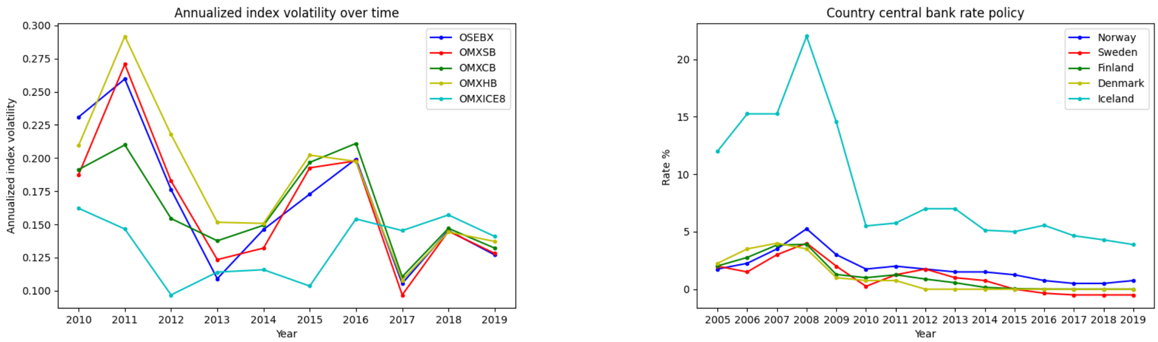
Figure 2.2: Schematic illustration of (a) development of firms with available ESG-score and (b) ESG-score over number of firms.

2.3 Market volatility in the Nordic countries

The volatility of a market may be used in measuring whether market efficiency models can be effectively used or not (Shiller, 1992, pp. 131–132). As high volatility indicates less effective models, higher uncertainty in the market is expected. Consequently, volatility may explain uncertainties and risks in a market for a given time period, relative to previous time periods. An overview of the annualized index volatility and central bank rate policy in the Nordic market during 2010-2019 is provided in Figure 2.3.

Figure 2.3 (a) uses data for the benchmark indices for each respective country such that an indication of the development in volatility reflects the weighted marked. Figure 2.3 (a) demonstrates large fluctuations in annualized index volatility in the time period 2010-2019. Sweden, Norway, Finland and Denmark by large follows the very same volatility pattern for the entire period, although with lesser spikes for Denmark. Iceland had far less annualized index volatility in the period 2010-2017 compared to the other countries, except from 2013. Similar to Denmark, Iceland had less spikes than Sweden, Norway and Finland. During 2017-2019, Iceland experienced the greatest annualized index volatility among the Nordic countries. Finally, in 2019 all five countries demonstrated very similar annualized index volatilities. Figure 2.3 (b), with the financial crisis in Iceland of 2008-2012 in mind, demonstrates a stable and similar central bank rate policy among Norway, Sweden, Finland and Denmark, even though Norway experienced a substantial increase in central bank rate from 2010-2012. Iceland, although relatively stable in the time period 2010-2019, demonstrates a far greater central bank rate compared to the other Nordic countries.

Also in Figure 2.3, the economical state of the Nordic countries after the financial crisis of 2008 is presented graphically. As highlighted in the section "The Nordic market" above, the volatility in the Nordic market peaked early in the period, namely during the recession after the financial crisis. However, a weakening of the currencies, illustrated as decreasing central bank rate, stimulated export and induced economical recovery until 2013, illustrated as decreasing annualized index volatility. However, as the petroleum prices plummeted in 2014, the annualized index volatility increased yet again until 2016, inducing a low central bank rate. In the period 2017-2019 the economies were rather stable, seen as less extreme fluctuations in annualized index volatility.



(a) Annualized index volatility over time

(b) Country central bank rate policy

Figure 2.3: Schematic illustration of (a) annualized index volatility over time and (b) country central bank rate policy.

2.4 The relationship between sustainability and market volatility in the Nordic countries

In section 2.2 and 2.3, there are indications that both annualized index volatility and GSCI-score are positively correlated across the different Nordic countries, with the exception of Iceland. To get a preliminary indication of the relationship between sustainability-ratings and volatility in the Nordic countries, a correlation matrix for the annualized index volatility and GSCI-score for each respective Nordic country is provided in the table below [4]. Norway, Sweden, Denmark and Finland demonstrates a modest negative correlation between GSCI-score and annualized index volatility, while Iceland demonstrates a rather large positive correlation between GSCI-score and annualized index volatility. Therefore, there are indications of sustainability-ratings being correlated with annualized index volatility in the Nordic countries during the time period 2012-2020.

[4]Note that this study uses ESG-score, and not GSCI-score in the later analyses. However, as firms with available ESG-score is very limited, GSCI-score is used as a more general proxy for the national sustainability rating for each country.

Table 2.1: Correlation matrix of GSCI-score and annualized index volatility

	OSEBX Volatility	OMXSB Volatility	OMXCB Volatility	OMXHB Volatility	OMXICE8 Volatility
GSCI Norway	-0.20				
GSCI Sweden		-0.25			
GSCI Denmark			-0.36		
GSCI Finland				-0.30	
GSCI Iceland					0.69

3. Theoretical framework

The theoretical framework will first thoroughly explore the key concepts to the study at hand. Then, a literature review will present relevant research in dept. Finally, a literature review summary is provided at the end, such that the key findings of the literature review are easily found.

3.1 ESG-score

ESG-investing serves as a common proxy for the collective concept of sustainability investing. The ESG-investing term has existed several decades though various epithets have been used to explain the investment strategy such as: "Socially Responsible Investment", "Ethical Investment" and "Social Investment" (Eccles N.S., 2011). As these terms might serve a different meaning for each researcher, the collective concept of sustainability, ESG, reduces the ambiguity in which it grasps all concepts in regard to environmental, social and governance.

ESG-scores tend to vary substantially with the rating provider. Research has shown examples of firms being ranked high by one provider and poorly by another provider (Feifei Li, 2020). As mentioned in the introduction, different frameworks are used when the rating providers create their ratings. A three folded framework may be described as: (Feifei Li, 2020)

1. Fundamental
    - Data is collected where publicly available. Normally, no ESG-score is created and the users must use their own methodology when implementing the information. Some providers are Refinitiv and Bloomberg (Feifei Li, 2020).
2. Comprehensive
    - Data collection is a combination of publicly available data and data is produced by the rating provider's analysts. Various metrics are then combined by a certain method resulting in a tangible ESG-score. Some providers are MSCI, Sustainalytics and ISS (Feifei Li, 2020).
3. Specialist

- Data is highly specific, such as carbon footprint and gender diversity. Some providers are TruCost and Equileap (Feifei Li, 2020).

Following, one rating provider from each part of the framework above, namely Refinitive, MSCI and TruCost, will be described briefly. The materiality matrix for Refinitiv is displayed first, and is categorized as "Fundamental" by the framework above.

ESG-score Refinitiv

Table 3.1: Refinitiv materiality matrix (Refinitiv, 2020).

Pillars	Categories	Themes	Data points	Weight method
Environmental	**Emmission**	Emissions	TR.AnalyticCO2	Quant industry median
		Waste	TR.AnalyticTotalWaste	
		Biodiversity	-	-
		Environmental management systems	-	-
	Innovation	Product innovation	TR.EnvProducts	Transparency weights
		Green revenues/R&D/ CapEx	TR.AnalyticENVRD	Quant industry median
	Resource use	Water	TR.AnalyticWaterUse	Quant industry median
		Energy	TR.AnalyticEnergyUse	
		Sustainable packaging	-	-
		Environmental supply chain	-	-
Governance	**CSR strategy**	CSR strategy		
		ESG reporting and transparency		
	Management	Structure (independence, diversity, committees)	Data points in governance category/data points in governance pillar	Count of data points in each governance category/All data points in governance pillar
		Compensation		
	Shareholders	Shareholder rights		
		Takeover defences		
Social	**Community**	Equally important to all industry groups, hence a median weight of 5 is assigned to all industy groups	-	Equally important to all industry groups
	Human rights	Human rights	TR.PolicyHumanRights	Transparency weights
	Product responsibility	Responsible marketing	TR.PolicyResponsibleMarketing	Transparency weights
		Product quality	TR.ProductQualityMonitoring	
		Data privacy	TR.PolicyDataPrivacy	
	Workforce	Diversity and inclusion	TR.WomanEmployees	Quant industry median
		Career development and training	TR.AvgTrainingHours	Transparency weights
		Working conditions	TR.TradeUnionRep	Quant industry median
		Health and safety	TR.AnalyticLostDays	Transparency weights

The Refinitive materiality matrix shows which themes and corresponding data points each

ESG-score constituent, namely the E-score, S-score and G-score, consists of in addition to how each theme is weighted (Refinitiv, 2020). Themes without corresponding data points are a consequence of lacking data for suitable proxies. While E-score and S-score are weighted by relative performance for the firms industrial sector, G-score is weighted by relative performance for the country of operation (Refinitiv, 2020). Refinitiv has some key principles in calculating their ESG-scores such as transparency simulation and ESG controversies overlay (Refinitiv, 2020). Transparency simulation is a principle that a firm's ESG-score will be negatively impacted if the firm fails to report "highly material". ESG-controversies overlay is a principle that adjusts a firm's company size to the controversy score (Refinitiv, 2020).

ESG-score MSCI

MSCI is categorized as "Comprehensive" by the three folded framework above. Following is the materiality matrix for MSCI.

Table 3.2: MSCI materiality matrix (MSCI, 2020).

ESG-pillar	Themes (10)	ESG Key Issues (35)
Environment	**Climate Change**	Carbon Emissions Product Carbon Footprint Financing Environmental Impact Climate Change Vulnerability
	Natural Capital	Water Stress Biodiversity & Land Use Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building Opportunities in Renewable Energy
Social	**Human Capital**	Labor Management Health & Safety Human Capital Development Supply Chain Labor Standards
	Product Liability	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing Community Relations
	Social Opportunities	Access to Communications Access to Finance Access to Health Care Opportunities in Nutrition & Health
Governance	**Corporate Governacne**	Ownership & Control Board Pay Accounting
	Corporate Behavior	Buisness Ethics Tax Transparency

Similarly to the Refinitiv materiality matrix, the MSCI materiality matrix shows which themes and corresponding key issues each ESG-pillar consists of. The MSCI ESG-score is a weighted average of the themes shown in the table above. In setting the weight of the themes, each key issue is assessed in expected time for risks to materialize, relative contribution to the specific industries and either positive or negative impacts on environmental and societal issues (MSCI, 2020). The ESG-score provided by MSCI is an attempt by MSCI to measure a firm's resilience to ESG risks related to financial performance. Thereby, which ESG-risks may cause severe costs for the firm in the long term, or conversely, which opportunities may occur to the firm in the long term as a result of the ESG-risks underlying the industry (MSCI, 2020).

ESG-score TruCost
TruCost is categorized as "Specialist" in the three folded framework above. The illustration below is an example of a climate specific scorecard.

Table 3.3: The Carbon Scorecard 2019 (Trucost, 2019).

Index	Carbon Footprint	Reserve Emissions	Coal Exposure	Energy Transition	Carbon Price Risk Exposure (2030)	2°C Alignment Assessment
S&P Latin America 40	7	7	1	1	6	6
S&P Emerging BMI	7	6	6	1	6	0
S&P 500 IG Corporate Bond Index	6	2	7	6	0	1
S&P/ASK 200	6	7	7	7	5	7
S&P Eurozone IG Corporate Bond Index	5	5	4	3	0	2
S&P Global 1200	5	4	6	3	3	5
S&P Developed Ex-U.S. BMI	4	5	4	2	5	5
S&P 500	3	3	3	5	2	3
S&P Europe 350	3	6	4	2	4	4
S&P/TOPIX 150	2	1	2	6	3	6
S&P 500 Carbon Efficient Index	2	3	3	5	2	3
S&P 500 Carbon Price Risk 2030 Adjusted Index	1	2	2	4	1	2
S&P 500 Fossil Fuel Free Index	1	1	1	7	1	1

The exposure ranges from 1-7 with 1 being the lowest exposure and 7 the highest exposure. 0 is undefined.

Contrary to the Refinitiv and MSCI materiality matrices, the TruCost indices are highly specific. In the illustration above, six distinct ways of measuring climate risk and opportunities, such as "Carbon Footprint", "Coal Exposure" and "Energy Transition", for a variety of indexes are shown (Trucost, 2019). In measuring exposure to carbon, the "Carbon Footprint" measures gas emissions, divided by revenues, multiplied with index weight for the close supply chain for each constituent of the index (Trucost, 2019). Similarly specific and intricate ways of measuring carbon exposure applies to the other ways of measuring climate risk and opportunities as well.

3.2 Volatility

Volatility, in the financial context, is used to describe fluctuations of economic indicators (Kotze, 2005). More precisely in the context of this study, volatility is the deviation of a stock's return from its mean return. Two common measures of SPV are variance and standard deviation of a firm's stock return.

For a sample of n observations; $x1$, $x2$, $x3$, ..., x_n, the sample mean, sample variance and sample standard deviation are defined respectively as: (Black, 1998)

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}, \tag{3.1}$$

$$\sigma^2 = \frac{\sum_{i=1}^{n} (\bar{x} - x_i)^2}{n-1}, \tag{3.2}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (\bar{x} - x_i)^2}{n-1}}, \tag{3.3}$$

Standard deviation, commonly represented as sigma (σ), is perhaps the most frequently used measure of risk for stock returns. However, the terms volatility and risk may be very different. The term risk might include the probability of loss (Horcher, 2005). This implies that the probability of loss is equally important as the magnitude of the potential loss in describing risk. Furthermore, risk may be measured by systematic and unsystematic risk. Systematic risk, is the risk of the underlying market conditions, commonly expressed as beta (β)[1] (Machdar, 2016). Diversification of stocks therefore fail to mitigate systematic risk. Unsystematic risk, on the other hand, may mitigate through diversification (Machdar, 2016). Volatility however, is merely a measure of fluctuations.

Traditionally, the assumption of independently and identically distributed stock returns with constant variance and zero mean has been prominent (Degiannakis & Xekalaki, 2004). Independently and identically distributed, in the context of stock returns, implies the stock return is independent of previous stock movements and each stock movement has identical probability distribution. Furthermore, the residuals (ϵ), were assumed constant for all independent variables (Degiannakis & Xekalaki, 2004). Constant residuals (ϵ) for all independent variables is denoted "homoscedasticity" in econometrics. Real data of stock returns has shown the above assumptions to fail (Degiannakis & Xekalaki, 2004).

The introduction of Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasitity (GARCH) addressed the issue of real data being heteroskedastic (Degiannakis & Xekalaki, 2004). Namely the conditional volatility implies that previous fluctuations affect current fluctuations. Hence, the ARCH/ GARCH models uses conditional data, in estimating current or future stock volatility.

[1] Note that this beta is unrelated to the beta associated with regression coefficients.

3.3 Literature review

This section will review in dept previous research related to the topic at hand. First, research justifying researching ESG-score and SPV will be provided. Then, previous research relating ESG-score to the Nordic countries will be provided followed by ESG-score pillar specific research. Next, research relating ESG-score and SPV to common financial parameters will be reviewed. Finally, research directly relating ESG and SPV will be explored in greater detail.

Justification of researching ESG-score and SPV
Literature has questioned the extent to which ESG-score measures sustainability as desired by investors (Drempetic et al., 2019). More precisely, what basis for an sustainable investment strategy the various ESG-score providers provide. The same literature argues the extent of congruence between what some rating providers provide in their ESG-scores and what investors want in their ESG-scores is not full-fledged. Furthermore, literature also argues that sustainability performance of a firm is not well designated by the firm's ESG-score, as data availability and capability of providing ESG data is dependent of firm size[2] (Drempetic et al., 2019). Therefore, it is crucial for an investor to understand what an ESG-score provider in fact measures with the ESG-score, how the respective scores are created and which firms that has ESG-scores.[3]

As businesses adapt ever more social responsibility, the literature has for decades demonstrated various views regarding in what way conducting business includes a social responsibility. Literature has demonstrated this, such as; business must strive to achieve social responsibility in addition to other parameters such as profit and business must be conducted such that it functions in society (Balasundaram, 2009). As the extent to which conducting business includes a social responsibility remains a qualitative inquiry, no perfect answer may be given.

A study relating a firm's earnings to its SPV has been conducted on firms contained in the Center for Research in Security Prices in the time period 1952-2001 (Sadka, 2007). The study indicates that whilst expected earning and expected return is strongly correlated, the identification of the exact contribution of each component constituting SPV is intricate. Therefore, further research in regards to SPV might reduce the uncertainty of components constituting SPV.

ESG-score in the Nordic countries
The Global Sustainable Competitiveness Index 2020 (GSCI 2020) presents a comprehensive list of sustainability competitiveness in 180 countries. The report finds that the top twenty constituents on the global sustainability competitiveness list are led by Nordic and Baltic countries. The sustainability competitiveness model is build upon different levels, where the previous level affects the next level. Natural Capital serves as the fundamental level of the hierarchy, and contains factors such as: "fossil energy prevalence", "population

[2]Meaning an undesired firm size bias might occur to the unaware investor.

[3]How the various rating providers create their ESG-scores can be found in chapter 3.1

density" and "land at risk of desertification". Next, Resource Intensity contains factors such as: "CO2 emissions / GDP — CO2 emissions / capita", "waste / GDP — waste / capita" and "hazardous waste per GDP". Then, Social Capital contains factors such as: "income quantile ratio", "human rights index" and "women in management positions". Then, next to last is Intellectual Capital, containing factors such as: "cost of business start-up", "primary education completion" and "pupil gender ratio". Finally, the Governance Performance contains factors such as: "manufacturing value added", "bank capital-asset ratio" and "access to electricity" (SolAbility, 2020). The scores ranges from 0-100 with higher being better. The table below summarizes the relevant findings in the report for this study:

Table 3.4: The ranking of the Nordic countries on the GSCI 2020 (SolAbility, 2020)

Country	**Rank / Score**			
	Global Index	**Resource Efficiency**	**Social Capital**	**Governance Performance**
Sweden	1 / 62.1	9 / 63.7	3 / 61.6	77 / 52.5
Denmark	2 / 61.0	6 / 65.6	14 / 57.8	14 / 63.1
Iceland	3 / 60.7	75 / 52.0	1 / 65.4	19 / 61.2
Finland	4 / 60.4	50 / 55.3	4 / 61.6	24 / 60.3
Norway	9 / 57.7	122 / 46.4	2 / 65.0	71 /52.8

For the 2020 Global Index, the Nordic countries are ranked as such: Sweden = 1 (62.1), Denmark = 2 (61), Iceland = 3 (60.7), Finland = 4 (60.4) and Norway = 9 (57.7) [4] (SolAbility, 2020). Furthermore, each country's respective ranking and score for the Resource efficiency, Social Capital and Governance Performance can be found in the table provided above.

ESG-score pillars

An article provided by MSCI found that time horizon may serve as a prominent indicator of ESG-score pillar significance (Giese et al., 2021). G-score was found to be more important in the short run, as the pillar is highly affected by event risks[5]. On the other hand, in the long term, E-score and S-score proved to be more important as risk of performance degrading issues culminates, such as carbon emissions. The article provided by MSCI also investigated the ESG-score pillars related to financial performance. The ESG-score pillars were measured by strength of significance against three "economic transmission channels", namely: a cash-flow channel, idiosyncratic risk channel and valuation channel. The study found that over a time period of one year G-score demonstrated the strongest significance, and S-score demonstrated the weakest significance (Giese et al., 2021).

Furthermore, the article provided by MSCI also analyzed sectoral differences. The sample used for the study of sectoral differences was the MSCI World Index in the time period 2006-2019, and sectors were classified according to the Global Industry Classification Standard (GICS). The study found that G-score was the prominent differentiator on average

[4]The numbers in parenthesis are the respective scores.

[5]Event risks, in the context of affecting ESG-score, may refer to scandals such as fraud.

across all industries (Giese et al., 2021). Furthermore, the study found that G-score was most important to the financial sector, E-score was most important to the materials sector and S-score was most important to the energy sector. Also, the article provided by MSCI analyzed ESG-score pillars against stock price risk and stock price performance. The study found that G-score demonstrated the most variation in stock-price risk, indicating issues such as fraud might affect stock prices immediately. Finally, the study found that for stock-price performance, the aggregated ESG-score, created by an industry weighting scheme, was more profound than each ESG-score pillar (Giese et al., 2021).

ESG-score influence

The influence of firm size on ESG-score with assets retrieved from the Thomson Reuters ASSET4 database has been researched. A significant positive correlation between a firm's ESG-score and firm size was found. The researchers suggests organizational legitimacy may elucidates this relationship. Organizational legitimacy in this context refers to the expectations of the firm to act on values inherent to society, thus implying the necessity for large firms to include ESG-improving measures. However, as there are limitations to the ASSET4 database, the researchers does not generalize the findings for all ESG-scores (Drempetic et al., 2019).

Also, other research presents the same results, in which a sample of 727 firms in 22 countries from 2006-2017 showed that firm size enhances the growth of a firm's ESG-score over time (Crespi & Migliavacca, 2020). Furthermore, research using 4000 firms in 58 countries from 2002-2011 found that ESG-controversies are related with greater firm value (Aouadi & Marsat, 2018). ESG-controversies are defined by the same research as news stories exploiting obvious violations of the three ESG pillars. However, this significant and positive direct effect of ESG-controversies on firm market value disappears as corporate social performance (CSP) is added as an interaction term.[6]

Research relating ESG and dividend policy with assets retrieved from the Stoxx Euro 600 from 2000-2019 concluded that firms categorized as "more sustainable" yields a more stable dividend payout. This research however, was mainly focused on lager firms in Europe (V Matos et al., 2020). Furthermore, a study of 3040 U.S. firms from 1991-2012 found that socially responsible firms have a higher dividend payout (Benlemlih, 2019). Also, the same study show that in adjusting dividend payout, socially responsible firms adjust slower than socially irresponsible firms. Finally, a study of 117 Nordic firms from 2008-2018 found that sustainability and dividend policy had a positive relationship (Johansson & Fahlén, 2019). More precisely, ESG-score and dividend payout ratio demonstrated a significant positive relationship, while ESG-score and dividend yield demonstrated no significant relationship.

Research relating ESG-score and leverage has been conducted on 119 firms listed on the Russell 100 index (Nega, 2017). The study indicated no significance between a firm's ESG-score and leverage. However, the same research refers to a study's findings of a significant positive relationship between ESG-score and leverage in a research conducted on

[6] The interaction effect in a regression occurs when an regressor's effect on the regrassand is affected by other regressors.

the Indonesian Stock Exchange (Maskun, 2013). This ambiguity is confirmed as previous research that conducted a comprehensive literature review connecting ESG-score and the financial capital structure (leverage) of firms, (Cantino et al., 2017) found no consensus between ESG-scores and leverage.

No direct literature relating ESG-score and firm earnings volatility was found. However, research suggests CSR (as a proxy for ESG) firms has a dissimilar earnings management compared to other firms (Gao & Zhang, 2015). Furthermore, the same study presumes firms that categorized as smoothers[7] has more stable earnings, and hence less earnings volatility.

Stock price volatility influence

A study of U.S. firms from 1857 to 1987 found, with weak evidence, that SPV may be predicted by macroeconomic risks (Schwert, 1989). The study also concluded that trading activity and SPV were related, in which a positive relation between SPV and trading days were found. Furthermore, the study also found that SPV increased by a number of factors during the Great Depression, indicating a recession might greatly affect SPV. Also, another study on the Association of Southeast Asian Nations (ASEAN) from 1991 to 2014 found that indicators associated with institutional freedom such as: regulation, size of government, sound money and trade freedom all negatively impacts SPV (Shi et al., 2021). Finally, a study from 1986 to 2000 on technology firms in the U.S. found a significant relationship between conditional volatility and price movements in oil, term premium and consumer price index (CPI) (Sadorsky, 2003).

Research relating stock price dynamics and firm size has been conducted on a sample consisting of 251 firms listed on then AMEX-NYSE (American Stock Exchange - New York Stock Exchange) in the time period 1962-1989 (Cheung & Ng, 1992). The study found that, by implementing EGARCH[8], conditional stock price volatility is negatively related to firm size. Furthermore, the same study found that the relation between stock price dynamics and firm size differ in strength with time. This might be explained by Baskin (1989), who found that firms greater in size tend to be more diversified, and hence more resilient to vicissitudes of individual markets (Baskin, 1989).

A study of 2344 firms in the U.S. found a strong inverse relationship between dividend yield and SPV (Baskin, 1989). In line with Baskin (1989), a study of 52 Swedish listed firms during 2010-2019 also found a negative relationship between dividend yield and SPV (Sörensen & Deboi, 2020). However, a study on dividend policy and share price volatility of 40 firms listed on Johannesburg Stock Exchange (JSE) in the time period 2007-2016 found a positive relationship between dividend yield and share price volatility (Pelcher, 2019). Another study from the U.K. also found that dividend yield had a positive relation to SPV while payout ratio had a negative relationhip with SPV (Hussainey et al., 2011). Finally, a study of 173 firms listed on the Australian exchanges in the period 1972 to 1985 found no significance in the relationship between SPV and dividend policy (Allen & Rachim, 1996).

[7]Smoothing earnings is a technique to flatten earning fluctuations (Michelson et al., 2011).

[8]Exponential Generalized Autoregressive Conditional Heteroskedasticity

The study of 173 firms listed on the Australian exchanges in the time period 1972-1985 also found that leverage and earnings volatility have a positive impact on SPV (Allen & Rachim, 1996). Furthermore, the same study also found a negative relationship between earnings volatility and payout ratio, implying firms with higher earnings volatility consequently pays less dividends and thus are regarded more volatile. Finally, the above mentioned study of 173 firms listed on the Australian exchanges in the time period 1972-1985 found that payout ratio, firm size, leverage and earnings volatility are major indicators of SPV. The study on the Australian exchanges is therefore in line with Baskin (1989) on how SPV is related to underlying risks in a firm's markets and earnings. Furthermore, a number of studies have found that under the same operating risk, greater financial leverage increases SPV (Hussainey et al., 2011), (Allen & Rachim, 1996) and (Sörensen & Deboi, 2020), which is also in line with Baskin (1989). However, a study of 500 firms, intended to reflect the S&P 500, retrieved from the Value Line Investment Survey database found some contradicting results in that leverage negatively impacts SPV (Profilet, 2013).

ESG-score and SPV

Research directly relating ESG-score and SPV is very limited. Existing research is mainly on large capitalization firms in the U.S., Asia, Australia and EU or on firms listed in the U.S. (Borovkova & Wu, 2020). The above mentioned study found that high ESG-score is related to lower return volatility in all four regions. Furthermore, a study of 37 U.S. banks from 2013-2017 found a positive correlation between ESG-score and SPV (Tasnia et al., 2020), indicating the relationship between ESG-score and SPV might be industry specific. Recently, a Chinese study from the COVID-19 period, found a negative relationship between ESG-score and SPV (Broadstock et al., 2021). Another recent study, from India, failed to prove any effect of ESG-score on SPV (Meher et al., 2020). Research also has argued that CSR, as a proxy for ESG, might increase market volatility in that it increases stock market noise (Orlitzky, 2013). Stock market noise, in the financial context, refers to information other than actual underlying market information that distorts the market behavior. Finally, a study on the relationship between idiosyncratic volatility and CSR concluded that CSR reduces flexibility in responding to productive shocks, hence CSR companies are exposed to higher idiosyncratic volatility (Becchetti et al., 2015).

3.3.1 Literature review summary

In the table below, a summary of the literature review is provided.

Table 3.5: Literature review summary

Article	**Time period**	**Exchange**	**ESG-rating provider**	**Key findings**
Drempetic et al., 2019	2008-2010	3828 Global firms	Refinitiv	Significant positive correlation between ESG-score and firm size.
Balasundaram, 2009	-	Case study from Bangladesh	-	No consensus in whether conducing business includes a social responsibility.
Sadka, 2007	1952-2001	CRSP	-	Expected return and expected earnings are strongly correlated.
SolAbility, 2020	2019	Global	Worlds Bank UN Available information	The top twenty constituents on the global sustainability competitiveness list are led by Nordic and Baltic countries.
Giese et al., 2021	2006-2019	Global	MSCI	G-score has the most significant effect on financial performance in the short run, while S-score and E-score increases their significance with longer time periods.
Crespi and Migliavacca, 2020	2006-2017	727 Global Financial firms	MSCI	Firm size enhances the growth of a firm's ESG-score over time.
Aouadi and Marsat, 2018	2002-2011	4312 firms from 58 countries	Refinitiv	ESG-controversies are related to greater firm value.
V Matos et al., 2020	2000-2019	Large european fims	Refinitiv	More sustainable firms yields a more stable dividend payout.
Benlemlih, 2019	1991-2012	3040 US firms	MSCI	Socially responsible firms have higher dividend payouts.
Johansson and Fahlén, 2019	2008-2018	117 Nordic firms	Refinitiv	Significant positive relationship between ESG-score and dividend payout ratio.
Nega, 2017	2015	119 firms from Russell 100	KLD from Bloomberg	No relationship between leverage and ESG-score.

Maskun, 2013	2009-2011	Indonesian stock exchange	-	Positive relationship between leverage and ESG-score.
Cantino et al., 2017	-	-	-	No consensus whether there are a relationship between ESG-score and leverage.
Gao and Zhang, 2015	1993-2010	2022 US firms	KLD	CSR firms have a dissimilar earnings management compared to other firms.
Schwert, 1989	1857-1987	US	-	With weak evidence, SPV may be predicted by macroeconomic risks.
Shi et al., 2021	1991-2014	ASEAN pluss three countries	-	Institutional freedom indicators have a negative impact on SPV.
Sadorsky, 2003	1986-2000	Technology firms in US.	-	Positive relationship between SPV and oil price movements, term premium, and consumer price index.
Cheung and Ng, 1992	1962-1989	251 firms at AMEX-NYSE	-	By implementing EGARCH, conditional SPV is negatively correlated to firm size.
Baskin, 1989	-	2344 firms in US	-	Large inverse relationship between SPV and dividend yield.
Sörensen and Deboi, 2020	2010-2019	52 firms on Swedish Stock Exchange	-	Inverse relationship between SPV and dividend yield.
Pelcher, 2019	2007-2016	40 firms at Johannesburg Stock Exchange	-	Positive relationship between SPV and dividend yield.
Hussainey et al., 2011	1998-2007	UK public listed firms	-	Negative relationship between SPV and dividend yield, negative relationship between SPV and payout ratio.
Allen and Rachim, 1996	1972-1985	173 firms at Australian exchanges	-	No significant relationship between SPV and dividend policy.
Profilet, 2013	-	599 firms in US	-	Negative effect from leverage on SPV.
Borovkova and Wu, 2020	2010-2018	2000+ Global large cap firms	Refinitiv	ESG-score is related to return volatility in the U.S. Asia, Australia and EU.

Tasnia et al., 2020	2013-2017	37 US Banks	Refinitiv	Positive correlation between ESG-score and SPV.
Broadstock et al., 2021	2020	Chinese market CSI300 stocks	SynTao Green Finance	Negative relationship between SPV and ESG-score during the covid-19 pandemic.
Meher et al., 2020	2014-2018	43 firms at NIFTY 100 Enhanced ESG India	Yahoo Finance based on Substainalytics	No effect from ESG-score on SPV.
Orlitzky, 2013	-	-	-	CSR might increase market volatility in that it increase stock market noise.
Becchetti et al., 2015	1992-2010	4383 US listed firms	KLD	CSR reduces flexibility in responding productive to shocks, hence CSR companies are more exposed to ideosyncratic volatility.

4. **Data framework**

The data framework will provide the fundamental theory used when conducting the regression analyses in this study. First, the various data samples relevant to this study will be reviewed. Then, regression analysis, including variables, the method used to estimate the regression coefficients and the various regression models will be explained.

4.1 Data sample construction

A data sample is a set of observations the researcher extracts from a population of data and then generalizes to the population. A population, or the data universe, is a pool of data in which the researcher may extract a data sample (Neuman, 2014, p. 247). As a data sample may be constructed in a variety of ways, certain features may need careful consideration (Wooldridge, 2014, p. 5). Following are four common data structures reviewed:

Cross sectional data
Cross sectional data consists of variables measured at a single point in time[1]. Often, cross sectional data may be assumed obtained from random sampling, which may be beneficial if the data gathered is desired to represent the entire population. A key violation of random sampling however, is sampling units relatively large to the population as this might result in the violation of assuming independent draws (Wooldridge, 2014, pp. 5–6).

Time series data
Time series data consists of variables measured over a time period. A major aspect of time series data, that must be taken into consideration, is that data rarely stay independent with time. Furthermore, the frequency in which data is collected may be important as many economic indicators follow certain seasonal patterns. Usually, daily, weekly, monthly, quarterly and annually serves as the most common frequencies in measuring economic indicators (Wooldridge, 2014, p. 8).

Pooled cross sections
Pooled cross sections may consist of both cross sectional and time series data. A pooled cross section may be constructed such that two years of cross sectional data with different data samples is combined (Wooldridge, 2014, p. 9). Pooled cross sections may therefore be efficient in measuring effects of a major impact on economic indicators over some years of

[1]Minor differences in time may be ignored if appropriate to the data sample (Wooldridge, 2014, p. 6).

interest.

Panel data
Panel data has for each constituent of the cross sectional data, a time series (Wooldridge, 2014, p. 10). The distinction between observation and constituent is crucial, as each constituent is likely to have several observations. A panel data set may have missing values for some cross sections in some time periods. The panel data set is depicted as an unbalanced panel data set in the case of containing missing values for some cross sections (Wooldridge, 2014, p. 394).

4.2 Regression analysis

Regression analysis is the method of explaining variability of a dependent variable in terms of independent variables. Regression analysis may be either simple or multivariate. A simple linear regression model has one independent variable and hence a change in the independent variable has a constant change on the dependent variable (Pedhazur & Schmelkin, 1996, p. 371). A multivariate regression analysis has two or more independent variables. Also, in a multiple regression analysis the effect of other variables may be controlled. Thus, a multiple regression analysis results in a more accurate estimation of the regression coefficients (Wooldridge, 2014, p. 57). Finally, the amount of variation of the dependent variable explained by the regression model (R^2), will likely increase as a result of including more independent variables (Wooldridge, 2014, p. 83).

4.2.1 Variables

A multivariate regression model may be constructed as in the formula below: (Wooldridge, 2014, p. 57)

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n + u \tag{4.1}$$

In the equation above, y is the dependent variable to be explained by the independent variables, x_1 and x_n. The regression coefficients, or the betas (β), are the slopes of the effect of the independent variables on the dependent variable. The error term is denoted as u (Wooldridge, 2014, p. 57).

The dependent and independent variable
The dependent variable is the variable to be explained by the regression model (Wooldridge, 2014, p. 570). The dependent variable is also commonly denoted as the regressand. The independent variables are the variables explaining the change of the dependent variable (Neuman, 2014, p. 181). The independent variables are commonly denoted as the regressors.

Control variable
A control variable is a type of an independent variable. However, one might categorize an independent variable as a "control variable" when the dependent variable is under the

researcher's control (Wooldridge, 2014, p. 19). Including control variables might serve as a tool to strengthen the causality of a regression as the effect of the control variable is included. Therefore, the causal effect between the independent and dependent variables might become less contaminated if control variables are added correctly (Hünermund & Louw, 2020).

Dummy variable
Dummy variables are variables categorized as binary. Therefore, the variable coefficient is multiplied by either 1 or 0, namely having an effect or not. Dummy variables are useful in describing the effect of factors such as gender, country and industry differences. A dummy variable trap may occur when dummy variables are included unconsciously, such as two dummy variables for gender.[2] Therefore, a base group is usually chosen such that the intercept (β_0) is for one group (the base), and including the dummy variables demonstrates the difference between the two groups (Wooldridge, 2014, p. 184).

Interaction term
Interaction terms are independent variables that have been constructed by multiplying two other independent variables. Commonly, a dummy variable is multiplied with an independent variables such that the difference between the two variables can be observed (Wooldridge, 2014, p. 573).

4.2.2 Coefficient of determination (R^2)

In measuring whether the variables used are well suited in estimating the dependent variable, the coefficient of determination, commonly denoted as R^2, is commonly used in regression analysis. The formula for calculating R^2 is shown in the equation below: (Wooldridge, 2014, p. 34).

$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} \tag{4.2}$$

SSR is the sum of the squared residuals and SST is the total sum of squares. Therefore, R^2 is defined as the ratio of variation in the dependent variable that is explained by the estimated model (Nagelkerke et al., 1991). Consequently, when SSR is equal to zero, $R^2 = 1$ and the model explains the variance in the dependent variable perfect. Similarly, when SSR is equal to SST, $R^2 = 0$ and the model does not explain the variance in the dependent variable at all.

What size of R^2 is acceptable is a qualitative inquiry, as some regression models have to a large extent unknown determinants. For cross-sectional analysis, a low R^2-value is common (Wooldridge, 2014, p. 35).

[2] Two dummy variables for gender, one for female and one for male, would result in perfect collinearity (Wooldridge, 2014, p. 184).

4.2.3 Ordinary Least Squares (OLS)

Ordinary Least Squares (OLS) is a method of estimating the regression coefficients by minimizing the sum of squared residuals (Studenmund, 2014, p. 37). Two key justifications of using OLS is the sum of residuals is zero and OLS, under a set of assumptions, makes the best estimators obtainable (Studenmund, 2014, p. 38). Furthermore, there is an OLS approach suitable to panel data, namely pooled OLS. In a pooled OLS, the data is pooled across time and across the cross-sectional units (Wooldridge, 2014, p. 360).

Assumptions of OLS
Using the classical model of OLS to estimate the regression coefficients, seven assumptions must hold such that the estimators are optimal[3] (Wooldridge, 2014, p. 133). The assumptions of the classical OLS model are reviewed in greater detail in this chapter.

The classical assumptions are: (Studenmund, 2014, p. 98)

1. The regression model is linear, is 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 (no serial correlation).
5. The error term has a constant variance (no heteroskedasticity).
6. No explanatory variable is a perfect linear function of any other explanatory variables (no perfect multicollinearity).
7. The error term is normally distributed (this assumption is optional but usually is invoked).

Following, the assumptions will be briefly reviewed.

The regression model is linear, is correctly specified, and has an additive error term.
The regression model is linear in parameters, when the coefficients (β) are constants[4] (Wooldridge, 2014, p. 71). Therefore, nonlinear coefficients, unable to be transformed such as the the natural logarithm, violates assumption one (Studenmund, 2014, p. 98).

The error term has a zero population mean.
Zero conditional mean, as the most important assumption for an unbiased OLS, mean the expected value of the error term is zero. The expected value of the error term is not zero when omitting important factors correlated with the independent variables. When the regression model has zero conditional mean, the variables are often categorized as exogenous[5]

[3]The assumptions of OLS differ some in how complicated the model of OLS one uses.
[4]A parameter is constant when neither multiplied nor divided by other parameters and only raised to the power of 1.
[5]An exogenous independent variable is an independent variable not correlated with the error term (u) (Wooldridge, 2014, p. 571).

(Wooldridge, 2014, pp. 74–75).

All explanatory variables are uncorrelated with the error term.
A correlation between independent variables and the error term may result in over estimating the variance in the dependent variable caused by the independent variables. In other words, some variation in the dependent variable caused by the error term is explained through the independent variables. Violation of assumption three commonly occurs when omitting variables correlated with the independent variables (Studenmund, 2014, p. 101).

Observations of the error term are uncorrelated with each other (no serial correlation).
A serial correlation of the error term violates assumption four. Serial correlation of an economic indicator, implies a dependency between two observation. As serial correlation is common for time series, where incidents may impacts economic indicators for a shorter or longer time period, obtaining zero serial correlation becomes difficult to avoid (Studenmund, 2014, p. 101).

The error term has a constant variance (no heteroskedasticity).
The regression model violates assumption five, non constant variance, when the error term (u) has varying variance for different values of the independent variables (Wooldridge, 2014, p. 81). A violation of assumption five therefore implies heteroskedasticity. Finally, when the homoskedasticity assumption holds, the OLS estimators have the least variance (Wooldridge, 2014, p. 134).

No explanatory variable is a perfect linear function of any other explanatory variables (no perfect multicollinearity).
Non-perfect collinearity, in contrast to perfect collinearity, is almost ineluctably in a multivariate regression analysis as the independent variables are likely to be correlated. As a result, a precise specification of the regression model is necessary in avoiding perfect collinearity, as including the same variable with different units, and hence a perfect collinearity between the two variables, violates assumption three (Wooldridge, 2014, pp. 72–73).

Normality
The normality assumptions states that the error term (u) is independent of the independent variables, has a zero mean and is normally distributed. Therefore, with the normality assumption, hypothesis testing may be conducted as obtaining precise t-statistics and F-statistics. This final assumption may be excluded if the sample size is sufficiently large (Wooldridge, 2014, p. 134).

4.2.4 Regression models

Pooling cross sections across time allows observing the same object of interest over a time period (Wooldridge, 2014, p. 360). Therefore, a pooled OLS may be suitable, under certain circumstances, when studying the cross sectional effect of an object of interest over time. However, an intricate problem relevant to many panel data sets, namely the unobserved effect, may cause pooled OLS to become an invalid estimator. The unobserved effect, usually represented as the variable α_i, is also commonly denoted as the "fixed effects". Therefore, for panel data, namely a data set with both cross-sectional and time-series features, effects constant of time, affecting the dependent variable is called the unobserved effect. Furthermore, the error term (u) is commonly named the "idiosyncratic error" (u_{it}), as it contains the unobserved factors affecting the dependent variable and changing with time. Therefore, for a panel data set containing unobserved effects, a simple regression can be modelled as shown below, where y_{it} is the dependent variable i for time t, β_0 is the intercept, $\beta_1 x_{it}$ is the independent variable's effect on the dependent variable, α_i is the unobserved effect on the dependent variable and u_{it} is the idiosyncratic error term (Wooldridge, 2014, p. 372).

$$y_{it} = \beta_0 + \beta_1 x_{it} + \alpha_i + u_{it} \tag{4.3}$$

In estimating $\beta_1 x_{it}$ one must assume the unobserved effect α_i is uncorrelated with the independent variable x_{it} in avoiding biasedness.[6] (Wooldridge, 2014, p. 372). Therefore, several methods addressing the issue of the unobserved effect may be used in order to get a valid regression model.

Following, three methods addressing the issue of the unobserved effect in panel data, namely first differencing, fixed effects transformation and random effects, will be presented.

First differencing

First differencing is a method of eliminating the unobserved effect from the estimated model, while obtaining the change/ intercept of the dependent variable between two time periods. In the formulas below, the estimation models of the dependent variable for two time periods are shown as well as the resulting new estimator model. By subtraction, the unobserved effect disappears, and the remaining estimator model is the change between the two periods. In the formulas below y_{i2} and y_{i1} are the dependent variables in time period two and one respectively, β_0 are the intercepts, α_i is the time constant, unobserved effect and u_{i2} and u_{i1} are the error terms for period two and one respectively (Wooldridge, 2014, p. 372). The estimation model for time period two then becomes[7]: (Wooldridge, 2014, p. 372)

$$y_{i2} = \beta_0 + \beta_1 x_{i2} + \alpha_i + u_{i2} \tag{4.4}$$

The estimation model for time period one becomes:

$$y_{i1} = \beta_0 + \beta_1 x_{i1} + \alpha_i + u_{i1} \tag{4.5}$$

Subtracting formula 4.5 from formula 4.4, the first difference estimation model becomes:

$$\Delta y = \beta_1 \Delta x_1 + \Delta u_i \tag{4.6}$$

[6] When the unobserved effect α_i and the independent variable x_{it} is correlated, it is commonly denoted "heterogeneity bias" (Wooldridge, 2014, p. 372).

[7] All three formulas are gathered from the same source.

Consequently, the first difference estimator model gives the difference of the dependent variable, between time period one and two whilst removing the unobserved effect.

Fixed effects transformation

Fixed effects transformation is another method of eliminating the unobserved effect. In addition to eliminating the unobserved effect, all constant independent variables are eliminated as well (Wooldridge, 2014, p. 387). Similar to the first differencing method, subtraction of two formulas eliminates the unobserved effect. However, in contrast to merely subtracting the cross sectional models of two time periods, the fixed effects transformation subtracts the average of the regression model from the regression model. As the unobserved effect is constant with time, it remains unchanged in both the ordinary regression model and the average regression model. Therefore, when subtracting the two formulas, the unobserved effect gets eliminated. The formulas below illustrates the fixed effects transformation (Wooldridge, 2014, p. 388)[8], where formula 4.7 is a regression model containing the unobserved effect for a time period denoted as t:

$$y_{it} = \beta_1 x_{it} + \alpha_i + u_{it} \tag{4.7}$$

Formula 4.8 is the result of averaging the regression model

$$\bar{y}_i = \beta_1 \bar{x}_i + \alpha_i + \bar{u}_i \tag{4.8}$$

Formula 4.9 is the resulting model after the fixed effects transformation, namely the subtraction of formula 4.8 from formula 4.7.

$$y_{it} - \bar{y}_i = \beta_1 (x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \tag{4.9}$$

Key to this transformation is the elimination of the unobserved effect. As the unobserved effect is eliminated, one may use pooled OLS. For a regression model containing several independent variables, the idiosyncratic error term u_{it} must stay uncorrelated with the independent variables to obtain an unbiased model (Wooldridge, 2014, p. 388).

Fixed effects transformation with an unbalanced panel data set

The fixed effects method may also be applied to unbalanced panel data sets. In taking the average of the original regression model, the number of observations used is corresponding to the number of time periods for the respective constituent. Having an unbalanced panel data set does not cause issues, given that the reason for the missing values is not correlated with the idiosyncratic errors (Wooldridge, 2014, p. 394).

Random effects

The random effects method is different from first differencing and fixed effects in that the unobserved effect is assumed uncorrelated with all independent variables. Therefore, contrary to the first differencing and fixed effects, elimination of the unobserved effect would result in inefficient estimators. The formula below demonstrates a random effects model, where the unobserved effect is assumed uncorrelated with all independent variables, where all variables are defined similarly to formula (4.4) (Wooldridge, 2014, p. 395).

[8] All three formulas are gathered from the same source.

$$y_{i1} = \beta_0 + \beta_1 x_{i1} + \alpha_i + u_{i1} \tag{4.10}$$

Key to this formula, when applying the random effects, is the assumption of no correlation between the random effect and the independent variables. This relationship can be depicted as such: (Wooldridge, 2014, p. 395)

$$Cov(\beta_1 x_{i1}, \alpha_i) = 0 \tag{4.11}$$

Therefore, for the random effects method to be ideal, all assumptions needed for the fixed effects method must be met, in addition to the uncorrelation between the unobserved effect and the independent variables for all time periods (Wooldridge, 2014, p. 395). The estimation of the independent variable may, however, be troublesome, in that using a composite error term[9] causes serial correlation in the composite error term, as the unobserved effect is constant with time. Therefore, generalised least squares (GLS), in contrast to OLS, may be used to address the issue of autoregressive serial correlation (Wooldridge, 2014, p. 396).

4.2.5 Choice of regression model

In the special case of having exactly two time periods, the estimates of the first difference and fixed effects transformation are identical. For more than two time periods, which method to implement is based on the respective model estimator's efficiency. The efficiency of the estimators are determined by the idiosyncratic error's serial correlation. As the idiosyncratic error is serial correlated, first differencing is the more efficient method. The random effects method are chosen over the fixed effects method when a prominent independent variable is constant over time, as the fixed effects model eliminates time constant variables (Wooldridge, 2014, p. 392). Therefore, as the random effects model does not allow arbitrary correlation between the unobserved effect and the independent variables, the random effects model is mostly used when the assumption of no correlation between the unobserved effect and independent variables (Wooldridge, 2014, p. 399).

In choosing between the fixed and random effects models, a Hausman specification test is commonly used. One logical and one statistical consideration must be taken into account. The logical consideration is whether a_i is considered randomly drawn, from an independent and identically distributed distribution and the statistical consideration is a comparison of the bias and efficiency of the estimators when estimating the coefficients (β) (Hausman, 1978). However, a common problem with the two considerations is that the two considerations implies different conclusions. In other words, the logical consideration may imply that the random effects is the appropriate model, while the statistical consideration imply the fixed effects model is the appropriate model. The Hausman specification test usually tests a set of random effects assumptions. In practice, the Hausman test is testing for correlation between the unobserved effect and all the independent variables (see the "Random Effects" section above) and all assumptions required for the fixed effects method (Wooldridge, 2014,

[9] A composite error term, in this context, serve as the sum of the unobserved effect and the error term (Wooldridge, 2014, p. 396)

p. 399). The null hypothesis in a Hausman test is using the random effects model, while the alternative hypothesis is using the fixed effects model.

5. Method

This chapter will first introduce the data sample and variables used in this study. Then, the regression models to be used in addition to the hypotheses of the study will be explained. Finally, the data validation chapter will validate the data by testing for and handling violations of the OLS assumptions.

5.1 Data sample

The analyses in this study uses yearly panel data for firms listed in the Nordic countries, namely Norway, Sweden, Denmark, Finland and Iceland. Through a screening process in Refinitiv, all firms listed with country of exchange in the Nordic countries were gathered. As of February 2021 there were 1568 firms listed on the Nordic exchanges available in Refinitiv. As this study aims at identifying the effect of a firm's ESG-score on SPV, the firms added in the data sample must contain ESG-scores for at least one year in the period 2010-2019. The initial ESG-score screening process in Refinitiv left an initial population of 259 firms. As the analysis required data for each firm on: dividend yield, payout ratio, stock price movements, earnings, firm size and debt, the final population size was still 259 firms after including the above mentioned parameters, even though some firms had unavailable data for certain time periods, as missing values does not cause issues when using an unbalanced panel data set. The missing data may have been retrieved in various ways, however, this would result in a usage of different data sources and consequently reduce the reliability of the study. As no firms with country of exchange were listed in Iceland after the initial screening processes, no conclusions in this study will be made for firms listed in Iceland. The sample therefore contains firms listed on the Oslo Stock Exchange, Nasdaq OMX Stockholm, Nasdaq OMX Copenhagen and Nasdaq OMX Helsinki.

The gold standard when retrieving a representative data set is through probability sampling. Probability sampling, in the context of this study, means the data sample is drawn randomly from all firms listed on the Nordic exchanges. However, this is impossible for this study as many firms lack available ESG-score in Refinitiv. The limited availability of ESG-scores among other key data makes a non-probability method for retrieving a data sample more appropriate for this study. A non-probability method, in the context of this study, means the data sample is created based on certain criterions such as data availability (Neuman, 2014, p. 248). There is no consensus in the literature whether the sample size or the relative sample size has the largest impact on the statistical accuracy. Sample size, unless larger than 10% of the population, has been argued to be more important in mitigating sample mean standard error than relative sample size (Black, 1998, pp. 136–137).

This study uses secondary data as the data sample is retrieved from Refintiv. Using secondary data might be problematic as data providers may cause data to be inappropriate (Neuman, 2014, pp. 378–380). However, Refinitiv serves as a reliable provider of data as Refinitiv serves 40000 institutions in approximately 190 countries with financial data. Furthermore, Refinitiv provides ESG-scores for more than 10000 firms in 76 countries (Refinitiv, 2021). Strong considerations regarding the data sample must be taken into consideration when using secondary data (Neuman, 2014, p. 380), which has been taking into account when retrieving data for this study. Other providers of ESG ratings were considered added to the study such that comparable results could have been made. MSCI and Sustainalytics, two global rating providers, have been used in similar studies. However, as Refinitiv was the most extensive data provider the authors had available, it was the chosen data provider for this study. As one comparison study found poor correlation between the various rating provider's ESG-scores (Feifei Li, 2020), this study uses only one rating provider, namely Refintiv.

5.1.1 Panel data

The "Data Framework" chapter described that panel data may be constructed using cross sections over time (Wooldridge, 2014, p. 360). Therefore, a panel data set consists of both cross-sectional data and time series data for the same individual observation over time. The data sample used in this study has yearly observations and at least one observation for each firm in the ten year period. More specifically, the data set in this study is an unbalanced panel data set, as not all firms have observations for all ten years. Using an unbalanced panel data set might cause computation and estimation errors. However, with the use of software tools, these issues are usually mitigated (Park, 2011).

5.2 Variables

5.2.1 Dependent Variable

The dependent variable is the variable to be explained (Stock & Watson, 2014, p. 818). As the purpose of this study is to measure whether ESG-score has an effect on SPV, a measure for SPV had to be selected.

Previous research has shown various calculation methods to measure volatility. This study uses standard deviation as a measure for volatility. The standard deviation is calculated using daily stock price changes for each year in the study. The annualized standard deviation is found by multiplying daily standard deviation with the square root of the number of trading days (Berk & DeMarzo, 2017). Daily standard deviation was calculated in Microsoft Excel as sample standard deviation. A prominent disadvantage of measuring volatility as standard deviation is the undesired influence of extreme values (Hussainey et al., 2011). However, despite the possibility of extreme values influencing the standard deviation, standard deviation serves as the most common measure of SPV (Sörensen & Deboi, 2020).

5.2.2 Independent Variable

As this study investigates the effect of ESG-score on SPV, ESG-score was selected as an independent variable. Furthermore, each pillar of the ESG-score, namely the E-score, S-score and G-score were included as an independent variable in each respective regression model, such that their respective effects on SPV could be observed. The literature review demonstrated that a lack of previous research on the relationship between ESG-score and SPV makes it difficult to predict whether the relationship is positive, negative or if there is a relationship at all. However, as literature has found beneficial effects from ESG on financial performance (Borovkova & Wu, 2020), a negative effect from ESG-score on SPV will may be obtained.

5.2.3 Control Variables

Control variables were added to the regression models to strengthen the causality of the possible findings (Hünermund & Louw, 2020). These variables are, similar to the other independent variables, determinants of the dependent variable, and increases the accuracy of the estimated model (Stock & Watson, 2014, p. 818). The control variables used in this study are; dividend yield, payout ratio, firm size, earnings volatility and leverage.

Dividend yield and payout ratio are both measures that were directly retrieved as yearly data from Refinitiv. Dividend yield is the dividend per share as a percentage of the share price and is averaged over the year. Payout ratio is the the dividend per share to earnings per share for the period considered. The literature review found no consensus whether dividend yield has a positive, negative or any effect on SPV. Therefore, the expected effect of dividend yield on SPV in this study is unclear.

Firm size is measured by a firm's market value and the data used to calculate a firm's market value is also retrieved from Refinitiv in this study. The market value of a firm is normally calculated as the price per share multiplied with the number of ordinary shares (Baskin, 1989). To reflect the order of magnitude of the market value, a logarithm transformation with base of 10 was applied. Other methods of calculating firm size has also been considered. A common method of calculating firm size used in similar studies, is taking the natural logarithm of a firm's total assets (Benlemlih, 2019), (Hussainey et al., 2011). However, the method of calculating a firm's size by taking the natural logarithm of a firm's total assets seems to be more commonly used when the effect on dividends are of interest, while the market value approach seems to be more commonly used as a control variable when the effect on SPV is of interest. Firm size is expected to have a negative effect on SPV as the literature review presented multiple studies that demonstrated a negative relationship between firm size and SPV.

Earnings volatility has no clear definition and hence this study considered multiple methods of estimating the firms' earnings volatilities. One method commonly used to calculate a firm's earnings volatility is the one presented by Baskin in 1989 (Baskin, 1989). However, this approach results in a constant earnings volatility for each firm in the respective years. Adding a constant variable to the data would make it impossible to use the fixed effects model, as it would only remove the constant variables from the model. Consequently, the only suitable regression models would be limited to the pooled OLS model and the random effect model, and if neither the pooled OLS model or the random effects model would be consistent, problems would arise. Earnings volatility in this study is therefore calculated by the standard deviation of a firm's recent five years EBIT, as the current earnings volatility has an effect five years into the future (Dichev & Tang, 2009). Data for EBIT were retrieved directly from Refinitiv and the standard deviation were calculated as sample standard deviation in Microsoft Excel. Earnings volatility is expected to have a positive relationship with SPV as this relationship has strong consensus in the existing literature.

Previous research has suggested that, given the presence of operating risk, a relationship between leverage and SPV exist (Allen & Rachim, 1996). Given constant operating risk, a greater leverage was found to imply a higher SPV (Baskin, 1989). Therefore, a proxy for leverage is included in the regression models as a control variable. The literature proposes several methods of calculating leverage. Whether to use total debt divided by total assets or long term debt divided on total assets seems to be the two main methods. As total debt divided by total assets includes a firm's obligations, it will be the method used to calculate leverage in this study (Johansson & Fahlén, 2019). Similarly to earnings volatility, leverage is expected to have a positive effect on SPV.

5.2.4 Interaction terms

In this study, interaction terms were included in the regression models such that differences of the effect ESG-score has on SPV in each respective country and industry could be observed. Country and industry specific dummy variables were therefore multiplied with the firms respective ESG-scores. The interaction terms for country/ industry specific differences will be different from zero only when the specific country/ industry match. Therefore, the size of the coefficient of the interaction terms will present the difference in effect of ESG-score on SPV in that specific country/ industry. The country dummy variables included are Sweden(120), Norway(58), Denmark(45) and Finland(34) [1]. Two firms listed on the Nordic exchanges have headquarters outside the Nordic countries, and consequently, neither of these two firms were included in the dummy variables [2]. The industry specific dummy variables are made accordingly with the industries specified by Refinitiv, namely: industrial(190), utility(8), transportation(14), bank/savings(16), insurance(7) and "other"(24) [3] Each interaction term results in a new regression model as only one interaction term could be included at a time in the regression models used in this study.

[1]The numbers in parenthesis are the number of firms in the respective countries.
[2]Both firms are listed on the exchange Nasdaq Stockholm.
[3]The number in the parenthesis is the number of firms in each respective industry.

5.3 Descriptive statistics of the initial data sample

The sampling process resulted in the use of nine independent variables, of which five were control variables. In addition to the nine originally designated independent variables, ten more independent variables were included, of which four were interaction terms for country specific differences and six were interaction terms for industry specific differences. In the table below, the data sample used in this study is presented.

Table 5.1: Descriptive statistics of the initial data sample

Statistic	N	Mean	Std.Dev	Min	Pctl(25)	Pctl(75)	Max
Year	2,590	2,014.500	2.873	2,010	2,012	2,017	2,019
SPV	2,107	0.337	0.206	0.027	0.239	0.367	3.571
ESG-score	1,490	53.885	18.967	3.940	40.685	68.810	91.040
E-score	1,490	51.677	26.366	0.000	31.760	73.823	95.110
S-score	1,490	57.386	21.641	0.470	42.900	74.685	96.080
G-score	1,490	49.834	22.301	2.060	31.077	68.007	97.540
EarnVol	2,017	1,667,938	5,054,336	2,228	105,373	1,266,340	87,805,052
Firm size	2,107	9.245	0.699	5.613	8.806	9.698	11.079
DivYield	2,107	2.558	2.632	0.000	0.000	3.805	40.650
PayoutRatio	2,174	36.821	29.826	0.000	0.000	58.987	99.880
Leverage	2,385	0.262	0.185	0.000	0.116	0.373	1.158
Sweden	2,590	0.463	0.499	0	0	1	1
Norway	2,590	0.224	0.417	0	0	0	1
Denmark	2,590	0.174	0.379	0	0	0	1
Finland	2,590	0.131	0.338	0	0	0	1
Industrial	2,590	0.734	0.442	0	0	1	1
Utility	2,590	0.031	0.173	0	0	0	1
Transportation	2,590	0.054	0.226	0	0	0	1
Bank.savings	2,590	0.062	0.241	0	0	0	1
Insurance	2,590	0.027	0.162	0	0	0	1
Other	2,590	0.093	0.290	0	0	0	1

The table demonstrates that 2590 observations are included in the panel data set. However, as the dependent variables has 2107 observations, only 2107 observations may be used. ESG-score, and each ESG-pillar all have 1490 observations. Furthermore, there is noteworthy that 46% of all observations are in the Swedish market, and 73% of all observations are from the industrial sector. Finally, earnings volatility has a magnitude, in absolute terms, vastly larger than any other variable in the data sample.

5.4 Regression analysis

As this study attempts to discover in several dimensions the relationship between ESG-score and SPV, multiple regression analysis will serve as the main tool in the attempt of obtaining a causal relationship. As factors such as firm size, dividend policy, leverage and earnings volatility are known to affect SPV, these factors are included in the regression models, and hence a single regression analysis fails to adequately explain the relationship between ESG-score and SPV. Including these factors, known to have an effect on SPV, the *ceteris paribus* effect of each independent variable can be controlled, as holding all other variables fixed allows for observing the effect of only the variable of interest (Wooldridge, 2014, p. 12). The results from this study's regression analyses may be subject to reversed causality. Reversed causality, in the context of a regression analysis, occurs when the dependent variable causes the effect on the independent variable (De Beer et al., 2013). In this study, reversed causality is unlikely to come about, as ESG-specific studies previously have been demonstrated to impact financial performance.

5.4.1 The regression models equations

In this section the regression equations will be presented. The regression equations are made using the numerous variables addressed earlier in the chapter. All regression models used in this study have the same dependent variable and control variables.

$$SPV = \beta_0 + \beta_1 ESGscore + \beta_2 DivYield + \beta_3 PayoutRatio + \beta_4 Firmsize + \beta_5 Leverage + \beta_6 EarnVol + \varepsilon$$

$$SPV = \beta_0 + \beta_1 Escore + \beta_2 DivYield + \beta_3 PayoutRatio + \beta_4 Firmsize + \beta_5 Leverage + \beta_6 EarnVol + \varepsilon$$

$$SPV = \beta_0 + \beta_1 Sscore + \beta_2 DivYield + \beta_3 PayoutRatio + \beta_4 Firmsize + \beta_5 Leverage + \beta_6 EarnVol + \varepsilon$$

$$SPV = \beta_0 + \beta_1 Gscore + \beta_2 DivYield + \beta_3 PayoutRatio + \beta_4 Firmsize + \beta_5 Leverage + \beta_6 EarnVol + \varepsilon$$

Country and industry specific dummy variables will then be added to measure the potential differences in the effect of ESG-score across countries and industries. These dummy variables will be added as interaction terms, using the same independent variables, as explained in the previous section. Below are the regression equations with country and industry specific interaction terms.

$$SPV = \beta_0 + \beta_1 ESGscore + \beta_2 DivYield + \beta_3 PayoutRatio + \beta_4 Firmsize + \beta_5 Leverage + \beta_6 EarnVol + \beta_7 (ESGscore \cdot Sweden) + \beta_8 (ESGscore \cdot Norway) + \beta_9 (ESGscore \cdot Finland) + \beta_{10} (ESGscore \cdot Denmark) + \varepsilon$$

$$SPV = \beta_0 + \beta_1 ESGscore + \beta_2 DivYield + \beta_3 PayoutRatio + \beta_4 Firmsize + \beta_5 Leverage + \beta_6 EarnVol + \beta_7 (ESGscore \cdot Industrial) + \beta_8 (ESGscore \cdot Utility) + \beta_9 (ESGscore \cdot Transportation) + \beta_{10} (ESGscore \cdot Bank) + \beta_{11} (ESGscore \cdot Insurance) + \beta_{12} (ESGscore \cdot Others) + \varepsilon$$

5.4.2 Hypotheses

This section introduces the hypothesis to be tested in this study. As this study aims to discover the effect of ESG-score on SPV in several dimensions, the hypothesis are as following:

Table 5.2: Table of hypotheses

Hypothesis number	**Null Hypothesis**	**Alternative Hypothesis**
1	There is no effect from ESG Score on SPV in Nordic firms.	There is an effect from ESG Score on SPV in Nordic firms.
2	There is no effect from Environmental-score on SPV in Nordic firms.	There is an effect from Environmental-score on SPV in Nordic firms.
3	There is no effect from Social-score on SPV in Nordic firms.	There is an effect from Social-score on SPV in Nordic firms.
4	There is no effect from Governance-score on SPV in Nordic firms.	There is an effect from Governance-score on SPV in Nordic firms.
5	There is no difference in the effect of ESG-score on SPV in Sweden relative to other Nordic countries.	There is a difference in the effect of ESG-score on SPV in Sweden relative to other Nordic countries.
6	There is no difference in the effect of ESG-score on SPV in Norway relative to other Nordic countries.	There is a difference in the effect of ESG-score on SPV in Norway relative to other Nordic countries.
7	There is no difference in the effect of ESG-score on SPV in Denmark relative to other Nordic countries.	There is a difference in the effect of ESG-score on SPV in Denmark relative to other Nordic countries.
8	There is no difference in the effect of ESG-score on SPV in Finland relative to other Nordic countries.	There is a difference in the effect of ESG-score on SPV in Finland relative to other Nordic countries.
9	There is no difference in the effect of ESG-score on SPV in industry ”industrial” relative to other industries in the Nordic countries.	There is a difference in the effect of ESG-score on SPV in industry ”industrial” relative to other industries in the Nordic countries.
10	There is no difference in the effect of ESG-score on SPV in industry ”utility” relative to other industries in the Nordic countries.	There is a difference in the effect of ESG-score on SPV in industry ”utility” relative to other industries in the Nordic countries.
11	There is no difference in the effect of ESG-score on SPV in industry ”transportation” relative to other industries in the Nordic countries.	There is a difference in the effect of ESG-score on SPV in industry ”transportation” relative to other industries in the Nordic countries.
12	There is no difference in the effect of ESG-score on SPV in industry ”bank” relative to other industries in the Nordic countries.	There is a difference in the effect of ESG-score on SPV in industry ”bank” relative to other industries in the Nordic countries.

13	There is no difference in the effect of ESG-score on SPV in industry "insurance" relative to other industries in the Nordic countries.	There is a difference in the effect of ESG-score on SPV in industry "insurance" relative to other industries in the Nordic countries.
14	There is no difference in the effect of ESG-score on SPV in industry "other" relative to other industries in the Nordic countries.	There is a difference in the effect of ESG-score on SPV in industry "other" relative to other industries in the Nordic countries.

Similarly to hypothesis 5-8 and hypothesis 9-14, E-score, S-score and G-score will be tested in a similar manner to observe differences in the effect from ESG-score in aggregate and each ESG-score pillar, across countries and industries [4].

5.5 Data Validation

Data validation is important when conducting quality research. Following, the data will be scrutinized against the assumptions of the classical OLS model. Also, where an assumption may be violated, the data transformation will be shown. The tests against the assumptions of the classical OLS model will be presented in the order in which they were conducted.

5.5.1 Distribution and Normality tests

In linear regression, normally distributed error terms are assumed (Wooldridge, 2014, pp. 95–96). Error terms failing to be normally distributed, may cause both t-statistics and F-statistics to fail, and consequently, other models in estimating the regression coefficients are more suitable (Wooldridge, 2014, p. 134). Furthermore, the distribution of the data set's variables may be interesting, as the distribution may indicate the existing of for instance extreme outliers, which may cause unreliable estimated coefficients (Stock & Watson, 2014, p. 179).

Two common measures in evaluating the normality of a distribution are skewness and kurtosis. Skewness measures how symmetrical the distribution is, while kurtosis measures the thickness of the distribution's tails (Wooldridge, 2014, pp. 574–581). The table below shows the data sample's skewness and kurtosis, and their respective p-values, calculated with the d'Augustino normality test.

[4] Presenting the exhaustive list of hypothesis for the ESG-pillars as well, another 30 hypothesis would have been included in the table, which proved to be impractical.

Table 5.3: Skewness and Kurtosis test

Variables	Skewness	Skewness p-value	Kurtosis	Kurtosis p-value
SPV	6.2992	0.0000	71.3199	0.0000
ESG-score	(-0.4213)	0.0000	2.4439	0.0000
E-score	(-0.3971)	0.0000	2.0618	0.0000
S-score	(-0.4675)	0.0000	2.3525	0.0000
G-score	0.0375	0.5579	2.0064	0.0000
EarnVol	9.1088	0.0000	117.1348	0.0000
Firm size	(-0.3971)	0.0000	4.1466	0.0000
DivYield	3.3239	0.0000	33.9647	0.0000
PayoutRatio	0.1913	0.0004	1.9213	0.0000
Leverage	0.7853	0.0000	3.8657	0.0000

The null hypothesis of normality is rejected with p-values below 5% and consequently, there is evidence of non-normality with p-values below 5%. As shown in the table, only G-score retain the null hypothesis. Therefore, all other variables in the table rejects the null hypothesis, and are not-normally distributed. To strengthen this finding, a Shapiro-Wilk test is conducted below. A Shapiro-Wilk test is known as one of the most powerful normality tests (Kim & Park, 2019).

Table 5.4: Shapiro-Wilk Normality test

Variable	W	p-value
SPV	0.5718	0.0000
ESG-score	0.9737	0.0000
E-score	0.9497	0.0000
S-score	0.9636	0.0000
G-score	0.9761	0.0000
EarnVol	0.2984	0.0000
Firm size	0.9858	0.0000
DivYield	0.7850	0.0000
PayoutRatio	0.9236	0.0000
Leverage	0.9542	0.0000

In the table above, a W-value close to 1 indicates a normally distributed variable, and conversely, a W-value close to 0 indicates a non-normally distributed variable (Kim & Park, 2019). The null hypothesis of normality is rejected with p-values below 5% and consequently, there is evidence of non-normality with p-values below 5%. Therefore, as shown in the table, the Shapiro-Wilk test demonstrates that all variables used in this study are not-normally distributed. However, extreme outliers might explain the smaller W-value of SPV, earnings volatility and dividend yield compared to the other variables.

Even though these variables fail to retain the null hypothesis, and consequently are not normally distributed, the validity of the regression models are not jeopardized. Normally distributed error terms however, serve as an important assumption of the classical OLS model although optionally invoked. Even though the error terms may fail to be normally distributed, the effect of not normally distributed error terms will be rather small in a large data sample (Schmidt & Finan, 2018). Therefore, in the table below, a Shapiro-Wilk test is conducted for the regression models' residuals with ESG-score in aggregate and for each ESG-pillar.

Table 5.5: Shapiro-Wilk Normality of residuals test

Regression model on SPV	W	p-value
Residuals (ESG-score)	0.6806	0.0000
Residuals (E-score)	0.6803	0.0000
Residuals (S-score)	0.6804	0.0000
Residuals (G-score)	0.6818	0.0000

The table above shows that all four regression models fail to demonstrate normally distributed error terms, and hence the Shapiro-Wilk null hypothesis for normally distributed error terms are rejected. A boxplot is provided in the appendix A.2 to demonstrate the extreme outliers, which might explain why the residuals fails to be normally distributed. As both the variables and residuals of the regression models fail to be normally distributed, data transformations will be conducted to increase the normality of the variables and error terms in this study. In handling extreme outliers, winsorizing may serve as an effective tool in mitigating the extreme outliers' effect on the properties of the data sample. Winsorizing replaces all values beyond a predetermined percentile with the value of the percentile (Tukey, 1962). Commonly, all values above the 95% percentile and below the 95% percentile are replaced (Ghosh & Vogt, 2012). However, in this study, in order to be less invasive, values above the 97.5% percentile and below the 2.5% percentile will be replaced, as the former percentiles altered a large proportion of the data sample. After winsorizing SPV, earnings volatility and dividend yield, the Shapiro-Wilk test was conducted on the residuals of the regression model with ESG-score in aggregate. The result is presented in the table below:

Table 5.6: Shapiro-Wilk Normality of residuals after winsorizing test

Regression model on SPV	W	p-value
Residuals (ESG-score)	0.9466	0.0000

The Shapiro-Wilk test after winsorizing the data demonstrates that the residuals of the regression model is closer to normally distributed as the W-value is closer to 1. However, as the p-value is below 5%, the residuals of the regression model are still not normally distributed, and hence a logarithmic transformation of SPV will be conducted. The table below shows the W-value of the residuals of the regression model after the logarithmic transformation of SPV. As the W-value is increasingly close to 1, even though the p-value is below 5%, the current regression model, with winsorized variables and the logarithmic transformation of SPV, will be used for this study. Note again, that the data sample may be valid without normally distributed residuals, especially for larger data samples (Schmidt & Finan, 2018).

Table 5.7: Shapiro-Wilk Normality of residuals after logarithmic transformation test

Regression model on SPV	W	p-value
Residuals (ESG-score)	0.9962	0.0019

5.5.2 Linearity and Homoskedasticity

In a deeper analysis of the residuals for the multiple regression model used in this study, a "Residuals vs Fitted plot" is provided below (Wooldridge, 2014, p. 31). A Residuals vs Fitted plot is useful in obtaining information about linearity, homoskedasticity and outliers. As the first assumption of the classical OLS model is linearity (see section 4.2.3), the figure below demonstrates that the data sample sufficiently meets the first assumption of the classical OLS model, as the residuals appears randomly distributed above, below and along the zero line. Furthermore, the OLS line can be observed as the slightly curved line below the zero line. As the second assumption of the classical OLS model is that the residuals have a zero population mean, the data sample sufficiently meets the second assumption of the OLS model, as the line is very close to the zero line. However, note that a negative OLS line might over predict the coefficients (the effect of the independent variable on the dependent variable) (Wooldridge, 2014, p. 31). The fifth assumption of the OLS model is constant variance of the error term, or homoskedastic error terms. Homoskedastic error terms will show as a constant residual variance along the fitted values, and heteroskedastic error terms will show not constant residual variance along the fitted values (Wooldridge, 2014, pp. 47–51). As it is difficult to visually determine whether the residuals have a constant variance, a Breusch-Pagan test will be conducted to determine whether assumption five of the classical OLS model is met (Wooldridge, 2014, pp. 221–224).

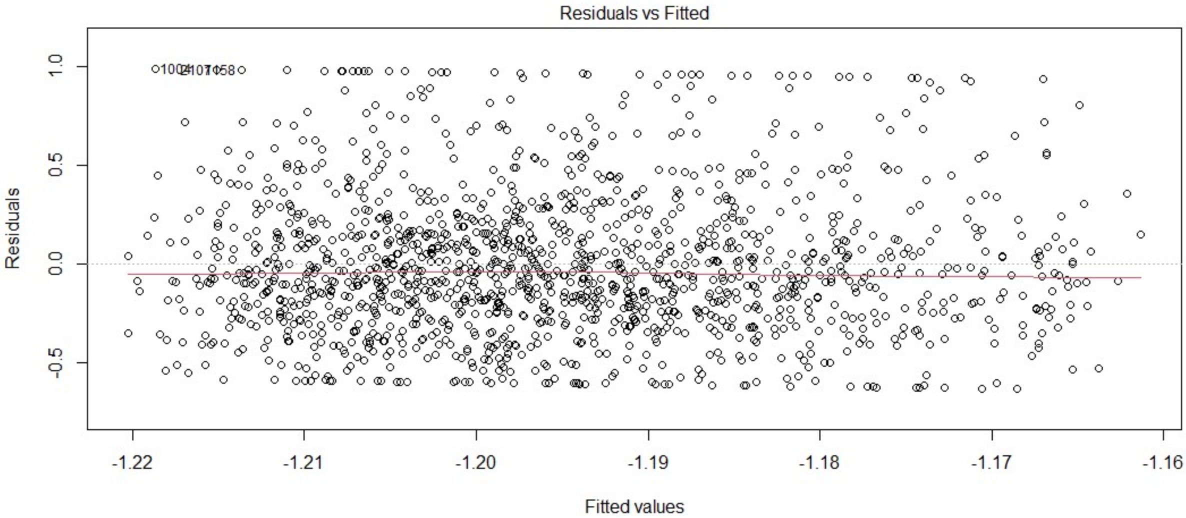


Figure 5.1: Residuals vs Fitted plot.

The null hypothesis of a Bresch-Pagan test is homoskedastic error terms, and the alternative hypothesis is heteroskedastic error terms. Therefore, with a p-value below 5% the null hypothesis is rejected and there is evidence of heteroskedasticity. As shown in the table below, the null hypothesis is rejected and the data sample contains heteroskedasticity. Therefore, the data must be corrected for heteroskedasticity, and consequently robust standard errors will be used rather than normal standard errors (Stock & Watson, 2014, p. 209).

Table 5.8: Breusch-Pagan heteroskedasticity test

Breusch-Pagan test	BP	p-value
SPV regression model	91.581	0.0000

Finally, as the data sample was winsorized prior to the plotting of the Residuals vs Fitted plot, no extreme outliers may be observed. The former extreme outliers can now be observed as a rather significant line on the top and bottom of the scatter plot.

5.5.3 Error term correlation

The third assumption of the classical OLS model is all independent variables shall be uncorrelated with the error term (u). A correlation between the independent variables and the error term might result in biased coefficients (Stock & Watson, 2014, pp. 368–371). A Pearson test is commonly used to test for correlation between the error term and the independent variables (Black, 1998, pp. 627–636).

Table 5.9: Pearson correlation test

Independent variable	OLS Model p-value
ESG-score	0.276
DivYield	0.847
PayoutRatio	0.116
Firm size	0.042
Leverage	0.313
EarnVol	0.385

The null hypothesis of a Pearson test is no correlation between the error term and the independent variables. Therefore, with a p-value below 5% the null hypothesis is rejected, and there is evidence of correlation between the error term and the independent variable. As firm size has a p-value less than 5%, there is evidence of firm size being correlated with the error term, and consequently, omitted variable bias might occur (Studenmund, 2014, p. 101).

5.5.4 Multicollinearity

The sixth assumption of the classical OLS model is no perfect multicollinearity between the the independent variables. To test for multicollinearity between the independent variables, a VIF-test is commonly conducted. A VIF-value above 10 is considered a high correlation (Wooldridge, 2014, p. 86). As shown in the table below, all variables demonstrated a low VIF-value and consequently, multicollinearity is no issue for the variables used in this study and the sixth assumption of the classical OLS model is met.

Table 5.10: VIF-test

Independent variable	VIF	1/VIF
ESG-score	1.013	0.987
DivYield	1.391	0.719
PayoutRatio	1.496	0.668
Firm size	1.623	0.616
Leverage	1.040	0.962
EarnVol	1.398	0.715

As multicollinearity might occur when using interaction terms, a VIF-test has been conducted for all variables in the regression models with interaction terms, see appendix A.2. None of the variables in the regression models with interaction terms demonstrated perfect multicollinearity, and all variables have VIF-values below 2.5.

5.5.5 Serial correlation

The fourth assumption of the classical OLS model is no serial correlation (auto correlation). As the data sample used in this study contains time series, auto correlation might be an issue as each consecutive year in a time series often correlate (Stock & Watson, 2014, p. 412). As a Wooldridge test is well suited to test for auto correlation when the data sample is large (Drukker, 2003), a Wooldridge test will be conducted to test the data sample used in this study for auto correlation.

Table 5.11: Wooldridge test for unobserved time effects

Wooldridge test	Z	p-value
SPV regression model	6.0152	0.0000

The null hypothesis is no auto correlation, and the alternative hypothesis is the existence of auto correlation. Therefore, with a p-value below 5% the null hypothesis is rejected, and there is evidence of auto correlation. As the Wooldridge test was significant, and the null hypothesis is rejected, there is evidence of auto correlation in the data sample used in this study. Therefore, as the classical OLS model is not suitable to the data used in this study, a more suitable model must be used. Below, a "Breusch-Pagan Lagrange Multiplier test" is conducted to test whether to use either the pooled OLS model or the fixed/ random effects models (Baltagi & Li, 1990).

Table 5.12: Breusch-Pagan Lagrange Multiplier test

Breusch-Pagan Lagrange Multiplier test	Chi-sq	p-value
SPV regression model	1027.8	0.0000

The null hypothesis is to use the pooled OLS model, and the alternative hypothesis is to use the fixed/ random effects models. Therefore, a p-value less than 5% will reject the null hypothesis and consequently pooled OLS is not suitable in estimating the coefficients in this study. As the Breusch-Pagan Lagrange Multiplier test was significant, the null hypothesis is rejected, and the fixed/ random effects models must be used in estimating the regression coefficients.

5.5.6 Hausman test

As presented in the chapter "Data framework", there are two main types of panel data regression models in addition to pooled OLS, namely the fixed effects model and the random effects model (Tsionas, 2019, pp. 58–59). The classical test in determining whether to use the fixed effects model or the random effects model is a Hausman specification test (Yaffee, 2003). The Hausman test tests for correlation between the unobserved effect and the independent variables. As the data sample contains heteroskedasticity, a robost Hausman test will be conducted.

Table 5.13: Robust Hausman test

Robust Hausman test	Chi-sq	p-value
SPV regression model	11.72	0.0685

The null hypothesis is no correlation between the unobserved effect and the independent variables, and the alternative hypothesis is correlation between the unobserved effect and the independent variables. With a p-value less than 5% the null hypothesis will be rejected. As the robost Hausman test was insignificant, the null hypothesis is retained, and there is no correlation between the unobserved effect and the independent variables in this study. Therefore, the random effects model is the chosen model in estimating the regression coefficients. While conducting the robost Hausman test, one issue occurred. As earnings volatility's number was large in absolute terms compared to the magnitude of the other variables, a natural logarithmic transformation of earnings volatility was conducted.

6. Descriptive statistics

This chapter will present the descriptive statistics of the data sample used in this study. First, a data summary with all variables used in this study will be presented. Then, a correlation matrix for all variables used will be provided. The descriptive statistics provided in this chapter will provide the reader with a tangible understanding of the data sample used in this study.

6.1 Data summary

The data summary table includes both central tendency and variability of the data sample. The number of observations and percentiles for all data used is also provided in the table.

Table 6.1: Data summary of the final data sample

Statistic	N	Mean	Std.Dev	Min	Pctl(25)	Pctl(75)	Max
SPV	2,107	−1.188	0.357	−1.798	−1.431	−1.003	−0.227
ESG-score	1,451	54.098	19.000	3.940	40.690	68.965	91.040
E-score	1,451	51.926	26.338	0.000	32.015	73.995	95.110
S-score	1,451	57.642	21.644	0.800	43.405	75.010	96.080
G-score	1,451	50.024	22.258	2.060	31.735	68.205	97.540
DivYield	2,107	2.459	2.144	0.000	0.000	3.805	8.011
PayoutRatio	2,084	37.694	29.705	0.000	0.000	59.417	99.880
Firm size	2,107	9.245	0.699	5.613	8.806	9.698	11.079
Leverage	2,104	0.255	0.178	0.000	0.116	0.359	1.158
EarnVol	1,997	12.829	1.693	9.317	11.565	14.052	16.321
Sweden	2,107	0.444	0.497	0	0	1	1
Norway	2,107	0.218	0.413	0	0	0	1
Denmark	2,107	0.188	0.391	0	0	0	1
Finland	2,107	0.144	0.351	0	0	0	1
Industrial	2,107	0.732	0.443	0	0	1	1
Utility	2,107	0.030	0.170	0	0	0	1
Transportation	2,107	0.060	0.238	0	0	0	1
Bank.savings	2,107	0.067	0.250	0	0	0	1
Insurance	2,107	0.033	0.178	0	0	0	1
Other	2,107	0.078	0.269	0	0	0	1

There are 2107 firm observations. While SPV[1], dividend yield and market value have 2107 firm observations, leverage has 2104 observations, earnings volatility has 1997 observations, payout ratio has 2084 observations and ESG-score has 1451 observations. This difference in number of observations is expected as price history data, dividend data and market cap data are readily accessible, while data on earnings and ESG-score are more difficult to retrieve. A mean of 2014,8 years implies that there are more observations in the last half of the time period used in this study. This is also expected, as firms with available ESG-score rapidly increases in the more recent years of the time period. Furthermore, ESG-score has a mean of 54.1 and standard deviation of 19.0. E-score has lower mean than ESG-score, and higher standard deviation than ESG-score. S-score has higher mean than ESG-score and the lowest standard deviation of the ESG-pillars. G-score has lower mean than ESG-score, and the lowest mean of the ESG-pillars in addition to the lowest standard deviation of the ESG-pillars. Finally, as dividend yield and payout ratio has a 0 25% percentile, at least 25% of the firms in the data sample payed no dividends during the time period.

The variable mean of the dummy variables represent the fraction of firms included in the dummy variable. The dummy variable Sweden contains 44% of all firms used in the study, while dummy variables Norway, Denmark and Finland contains 22%, 19% and 14% of all firms used in the study respectively. The dummy variable industrial contains 73% of all firms used in this study, while all other industry specific dummy variables contains between 3% and 8% of the firms used in this study.

The processing of the data sample in obtaining valid regression models made some implications on the variables. All variables decreased in number of observations, with the exception of SPV, due to the elimination of firm observations with missing values for SPV. Consequently, minor changes in the respective means and standard deviations of variables occurred. However, some more prominent changes in the data set can be observed in the variables SPV and earnings volatility, which both has been logarithmically transformed. It is also noteworthy that the mean of dummy variable Sweden increased to 46%.

6.2 Correlation matrix of the variables used in this study

A correlation matrix has been made to provide an indication of the dependence between the variables used in this study.

[1] All negative values of SPV are due of the logarithmic transformation.

Table 6.2: Correlation matrix of the variables used in this study

	SPV	ESG-score	E-score	S-score	G-score	DivYield	PayoutRatio	Firm size	Leverage	EarnVol
SPV	1									
ESG-score	− 0.048	1								
E-score	− 0.042	0.852	1							
S-score	− 0.057	0.888	0.705	1						
G-score	− 0.028	0.678	0.361	0.400	1					
DivYield	− 0.366	0.081	0.096	0.062	0.065	1				
PayoutRatio	− 0.399	0.058	0.053	0.057	0.038	0.497	1			
Firm size	− 0.466	0.088	0.079	0.086	0.064	0.286	0.348	1		
Leverage	0.024	0.008	0.027	− 0.010	0.021	0.085	− 0.084	− 0.087	1	
EarnVol	− 0.185	0.070	0.057	0.061	0.069	0.052	− 0.049	0.610	0.073	1

ESG-score and SPV has a weak negative correlation coefficient of -0.048. E-score and SPV, S-score and SPV and G-score and SPV have correlation coefficients of -0.042, -0.057 and -0.028 respectively. These negative correlation coefficients were expected, as the chapter "Analysis of the Nordic market" demonstrated similar, though smaller correlation coefficients between GSCI-score and annualized index volatility. Dividend yield, payout ratio, earnings volatility and firm size are negatively correlated with SPV. These correlations are both in line and contrary with the literature review, in which dividend yield was found to be negatively related to SPV and earnings volatility was found to be positively related to SPV. Leverage however, is positively correlated with SPV, which supports the findings in the literature review. Furthermore, E-score, S-score and G-score are strongly and positively correlated with ESG-score, as expected given that the pillars constitutes the overall ESG-score. Finally, dividend yield and payout ratio are positively and strongly correlated, which is also expected as both are measures for dividends.

7. Empirical results

This chapter will present the empirical results found in this study. First, the single regressions results followed by the multiple regressions results will be presented. Finally, a summary table of the empirical results will be provided. The results will be commented, but not discussed.

7.1 The regression model

As SPV in this study is measured as the natural logarithm of a stock return's standard deviation, the final regression models used in this study are log-level models (Wooldridge, 2014, p. 40). In the formula below, the interpretation of β_1 is shown for a log-level model (Wooldridge, 2014, p. 40). The interpretation is an one unit increase of x increases y by a percentage, of magnitude β_1 * 100.

$$\%\Delta y = (100\beta_1)\Delta x \tag{7.1}$$

Due to the findings of heteroskedasticity and auto correlation in section 5.5.2 and 5.5.5, all succeeding results will be presented with Driscoll Kraay robost standard errors.

7.2 The single regression models

The single regression models have been conducted to estimate the significance of the relationship between ESG-score, in aggregate and for each respective ESG-pillar, with SPV. Following are the single regression models presented:

Table 7.1: The single regression models results

	Dependent variable: SPV			
	(1)	(2)	(3)	(4)
ESG-score	− 0.0004 (0.0004) p = 0.300			
E-score		−0.0003 (0.0003) p = 0.233		
S-score			−0.001 (0.0004) p = 0.111	
G-score				0.0002 (0.0003) p = 0.513
Constant	− 1.149*** (0.096) p = 0.000	− 1.154*** (0.093) p = 0.000	− 1.134*** (0.099) p = 0.000	− 1.180*** (0.096) p = 0.000
Observations	1,451	1,451	1,451	1,451
R^2	0.071	0.071	0.073	0.071
Note:				*p<0.1; **p<0.05; ***p<0.01

The single regressions demonstrated no significant relationship between ESG-score, neither in aggregate nor separately, with SPV. E-score and G-score strongly fails to demonstrate significance, while S-score scarcely fail to demonstrate significance. Also, alike the findings in the correlation matrix, ESG-score, E-score and S-score demonstrates a negative effect on SPV. However, contrary to the findings in the correlation matrix, G-score demonstrates a weak positive effect on SPV. R^2 is roughly 7%, indicating that ESG-score, neither in aggregate nor in pillars, is not well suited to explain the variation of SPV alone. However, as neither of these findings are significant, the findings of the single regression models are not valid estimations of their effects on SPV.

7.3 The multiple regression models

The multiple regression models allowed the inclusion of control variables and country/ industry specific interaction terms. Following, the multiple regression models will be presented.

7.3.1 ESG-score in aggregate on Stock Price Volatility

Table 7.2: The multiple regression of ESG-score on Stock Price Volatility result

	Dependent variable: SPV
ESG-score	-0.001^{**}
	(0.0003)
	p = 0.045
DivYield	-0.021^{***}
	(0.007)
	p = 0.005
PayoutRatio	-0.002^{***}
	(0.0003)
	p = 0.000
Firm size	-0.245^{***}
	(0.022)
	p = 0.000
Leverage	-0.019
	(0.024)
	p = 0.410
EarnVol	0.024^{**}
	(0.009)
	p = 0.012
Constant	0.929^{***}
	(0.192)
	p = 0.00001
Observations	1,369
R^2	0.2528
Note:	*p<0.1; **p<0.05; ***p<0.01

In Table 7.2 the multiple regression model with ESG-score in aggregate has been conducted. ESG-score demonstrates a statistically significant negative relationship with SPV. Hence, the null hypothesis in hypothesis 1 is rejected. All control variables, except for leverage, demonstrates a statistically significant relationship with SPV. All independent variables have a negative coefficient, except for earnings volatility. Both earnings volatility and leverage have different coefficient signs compared to the correlation matrix. Furthermore, an unit increase in ESG-score induces a 0.1 % decrease in SPV. Similarly, an unit increase in dividend yield and payout ratio induces a 2.1% and 0.2% decrease in SPV respectively. As firm size and earnings volatility are logarithmic transformed, they must be interpreted accordingly with the log-log model (Wooldridge, 2014, p. 40). Therefore, an one percent increase in firm size and earnings volatility induces a 0.245% decrease and 0.024% increase in SPV respectively. R^2 is roughly 25%, which is an immense enlargement from the single regression model. Consequently, there is evidence that the control variables are well suited in explaining the variability of SPV.

7.3.2 ESG-score pillars on Stock Price Volatility

Table 7.3: The multiple regressions of ESG-score pillars on Stock Price Volatility results

	Dependent variable: SPV		
	(1)	(2)	(3)
E-score	-0.0004^{**}		
	(0.0002)		
	p = 0.021		
S-score		-0.001^{*}	
		(0.0003)	
		p = 0.074	
G-score			-0.0001
			(0.0003)
			p = 0.693
DivYield	-0.021^{***}	-0.021^{***}	-0.021^{***}
	(0.007)	(0.007)	(0.007)
	p = 0.006	p = 0.004	p = 0.004
PayoutRatio	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.00000	p = 0.000
Firm size	-0.245^{***}	-0.244^{***}	-0.244^{***}
	(0.022)	(0.021)	(0.022)
	p = 0.000	p = 0.000	p = 0.000
Leverage	-0.021	-0.019	-0.021
	(0.023)	(0.023)	(0.025)
	p = 0.366	p = 0.408	p = 0.404
EarnVol	0.023^{**}	0.023^{**}	0.023^{**}
	(0.009)	(0.009)	(0.010)
	p = 0.013	p = 0.012	p = 0.015
Constant	0.926^{***}	0.924^{***}	0.904^{***}
	(0.197)	(0.194)	(0.197)
	p = 0.00001	p = 0.00001	p = 0.00001
Observations	1,369	1,369	1,369
R^2	0.253	0.253	0.251
Note:			*p<0.1; **p<0.05; ***p<0.01

In Table 7.3 the multiple regression models with ESG-pillars have been conducted. E-score demonstrates a statistically significant negative relationship with SPV, although the effect is minuscule. Therefore, the null hypothesis of hypothesis 2 is rejected. S-score and G-score fails to demonstrate a statistically significant effect on SPV. Therefore, the null hypothesis in hypothesis 3 and 4 is retained. However, S-score scarcely fail to demonstrate significance at the 5% level, while G-score strongly fails to demonstrate significance with a p-value of 0.693. All ESG-pillars, except for G-score, demonstrates similar coefficient signs with the correlation matrix and the single regressions.

Dividend yield, payout ratio and firm size demonstrates a statistically negative relationship with SPV for all ESG-pillars. Earnings volatility demonstrates a statistically positive relationship with SPV for all ESG-pillars. Leverage fails to demonstrate any significance for any of the ESG-pillars. In comparison to the multiple regression with ESG-score in aggregate, most results are similar, with leverage demonstrating a minuscule larger effect on SPV in the regression models with ESG-pillars. However, as leverage is still insignificant, this minuscule difference in effect is ignored. R^2 is similar to the regression model with ESG-score in aggregate, even though a minuscule decrease in R^2 for G-score is observed.

7.3.3 The multiple regression models of country differences

This section will present the results from the multiple regressions with interaction terms for geographical differences. In Table 7.4 below, the results of the regression models with ESG-score in aggregate and country specific interaction terms are provided. The regression models in Table 7.4 uses one country as the interaction term, and the other countries as the base group. The regression models with ESG-pillars and country specific interaction terms are provided in the appendix, A.3.1.

Table 7.4: The multiple regressions with country specific interaction terms results

	Dependent variable: SPV			
	(1)	(2)	(3)	(4)
ESG-score	-0.0002	-0.001^{**}	-0.0003	-0.001^{***}
	(0.0003)	(0.0004)	(0.0003)	(0.0003)
	p = 0.470	p = 0.021	p = 0.337	p = 0.003
ESG_Sweden	-0.001^{***}			
	(0.0002)			
	p = 0.0004			
ESG_Norway		0.001^{**}		
		(0.001)		
		p = 0.036		
ESG_Denmark			-0.002	
			(0.001)	
			p = 0.172	
ESG_Finland				0.001
				(0.001)
				p = 0.158
DivYield	-0.021^{***}	-0.022^{***}	-0.022^{***}	-0.022^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.004	p = 0.003	p = 0.002	p = 0.003
PayoutRatio	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.000	p = 0.00000	p = 0.000
Firm size	-0.248^{***}	-0.240^{***}	-0.242^{***}	-0.253^{***}
	(0.020)	(0.021)	(0.022)	(0.019)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	-0.018	-0.025	-0.034^{**}	-0.025
	(0.025)	(0.023)	(0.017)	(0.022)
	p = 0.481	p = 0.270	p = 0.047	p = 0.263
EarnVol	0.025^{**}	0.021^{**}	0.024^{**}	0.029^{***}
	(0.010)	(0.009)	(0.009)	(0.011)
	p = 0.011	p = 0.018	p = 0.012	p = 0.009
Constant	0.936^{***}	0.918^{***}	0.911^{***}	0.946^{***}
	(0.188)	(0.192)	(0.195)	(0.176)
	p = 0.00000	p = 0.00001	p = 0.00001	p = 0.00000
Observations	1,369	1,369	1,369	1,369
R^2	0.257	0.260	0.259	0.260
Note:				*p<0.1; **p<0.05; ***p<0.01

In the regression model with Sweden as interaction term, ESG-score fails to demonstrate a significant effect on SPV, although the interaction term demonstrates a negative statistically significant effect. This indicates that Swedish firms have a greater negative effect of ESG-score on SPV compared to the other Nordic countries. Furthermore, in the regression model with the Norwegian interaction term, ESG-score demonstrates a negative statistical significant effect on SPV, while the interaction term demonstrates a positive statistical significant effect from ESG-score in Norway on SPV. This indicates that Norwegian firms have a less negative effect of ESG-score on SPV. While the regression model with Finland as interaction term demonstrates a negative statistical significant relationship from ESG-score on SPV, the interaction term fail to demonstrate significance. Therefore, the null hypothesis for hypothesis 5 and 6 are rejected (Norway and Sweden). However, the null hypothesis for hypothesis 7 and 8 (Denmark and Finland) are retained. This means that there are differences in the effect from ESG-score on SPV in the Nordic countries.

In the regression models for the ESG-pillars with country specific interaction terms, provided in the appendix A.3.1, S-score demonstrates the same exact conclusions made for ESG-score in aggregate, and that country specific interaction terms on E-score only demonstrates a statistically significant effect on SPV in Denmark. The regression models with country specific interaction terms on G-score demonstrated a negative statistical significant effect of ESG-score on SPV in Sweden and a positive statistical significant effect of ESG-score on SPV in Norway. However, the multiple regressions with country specific interaction terms on E-score scarcely fail to demonstrate a statistical significant effect in Sweden and Norway with p-values of 0.063 and 0.051 respectively. R^2 have increased a negligibly amount to around 0.256-0.260. The minuscule increase might be due to the extra variable added to the regression models. The other variables remain similar in coefficients, standard deviation and p-value levels.

7.3.4 The multiple regression models of industrial differences

This section will present the results from the multiple regressions with industry specific interaction terms. Similarly to the multiple regressions with country specific interaction terms, there are several regression models each with one industry specific interaction term. Following are the multiple regressions with ESG-score in aggregate on the industry specific interaction terms. The multiple regressions with ESG-score pillars on the interaction terms are provided in the appendix, A.3.2. ESG-score industry differences

Table 7.5: The multiple regressions with industry specific interaction terms results

	Dependent variable: SPV					
	(1)	(2)	(3)	(4)	(5)	(6)
ESG-score	-0.002^{***}	-0.001^{*}	-0.001^{**}	-0.0004	-0.001^{*}	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.00000	p = 0.058	p = 0.042	p = 0.126	p = 0.053	p = 0.392
ESG_Industrial	0.002^{***}					
	(0.001)					
	p = 0.0003					
ESG_Utility		-0.0004				
		(0.001)				
		p = 0.500				
ESG_Transportation			0.001			
			(0.001)			
			p = 0.282			
ESG_Bank				-0.002^{**}		
				(0.001)		
				p = 0.040		
ESG_Insurance					-0.00004	
					(0.001)	
					p = 0.958	
ESG_Other						-0.004^{***}
						(0.001)
						p = 0.003
DivYield	-0.021^{***}	-0.021^{***}	-0.021^{***}	-0.021^{***}	-0.021^{***}	-0.021^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.005	p = 0.005	p = 0.005	p = 0.004	p = 0.005	p = 0.004
PayoutRatio	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.00000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Firm size	-0.242^{***}	-0.245^{***}	-0.244^{***}	-0.241^{***}	-0.245^{***}	-0.247^{***}
	(0.020)	(0.022)	(0.021)	(0.021)	(0.022)	(0.020)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	0.003	-0.018	-0.022	-0.011	-0.020	-0.005
	(0.017)	(0.023)	(0.025)	(0.026)	(0.025)	(0.017)
	p = 0.874	p = 0.431	p = 0.374	p = 0.669	p = 0.425	p = 0.763
EarnVol	0.026^{***}	0.024^{**}	0.023^{**}	0.023^{**}	0.023^{**}	0.027^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
	p = 0.003	p = 0.011	p = 0.015	p = 0.013	p = 0.012	p = 0.003
Constant	0.861^{***}	0.923^{***}	0.927^{***}	0.900^{***}	0.929^{***}	0.907^{***}
	(0.169)	(0.187)	(0.190)	(0.192)	(0.192)	(0.175)
	p = 0.00000	p = 0.00000	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00000
Observations	1,369	1,369	1,369	1,369	1,369	1,369
R^2	0.270	0.253	0.253	0.258	0.254	0.274
Note:						*p<0.1; **p<0.05; ***p<0.01

The multiple regressions with industry specific interaction terms demonstrates a negative statistical effect from ESG-score on SPV for regression models 1 and 3 (industrial and transportation). However, regression models 1 and 3 only demonstrate statistical significance for the interaction term industrial. Therefore, the null hypothesis in hypothesis 9 is rejected, while null hypothesis in hypothesis 11 is retained. Furthermore, regression models 2 and 5 (utility and insurance) scarcely fail to demonstrate statistical significance for ESG-score on SPV at the five percent level, even though the interaction terms for utility and insurance immensely fails to demonstrate a significant effect on SPV. Therefore, the null hypothesis in hypotheses 10 and 13 are retained. In regression model 4 (bank) ESG-score fail to demonstrate a significant effect on SPV at the ten percent level, however, the interaction term bank demonstrates a negative statistical significant effect on SPV, and hence the null hypothesis in hypothesis 12 has been rejected. Finally, regression model 6 ("other") also fail to demonstrate a significant effect from ESG-score on SPV, even though the interaction term "other" demonstrates a negative statistical relationship. Therefore, the null hypothesis in hypothesis 14 has been rejected.

The multiple regressions with ESG-pillars and industry specific interaction terms (see Appendix A.3.2) demonstrated that for E-score, all models except for bank and "other" demonstrates a statistically significant effect from E-score on SPV. However, only regression models 1 and 6 (industrial and "other") demonstrates a statistically significant effect from the interaction term and E-score on SPV. Therefore, the null hypothesis in hypothesis (E-score/industrial)[1] and (E-score/"other") has been rejected. Furthermore, the multiple regressions with S-score and industry specific interaction terms demonstrated that only regression model 1 (industrial) had a statistically significant effect from S-score on SPV[2]. However, both interaction terms industrial and "other" with S-score demonstrated a statistically significant effect on SPV. Therefore, the null hypothesis in hypothesis (S-score/industrial and S-score/"other") has been rejected. Finally, the multiple regressions with G-score and industry specific interaction terms only demonstrated significance from G-score on SPV in regression model 1 (industrial). However, the regression models with interaction terms industrial, bank, insurance and "other" on governance score all demonstrate a statistically significant effect on SPV, all with negative coefficients except for industrial. Therefore, the null hypothesis in hypothesis (G-score/industrial), (G-score/bank), (G-score/insurance) and (G-score/"other") has been rejected. The control variables does not vary substantially in coefficients, standard deviation and p-values with the models presented above. R^2, however, does vary between 0.253 to 0.274.

[1]Note that these hypothesis were not numbered due to practical reasons. See section 5.4.2.

[2]Note that regression models 2, 3 and 5 (utility, transportation and insurance) all fail to demonstrate significance at the five percent level, but do in fact demonstrate significance at the ten percent level.

7.4 Results summary

Table 7.6: Results summary

Model	Reject/Retain null hypothesis	Comment
ESG-score		
Multiple regression on SPV	Reject	ESG-score demonstrates a statistically significant negative effect of 0.001 on SPV.
Country specific interaction terms	Reject for Sweden and Norway	The regression model demonstrates a significant negative effect of ESG-score on SPV in Sweden and a significant positive effect of ESG-score on SPV in Norway compared to the other Nordic countries. Denmark and Finland fails to demonstrate a significant country specific difference.
Industry specific interaction terms	Reject for Industrial, Bank and Other	The regression model demonstrates a significant negative effect of ESG-score on SPV in Bank and Other and a significant positive effect of ESG-score on SPV in Industrial compared to the other industry segments.
E-score		
Multiple regression on SPV	Reject	E-score demonstrates a statistically significant negative effect of 0.0004 on SPV.
Country specific interaction terms	Reject for Denmark	The regression model demonstrates a significant negative effect of E-score on SPV in Denmark while Sweden and Norway scarcely fail to demonstrate a significant effect of E-score on SPV compared to the other Nordic countries. Finland fail to demonstrate a significant country specific difference.
Industry specific interaction terms	Reject for Industrial and Other	The regression model demonstrates a significant negative effect of E-score on SPV in Other and a significant positive effect of E-score on SPV in Industrial compared to the other industry segments.
S-score		
Multiple regression on SPV	Retain	S-score fails to demonstrate a significant effect on SPV at the 5% level. However, S-score demonstrates a significant effect on SPV at the 10% level, with a negative coefficient of 0.001.
Country specific interaction terms	Reject Sweden and Norway	The regression model demonstrates a significant negative effect of S-score on SPV in Sweden and a significant positive effect of S-score on SPV in Norway compared to the other Nordic countries. Denmark and Finland fails to demonstrate a significant country specific difference.
Industry specific interaction terms	Reject for Industrial and Other	The regression model demonstrates a significant negative effect of S-score on SPV in Other and a significant positive effect of S-score on SPV in Industrial compared to the other industry segments. Bank scarcely fail to demonstrate a significant effect.
G-score		

Multiple regression on SPV	Retain	G-score fail demonstrate a statistically significant effect on SPV.
Country specific interaction terms	Reject for Sweden and Norway	The regression model demonstrates a significant negative effect of G-score on SPV in Sweden and a significant positive effect of G-score on SPV in Norway compared to the other Nordic countries. Denmark and Finland fails to demonstrate a significant country specific difference.
Industry specific interaction terms	Reject for Industrials, Bank, Insurance and Other	The regression model demonstrates a significant negative effect of G-score on SPV in Bank, Insurance and Other and a significant positive effect of G-score on SPV in Industrial compared to the other industry segments.

8. Discussion and analysis

This chapter will discuss and analyse the empirical results presented in the previous chapter. The empirical results will also be connected and compared to the existing literature. Furthermore, the research quality of this study will be discussed, including the limitations, sources of error, validity, reliability, genereralizability and replicability of the study.

8.1 Discussion

ESG-score and Stock Price Volatility

All single regression models demonstrated that while minuscule, no significance were found for any of the ESG-scores analyzed. As no literature has been found relating ESG-score and SPV by means of a single regression, no comparison to previous literature may be given. In line with the literature (Wooldridge, 2014, p. 83), using one independent variable, namely the various ESG-scores, results in a small R^2. The single regressions, even though insignificant, has demonstrated a pattern that holds for the multiple regression of ESG-score pillars and SPV as well, namely that the coefficient of S-score is greater than the other coefficients by a magnitude of ten, and the insignificance of the G-score is immense. However, as the single regression model has no previous literature nor significance, it will not be discussed further.

Previous research, by means of a multiple regression of ESG-score on return volatility, lack consensus. Two studies found that ESG-score is negatively related to return volatility (Borovkova & Wu, 2020) (Broadstock et al., 2021). One study found a positive relationship between ESG-score and SPV (Tasnia et al., 2020) and one study found no relationship between ESG-score and SPV (Meher et al., 2020). However, the study which found a positive relationship between ESG-score and SPV was exclusively in the industry sector bank and is therefore not directly comparable to the study at hand. Similarly, the study which found no relationship between ESG-score and SPV was exclusively in the Indian market and used Sustainalytics as the ESG-score provider and is therefore not directly comparable to the study at hand. Therefore, in line with existing literature (Borovkova & Wu, 2020), a negatively statistically significant relationship between ESG-score and SPV has been found. This relationship may be explained as bigger firms tend to exhibit greater ESG-score (Drempetic et al., 2019), and bigger firms tend to have lower SPV (Cheung & Ng, 1992). Previous research has also argued that CSR might increase market volatility as it increases noise in the stock market (Orlitzky, 2013), in which there is no evidence for in this study. Furthermore, R^2 increased as several control variables were included. To the extent a R^2 value of 25.3% is a sufficient value proves to be a qualitative inquiry. As SPV is affected by a variety of factors, not all factors may be possible to include in the regression models. As described in the chapter "Data framework", a low R^2 is not uncommon in cross-sectional regression analysis and therefore the R^2 values obtained for the multiple regressions in this study are not considered to cause invalid results.

As the term ESG was coined in 2005 with the assumption of a beneficial financial effect was linked to implementing ESG-measures (Kell, 2018), this study has found evidence for this assumption as implementing ESG-measures reduces a firm's SPV in the Nordic countries during 2010-2019.

ESG-score pillars and Stock Price Volatility

The multiple regressions of ESG-score pillars on SPV demonstrated statistical significance at the level of five percent for E-score. Furthermore, S-score demonstrated a p-value of 0.074, which is significant at the 10% level. S-score also demonstrated a coefficient larger than all other pillars by a factor of ten. G-score demonstrated immense insignificance. Therefore, in line with existing literature relating the significance of ESG-score pillars (Giese et al., 2021), the significance/ insignificance found in the multiple regression models of ESG-score pillars on SPV may be explained due to the time period of the data sample. As the time period used in this study is ten years, with one yearly observation, factors determining the significance of the effect of E-score and S-score on SPV may have culminated and become significant. Furthermore, as the time period is vast, factors determining G-score have failed to culminate and become significant, as event risks such as fraud may be viewed as one time incidents. Given the theory of time period being an important determiner for the significance of ESG-pillars is true for this study as well (Giese et al., 2021), the significance of G-score may would have been better if the data observations used in this study were daily or weekly.

Country differences

The multiple regressions of ESG-score on SPV with country specific interaction terms found significance for both Sweden and Norway, and hence insignificance for Denmark and Finland. Furthermore, the interaction terms with Norway and Finland, contrary to the interaction terms with Sweden and Denmark, demonstrated a positive relationship between ESG-score and SPV. As no literature exists on the relationship between ESG-score and SPV for regional differences, the GSCI 2020 will be used to discuss the above mentioned causality. Given that the sample used in this study only contains Nordic countries, considering the Global Index rating only, the interaction terms with Sweden and Denmark would be expected to have negative coefficients, and similarly the interaction terms with Finland and Norway would be expected to have positive coefficients. As ESG-score was found to negatively impact SPV, the interaction term with a country having a Global Index score above average in the sample may be expected to have a greater negative effect on SPV. The minuscule effect between Nordic countries may be explained as all the Nordic countries are performing quite similarly in terms of score achieved on the GSCI rating ranging from Sweden (62.1) to Norway (57.7).

The multiple regression of interaction terms with ESG-pillars and country demonstrated a significant negative relationship between E-score for Denmark, a significant negative relationship between S-score and G-score for Sweden and a significant positive relationship between all ESG-pillars for Norway[1]. As there is no existing literature on the difference between ESG-pillar on SPV across countries, the GSCI 2020 report will be used once again to discuss the causalities found. Using the "Resource Efficiency" as a proxy for the E-score both Denmark and Sweden demonstrated a negative relationship with respect to the sample as suggested by their respective ranking on the "Resource Efficiency" list, suggesting the GSCI 2020 report may describe the causality found. However, even though the interaction term with S-score and Denmark was insignificant, both Sweden and Denmark demonstrated a negative relationship with respect to the sample for S-score. Therefore, using "Social Capital" as a proxy for S-score, the GSCI 2020 report fails to describe the causality found as Denmark is the poorest ranked country on the "Social Capital" list in the sample. Similarly to the S-score the GSCI 2020 report fails to describe the causality found between G-score and country differences.

Industrial differences

The multiple regressions of ESG-score on SPV with industry specific interaction terms found positive significance for the sector industrial and negative significance for the sector bank. Therefore, firms operating in the industry bank have a lager effect of ESG-score on SPV in the Nordic countries. As this effect is negative, there is reason to believe this result contradict the findings of the 37 U.S banks, which found a positive effect from ESG-score on SPV (Tasnia et al., 2020)[2]. An explanation might be that firms categorized as operating in the sector of bank experiences more effect of ESG-score on SPV as incorporating sustainability measures such as conducting good governance decreases the likelihood of negative event risks such as fraud. Firms categorized as operating in the sector of industrial may experience less effect of ESG-score on SPV as implementing measures such as announcing measures to reduce carbon emissions make the firms more valuable to investors in the long term and hence the firms' SPV increases as the firms' stocks move more heavily.

The multiple regression of interaction terms with ESG-score pillars and sectoral differences demonstrated a positive statistical significant relationship between all ESG-pillars and the sector industrial. Furthermore, a negative statistical relationship between G-score and the sectors bank and insurance were found. No comparable existing literature has been found, even though the literature has demonstrated sectoral differences across dissimilar sectors used in this study. However, a study found that G-score was the most prominent differentiator on average across all industries (Giese et al., 2021). As the industrial sector is the only significant differentiator on E-score and S-score, while industrial, bank and insurance are all significant differetiators on G-score, G-score may be the more prominent ESG-pillar for sectoral differences in the Nordic market as well.

[1] E-score for Norway has p-value = 0.051 and will for simplicity be treated as significant at the five percent level.

[2] Note that the study of 37 U.S. banks hardly is comparable, and hence the contradiction should not be heavily emphasized.

There might be various explanations to why the different industries have different effects on E-score, S-score and G-score. One explanation for the industry differences between ESG-pillars is how the aggregate ESG-score is calculated. A deeper analysis of the methodology in which Refinitiv makes their ESG-scores (Refinitiv, 2020), reveals that firms in the bank and insurance sectors are more heavily weighted on governance[3], firms in the industrial sector are more heavily weighted on social and firms in the utility sector are more heavily weighted on environmental. Contrary to environmental and social, governance seems to have an effect on the effect of ESG-score on SPV in the industries bank and insurance, which might be explained as firms in the industries bank and insurance are more susceptible to event risks such as fraud. Finally, the industry sector industrial seems to have, in comparison to the other industry sectors, a positive effect on the effect of ESG-score on SPV.

Other relationships

The regression results also provided other significant relationships than merely between ESG-score and SPV. Dividend yield, payout ratio, firm size and earnings volatility all demonstrated significant effects on SPV. Leverage however, failed to demonstrate any significant relationship with SPV in all regressions conducted in this study.

Dividend yield and Payout Ratio demonstrated a negative effect on SPV, in line with existing research in which a large inverse relationship between dividend yield and SPV was found (Baskin, 1989). This finding has been hypothesised to be due of firms paying dividends provides sooner positive cash flows for the investors and consequently, the risk of investing in firms paying dividends decreases. This finding is supported by multiple studies, such as (Sörensen & Deboi, 2020) and (Hussainey et al., 2011) for firms in Sweden and the U.K. The opposite result was found in South Africa (Pelcher, 2019), and no tangible relationship between dividend yield and SPV was found in Australia (Allen & Rachim, 1996). A possible explanation for these contradicting results may be that the study from South Africa only included the 40 largest firms listed in South Africa, while the study from the U.S. used 2344 firms listed in the U.S, and consequently the firm sizes included in these studies may greatly differ.

Similarly to the variables of dividend policy, firm size also demonstrated a significant negative relationship with SPV. This is in line with existing literature, such as: (Baskin, 1989), (Cheung & Ng, 1992) and (Hussainey et al., 2011). The hypothesis for this finding is that larger firms tend to be more diversified and consequently less exposed to market fluctuations than smaller firms.

Earnings volatility was the only variable to demonstrate a significant positive relationship with SPV in this study. This finding is in line with existing literature such as: (Allen & Rachim, 1996), (Baskin, 1989), (Dichev & Tang, 2009) and (Hussainey et al., 2011). It seems to be a clear consensus, in which higher earnings volatility induces higher volatility in a firm's stock price, as the uncertainty about earnings increases. Since earnings volatility

[3]ESG-scores in industry sectors bank and insurance are weighted 35%-50% on governance (Refinitiv, 2020).

has no clear definition however, many interpretations in how to correctly calculate earnings volatility exists. On one hand, studies like (Baskin, 1989) uses a method where earnings volatility is fixed over all years. On the other hand, studies like (Hussainey et al., 2011) and (Dichev & Tang, 2009) uses a method where earnings volatility differs from year to year. However, the size of earnings volatility on SPV varies in different studies. This might therefore be, as there are different calculation methods of earnings volatility and the different markets in which these studies are conducted.

Leverage is the only control variable not to demonstrate a significant relationship with SPV in this study. The coefficient sign of leverage is negative, despite being insignificant, which is contrasting to a major part of the existing literature. Studies, such as: (Baskin, 1989), (Hussainey et al., 2011) and (Sörensen & Deboi, 2020) all found a significant positive relationship between leverage and SPV. The hypothesis for this finding seems to be larger uncertainty in high leverage compared to low leverage. The time period in which these studies were conducted might be crucial however, as a large proportion of these studies were conducted before 2010. After the financial crisis of 2008, the world economy underwent major changes in regard to debt policy, in which one study found that debt-to-GDP ratio had decreased after the financial crisis (Bauer & Granziera, 2016). This decrease in the ratio of debt-to-GDP is a result of banks reduced willingness to issue risky loans to firms. Therefore, the changing debt policy in the world economy might induce a less significant effect of leverage on SPV. In some cases, as a consequence to the changing debt policy in the world economy, the effect may be opposite as banks may be more inclined to issue loans to less risky firms[4].

The relationship between the control variables and SPV may give explanatory indications of the effects found in this study of ESG-score on SPV. One prominent relationship is that ESG-controversies are positively related to firm size (Giese et al., 2021) (Crespi & Migliavacca, 2020). Therefore, as firm size is well known to negatively impact SPV, there might be crossover effects in which ESG-controversies are positively related to firm size. Furthermore, as most research found indicates a negative relationship between dividend yield and SPV, there might be crossover effects as previous studies have found a positive relationship between dividend policy and ESG-score (Johansson & Fahlén, 2019)(Benlemlih, 2019)[5].

8.2 Research quality

This section will discuss the research quality of this study in greater detail. First, the inevitable limitations of the study will be presented. Next, sources of error followed by the validity and reliability of this study will be discussed. Finally, the genereralizability and replicability of the study will be embodied.

Limitations

The first and foremost limitation of this study, in getting accurate results, is the limited

[4]Firms categorized as less risky due to smaller debt/equity ratio.

[5]Note that these crossover effects are mere speculations.

adequate data in Refinitiv on the Nordic exchanges. Therefore, only a fraction of all firms listed on the exchanges could be included in the regressions. Also, only a fraction of all firms with necessary data to conduct the regression analysis had data for the entire intended time period, namely 2010-2019. Furthermore, as the study intended to address the relationship between ESG-score and SPV in the Nordic countries, no conclusions may be given for the Icelandic stock exchange, as no firms remained in the Icelandic stock exchange after the comprehensive screening process. As a key limitation in conducting a viable research in the Nordic market, prior research relating ESG-score and SPV in the Nordic market is non-existent, even though there is limited prior research relating ESG-score and SPV on the international market. Therefore, in creating the data sample and regression models for this study, a lack of similar research made conducting precise and quality research an exhaustive endeavour.

Sources of error

The data sample was screened comprehensively such that the data sample would fulfill the exhaustive list of requirements, such as available ESG-scores and necessary data for the control variables. Furthermore, in avoiding ambiguous data collection, all raw data had to be collected from the same data provider, namely Refinitiv. Therefore, many firms failed to achieve the criterions needed to be included in the study. Furthermore, as previously discussed, firm size tend to exhibit a greater ESG-score. Hence, the entire data sample may be subject to a firm size bias. Consequently, to the extent the data sample accurately reflects the Nordic market remains a qualitative inquiry. Furthermore, the results were produced with a rather intricate method. As the authors had limited experience in extracting data, creating data samples and producing valid regressions, a valid methodology had to be created by inspiration of previous literature and studies. Therefore, even though the methodology used is the most precise methodology to the authors best beliefs, it may exist more specific methodologies in producing comparable/ better results.

The construction of the data sample may also serve as subject to errors. Using a large panel data set easily results in an ambiguous data sample during the creation of the panel data set. Including firms without sufficient available data for the entire time period resulted in missing values for several years, and consequently an unbalanced panel data set was made. Using an unbalanced panel data set is by it self no issue as it is easily handled by computer programs (Wooldridge, 2014, p. 394). However, a common problem in using an unbalanced panel data set is explaining why there are missing values. The reason for having missing values is well understood in this study, and consequently does not cause any further issues. The missing values in this study are a consequence of including firms without adequate available data for the entire time period.

As the objective of this study was to discover whether there is a causal relationship between ESG-score and SPV in the Nordic countries, the very definition of ESG-score will greatly impact the credibility of the study. To the extent an ESG-score may be defined and weighted differently directly questions the causalities found in this study. Therefore, when interpreting the results found in this study, one must bear in mind that the true ESG-score may differ upon whom to interpret.

There are especially two types of errors that might occur when conducting a quantitative analysis, namely type 1 error and type 2 error (Neuman, 2014, pp. 424–426). A type 1 error occurs when making a false conclusion that is not really true, while type 2 error occurs when not making the conclusion while it really is true. The Residual vs Fitted plot provided in the data validation section demonstrated that the OLS line was scarcely below the zero line. This might cause a type 1 error, as an over-prediction of the regression's significance may induce significance wrongfully (Wooldridge, 2014, p. 31). However, the minor offset of the OLS-line was judged to be minuscule and not to interfere with the results in this study. Furthermore, some of the assumptions of the classical OLS model were violated in this study, and consequently the random effects model was chosen rather than the pooled OLS model, and Driscoll Kraay robust standard errors were used given heteroskedasticity and serial correlation. As this process was rather intricate, full transparency is provided through the data validation chapter, such that the belief of the authors of this study not being subject to neither type 1 error nor type 2 error can be readily understood.

As this study is heavily dependent on previous research used for constructing the theoretical framework, method and interpreting the results, errors in the literature may serve as a source of error in this study. Some articles may be biased in that they are provided by authors with their own agenda. Therefore, the authors of this study have viewed all sources used in this study with a critical view.

All empirical results in this study are subject to a large amount of R-programming. Therefore, as the authors had limited experience in R-studio, the programming in R-studio may be a source of error. Previous studies in addition to R-package user manuals have been extensively studied to mitigate the risk of obtaining errors when programming in R-studio.

Validity and reliability

When conducting a study, the terms "reliability" and "validity" refers to the consistency and truthfulness of the study respectively (Neuman, 2014, pp. 212–216). Consistency is the anticipation of retrieving the same result when conducting the study again. Truthfulness is the degree of fit between what the results presents and what actually occurs in the real world.

One important concept with regards to reliability is stability (Neuman, 2014, pp. 212–213). As the data gathered in this study is retrieved from Refinitiv, the data does not vary significantly with time. Therefore, the data used in this study will remain the same unless Refintiv makes major changes in their data calculation methods, and consequently the same results found in this study should be obtained when conducting the exact same study another time. Furthermore, due to the large sample fraction size compared to the population, similar research on the same population would likely produce very similar results to this study. Therefore, the authors perceive this study to be stable, and hence have high reliability.

The validity of the study depends on whether the empirical indicators[6] correctly measures what the empirical indicators are suppose to measure. Furthermore, validity may be divided into four categories, namely: face, content, criterion and construct (Neuman, 2014, p. 215). As face validity refers to what degree the study measures what its put forward to measure, a qualitative inquire arises, namely to which extent the ESG-score provided by Refinitiv actually is the "true" ESG-score. As discussed in the theoretical framework, ESG-scores tend to vary substantially with the various rating providers, and consequently, using another rating provided might cause greatly different results. However, as Refinitiv is a world known leading provider of ESG-scores, and the rating provider the authors had available, Refinitiv was the chosen rating provider. Similarly, to which extent a stock return's standard deviation is the "true" SPV remains a qualitative inquiry as there are several calculation methods of SPV and the SPV used in this study was subject to processing. Therefore, given the lack of existing literature directly relating ESG-score and SPV, especially in the Nordic market, the conclusions made are less tenable compared to studies with a comprehensive existing background. Content validity, which addresses the aspects of variation (Neuman, 2014, pp. 216–217), was strengthen in this study with the inclusion of control variables. As all control variables used in this study have been shown to have an effect on SPV in the existing literature, similar results in comparison to the existing literature indicates that proper regression models were made. However, as R^2 is only 25%, there is an indication of some important variables being omitted. Criterion validity, which addresses whether a standard criterion was used in obtaining the relationships of interest (Neuman, 2014, p. 217), is by definition upheld in this study as the regression models made in this study were scrutinized against the assumptions of the classical OLS model, which results in the best estimators obtainable.

Generalizability and replicability

The results found and conclusions made in this study have to be treated carefully when generalized to the broader sense for several reasons. First, as discussed, the choice of ESG-score provider may immensely impact the causalities found in this study. Refinitiv, compared to other rating providers such as MSCI and Sustainalytics, value transparency highly as ESG-score calculated by Refinitiv to a large extent are based on official reports. Differences of equal importance makes the respective ESG-scores from each rating provider unique. Therefore, in replicating this study, one must use the same rating provider to obtain similar results. Furthermore, the findings in this study might fail to be generalized to the broader sense, as all Nordic countries tend to score extremely well on sustainability ratings (SolAbility, 2019), which might cause implications when replicating this study as high sustainability ratings might be correlated with variables inducing biased results when included carelessly. Also, which firms displaying available and necessary data to conduct comparable studies is highly dependent on the time period chosen. A more recent and shorter time period will increase the ratio of firms with available data for the entire time period, which might impact the causality found between ESG-score and SPV. However, in using a shorter time period specific event risks such as the oil price crisis of 2014 are more likely to have a larger impact on the results found and consequently make the study less comparable to the study at hand.

[6] In this study, the empirical indicators are ESG-score and SPV

9. Conclusion

In promoting the green shift, this study has attempted to provide investors, businesses, firms and politicians through a tangible relationship between ESG-score and stock price volatility, other than ethical reasons, a rationale for including sustainable investments in their endeavors. Existing research directly relating ESG-score and stock price volatility is limited and without consensus. Therefore, to determine whether ESG-score has a causal impact on stock price volatility, various regression analyses with panel data of 259 Nordic firms in the period 2010-2019 have been conducted.

This study has found that ESG-score and E-score were found to negatively impact stock price volatility in the Nordic market in the time period 2010-2019. Furthermore, the industry sectors industrial and bank were found to positively and negatively impact the effect of ESG-score on stock price volatility in the Nordic market respectively. Firms listed in Denmark had a negative impact of E-score on stock price volatility, firms listed in Sweden and Norway had a negative and positive impact of S-score and G-score respectively. Finally, E-score and S-score were found to positively impact the effect of industry sector industrial on stock price volatility and negatively impact the effect of industry sector "other" on stock price volatility. G-score was found to positively impact the effect of industry sector industrial on stock price volatility and negatively impact the effect of industry sectors bank and "other" on stock price volatility.

As a casual relationship between ESG-score and stock price volatility has been found in several dimensions in the Nordic market during the time period 2010-2019, the negative effect of ESG-score on stock price volatility implies that implementing ESG-measures is beneficial in reducing a firm's stock price volatility. The findings in this study therefore strengthens the findings of existing literature relating ESG-measures and corporate financial performance. However, as the comprehension for the causalities found in this study remains inadequate, breeding ground for further research is provided.

10. Further work

This study has found several significant relationships between ESG-score and stock price volatility in the Nordic countries during 2010-2019 across several dimensions. As the scope of this study were limited such that the study could be conducted in a feasible manner, some delimitations had to be made. Therefore, with the findings and delimitations of this study, breeding ground for highly intriguing further research is provided.

As this study has found a significant negative effect from ESG-score on SPV without a thorough understanding of why the relationship exists, further research question one is:
An empirical study explaining the causal relationship between ESG-score and SPV in the Nordic market.

This study used only one ESG-rating provider, namely Refinitiv. As literature has demonstrated that ESG-scores tend to vary substantially with the different rating providers, further research question 2 is:
An empirical study of ESG-score on SPV in the Nordic market. Comparing the relationship with various rating providers.

Literature has found a strong correlation between sustainability performance and firm size. Therefore, further research question 3 is:
An empirical study of the effect of firm size bias on the relationship between ESG-score and SPV in the Nordic market.

The beneficial effect of ESG-measures on corporate financial performance were found to likely be independent with time in the existing literature. In the view of relevant stakeholders, whether the findings of this study are independent with time might be of great importance. Therefore, research question four is:
An empirical study measuring the effect of time on the effect of ESG-score on SPV.

Initiatives for a more general classification system for sustainable investments have been made in the European Union with the EU Taxonomy for sustainable activities (Europa Commission, 2021). As this classification system is likely to become more comprehensive and inclusive in the upcoming years, the fifth research question is:
An empirical study measuring the effect of sustainability-scores on SPV using ratings provided by the EU Taxonomy.

11. References

Allen, D. E., & Rachim, V. S. (1996). Dividend policy and stock price volatility: Australian evidence. *Applied financial economics*, *6*(2), 175–188.

Andri et mult. al., S. (2021). *DescTools: Tools for descriptive statistics* [R package version 0.99.40]. https://cran.r-project.org/package=DescTools

Aouadi, A., & Marsat, S. (2018). Do esg controversies matter for firm value? evidence from international data. *Journal of Business Ethics*, *151*(4), 1027–1047.

Artmann, S., Finter, P., & Kempf, A. (2012). Determinants of expected stock returns: Large sample evidence from the german market. *Journal of Business Finance & Accounting*, *39*(5-6), 758–784.

Bache, S. M., Wickham, H., & Bache, M. S. M. (2016). Package 'magrittr'.

Balasundaram, N. (2009). Social responsibility of business. *Annals of University of Bucharest, Economic and Administrative Series*, *3*, 227–236.

Baltagi, B. H., & Li, Q. (1990). A lagrange multiplier test for the error components model with incomplete panels. *Econometric Reviews*, *9*(1), 103–107.

Baskin, J. (1989). Dividend policy and the volatility of common stocks. *Journal of portfolio Management*, *15*(3), 19.

Bauer, G. H., & Granziera, E. (2016). Monetary policy, private debt and financial stability risks. *Private Debt and Financial Stability Risks (November 11, 2016).*

Becchetti, L., Ciciretti, R., & Hasan, I. (2015). Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. *Journal of Corporate Finance*, *35*, 297–309.

Benlemlih, M. (2019). Corporate social responsibility and dividend policy. *Research in International Business and Finance*, *47*, 114–138.

Berk, J., & DeMarzo, P. (2017). *Corporate finance (; global ed.)* Pearson.

Black, T. R. (1998). *Doing quantitative research in the social sciences: An integrated approach to research design, measurement and statistics.* Sage.

Borovkova, S., & Wu, Y. (2020). *Esg versus financial performance of large cap firms: The case of eu,u.s., australia and south-east asia.* Retrieved February 8, 2021, from https://www.refinitiv.com/content/dam/marketing/en_us/documents/gated/white-papers/esg-vs-financial-performance-of-large-cap-firms.pdf?utm_campaign=230359_2020GlobalQuant&elqCampaignId=9966&utm_source=Perspectives&utm_medium=Blog&utm_content=Blog&utm_term=QuantsESG

Broadstock, D. C., Chan, K., Cheng, L. T., & Wang, X. (2021). The role of esg performance during times of financial crisis: Evidence from covid-19 in china. *Finance research letters*, *38*, 101716.

Cantino, V., Devalle, A., Fiandrino, S., et al. (2017). Esg sustainability and financial capital structure: Where they stand nowadays.

Cauchie, S., Hoesli, M., & Isakov, D. (2004). The determinants of stock returns in a small open economy. *International Review of Economics & Finance*, *13*(2), 167–185.

Cheung, Y.-W., & Ng, L. K. (1992). Stock price dynamics and firm size: An empirical investigation. *The Journal of Finance*, *47*(5), 1985–1997.

Crespi, F., & Migliavacca, M. (2020). The determinants of esg rating in the financial industry: The same old story or a different tale? *Sustainability*, *12*(16). https://www.mdpi.com/2071-1050/12/16/6398

Croissant, Y., Millo, G., Tappe, K., Toomet, O., Kleiber, C., Zeileis, A., Henningsen, A., Andronic, L., Schoenfelder, N., & Croissant, M. Y. (2020). Package 'plm'. *Choice*, *139*(1), 227–240.

De Beer, L. T., Pienaar, J., & Rothmann Jr, S. (2013). Investigating the reversed causality of engagement and burnout in job demands-resources theory. *SA Journal of Industrial Psychology*, *39*(1), 01–09.

Degiannakis, S., & Xekalaki, E. (2004). Autoregressive conditional heteroscedasticity (arch) models: A review. *Quality Technology and Quantitative Management*, *1*. https://doi.org/10.1080/16843703.2004.11673078

Dichev, I. D., & Tang, V. W. (2009). Earnings volatility and earnings predictability. *Journal of accounting and Economics*, *47*(1-2), 160–181.

Drempetic, S., Klein, C., & Zwergel, B. (2019). The influence of firm size on the esg score: Corporate sustainability ratings under review. *Journal of Business Ethics*, 1–28.

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The stata journal*, *3*(2), 168–177.

Eccles N.S., V. S. (2011). The origins and meanings of names describing investment practices that integrate a consideration of esg issues in the academic literature. *J Bus Ethics*, *104*, 389–402.

Ekonomifakta. (2020). *Bnp - sverige*. Retrieved May 6, 2021, from https://www.ekonomifakta.se/Fakta/Ekonomi/Tillvaxt/BNP---Sverige/

Europa Commission. (2021). *Eu taxonomy for sustainable activities*. Retrieved June 4, 2021, from https://ec.europa.eu/info/business-economy-euro/banking-and-finance/sustainable-finance/eu-taxonomy-sustainable-activities_en

Feifei Li, A. P. (2020). *What a difference an esg ratings provider makes!* Retrieved February 8, 2021, from https://www.researchaffiliates.com/en_us/publications/articles/what-a-difference-an-esg-ratings-provider-makes.html

Fellmann, S. (2019). *Economic development in the nordic countries*. Retrieved May 3, 2021, from https://nordics.info/show/artikel/economic-development-in-the-nordic-countries/

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.

Gao, L., & Zhang, J. H. (2015). Firms' earnings smoothing, corporate social responsibility, and valuation. *Journal of Corporate Finance*, *32*, 108–127. https://doi.org/https://doi.org/10.1016/j.jcorpfin.2015.03.004

Ghosh, D., & Vogt, A. Outliers: An evaluation of methodologies. In: *Joint statistical meetings. 2012*. 2012.

Giese, G., Nagy, Z., & Lee, L.-E. (2021). Deconstructing esg ratings performance: Risk and return for e, s, and g by time horizon, sector, and weighting. *The Journal of Portfolio Management*, *47*(3), 94–111. https://doi.org/10.3905/jpm.2020.1.198

Haugen, R. A., & Baker, N. L. (1996). Commonality in the determinants of expected stock returns. *Journal of financial economics*, *41*(3), 401–439.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251–1271.

Hlavac, M. (2018). *Stargazer: Well-formatted regression and summary statistics tables* [R package version 5.2.2]. https://CRAN.R-project.org/package=stargazer

Horcher, K. A. (2005). *Essentials of financial risk management*. Wiley.

Hothorn, T., Zeileis, A., Farebrother, R. W., Cummins, C., Millo, G., Mitchell, D., & Zeileis, M. A. (2015). Package 'lmtest'. *Testing linear regression models. https://cran. r-project. org/web/packages/lmtest/lmtest. pdf. Accessed*, *6*.

Hünermund, P., & Louw, B. (2020). On the nuisance of control variables in regression analysis. *arXiv preprint arXiv:2005.10314*.

Hussainey, K., Mgbame, C. O., & Chijoke-Mgbame, A. M. (2011). Dividend policy and share price volatility: Uk evidence. *The Journal of risk finance*.

Johansson, A., & Fahlén, A. (2019). Does sustainability affect dividend policy?: A panel data study on nordic firms.

Kell, G. (2018). The remarkable rise of esg. *Forbes. com*, *11*.

Kim, T. K., & Park, J. H. (2019). More about the basic assumptions of t-test: Normality and sample size. *Korean journal of anesthesiology*, *72*(4), 331.

Kotze, A. (2005). Stock price volatility: A primer. *The South African Financial Markets Journal*.

Machdar, N. (2016). The effect of capital structure, systematic risk, and unsystematic risk on stock return. *Business and Entrepreneurial Review*, *14*, 149. https://doi.org/10.25105/ber.v14i2.1148

Markowitz, H. (1959). *Portfolio selection : Efficient diversification of investments* (Vol. 16). Yale University Press.

Maskun, A. (2013). Leverage level, company size, profitability toward the disclosure of csr of lq-45 companies in indonesia stock exchange. *International Journal of Academic Research*, *5*, 140–144.

Meher, B. K., Hawaldar, I. T., Mohapatra, L., Spulbar, C. M., & Birau, F. R. (2020). The effects of environment, society and governance scores on investment returns and stock market volatility. *International Journal of Energy Economics and Policy*, *10*(4), 234–239.

Michelson, S., Wootton, C., & Jordan-Wagner, J. (2011). An analysis of income smoothing. *International Business Economics Research Journal (IBER)*, *2*. https://doi.org/10.19030/iber.v2i1.3758

MSCI. (2020). *Msci esg ratings methodology*. Retrieved April 22, 2021, from https://www.msci.com/documents/1296102/21901542/MSCI+ESG+Ratings+Methodology+-+Exec+Summary+Nov+2020.pdf

Nagelkerke, N. J. et al. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, *78*(3), 691–692.

Nega, F. T. (2017). The relationship between financial performance, firm size, leverage and corporate social responsibility.

Neuman, W. L. (2014). *Social research methods : Qualitative and quantitative approaches* (7th ed.; Pearson new international edition.). Pearson.

Orlitzky, M. (2013). Corporate social responsibility, noise, and stock market volatility. *Academy of Management Perspectives*, *27*, 238–254. https://doi.org/10.5465/amp.2012.0097

Park, H. M. (2011). Practical guides to panel data modeling: A step-by-step analysis using stata. *Public Management and Policy Analysis Program, Graduate School of International Relations, International University of Japan*, *12*, 1–52.

Pedhazur, E. J., & Schmelkin, L. P. (1996). *Measurement, design, and analysis*. Lawrence Erlbaum Associates Inc., Publishers.

Pelcher, L. (2019). The role of dividend policy in share price volatility. *Journal of Economic and Financial Sciences*, *12*. https://doi.org/10.4102/jef.v12i1.221

Profilet, K. A. (2013). Dividend policy and stock price volatility in the us equity capital market.

Refinitiv. (2020). *Environmental, social and governance (esg) scores from refinitiv*. Retrieved February 17, 2021, from https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Refinitiv. (2021). *An overview of environmental, social and corporate governance - esg*. Retrieved February 16, 2021, from https://www.refinitiv.com/en/financial-data/company-data/esg-data#feature-and-benefits

Revelli, C., & Viviani, J.-L. (2015). Financial performance of socially responsible investing (sri): What have we learned? a meta-analysis. *Business Ethics: A European Review*, *24*, 158–185. https://doi.org/10.1111/beer.12076

Sadka, G. (2007). Understanding stock price volatility: The role of earnings. *Journal of Accounting Research*, *45*, 199–228. https://doi.org/10.1111/j.1475-679X.2007.00230.x

Sadorsky, P. (2003). The macroeconomic determinants of technology stock price volatility. *Review of financial economics*, *12*(2), 191–205.

Schmidt, A. F., & Finan, C. (2018). Linear regression and the normality assumption. *Journal of clinical epidemiology*, *98*, 146–151.

Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of finance (New York)*, *44*(5), 1115–1153.

Shi, Y., Ahmed, K., & Paramati, S. R. (2021). Determinants of stock market development and price volatility in asean plus three countries: The role of institutional quality. *International journal of finance and economics*, *26*(1), 560–572.

Shiller, R. J. (1992). *Market volatility*. MIT press.

SolAbility. (2013). *The global sustainable competitiveness index 2013*. Retrieved April 13, 2021, from file:///C:/Users/hans_/Downloads/Sustainable_Competitiveness_Index_2013.pdf

SolAbility. (2014). *The global sustainable competitiveness index 2014*. Retrieved May 3, 2021, from file:///C:/Users/hans_/Downloads/The-Sustainable-Competitiveness-Index-2014.pdf

SolAbility. (2015). *The global sustainable competitiveness index 2015*. Retrieved May 3, 2021, from file:///C:/Users/hans_/Downloads/The-Global-Sustainable-Competitiveness-Index-2015.pdf

SolAbility. (2016). *The global sustainable competitiveness index 2016*. Retrieved May 3, 2021, from file:///C:/Users/hans_/Downloads/The-Global-Sustainable-Competitiveness-Index-2016.pdf

SolAbility. (2017). *The global sustainable competitiveness index 2017*. Retrieved May 3, 2021, from file:///C:/Users/hans_/Downloads/The-Global-Sustainable-Competitiveness-Report-2017-1.pdf

SolAbility. (2018). *The global sustainable competitiveness index 2018*. Retrieved May 3, 2021, from file:///C:/Users/hans_/Downloads/The-Global-Sustainable-Competitiveness-Index-2018.pdf

SolAbility. (2019). *The global sustainable competitiveness index 2019*. Retrieved May 3, 2021, from file:///C:/Users/hans_/Downloads/The-Global-Sustainable-Competitiveness-Index-2019.pdf

SolAbility. (2020). *The global sustainable competitiveness index 2020*. Retrieved April 13, 2021, from https://solability.com/download/the-global-sustainable-competitiveness-index-2020/

Sörensen, W., & Deboi, O. (2020). Stock price volatility and dividend yield: Evidence from sweden.

Stock, J. H., & Watson, M. W. (2014). *Introduction to econometrics, update, global edition*. Pearson Education UK.

Studenmund, A. H. (2014). *Using econometrics a practical guide*. Pearson.

Tarazi, R., & Gallato, C. (2012). Determinants of expected stock returns: Evidence from the malaysian and thai markets. *Available at SSRN, 2167679*.

Tasnia, M., AlHabshi, S., & Rosman, R. (2020). The impact of corporate social responsibility on stock price volatility of the us banks: A moderating role of tax. *Journal of Financial Reporting and Accounting*. https://doi.org/10.1108/JFRA-01-2020-0020

Trucost. (2019). *The carbon scorecard 2019*. Retrieved April 22, 2021, from https://www.spglobal.com/en/Perspectives/IIF-2019/Trucost-Carbon-Scorecard-2019.pdf

Tsionas, M. (2019). *Panel data econometrics: Theory*. Elsevier Science Technology.

Tukey, J. W. (1962). The future of data analysis. *The annals of mathematical statistics*, *33*(1), 1–67.

V Matos, P., Barros, V., & Sarmento, J. (2020). Does esg affect the stability of dividend policies in europe? *Sustainability*, *12*, 8804. https://doi.org/10.3390/su12218804

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., et al. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, *4*(43), 1686.

Wooldridge, J. M. (2014). *Introduction to econometrics: Europe, middle east and africa edition*. Cengage Learning.

Yaffee, R. (2003). A primer for panel data analysis. *Connect: Information Technology at NYU*, 1–11.

A. Appendix

The appendix will provide data unsuitable to be contained in the running text.

A.1 R-packages

As this study is based on empirical data, data tools were needed to handle the large amounts of data. R was the chosen programming language in conducting the regression analyses as R-studio is a well established statistics programming software, with a comprehensive library readily available to the user. Following, the R-packages used in this study will be briefly described:

Tidyverse is a set of packages used for downloading other packages (Wickham et al., 2019). In this study, *Tidyverse* were used to download the following packages.

The *Magrittr* package forwards values onto the succeeding function with the operator %>% (Bache et al., 2016).

The *Plm* package provides a set of tests for panel data (Croissant et al., 2020). The *Plm* package uses linear models to estimate the regression coefficients. Missing values are skipped, rather than removed, which allows for using large data samples with missing values. The Plm package also allows for using various regression models such as the classical OLS model and the Fixed/ Random effects models. Furthermore, a Hausman test can be conducted using the function *phtest* provided by the *Plm* package (Croissant et al., 2020).

The *DescTools* package provides numerous statistical functions useful for describing data efficiently (Andri et mult. al., 2021). In this study, the DescTools package was used to deal with extreme outliers, by applying the function *winsorizing*. Winsorizing is explained in greater detail in section 5.5.1.

The *Stargazer* package allows for extracting well-formatted tables into LaTex. The table output may be extracted in TeX (Hlavac, 2018), which is the typesetting program used in this study. In this study, all regression tables and some tables presented in the descriptive statistics were produced using the *Stargazer* package.

The *lmtest* package is a collection of tests suitable to linear regression models (Hothorn et al., 2015). In this study, the lmtest was used to conduct the Breusch-Pagan test.

A.2 Data Appendix

Stock price volatility's extreme outliers of residuals
Box plot of stock price volatility's residuals to demonstrate the extreme outliers found in section 5.5.1.

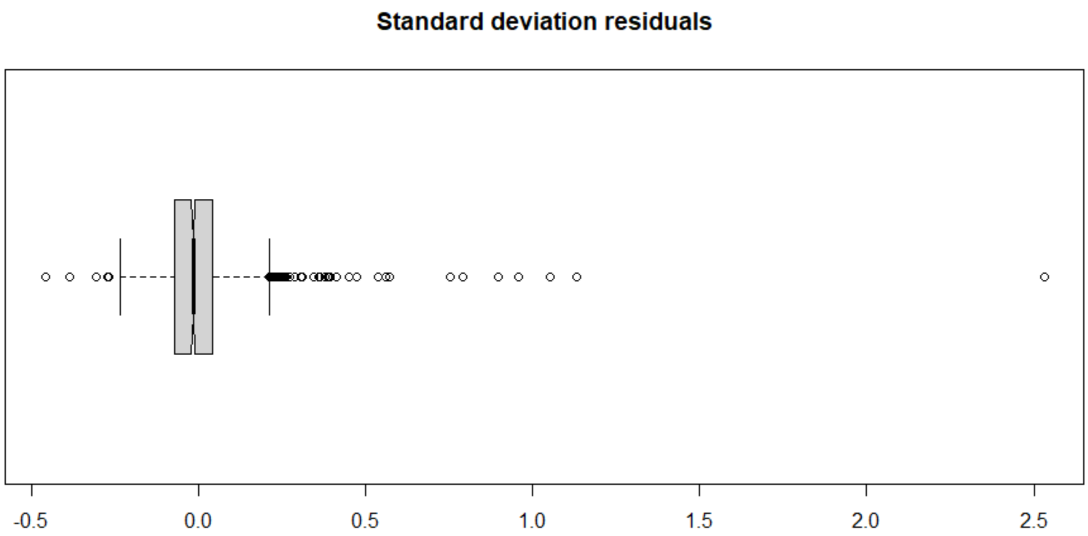


Figure A.1: Stock price volatility's extreme residual outliers.

VIF-test of the regression models with interaction terms.
VIF-test for testing the existence of multicollinearity in the regression models with interaction terms.

Table A.1: The VIF-test for country specific interaction terms

Variables	Regression model, VIF			
	1	2	3	4
ESG-score	1.329	1.132	1.069	1.129
ESG_Sweden	1.346			
ESG_Norway		1.146		
ESG_Denmark			1.086	
ESG_Finland				1.239
DivYield	1.073	1.086	1.086	1.077
PayoutRatio	1.120	1.121	1.121	1.123
Firm size	1.399	1.403	1.391	1.451
Leverage	1.040	1.039	1.047	1.039
EarnVol	1.320	1.319	1.302	1.435

Table A.2: The VIF-test for industry specific interaction terms

Variables	Regression model, VIF					
	1	2	3	4	5	6
ESG-score	2.285	1.031	1.030	1.021	1.019	1.036
ESG_Industrial	2.304					
ESG_Utility		1.051				
ESG_Bank			1.041			
ESG_Transportation				1.027		
ESG_Insurance					1.023	
ESG_Other						1.057
DivYield	1.083	1.073	1.073	1.069	1.070	1.081
PayoutRatio	1.133	1.121	1.121	1.118	1.118	1.135
Firm size	1.424	1.376	1.399	1.376	1.379	1.424
Leverage	1.057	1.042	1.049	1.042	1.047	1.045
EarnVol	1.349	1.290	1.303	1.294	1.296	1.345

A.3 Results appendix

This chapter will present the results not included in the running text. The results presented in this section was commented and discussed similarly to the other findings in this study.

A.3.1 Country specific differences in the effect of ESG-score pillars on SPV

Country specific differences of E-score's effect on SPV

Table A.3: The multiple regressions of E-score on country specific differences

	Dependent variable:			
	(1)	(2)	(3)	(4)
E-score	-0.0002	-0.001^{***}	-0.0002	-0.001^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
	p = 0.409	p = 0.005	p = 0.393	p = 0.00004
E_Sweden	-0.0004^{*}			
	(0.0002)			
	p = 0.063			
E_Norway		0.001^{*}		
		(0.0005)		
		p = 0.051		
E_Denmark			-0.001^{**}	
			(0.001)	
			p = 0.016	
E_Finland				0.001
				(0.001)
				p = 0.156
DivYield	-0.021^{***}	-0.022^{***}	-0.022^{***}	-0.022^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.005	p = 0.004	p = 0.003	p = 0.004
PayoutRatio	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.000	p = 0.00000	p = 0.000
Firm size	-0.247^{***}	-0.242^{***}	-0.243^{***}	-0.251^{***}
	(0.021)	(0.021)	(0.023)	(0.021)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	-0.022	-0.025	-0.032^{*}	-0.027
	(0.024)	(0.022)	(0.018)	(0.021)
	p = 0.365	p = 0.243	p = 0.076	p = 0.216
EarnVol	0.024^{**}	0.022^{**}	0.023^{***}	0.027^{***}
	(0.010)	(0.009)	(0.009)	(0.010)
	p = 0.015	p = 0.016	p = 0.010	p = 0.008
Constant	0.929^{***}	0.920^{***}	0.912^{***}	0.938^{***}
	(0.194)	(0.196)	(0.197)	(0.187)
	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00000
Observations	1,369	1,369	1,369	1,369
R^2	0.257	0.259	0.260	0.259
Note:				*p<0.1; **p<0.05; ***p<0.01

Country specific differences of S-score's effect on SPV

Table A.4: The multiple regressions of S-score on country specific differences

	Dependent variable:			
	(1)	(2)	(3)	(4)
S-score	−0.0003	−0.001**	−0.0004	−0.001**
	(0.0003)	(0.0004)	(0.0004)	(0.0003)
	p = 0.399	p = 0.027	p = 0.269	p = 0.013
S_Sweden	−0.001***			
	(0.0002)			
	p = 0.002			
S_Norway		0.001**		
		(0.001)		
		p = 0.045		
S_Denmark			−0.001	
			(0.001)	
			p = 0.252	
S_Finland				0.001
				(0.001)
				p = 0.203
DivYield	−0.021***	−0.022***	−0.022***	−0.022***
	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.003	p = 0.002	p = 0.002	p = 0.003
PayoutRatio	−0.002***	−0.002***	−0.002***	−0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.000	p = 0.00000	p = 0.000
Firm size	−0.246***	−0.239***	−0.242***	−0.250***
	(0.020)	(0.021)	(0.022)	(0.019)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	−0.018	−0.025	−0.034**	−0.025
	(0.025)	(0.023)	(0.016)	(0.022)
	p = 0.484	p = 0.270	p = 0.034	p = 0.258
EarnVol	0.025***	0.021**	0.024**	0.027***
	(0.009)	(0.009)	(0.009)	(0.010)
	p = 0.009	p = 0.017	p = 0.012	p = 0.010
Constant	0.928***	0.912***	0.914***	0.935***
	(0.193)	(0.196)	(0.196)	(0.184)
	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00000
Observations	1,369	1,369	1,369	1,369
R^2	0.258	0.260	0.259	0.259
Note:				*p<0.1; **p<0.05; ***p<0.01

Country specific differences of G-score's effect on SPV

Table A.5: The multiple regressions of G-score on country specific differences

	Dependent variable:			
	(1)	(2)	(3)	(4)
G-score	0.0003	−0.0003	0.0001	−0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
	p = 0.304	p = 0.295	p = 0.698	p = 0.329
G_Sweden	-0.001^{***}			
	(0.0001)			
	p = 0.000			
G_Norway		0.001^{**}		
		(0.0005)		
		p = 0.013		
G_Denmark			−0.001	
			(0.001)	
			p = 0.276	
G_Finland				0.001
				(0.001)
				p = 0.150
DivYield	-0.022^{***}	-0.022^{***}	-0.022^{***}	-0.022^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.004	p = 0.003	p = 0.003	p = 0.003
PayoutRatio	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.000	p = 0.00000	p = 0.000
Firm size	-0.248^{***}	-0.240^{***}	-0.241^{***}	-0.253^{***}
	(0.020)	(0.021)	(0.023)	(0.018)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	−0.019	−0.024	−0.028	−0.023
	(0.026)	(0.025)	(0.021)	(0.025)
	p = 0.477	p = 0.333	p = 0.172	p = 0.367
EarnVol	0.025^{**}	0.021^{**}	0.023^{**}	0.028^{**}
	(0.010)	(0.009)	(0.009)	(0.011)
	p = 0.013	p = 0.027	p = 0.016	p = 0.013
Constant	0.916^{***}	0.895^{***}	0.883^{***}	0.921^{***}
	(0.194)	(0.196)	(0.207)	(0.182)
	p = 0.00001	p = 0.00001	p = 0.00003	p = 0.00000
Observations	1,369	1,369	1,369	1,369
R^2	0.256	0.258	0.257	0.259
Note:				*p<0.1; **p<0.05; ***p<0.01

A.3.2 Industry specific differences in the effect of ESG-score pillars on SPV

Industry specific differences of E-score's effect on SPV

Table A.6: The multiple regressions of E-score on industry specific differences

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
E-score	−0.001***	−0.0004**	−0.0003*	−0.0004**	−0.0004**	−0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
	p = 0.0001	p = 0.019	p = 0.089	p = 0.015	p = 0.021	p = 0.358
E_Industrial	0.001***					
	(0.0004)					
	p = 0.006					
E_Utility		0.0001				
		(0.0004)				
		p = 0.726				
E_Bank			−0.001			
			(0.001)			
			p = 0.145			
E_Transportation				0.001		
				(0.001)		
				p = 0.416		
E_Insurance					0.001	
					(0.001)	
					p = 0.427	
E_Other						−0.003***
						(0.001)
						p = 0.00004
DivYield	−0.021***	−0.021***	−0.021***	−0.021***	−0.021***	−0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.005	p = 0.006	p = 0.005	p = 0.006	p = 0.006	p = 0.004
PayoutRatio	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.00000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Firm size	−0.242***	−0.246***	−0.242***	−0.245***	−0.245***	−0.247***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	−0.008	−0.021	−0.016	−0.025	−0.019	−0.013
	(0.020)	(0.023)	(0.025)	(0.025)	(0.025)	(0.019)
	p = 0.684	p = 0.352	p = 0.523	p = 0.323	p = 0.456	p = 0.510
EarnVol	0.024***	0.023**	0.023**	0.023**	0.023**	0.025***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
	p = 0.009	p = 0.012	p = 0.014	p = 0.016	p = 0.014	p = 0.008
Constant	0.885***	0.927***	0.902***	0.923***	0.925***	0.916***
	(0.191)	(0.194)	(0.202)	(0.195)	(0.197)	(0.192)
	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00001
Observations	1,369	1,369	1,369	1,369	1,369	1,369
R^2	0.266	0.253	0.257	0.254	0.254	0.271
Note:						*p<0.1; **p<0.05; ***p<0.01

Industry specific differences of S-score's effect on SPV

Table A.7: The multiple regressions of S-score on industry specific differences

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
S-score	−0.002***	−0.001*	−0.001	−0.001*	−0.001*	−0.0003
	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
	p = 0.0002	p = 0.077	p = 0.140	p = 0.074	p = 0.072	p = 0.308
S_Industrial	0.002***					
	(0.001)					
	p = 0.009					
S_Utility		−0.0002				
		(0.001)				
		p = 0.683				
S_Bank			−0.001*			
			(0.001)			
			p = 0.087			
S_Transportation				0.001		
				(0.001)		
				p = 0.235		
S_Insurance					0.001	
					(0.001)	
					p = 0.297	
S_Other						−0.004***
						(0.001)
						p = 0.001
DivYield	−0.021***	−0.021***	−0.021***	−0.021***	−0.021***	−0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.005	p = 0.004	p = 0.004	p = 0.004	p = 0.004	p = 0.003
PayoutRatio	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.00000	p = 0.00000	p = 0.000	p = 0.00000	p = 0.000	p = 0.000
Firm size	−0.241***	−0.244***	−0.241***	−0.243***	−0.244***	−0.245***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	−0.001	−0.018	−0.014	−0.022	−0.017	−0.002
	(0.018)	(0.023)	(0.025)	(0.024)	(0.025)	(0.016)
	p = 0.961	p = 0.426	p = 0.575	p = 0.366	p = 0.494	p = 0.880
EarnVol	0.026***	0.023**	0.023**	0.023**	0.023**	0.027***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
	p = 0.003	p = 0.011	p = 0.013	p = 0.014	p = 0.012	p = 0.002
Constant	0.867***	0.921***	0.903***	0.922***	0.925***	0.892***
	(0.170)	(0.191)	(0.193)	(0.193)	(0.194)	(0.169)
	p = 0.00000	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00000
Observations	1,369	1,369	1,369	1,369	1,369	1,369
R^2	0.268	0.253	0.258	0.254	0.255	0.276
Note:						*p<0.1; **p<0.05; ***p<0.01

Industry specific differences of G-score's effect on SPV

Table A.8: The multiple regressions of G-score on industry specific differences

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
G-score	-0.002^{***}	-0.0001	-0.00001	-0.0001	-0.00004	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.793	p = 0.980	p = 0.625	p = 0.864	p = 0.722
G_Industrial	0.002^{***}					
	(0.0004)					
	p = 0.00000					
G_Utility		-0.001				
		(0.001)				
		p = 0.182				
G_Bank			-0.002^{**}			
			(0.001)			
			p = 0.024			
G_Transportation				0.0004		
				(0.001)		
				p = 0.443		
G_Insurance					-0.002^{**}	
					(0.001)	
					p = 0.048	
G_Other						-0.003^{**}
						(0.002)
						p = 0.030
DivYield	-0.021^{***}	-0.021^{***}	-0.021^{***}	-0.022^{***}	-0.021^{***}	-0.022^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
	p = 0.005	p = 0.005	p = 0.004	p = 0.004	p = 0.004	p = 0.003
PayoutRatio	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
	p = 0.000	p = 0.00000	p = 0.000	p = 0.000	p = 0.00000	p = 0.000
Firm size	-0.241^{***}	-0.244^{***}	-0.242^{***}	-0.244^{***}	-0.244^{***}	-0.247^{***}
	(0.020)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	-0.004	-0.019	-0.013	-0.022	-0.028	-0.014
	(0.018)	(0.024)	(0.026)	(0.026)	(0.026)	(0.020)
	p = 0.841	p = 0.431	p = 0.606	p = 0.409	p = 0.281	p = 0.510
EarnVol	0.026^{***}	0.024^{**}	0.023^{**}	0.023^{**}	0.024^{**}	0.026^{***}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
	p = 0.004	p = 0.011	p = 0.016	p = 0.016	p = 0.014	p = 0.004
Constant	0.834^{***}	0.890^{***}	0.882^{***}	0.905^{***}	0.901^{***}	0.897^{***}
	(0.169)	(0.189)	(0.195)	(0.197)	(0.198)	(0.183)
	p = 0.00000	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00001	p = 0.00001
Observations	1,369	1,369	1,369	1,369	1,369	1,369
R^2	0.270	0.251	0.257	0.251	0.253	0.269
Note:						*p<0.1; **p<0.05; ***p<0.01

A.4 Miscellaneous

Below, the table used to plot Figure 2.1 (b) is provided[1] [2]. The plot was created with Python.

Table A.9: The Nordic countries ranking on GSCI from 2010-2020

Year	Country / (Rank & Score) Sweden	Denmark	Iceland	Finland	Norway
2020	1 (62.1)	2 (61)	3 (60.7)	4 (60.4)	9 (57.4)
2019	1 (60.6)	4 (57)	3 (57.3)	2 (59.5)	6 (56.9)
2018	1 (60.5)	5 (57.2)	3 (57.6)	4 (57.4)	2 (58.2)
2017	1 (60.5)	5 (57.2)	3 (57.6)	4 (57.4)	2 (58.2)
2016	1 (60.9)	4 (56.4)	5 (56)	3 (56.2)	2 (59.4)
2015	2 (55.5)	9 (52.7)	1 (56.1)	4 (54.4)	3 (54.6)
2014	2 (54.1)	8 (51.6)	1 (56.2)	3 (53.6)	4 (53.4)
2013	2 (61.6)	1 (62.8)	13 (55.1)	3 (60.9)	4 (60.8)
2012	2 (58.5)	1 (58.8)	11 (55.7)	3 (57.6)	3 (57.6)
2011	-	-	-	-	-
2010	-	-	-	-	-

Below, statistics for the development of GSCI-score over time is provided.

Table A.10: Descriptive statistics of the Nordic countries ranking on GSCI from 2010-2020

GSCI Score	Country Sweden	Denmark	Iceland	Finland	Norway
Mean	59.4	57.2	56.9	57.5	57.4
Median	60.5	57.2	56.2	57.4	57.6
Mode	60.5	57.2	57.6	57.4	58.2
Std.dev	2.79	3.55	1.67	2.51	2.26

[1] The authors were not able to retrieve or find The Global Sustainable Competitiveness Index for 2010 and 2011.

[2] Sources: (SolAbility, 2020), (SolAbility, 2019), (SolAbility, 2018), (SolAbility, 2017), (SolAbility, 2016), (SolAbility, 2015), (SolAbility, 2014), (SolAbility, 2013)