



Vaasan yliopisto  
UNIVERSITY OF VAASA

Dan Lampinen

# **Problems with using ESG data in investment decisions**

School of Accounting and Finance  
Bachelor's thesis in finance  
Accounting and Finance

Vaasa 2025

---

**UNIVERSITY OF VAASA****School of Accounting and Finance**

**Author:** Dan Lampinen  
**Title of the thesis:** Problems with using ESG data in investment decisions  
**Degree:** Bachelor of Science in Economics and Business Administration  
**Degree Programme:** Accounting and Finance  
**Supervisor:** Veda Fatmy  
**Year:** 2025      **Pages:** 53

---

**ABSTRACT:**

This thesis examines the problems investors may encounter when using ESG data. The thesis uses literature to examine whether ESG data measures the right things and whether the data is of sufficient quality to be used to support investment decisions. The study also takes a position on how fragmented reporting and a lack of standardization can create information asymmetry. The review summarizes previous research and presents a few case examples, such as Case Volkswagen, to show that a high level of reporting by companies does not guarantee true responsibility. The results of the study suggest that limited data comparability, coverage, and inconsistent metrics may lead investors to make incorrect assessments and allocate capital incorrectly. The study also emphasizes the importance of reporting frameworks and transparent data as part of efficient markets and responsible investing.

---

**KEYWORDS:** ESG data, ESG rating, Sustainability, Information asymmetry, Cognitive biases, Transparency, Data Quality, Standardization, Disclosure, Investor, Data service providers.

---

**VAASAN YLIOPISTO****Laskentatoimen ja rahoituksen akateeminen yksikkö**

<b>Tekijä:</b>	Dan Lampinen		
<b>Tutkielman nimi:</b>	Problems with using ESG data in investment decisions		
<b>Tutkinto:</b>	Kauppateiden Kandidaatti		
<b>Koulutusohjelma:</b>	Laskentatoimen ja Rahoituksen Kandidaatinohjelma		
<b>Opintosuunta:</b>	Laskentatoimi ja Rahoitus		
<b>Työn ohjaaja:</b>	Veda Fatmy		
<b>Valmistumisvuosi:</b>	2025	<b>Sivumäärä:</b>	<b>53</b>

---

**TIIVISTELMÄ:**

Tämä tutkielma tarkastelee, millaisia ongelmia sijoittajilla saattaa esiintyä, kun he käyttävät ESG-dataa. Työssä perehdytään kirjallisuuden avulla tarkastelemaan mittaako ESG-data oikeita asioita ja onko data tarpeeksi laadukasta käytettäväksi sijoituspäätöksiä tukena. Työ ottaa myös kantaa siihen, miten raportoinnin hajanaisuus sekä standardoinnin puute voivat luoda informaation asymmetriaa. Katsaus kokoaa yhteen aiempaa tutkimusta sekä esittää muutaman esimerkki tapauksen, kuten Case Volkswagenin osoittaakseen, että yritysten korkea raportointi taso ei takaa todellista vastuullisuutta. Tulokset tutkimuksessa viittaavat siihen, että rajoittunut datan vertailtavuus, kattavuus sekä epäyhtenäiset mittarit saattavat johtaa sijoittajia virheellisiin arvioihin sekä väärään pääoman allokointiin. Työ korostaa myös raportointikehyksien ja läpinäkyvän datan merkitystä osana tehokkaita markkinoita ja vastuullista sijoittamista.

---

**AVAINSANAT:** ESG-data, ESG-rating, Kestävyys, Informaation Asymmetria, Kognitiiviset Viinomat, Läpinäkyvyys, Datan Laatu, Standardointi, Paljastaminen, Sijoittaja, Datapalveluntarjoajat

## Contents

1	Introduction	7
1.1	Purpose of the study	8
1.2	Structure of the study	10
2	Defining ESG data	11
2.1	ESG data components	12
2.2	How is the data sourced	12
2.3	Use case of ESG data in investing	13
3	Theoretical background	15
3.1	Visual model of theoretical framework	15
3.2	Efficient market hypothesis and Information asymmetry	16
3.2.1	How ESG data is related to Efficient market hypothesis and Information asymmetry?	17
3.3	Signaling theory	19
3.3.1	How is ESG data related to Signaling theory	19
3.4	Behavioural finance and Cognitive biases	20
3.4.1	Heuristic biases	21
3.4.2	Anchoring bias	22
3.4.3	Availability bias	22
3.4.4	Overconfidence/Confirmation bias	23
4	Qualitative and structural problems with ESG data in investment decisions	24
4.1	Poor consistency of ESG classification	24
4.2	Measurement and reporting errors	26
4.3	Subjectivity and uncertainty in data sources	28
4.4	Data dynamism and temporal instability	29
4.5	Relation to H1	31
5	Lack of standardization in ESG reporting and information asymmetry	33
5.1	Fragmentation of reporting frameworks	34

5.2	ESG Industrial Materiality	36
5.3	Information Asymmetry and ESG reporting	38
5.4	Examples of the consequences of poor ESG reporting practices	40
6	Conclusion	42
	References	45

**Figures**

Figure 1. The most common ESG-metrics (GlobalTrading, 2023)..	11
Figure 2. Visual model of theoretical framework. .	15
Figure 3. Materiality map (SASB,2018).	37

## 1 Introduction

The quality, coverage, and content of ESG data are key factors when assessing how the data should be used and from whom it should be obtained. ESG data refers to various types of content related to companies' environmental, social, and governance factors. The purpose of the data is to assess responsibility and sustainability. The quality of ESG data refers to how reliable, accurate, and up-to-date the data is. Coverage refers to how extensively the data covers different themes and activities. Content, on the other hand, refers to what information data has about companies. The quality, coverage, and content of ESG data play a significant role in investment activities today. According to In et al. (2019), ESG data can be used to assess the behavior of the following factors: assets held by investors that can be used to steer returns toward specific risk factors products; purchased by investors that provide access to the above-mentioned assets and risk factors, achieving the return targets of different investment portfolios, and obtaining indicators that show whether long-term investments are heading in the right direction. ESG data also plays a significant role in investment risk assessment.

An important part of ESG is the metrics it encompasses. These are metrics that describe, for example, companies' emissions, water consumption, employee well-being, or gender diversity on the board of directors (Esgthereport, 2024). Investors are very interested in these indicators because, like ESG data, they can be used to a significant extent in investment decisions. In their article, Amel-Zaheh and Serafeim (2018) explain how investors actually use these factors in their investment decisions. They conducted a survey of various investors, who explained why they are interested in these indicators. The reasons mentioned include their impact on returns, the desire to invest ethically, and the growing importance of responsibility in the future. As many as 60 % of investors consider ESG factors to be relevant to investment returns. This explains why investors want to make increasing use of them and why it is important for them to be able to trust the quality of the data and metrics. This also includes ESG ratings, which are based on the aforementioned metrics. Responsible investors mainly use these, which may be problematic due to potential inconsistencies and varying quality of ratings, as will be discussed later.

All three of these factors are strongly interlinked, which is why it is extremely important to consider them as a whole. However, ESG data is the most important part of these three, as the metrics and ratings are based on this data.

ESG data is indeed important, but there are also problems with its use that need to be taken into account. According to Jónsdóttir et al. (2022), one such problem could be the reliability of the data. They argue that a problem with ESG data may be self-reporting by companies, which exposes the data to distortion. This and other problems such as lack of standards, different methodologies, information asymmetry make it considerably more difficult to utilize ESG data in investment decisions. These raise the question of whether ESG data and ratings actually measure what they are supposed to measure and whether investors can rely on them sufficiently when making decisions. This is the core of the study, which will be discussed as the study progresses.

## **1.1 Purpose of the study**

The purpose of this thesis is to examine how ESG data affects investment decisions and what problems there are in its use. The thesis focuses on a few main points, which are the impact of the quality, coverage, and content of ESG data on investment decisions and the problems associated with the use of such data. The thesis also highlights ESG metrics and ratings, as they are strongly linked to the data. The aim is to show that there are still many problems with ESG data, which distort investment decisions. It follows that there are shortcomings not only in the quality of the data but also in its standardization. The quality of ESG data can be considered poor for a number of reasons (Berg et al., 2022; Cruz and Matos, 2023; Jónsdóttir et al., 2023). ESG data is generally considered poor because it does not measure what it should measure (Berg et al., 2022). ESG data often measures the same thing using different methodologies, which leads to investors not trusting its quality. According to Zumente and Lāce (2021), data cannot be compared with each other as a result of these factors. However, comparability is an important part of data quality. Data must be of high quality so that it can be used as part of investment

decisions and so that these decisions are not distorted by poor data (Liu, 2022). This leads to the first hypothesis:

H1: Poor ESG data quality distorts investment decisions by providing investors with unreliable and inconsistent information.

In line with this hypothesis, it is important to consider why the quality is poor, how it distorts investment decisions, and why ESG data is unreliable and sometimes misleading. In addition to quality, there are other problems associated with ESG data that undermine its reliability. Data standardization and uneven coverage create further problems for investors. Often, companies that are better able to report on their responsibility are more highly valued by investors (Grewal et al., 2017). These companies appear less vulnerable to various ESG risks to investors because they report as comprehensively as possible, even though this does not guarantee sustainability, as various greenwashing cases show. Drempetic et al. (2019) suggest that these companies are "rewarded" for this reason. Weak standardization allows companies to adopt this approach. This results in a situation where reporting practices guide investors rather than actual ESG performance, which is an example of information asymmetry. This leads to a second hypothesis:

H2: Limited ESG data coverage and standardization deficiencies create information asymmetry, which leads investors to favor companies that report comprehensively over those that are truly responsible.

These hypotheses are based on existing literature and studies on the poor quality of ESG data and the lack of standardization, which have been discussed most extensively in relation to the quality of ESG data. Unfortunately, this topic is fairly new and there is not much research on it yet. There is much more research available on ESG ratings, which are often used in responsible investing. However, ratings are based on ESG data, so it is surprising that the topic has not been studied further. This, however, highlights the importance of the topic and the need for further research.

## **1.2 Structure of the study**

The first section provides a brief overview of the topic and introduces ESG data and the benefits and challenges associated with its use. The aim is to familiarize the reader with the topic and generate interest. It also aims to show why the topic is important for investment decisions. In addition, the hypotheses and assumptions of the study regarding the validity of the claims are presented.

The second chapter takes a closer look at what ESG data is, how it is used in investment decisions, why it is important, and highlights some of its problems. The third chapter discusses financial theories that are relevant to the topic of the thesis.

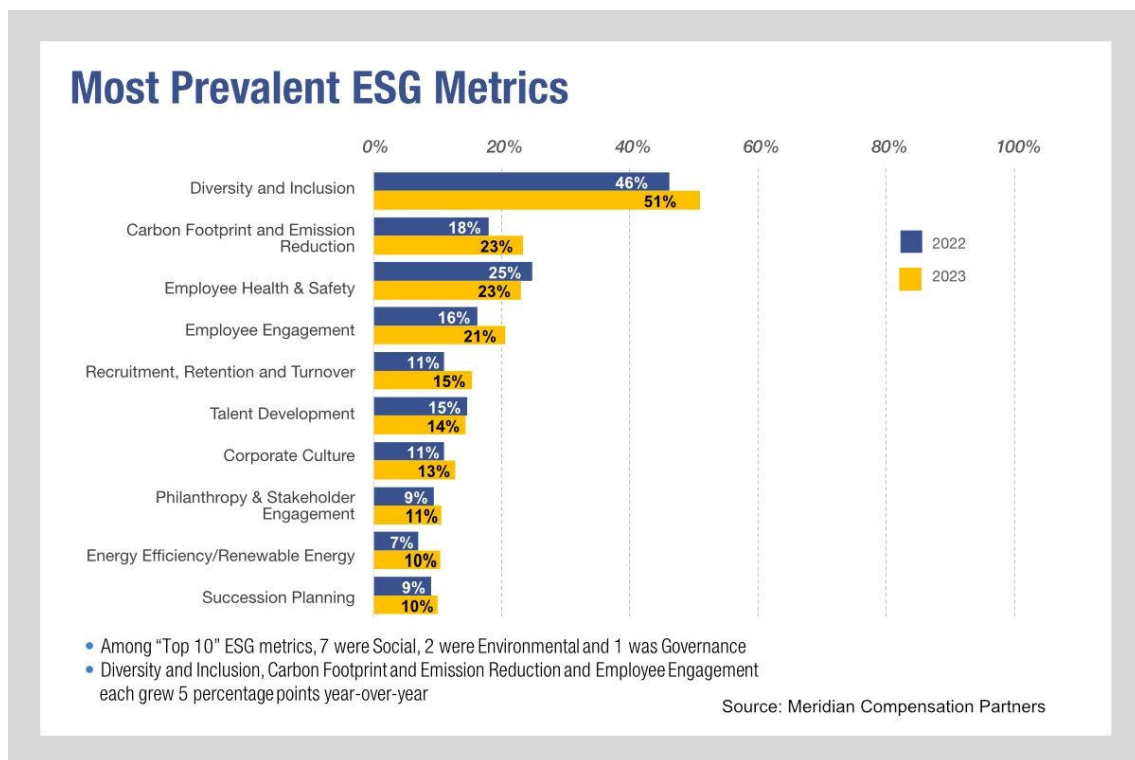
The purpose of the fourth and fifth chapter is to provide a comprehensive review of the literature on the subject. The literature is analysed and it should inform conclusions regarding H1 and H2. The literature takes into account different perspectives and attempts to select works that are relevant to the subject.

The purpose of the last chapter is to summarise the motivations, purpose, and findings of the research. This paragraph also considers whether the hypotheses presented at the beginning were realized.

Various AI-based tools were used in writing this paper. The ChatGPT-4o and DeepL tools were used most extensively in writing the text. These tools were used for brainstorming ideas, language editing, and searching for sources, for example. Nothing has been copied directly from artificial intelligence, and all information provided by it has been verified, including the sources it provides. All text has been produced by me, even though artificial intelligence-based tools have been used.

## 2 Defining ESG data

The term ESG refers to various environmental issues, management responsibilities, and corporate governance factors (Khamisu & Paluri, 2024). These factors are traditionally included in the definition of ESG. In practice, ESG data contains information provided by companies and estimated data on these factors. The main purpose of the data is to create ESG metrics that provide as accurate a picture as possible of a company's performance in one of these three areas (Kotsantoni & Serafeim, 2019). ESG data is a broad concept, but ESG investing and the factors related to its use are strongly linked to it. To understand ESG data, it is important to highlight everything it contains. The most common ESG metrics used by rating agencies are described in the figure below.



**Figure 1.** The most common ESG-metrics (GlobalTrading, 2023).

## **2.1 ESG data components**

ESG data consists of three different non-financial indicators: environmental, social, and governance (Park et al., 2022). All of these areas consist of data that measures companies' performance in each of these areas. The purpose of environmental data is to measure companies' environmental risks and opportunities (Saha, 2025). This may include, for example, carbon dioxide emissions, waste, water-related characteristics, biodiversity, forest-related factors, and impact on climate change. The purpose of social data is to measure the implementation of human rights and equality in companies' operations (Saha, 2025). This includes, for example, health and safety factors in the working environment, the use of child labor, working conditions, employment levels, and product safety. Finally, administrative data refers to governance activities and decision-making (Saha, 2025). This data includes, for example, owner rights, board structure, tax practices, corruption, bribery, and compliance with business ethics. All these factors together form the basis for a vast amount of data which is complex to handle and understand.

## **2.2 How is the data sourced**

Data is generally obtained from various ESG data providers (Liu et al., 2023). There are quite a few of these providers, but, as with credit rating agencies, for example, there are a few larger companies from which this data is often obtained. These include MSCI, Sustainlytics, LSEG, and RobecoSam (Dell'Erba and Doronzo, 2021). Other major providers include ISS, Bloomberg, Reprisk, and S&P Global. In addition to these, there are other smaller companies that focus their ESG data on a specific area (Dell'Erba and Doronzo, 2021). Examples of these include Clarity Ai, Inrate, and Upright Projects. These companies focus their data on environmental impact, for example. The Upright project, on the other hand, operates differently from traditional ESG data providers. They provide data that measures, for example, the environmental impact of companies as a net benefit or detriment to society.

These different service providers collect their ESG data in a few different ways, such as using self-reported sustainability data from companies, including sustainability reports, website information, and annual reports. Another common method is to search for data from non-profit organizations, such as the CDP (Carbon Disclosure Project). One of the newest methods for service providers is to use artificial intelligence and various machine learning models to create data that would not otherwise be available. Artificial intelligence can be used, for example, to collect data (Lee et al., 2025). Another example where service providers often use artificial intelligence and machine learning is to model Scope 3 emissions and ESG data from developing countries. There is often little data available on these, or they are difficult to measure, as in the case of Scope 3 emissions. Often, all these methods are combined in an effort to obtain the highest quality data possible. However, the data may still be of poor quality because its accuracy is difficult to verify, and AI-based estimates in particular can be unreliable.

### **2.3 Use case of ESG data in investing**

ESG data has many different uses. It is utilized by various parties operating in the investment market. These include investors, banks, pension companies, and other asset managers. The range is therefore broad, and as responsibility becomes increasingly important, more and more parties want to utilize ESG data.

Investors and asset managers use ESG data for purposes such as allocating investments, managing risk, and building portfolios (Pinchot and Christianson, 2019). This allows investors to build the broadest possible investment outlook or engage in responsible investing.

Responsible investors also often use ESG data for screening, i.e., avoiding stocks that are involved in controversial activities such as the arms trade. There are several strategies for this, such as "best in class investing," active ownership, and ESG integration (Trinks and Scholten, 2015). These are all common ways of utilizing data, and they are often

combined with financial data to identify companies that are both responsible and have strong financial performance.

Companies also use ESG data, but for slightly different purposes than investors. Companies often use this data to compare their sustainability performance with other companies in the same sector, to develop their own sustainability practices, and for ESG reporting (Climatetrackerinitiative, 2024). In this way, companies can improve their own operations and respond to various requirements.

Credit institutions and banks often use ESG data to assess companies' responsibility and various risks. Banks and credit institutions often use ESG data to assess companies' various risk levels related to climate factors, particularly when granting credit. Nowadays, credit rating agencies often consider ESG issues in particular to be a potential risk to creditworthiness (Dogan et al., 2025). This shows that it is important for them to ensure that creditworthiness is not weakened as a result of ESG factors. Banks may also use ESG data to set ESG targets and integrate sustainability into all of their operational activities (UniCredit, 2025).

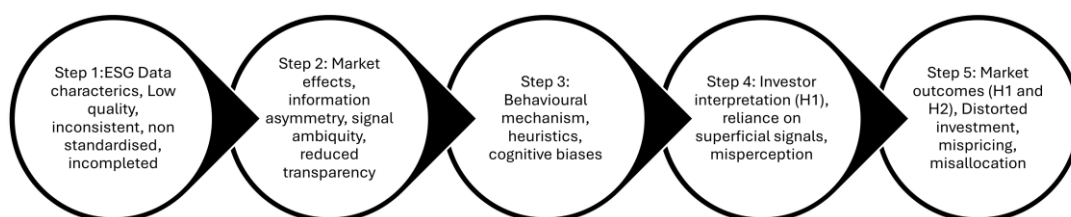
All of the above parties also use data to comply with regulations and reporting requirements. As these requirements continue to grow, parties operating in the investment sector will increasingly need high-quality ESG data on their activities in order to meet the ever-increasing demands related to these factors. However, reporting and regulation are still relatively limited at present (Tsang et al., 2023). According to Bancel et al. (2023), ESG reporting is likely to be more regulated in the future. As a result, all parties are likely to be more willing to increase their disclosure and actions related to ESG data.

### 3 Theoretical background

The research mainly deals with ESG data and its problems. However, it is also important to highlight traditional financial theories and, in particular, behavioral finance concepts. ESG data is strongly linked to information and is often used in investment decisions. Several themes that are strongly linked to these factors can be associated with the topic. The use of ESG data in investment decisions is reflected, by information asymmetry theory, (an important part of the second hypothesis), signaling theory and efficient market hypothesis. These theories can be used to explain the effects that poor-quality ESG data may have on investment decisions. Traditional financial theories are rarely used in this subject, but they can be linked to it. They can be used to demonstrate the effects of poor-quality ESG data on decision-making.

#### 3.1 Visual model of theoretical framework

The image below illustrates how the theoretical framework is reflected in the use of ESG data in investment decisions and how its cycle progresses. The purpose of the image is to provide a quick overview of the theories applied and how they relate to the hypotheses (see Table 2).



**Figure 2.** Visual model of theoretical framework.

### 3.2 Efficient market hypothesis and Information asymmetry

The efficient market hypothesis (EMH) is a theory presented by Eugene Fama in the 1960s. In this theory, he argues that the prices of all assets reflect all available information at any given time (Fama, 1970). According to the theory, no one can beat the market by buying undervalued stocks or selling them at a high price. The only way investors could beat the market is by increasing their level of risk. According to the theory, arbitrage would also quickly disappear from the market and prices would return to normal levels as a result. However, there are several practical problems with the theory, and ESG data can be used to demonstrate this consequence in investment decisions. ESG data often suffers from inconsistency and poor transparency (Almeida Cruz and Matos, 2023). This may result in investors and companies having different access to actual information. This leads us to the next theory, which describes information asymmetry.

George Akerlof's (1970) article entitled "The market for 'lemons'" discusses how information asymmetry between buyers and sellers can lead to market failure (Long, 2023). The article illustrates this point using the example of used car sales. Akerlof presents the issue as follows (1970): There are only four different types of cars: new and old, and good and bad ("lemons"). However, buyers do not know whether the car they are buying is good or bad. The probability that the car purchased by the buyer is good is  $q$ , and the probability that it is poor is  $1-q$ . However, when you own a car for a certain period of time, it becomes easier to recognize how good the car is. A new probability arises, which in turn leads to asymmetry in the existing information (Akerlof, 1970). In this case, one party has more information than the other.

ESG data can be thought of as functioning in the context of a car in Akerlof's example. The basic idea is that ESG data providers and the entities on which the data is based have more information available about the quality and accuracy of the data. Investors are therefore not necessarily able to distinguish between genuinely responsible companies and those that merely appear to be responsible. According to Wang and Nishihara (2025),

this is evident, for example, in the publication of companies' ESG data, as ESG metrics are difficult to interpret and companies may therefore only publish positive information related to responsibility. In this situation, companies have more information available than investors. This directly leads to investments in companies based on false information, which distorts the information.

This is a classic example of what can happen when buyers do not have reliable information about the actual quality of a company's products. The theory is quite old, but it is relevant to the topic and can also be applied to the effects of ESG data. There are many similarities between ESG data and the example presented by Akerlof.

### **3.2.1 How ESG data is related to Efficient market hypothesis and Information asymmetry?**

ESG data can have both positive and negative effects on share prices. According to Yin et al. (2020), ESG performance have a direct impact on returns on shares. This proves that ESG data has a significant impact on stock prices. According to Fama (1970), stock prices should therefore already reflect the effects of ESG data, provided that such information is publicly available and reliably measured. The quality of ESG data should therefore be reliable in order for this condition to be met. However, the correlation between ESG ratings is sometimes quite weak, ranging from 0.38 to 0.71, with an average of around 0.54 according to Pearson's correlation coefficient (Berg et al., 2022). This is one indication that the quality of the data is poor. According to Berg et al. (2022), correlations vary between environmental, social, and governance factors.

ESG data is therefore likely to be reflected in share prices and thus information asymmetry could distort their price. The markets misprice shares, which means that Fama's claim can be said to be purely theoretical. ESG data may lead investors to make incorrect investment decisions. The markets therefore do not correctly assess the impact of ESG on stock prices.

Inaccurate ESG assessments and metrics also lead to a distorted picture of corporate responsibility. Investor interest in responsible investing has grown significantly in recent years (Kräusll et al., 2023). Data distortion also has an impact on this form of investing. Distorted sustainability data may give those engaged in responsible investing a false picture of companies. Companies may appear to be more or less responsible than they actually are.

Wang and Nishara (2025) highlight how information asymmetry could be reduced. According to them, if companies were more transparent about their ESG factors, trust would increase and information asymmetry would decrease. This would be one way to improve trust, but as noted earlier, it would be unfavorable for companies, so they do not act in this way because they want to maintain a good public image of themselves. When companies have the opportunity to present their responsible actions in as positive a light as possible, they also do so in order to gain validation for themselves.

Data providers that collect ESG data often collect data from companies' own reports (Jónsdóttir et al., 2022), and this problem has been identified previously. As a result, there may sometimes be too much data available, which reduces its quality. Companies often add data to reports that is not necessarily relevant, but makes them appear more credible. However, it is difficult for investors to see this, and information asymmetry arises again. Additional information that is not relevant provides investors with an increasing amount of information that is not necessarily accurate. This further increases asymmetry.

According to Jónsdóttir et al. (2022), companies report what they want and try to only include positive things in their ESG reports, covering up negative factors. This, in turn, leads to "whitewashing" or "greenwashing," which is problematic, especially for investors. Bu et al. (2024) also identify the same problem, arguing that greenwashing leads to information asymmetry because investors are unable to recognize it. They also argue that this weakens market efficiency and prevents truly responsible companies from

being visible in the investment market. This leads to similar consequences as in the efficient market hypothesis.

### **3.3 Signaling theory**

Signaling theory is a theory presented by Michael Spence (1973) in which two parties have different opportunities to obtain information about a certain factor or have different information about a certain factor. The theory is also strongly linked to information asymmetry and, in practice, means the same thing, but in the light of a slightly different example. In his theory, Spence uses the labor market as an example. According to Spence (1973), employers do not immediately have the opportunity to know the productivity of a hired employee, and often identifying it requires learning. However, he argues that employers can assess employees using signals before hiring them. Employees can seek to prove their productivity through education, for example. Education increases credibility in productivity, even though it does not necessarily correlate with it.

Signaling theory is also highly relevant to ESG data. Spence's example illustrates well the situation investors often find themselves in when using ESG data. Spence's theory relates to the labor market, but it is applicable to the use of ESG data. Companies use ESG data to "signal" their responsibility to investors, but investors do not necessarily have access to all the same information that companies have.

#### **3.3.1 How is ESG data related to Signaling theory**

Signaling theory has many elements in common with the asymmetry problem. Many of the same factors also apply here as in asymmetric information. According to Di Chiaccio et al. (2024), companies try to signal to investors and stakeholders through sustainability reporting in order to gain credibility and trust. This factor also appears as a weakness in the quality of ESG data in this context. The information presented by a company may be false, and this may not necessarily be taken into account or considered. Companies often try to use strategies that do not publish incomplete financial data (Di Chiaccio et al.,

2024). This sends the wrong signal to stakeholders and investors, which may distort their decisions. This is also clearly reflected in the data, as the companies providing it often use self-reported sustainability data (Liu et al., 2023). Whether investors use ESG data provided by service providers or obtain it themselves, the end result is the same: the data is distorted.

The problem with ESG data is its poor standardization, which means that companies can report whatever they want (Lampinen, 2025). A good example of this is CSR reporting, which is often the source of ESG data. According to Christensen et al. (2021), standardizing CSR reporting could have many positive effects for investors. This proves that standardization could prevent investors from receiving false signals from companies. With standardization, companies would not be able to distort their own responsibility so easily.

However, sending false signals is the rewarding approach for companies, as it allows them to present and send signals to investors about their responsibility. That is misleading but it benefits companies because they gain more credibility. This is very problematic and makes it difficult for investors to operate in the market purely from a responsibility perspective.

### **3.4 Behavioural finance and Cognitive biases**

Behavioral finance is an essential part of investment decisions, as investors often emphasize certain financial and information factors that are influenced by behavioural biases, such as heuristics or overconfidence. These factors are also linked to the use of ESG data in investment decisions. As previously noted, ESG data may be incomplete, complex, and unclear, which further emphasizes behavioral phenomena. Daniel Kahneman and Amos Tversky (1979) described several different biases that arise in different situations and how they affect people. Many of these factors also apply to the use of ESG data in investment decisions. According to Peon and Antelo (2021), people are prone to making mistakes when making various decisions. ESG data has the potential to expose people to making wrong decisions when investing. Factors contributing to this may

include, for example, sustainability trends and following others. The aim is to present a few behavioral patterns that are linked to this topic.

### **3.4.1 Heuristic biases**

Heuristics refers to the mind's way of seeking opportunities to reach a decision more quickly without in-depth analysis and information gathering (Dale, 2015). Investors often use this approach when information may be unclear or contradictory. Investors often ignore some of the available information (Jain et al., 2023). This approach aims to speed up the investment decision-making process. The problem with this is that it often leads to distorted decisions (Jain et al., 2023).

ESG data is often characterized by ambiguity in its methodologies (Richter, 2021). In such cases, heuristic biases are emphasized. Investors then seek ways to speed up investment decisions based on ESG data. However, this is quite problematic, as it rarely leads to the right decisions. As ESG data is very complex, it is important to have a deeper understanding of it and to search for information on the responsibility of a particular company. As mentioned earlier, companies tend to embellish their responsibility, which means that the use of heuristics significantly affects the effectiveness of decisions. Decisions are overly influenced by incomplete data, which often leads investors astray and causes them to lose capital.

There are several examples of this phenomenon, such as investors only looking at companies' ESG scores. However, ESG scores often do not tell the whole truth about how companies operate. There is considerable variation in ESG scores between the companies that provide them (Bissoondoyal-Bheenick et al., 2024). In such cases, it would be wise to examine the matter closely and verify the quality of the ESG data behind the scores. However, this may not be done because it would significantly slow down the decision-making process. This could result in a distorted investment decision.

### **3.4.2 Anchoring bias**

Anchoring refers to a phenomenon whereby people rely too heavily on certain information (Andersen, 2010). Anchoring is a fairly common problem in financial markets and investing. Andersen (2010) describes this behavior as follows: price changes are often rigid, and as a result, investors anchor themselves to recent prices when determining overvaluation or undervaluation when considering investing in an asset. This phenomenon can also often occur when investors use ESG data in the market. This leads to similar problems as in heuristic biases.

When using ESG data, investors often rely on the information that is first available about a company's responsibility. According to Hanyu (2023), even if different sources indicate that the first ESG data they see is inaccurate, investors often rely on the original ESG data in their decisions. Research by Mahmood et al. (2024) supports this claim. Anchoring has a significant impact on investors' decisions. This is also linked to the use of ESG data, as Hanyu (2023) points out. As a result, the anchoring effect leads to the use of weaker data, even though higher-quality data may be available. This, in turn, means that decisions may be distorted by psychological factors. This is a fairly common problem with data, which investors may not even be aware of. These factors can have cross-sectoral effects on poor investment decisions.

### **3.4.3 Availability bias**

Availability bias refers to an investor's tendency to rely on information that is easily accessible (Jain et al., 2023). Investors often exhibit this behavior because it requires less effort because they don't need to search extensively for information. However, this can be quite problematic, as it may lead them to overlook important and relevant data. This bias also applies to ESG data, where investors frequently rely on readily available information and ignore potentially crucial sustainability data that would require more effort to obtain.

Publicly visible information often shapes people's perceptions and influences their actions. Lengthy ESG reports or widely publicized details about a company's sustainability practices can affect investment decisions. As a result, investors tend to use the most easily accessible ESG data, which may not always be accurate. This behavior closely resembles the patterns described earlier.

#### **3.4.4 Overconfidence/Confirmation bias**

Overconfidence bias is a well-known concept in psychology, where individuals tend to overestimate their knowledge and abilities (Jain et al., 2023). This is also very common in investing, where many people assume they are more capable investors than others. Such overestimation can lead to misjudgments when selecting investments. This bias can also be observed in the context of ESG data. When engaging in ESG investing, investors may overestimate their understanding of ESG data, which can result in flawed decision-making when choosing investments based on sustainability criteria.

Often, investors who experience success in their investments may develop an overly positive perception of their own abilities, which can lead to increased trading activity (Ding, 2025). A similar phenomenon can occur in the use of ESG data in investing. This bias may cause investors to be overly optimistic about their ability to interpret ESG data and sustainability reports. However, as previously mentioned, ESG data is often complex and ambiguous, and using it effectively requires subject-matter expertise. Investors frequently misunderstand this, leading to undesirable outcomes.

This is especially evident among investors who are not particularly interested in ESG factors. According to Bhojnagarwala (2025), those who are not interested in ESG issues are the most likely to make erroneous decisions in ESG investing. They often overestimate their understanding of ESG factors, and this overconfidence leads to poor investment choices.

## **4 Qualitative and structural problems with ESG data in investment decisions**

One of the most common concerns regarding ESG data is its poor quality (Almeida Cruz and Matos, 2023). The quality of ESG data is affected by several factors, which can sometimes make it difficult to use as a basis for investment decisions. These factors may include lack of consistency, lack of transparency, data normalization, and the omission of certain ESG areas (Almeida Cruz and Matos, 2023). These and many other factors often emerge in studies and expert assessments of the use of ESG data in investment decisions. This is reflected in the problems faced by investors. Companies often claim that they also have problems with these issues, and the problem cannot be considered to be solely the fault of the companies. Quality deteriorates as a result of multiple factors, which in turn easily leads to a decrease in its usability.

Structural challenges with data are also often a problem, which can make it harder to use data for investment decisions. Structurally weak ESG reports make it way harder to get data (Zou et al., 2025). These quality issues are common reasons for exposing investors to misuse of data, as finding reliable data can sometimes be difficult.

The purpose of this section is to present the potential problems that poor ESG data quality can cause for investment decisions. This is directly related to Hypothesis One, the implications of which will be presented. Hypothesis One has already been attempted to be proven in previous sections, and now concrete problems related to quality are added to the theory.

### **4.1 Poor consistency of ESG classification**

The problem with ESG ratings is often their high variability between different service providers (Doyle, 2018; Berg et al., 2022). This often makes them difficult to use in investment decisions. According to Berg et al. (2022), ESG factors affect asset prices, so if

they indicate the wrong thing, it has a significant impact on investment decisions because that could limit their practical usability. This is reflected in the fact that investors are reluctant to use them themselves, as they may lead to wrong decisions.

According to Doyle (2018), another significant reason why data can be considered weak is geographical favoritism towards companies from continents where the required level of reporting is higher. Many European countries may have requirements to report on certain sustainability factors in more detail, which means that assessments are more favorable towards companies located there. According to Kotsatonis and Serafeim (2019), for example, assessments are influenced by how much companies publish the sustainability data on which the ratings are based. These factors influence each other and indicate that assessments are distorted as a result of reporting volumes. This is also linked to Doyle's second argument, in which he suggests that larger companies are better able to produce sustainability reports. Investors are often unable to select the right data, which makes decision-making difficult (Kotsatonis and Serafeim, 2019).

Thirdly, studies have often highlighted the weightings used in assessments and the industries in which companies operate. According to Doyle (2018), companies' assessments are often based on incorrect weightings because they do not take sufficient account of the impact of the industry on the assessments, and thus industry-specific risks are often overlooked. Capizzi et al. (2021) identify the same phenomenon as Doyle. There is variation among different service providers in how much weight they give to a particular indicator in their scoring. This phenomenon can be observed in all ESG areas. However, it is most pronounced in the governance area (Capizzi et al., 2021). There may be significant differences between categories, so special attention should be paid to their use in decision-making. The study by Berg et al. (2022) highlights the differences between the categories in concrete terms. According to them, the biggest differences between data providers are seen in their responses to corruption and climate risks. This shows that particular attention should be paid to the assessments.

Another problem with ESG data and ratings is considered to be their comparability (Zumente and Lāce, 2021). However, the comparability of these assessments is important because investors use this data when making investment decisions. Ratings and data have been found to be poorly comparable, making it difficult to choose between providers and leaving investors unsure of how to use them. Correlations between ratings have been found to be low (Berg et al., 2022; Chatterji et al., 2016; Capizzi et al., 2021). With low correlations, the variability in data quality can be considered significant. Data quality is important so that it can be used correctly to support investment decisions (Liu et al., 2023). Based on these studies, it is difficult or even impossible to compare data. In light of these studies, investors should use data for which reliability is not guaranteed. This may lead to investors not wanting to use the data or having to make decisions without real confidence in the data. However, in responsible investing, it is practically impossible not to use this data, which may distort investment decisions or make it impossible to invest at all.

## **4.2 Measurement and reporting errors**

Service providers use a variety of methods to collect and measure data. There are many ways to measure data, which can distort its usability and make it difficult to interpret (Jónsdóttir et al., 2022). Often, the problem lies in interpreting these methods, and it is difficult for investors to understand the basis on which the data has been collected. The methodologies used to measure and collect data are also difficult to interpret and may change rapidly (Świniarska, 2024). Together, these biases can lead to a decline in data quality, and studies often highlight the difficulty of interpreting data and the various measurement methods, which can be difficult to understand.

Service providers often use data available from public sources, which, according to them, should comply with scientific methods of obtaining information (Chatterji et al., 2016). However, they argue that the problem often lies in the way service providers use different methods to evaluate exactly the same information. Chatterji et al. (2016) argue that this makes it very difficult for investors to assess the quality of the data in question. This

results in different emphases, which can distort the data, even if it appears to be correct. Liu (2022) highlights the same problem as Chatterji et al. in their study. Evaluating the same data using different methodologies exposes the data to distortion. This creates differences between the data provided by different service providers. Methodologies related to data acquisition are also highlighted in relation to this phenomenon. According to Lukács et al. (2024), ESG methodologies often contain many inconsistencies that may mislead investors. The methodologies are directly linked to the presented way of utilizing the same information in different ways. González-Pozo et al. (2024) and Benuzzi et al. (2025) highlight the same problem in their research. Methodologies are often difficult to interpret and may contain several inconsistencies (Lampinen, 2025). This also affects investors' ability to interpret ESG data and use it in their investment decisions. Methodologies should be more clearly aligned with each other so that investors can use them to understand ESG data more effectively and utilize it when selecting their investments. However, with the current methodologies, this is very difficult because investors cannot be sure of the quality of the data. This leads to a closely related problem concerning the availability of information and the size of companies (Benuzzi et al., 2025).

The size of companies has a significant impact on the type of ESG data available, and the effects of size are often problematic. According to Dobrick et al. (2023), the size of a company has a significant impact on the score it receives from the service provider, which in turn has a direct impact on the quality of data investors can obtain about their investment targets. The study focuses on Refinitiv's data, but according to Dobrick et al., the phenomenon is generally observable. The findings support Doyle's (2018) earlier observations on size biases in ESG ratings. Size biases have been found to directly affect investors, for example, in the creation of portfolios, because more information is available, investors allocate capital to these companies, even though the data may not necessarily be reliable. Drempetic et al. (2019) point out in their study that the size of a company has a significant impact on its ability to report ESG data, which also causes a bias in the use of data. This leads to the next data problem, where companies that report more do not necessarily operate more responsibly in reality.

Drempetic et al. (2019) suggest that the size of companies often affects data quality, as larger companies are significantly better equipped to produce ESG data that can be used by all stakeholders. Service providers often reward companies for this, which is directly reflected in their ESG ratings. This is also a way of demonstrating responsibility to investors and other stakeholders, even if there is no correlation between them. In their study, they also point out that what the data (responsibility reports) contain is not important, but rather that it is produced. Gold and Heikkurinen (2017) also point out in their study that maximum transparency does not actually guarantee that a company will operate responsibly. This shows how difficult it is for investors to identify and find responsible companies when selecting their investment targets. As a result, the entire field of responsible investing may be jeopardized, as large companies receive more approval from data providers (Drempetic et al., 2019). This does not create added value for investors, and their decisions may be based on poor-quality data. This is also evident in the fact that companies are often selected for responsibility-based funds based on size bias. As a result, these funds may end up including Sin stocks, which responsible investors seek to avoid. This happens because larger companies may report better on their responsibility based on their size, even if they have activities related to controversial issues.

### **4.3 Subjectivity and uncertainty in data sources**

ESG data sources often vary considerably, and their interpretation is rather subjective, as their underlying principles are not always easy to understand (Mayer and Ducsai, 2023). This is one concern that is often discussed in studies. However, the interpretation of data is important for its usability, so understanding it is quite essential. The main sources of ESG data are usually the information reported by the companies themselves (Vissalli et al., 2023). According to them, this is problematic because the data may be distorted as a result of self-reporting, as companies can choose what they report due to weak standardization. As a result, the data is not transparent and difficult to use as a basis for decision-making. The reliability of the data suffers, and it is impossible to be certain whether the data is of high quality or not.

According to Bongerman and Romagnoli (2025), the scarcity of ESG data exposes investors and other stakeholders to the use of subjective data, as it is difficult for them to operate in the market based on data alone. This phenomenon has also been observed in several other contexts, where investors are required to rely on subjective data when making various investment decisions. This phenomenon is also strongly reflected in the sources from which the data is obtained. Shi and Yao (2025) highlight how service providers may select data sources on this basis. This phenomenon is also often reflected in the data used by investors. Each party using the data has to interpret it to a considerable extent, which may lead to distortions in decision-making. The quality of the data cannot therefore necessarily be relied upon, and the risk of misinterpretation further exacerbates this phenomenon. This phenomenon is further exacerbated by cognitive biases, which were highlighted in the theoretical framework (Shi and Yao, 2025). For example, availability bias is evident in this phenomenon, as investors often use the sources that are first available.

As the data is largely based on companies' self-reporting, it is rather difficult to measure. Furthermore, based on the sources presented, the data cannot be considered very objective, and it is rather difficult to verify. On this basis, the data can be considered subjective. Comparing data is also difficult based on these and the above-mentioned examples (Liu et al., 2023). The sources used by service providers vary greatly and, as a result, often cannot be interpreted correctly. Kotsantonis and Serafeim (2019) suggest that the data can be considered "judgment-based" because the reliability of the data depends as much on the methodologies as on the actual operations of the company. It is therefore important for investors to be aware of the limitations of the data and to bear in mind that, due to a number of factors, the information may be more limited than is implied.

#### **4.4 Data dynamism and temporal instability**

ESG data is sensitive to change, and its criteria and assessment methods may change rapidly (Eskantar et al., 2024). ESG data can therefore be considered fairly dynamic,

which makes its assessment more difficult. According to Eskantar et al. (2024), data should be approached with an awareness of its rapid changes. Data and rating methodologies are also sensitive to this, as noted by Liu (2022), Chatterji et al. (2016), and Lukács (2024). Rapid changes in data may expose investors to making wrong decisions, as data changes quickly and ESG metrics are highly volatile. Reliable metrics should be more stable over time, unless the company's operations actually change. However, ESG data and assessments often change based on the decisions of service providers rather than on how the company actually operates (Escrig-Olmedo et al., 2019). As a result, the data does not measure what it should measure.

ESG ratings have a rapid impact on the markets and often change very quickly, which means that investors need to be careful when using the data. According to Cauthorn et al. (2023), investor behavior changes as ESG ratings change. Investors begin to use different investment strategies because they feel that these affect the potential profits they can make by reacting to changes. As a result of rapid changes in data, this can have a significant impact on their investment decisions. This phenomenon is due to the practices of service providers. According to Berg et al. (2022) change in ratings are not due to actual changes in companies but to changes in methodologies. This phenomenon was demonstrated in 2018 by a change in the methodology of one major service provider, which changed estimates by almost 20 % (Berg et al., 2021). Given the magnitude of the change and the absence of significant changes in the operations of the companies assessed, this can be considered alarming. The changes also affected historical results, compromising the reliability of the data. The changes in the data may have led investors to use incorrect information in the past, which may have distorted their decisions. The indicators therefore do not necessarily reflect reality, meaning that investors cannot use them reliably. As Cauthorn et al. (2023) point out, rapid changes in data affect investors' decision-making; if the changes were random and occurred at longer intervals, this problem would not arise. Data is therefore not very reliable, as changes in its quality cannot really be predicted in any way.

## 4.5 Relation to H1

In summary, the first part of the literature review provides strong evidence that H1 is correct. Several problems have been identified in ESG data, as demonstrated in the first part of the review in light of existing literature and research. All of the studies used highlight problems with the quality of ESG data. In most cases, the data is not reliable enough to be used without significant risk to support decision-making. Not all studies take a position on the investment perspective, but they prove and systematically review the data quality problem, which is why they have been included in the review. The selected studies provide strong support for hypothesis 1 and take into account several different ESG areas.

All of the selected studies present the quality of ESG data as poor, and no literature was found to refuse their claims. According to the literature used, the quality can be considered poor as a result of structural problems such as poor consistency, measurement and reporting biases, subjective criteria, and temporal instability. The purpose of H1 was to prove, first of all, that the quality of the data is too poor, and this can be confirmed based on the literature used. The poor quality is also supported by theoretical considerations, such as cognitive biases, which amplify the impact of unstable data on investors.

According to H1, weak data should also distort investment decisions. This point was often raised in the studies used. For example, Cauthorn et al. (2023) and Bongermينو and Romagnoli (2025) argue that data is very important for investors' decision-making, which means that data should be of high quality in order to be usable. However, the above-mentioned studies conclude that data creates uncertainty about the accuracy of information, making it difficult for investors to use data correctly. Data is measured using different methodologies and measurement methods, which means that it is not consistent and does not necessarily reflect actual responsibility. This increases information asymmetry and sends false signals to investors, thereby compromising the market's ability to interpret and price responsibility in a natural way. This leads to H2, which is discussed in the next section. When all these factors combine, structural weaknesses can lead to

incorrect decisions, false perceptions of risk, and suboptimal investment decisions. It can be said that the literature supports the validity of the first hypothesis by combining all the assumed parts of the argument.

## **5 Lack of standardization in ESG reporting and information asymmetry**

One of the biggest problems with ESG data is considered to be data standardization, as it is weak and insufficient (Liu et al., 2024). Although there are various standards for ESG data, the problem often arises from their voluntary use and application. Data must be reliable in order for its use to be worthwhile. One factor that prevents this is the lack of reporting standards. According to Cortin and Esty (2020), one way to avoid data ambiguities would be to improve standardization for ESG data acquisition and quality assurance. This would help to avoid at least certain problems related to data quality and the resulting information asymmetry.

There are frameworks for ESG reporting, but they are not universal. Different standards contain different objectives, metrics, and emphases, which can make them difficult to compare and interpret. This issue is closely linked to the previously mentioned lack of consistency in methodologies (Lukács et al., 2024; González-Pozo et al., 2024; and Benuzzi et al., 2025). One major reason for the differences in methodologies is the lack of standards. Methodologies also have a significant impact on data quality. As a result, investors may have access to incorrect data, compromising their ability to evaluate companies. Eccles and Stroehle (2018) highlight the same problem as presented in the hypothesis 2, namely that ESG data tends to create information asymmetry between companies and investors. This may indicate that the standards are open to interpretation. This, in turn, may lead to investors being unable to find truly responsible companies when they want to.

Weak standardization also has a direct impact on market efficiency, as discussed in the theory section. Weak ESG ratings and data have been found to affect, for example, stock volatility (Brandon et al., 2021). This illustrates the potential impact of poor data on the pricing of sustainability (see section 3.1). This factor also indicates the existence of information asymmetry. One explanatory factor for this phenomenon is the poor

standardization of ESG data. Reporting does not always reflect actual sustainability, as companies can circumvent this by embellishing reality.

The purpose of this section is to prove the existence of H2. H2 is proven using existing literature and finding connections to it. The phenomena presented at the beginning of this section are concrete and form the central basis for this section. The quality of the ESG data presented in section 4 has already been found to be poor in the light of the literature, and this section continues from there and takes up a more concrete phenomenon, the asymmetry of information presented earlier.

## **5.1 Fragmentation of reporting frameworks**

There are a large number of ESG reporting frameworks, and there is considerable variation between them. Different reporting frameworks take different factors into account and often approach them from different perspectives. Some of the more common standards are following: GRI is widely known around the world and provides various standard for organizations that they can use in their operations. Its purpose is to be universal and suitable for all organizations regardless of size (Sustainability Directory, 2025). Sustainability Accounting Standards Board (SASB) standards are industry-specific and, for example, emphasize industry-specific metrics (Sustainability Directory, 2025). Task Force on Climate-related Financial Disclosure (TCFD) standard focuses only on climate-specific indicators (Sustainability Directory, 2025). This already shows how different these standards actually are. These presented standards are only a small sample of all those that exist. The standards are not universal, and companies can use those they see as best serving their interest. According to Cortin and Esty (2020), this phenomenon is also observable in practice. For example, TCFD gives companies too many opportunities to select data that suits them, according to them. This illustrates how difficult it is for investor to choose companies based on genuine responsibility. As a result, reporting between companies is very different, even when they use the same reporting framework (Cortin and Esty, 2020). The information may therefore be very different even if it is meant to

describe the same thing. Investors thus find it difficult to detect this phenomenon, which may create information asymmetry between investors and companies.

In terms of reporting, the weakness of standards in measuring certain factors, such as labour conditions, has also often been raised in discussions. According to Eccles and Strohle (2018), proper standardisation does not exist when talking about certain factors. This is quite problematic if none of the reporting frameworks can provide objective guidance on how, for example, labour-related indicators should be measured and reported. Chopra et al. (2024) present the same issue in their article. According to them, ESG reporting and the related data suffer from significant problems because everyone uses different methodologies and measurement practices, since there are no universal frameworks that all parties would use. According to them, this may lead to unclear and even incorrect data. This is problematic because investors do not, as a result, have access to accurate data, which may lead to information asymmetry and weak investment decisions.

When companies take advantage of this problematic situation caused by differing methodologies and weak standardisation, they can choose the reporting method that is most favourable to them, which in turn leads to systematic selection and reporting bias. Fagbemi et al. (2025) highlight these problems in their study. According to them, standardization is still insufficient, which leads to the problems mentioned above. A good example of this is a hypothetical case where two companies report according to different standards, such as SASB and GRI. These reporting frameworks emphasise different factors, making it very difficult to produce comparable evaluations. The fragmentation of the frameworks may increase information asymmetry and uncertainty, which in turn supports H2. The ability of companies to choose their own reporting standard therefore likely results in lower-quality data and makes investment decision-making more difficult for investors.

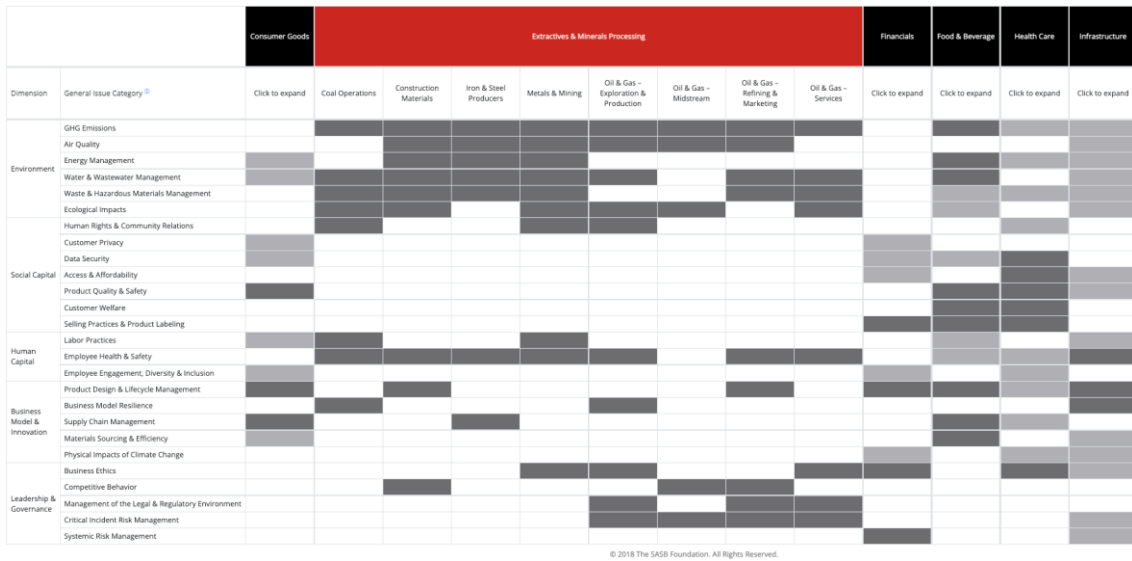
## 5.2 ESG Industrial Materiality

The industry-specific materiality perspective of ESG is considered an important part of ESG assessments (Madison and Schiehl, 2021). This refers to how certain areas should be weighted when evaluating the responsibility perspective of a company or an industry. The problem is often the limited attention that service providers pay to materiality (Madison and Schiehl, 2021). For this purpose, various reporting frameworks such as SASB have been developed, but the problem is that they are not systematic enough. Oluwakemi and Mishelle (2025) highlight the same issue. Deficiencies in materiality and unclear reporting frameworks weaken the transparency and usability of ESG data. In company evaluations, materiality problems may distort investment decisions (Madison and Schiehl, 2021). As a result, industry-specific ESG issues should be assessed more on an industry basis instead of relying only on generic ESG scores.

Risks vary significantly between industries, and therefore they should be better taken into account as part of ESG data and ratings. In the energy sector, for example, key risks include non-renewable energy sources, while in the industrial sector the key risks relate to labour conditions and safety measures (Egorova et al., 2024). The main issues in these industries therefore differ from each other quite substantially, even though they may include some of the same risks. ESG scores may not provide a comprehensive overall picture if they do not attempt to account for industry-specific differences. Matakanye et al. (2021) state in their study that ESG data should better and more comprehensively reflect industry-specific perspectives so that investors have access to better and more comparable data. Traditional metrics used by investors to evaluate companies do not necessarily give an accurate picture of the risks and quality of a specific industry. It is therefore difficult for investors to identify industry-specific companies that operate responsibly enough according to their preferences. This may expose investors to investing in companies that do not actually operate responsibly.

The SASB materiality map illustrates well how sector-specific assessments are relevant and why more attention should be paid to them. The purpose of SASB is to help

companies identify and manage ESG data in a reliable and comparable way across different sectors (Madison and Schiehl, 2021). It divides ESG issues into five categories and 26 specific issues. The standards are industry-specific, which makes them more suitable for comparison than generic ESG descriptions. Below is a figure that illustrates this more clearly (See Table 3).



**Figure 3.** Materiality map (SASB,2018).

In the figure, the areas that have the greatest impact on the specific industry are highlighted. This shows concretely which ESG factors are material in certain industries but not necessarily in others. This demonstrates that the claims made in the literature about the importance of materiality are not merely theoretical. As a result, a single ESG score is not sufficient, because it does not adequately account for the diversity of industries. When investors rely only on a generic ESG score without proper industry-specific consideration, it may easily lead to incorrect evaluations of companies. By overlooking these factors, investors may invest in companies that are not actually operating responsibly and, on this basis, make a poor investment decision. This supports H2, because investors may not necessarily have access to data that is relevant for their decision-making.

### 5.3 Information Asymmetry and ESG reporting

Several of the same issues that affect the quality of ESG data also contribute to the creation of information asymmetry. Information asymmetry often arises from the very same reasons that cause the previously mentioned poor data quality, namely the problems related to reporting, which are also connected to the lack of standardisation. According to Grewal et al. (2017), mandatory ESG reporting especially benefits companies that have better opportunities to report on responsibility-related factors. The earlier presented articles by Doyle (2018) and Drempetic et al. (2019) also support this claim. Companies with greater resources have better possibilities to report on the essential ESG factors that investors and stakeholders value. This is strongly related to data quality, but it also causes information asymmetry in the markets, which is why it is important to highlight it in this context as well. Liang and Renneboog (2020) also emphasise size as a major issue in ESG data. Many studies confirm the existence of this phenomenon. There is therefore a clear problem in the market from which larger companies benefit, because reporting frameworks do not at all standardise the effects of company size. However, this does not prove or mean that companies that report more are actually more responsible, even if it easily gives that impression. Various cognitive biases reinforce this phenomenon. As a result, investors may more easily invest in companies based on incorrect information, even if those companies are not actually as responsible as they appear to be. This leads to a situation where investors may “punish” companies for a lack of data.

According to Liu et al. (2024), companies that disclose more ESG data generally receive more appreciation and their operations may be regarded as high-quality because they report more. They argue that one reason why there are differences between companies is the so-called missing data. In such cases, data users fear that the company contains more ESG risks, which results in lower valuation for those companies. These factors may lead to information asymmetry between investors and companies. Christensen et al. (2021) propose in their study that reporting frameworks could be very useful at a certain level, even if they might lead to some problems. The lack of standards may lead investors to use the amount of reporting as a metric for a company’s responsibility. This may,

however, be misleading, because the use of standards is largely voluntary. This claim is supported by the fact that broad ESG disclosure strengthens investors' perceptions, and because of this they reward such companies (Siew et al., 2016). Companies that report less may therefore be excluded from investment evaluations simply because they do not report enough. Siew et al. (2016) argue that the disclosure of ESG data affects information asymmetry, and therefore more regulation would be needed to define what ESG data should be like. This would better ensure that everyone has equal access to high-quality information. The lack of regulation thus has a significant impact on the creation of information asymmetry. The phenomenon is further reinforced by the tendency of ESG data providers to act similarly to investors. As Dremptic et al. (2019) state, service providers also reward companies for the broadest possible disclosure. In the eyes of the market, this often signifies more responsible behaviour and may lead to distorted conclusions.

The same phenomenon occurs when discussing companies operating in developing countries. According to Cahan et al. (2016), companies located in developed countries report more and better on their responsibility. Doyle (2018) highlights the same issue. Investors therefore often consider companies more responsible when they have better capabilities to report ESG-related factors. Companies operating in developing markets do not have equally extensive possibilities to report on these factors, even though they may act more responsibly than some companies operating in developed markets. For example, Meng et al. (2025) note that in the Chinese market, some companies in the energy sector disclose much more comprehensively than companies in the same sector in the United States. However, these companies do not receive the same level of attention because standardisation differs across countries. This illustrates why more standardisation between countries is needed in order to harmonise the differences (Meng et al., 2025). In this way, investors would have better opportunities to invest in truly responsible companies and avoid misleading information.

Overall, it can be said that all the mechanisms presented together expose investors to using data that is abundant rather than data that is actually high-quality and accurate. Companies that have the ability to disclose as comprehensively as possible benefit the most from this, and they appear more responsible regardless of the reality. This describes how the lack of standardisation and the extent of data disclosure lead to information asymmetry, because the investor cannot easily detect the company's actual level of responsibility. This supports H2.

#### **5.4 Examples of the consequences of poor ESG reporting practices**

Market scandals can clearly demonstrate the consequences that may arise when ESG reporting and data are not properly monitored. The problem culminates in the previously discussed outcomes resulting from information asymmetry and weak standardisation. Broad reports and ESG scores do not guarantee actual responsibility.

Jung and Sharon (2019) describe in their article the 2015 Volkswagen scandal. In this case, the company attempted to pass certain emissions tests through the use of equipment. In 2014, Volkswagen was one of the leading companies in terms of responsibility and was included in RobecoSAM's gold classification, the highest possible rating (RobecoSAM, 2014). This demonstrates how misleading reporting can result in high ESG ratings. In reality, Volkswagen was not acting responsibly. It engaged in greenwashing and manipulated its ESG data to appear better in the eyes of investors. As a result, it is extremely difficult for investors to verify the responsibility of companies using only ESG data. This could possibly have been prevented with more effective reporting frameworks, which would have made it harder for Volkswagen to engage in such blatant greenwashing. The scandal had severe consequences for investors, as the stock price dropped by 40 % (Jung and Sharon, 2019). Cases like this demonstrate that information asymmetry exposes investors to poor investment decisions. Investors likely would not have traded or trusted the company if they had access to accurate information. Investment decisions also could not have been properly allocated to a truly responsible company.

Another illustrative example is the operations of fast fashion companies. According to Turker and Altuntas (2014), for instance, H&M reports extensively on its responsibility practices. The company emphasises circular economy, labour conditions, and ethical supply chains. In this way, it seeks legitimacy from the market and projects an image of responsibility, even though the reality may be different. This does not prove actual responsibility, and reports of all responsible actions are often exaggerated (Turker and Altuntas, 2014). Companies benefit significantly from operating in such markets and are aware of it. This also demonstrates the biases associated with extensive reporting. Similar to the Volkswagen case, extensive reporting is used to create an impression of responsibility for investors. It may be difficult for investors to detect this, and they may invest in seemingly responsible companies. Information asymmetry arises between the company and investors because investors do not receive all the same information as the company.

A final example of greenwashing is the case of BP. The company experienced a serious oil accident, yet at the same time promoted itself as responsible (Cherry and Sneirson, 2011). Due to this promotion, the company gained a very good reputation and led rankings in several responsibility metrics. This clearly illustrates the phenomenon in which the outward appearance is very different from reality. The same issues arise as in the other cases. Companies often use responsibility reporting to manage reputation and legitimacy rather than to reflect true responsibility. Companies can use this tool because proper standardisation does not exist, allowing them to embellish and improve their apparent responsibility practices. This directly affects the quality of ESG data, as the primary source is often the companies' own reports. These factors are connected to Hypothesis 2, because investors often do not have access to actual data, which prevents them from identifying companies that truly operate responsibly.

## 6 Conclusion

This thesis examined from various perspectives how ESG data influences investment decisions and what kinds of problems it entails. The aim was to find evidence for the hypotheses and prove them either false or true. Chapter four discussed how quality and structural problems with ESG data are reflected in investment decisions. The fourth chapter dealt with the lack of standardization in terms of responsibility and the related information asymmetry. The purpose of the selected hypotheses was to highlight the most critical problems in the use of ESG data with the help of financial theories and literature.

The findings in section four provide strong evidence for hypothesis 1. It can be concluded that poor-quality ESG data makes investment decisions difficult and may even distort them as a result. According to the literature, when data and ratings contain numerous shortcomings and inconsistencies, it becomes difficult to use the data. No literature was found that would present the data as completely objective, which supports the claim that there is a problem. However, ESG data is often more complex than traditional financial data on companies. Certain areas are much more difficult to measure in terms of ESG issues, such as Scope 3 emissions, which contain a significant variable. It can be said that the problems with the data are not solely due to a lack of willingness to correct them. However, the data is constantly evolving and increasingly better reflects what it is supposed to describe. However, it is impossible for responsible investors not to use this data, which exposes them to the risk of false information. The problem can therefore be seen in light of this evidence.

The findings in section five can also be said to indicate the existence of hypothesis 2. According to the literature, there are still several shortcomings in data standardization and coverage. Standards do exist, but they are not universal, and as a result, there are several differences in companies' reporting frameworks, and there may be no reporting available at all from developing countries because standards are not in use. As a result, investors may not be able to obtain the same information on sustainability as companies

have on their operations. Overly liberal reporting exposes companies to publishing data that is favorable to them, thereby creating a better image of the company for stakeholders. The greater financial capacity of larger companies to produce more comprehensive sustainability reports exacerbates this phenomenon. Better reporting does not guarantee true sustainability, as the literature suggests. This may mislead investors, especially responsible investors, due to a number of factors. Examples from the market, such as Volkswagen's Dieselgate scandal, clearly illustrate the existence of this phenomenon. The hypothesis can be said to be true, but it should be noted that not all companies operate in this way. Investors should be aware of the possibility of this bias, but not assume that it exists in every case. It is likely that this phenomenon will also disappear in the future as a result of universal standards.

The study also shows, in light of theory, that the phenomena observed do not occur randomly, but are also demonstrated quite well by financial theories. In particular, information asymmetry, signaling theory, and behavioral finance are well suited to describing the quality problems of ESG data. Information asymmetry, for example, describes how investors and companies may have different information about a company's actual responsibility. Signaling Theory, on the other hand, illustrates well how companies can use ESG data to demonstrate their responsibility by sending "signals" to investors and thus gaining their trust. Behavioral finance, in turn, illustrates how behavior further exacerbates these existing problems. These theories help explain the existence of these phenomena.

However, ESG data is essential for certain types of investors and, despite the problems, can be considered an important part of investment activities. In the future, however, it should be possible to remedy the problems that have been identified. It would be important for researchers to focus on finding solutions to these problems. Several studies already present possible solutions, such as a universal reporting framework and various technological solutions, such as artificial intelligence. In conclusion, the study provides

strong evidence for the hypotheses, but their existence should be viewed with caution. However, they do not apply in all situations.

## References

- Akerlof, G. A. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488–500. <https://doi.org/10.2307/1879431>
- Almeida Cruz, C., & Matos, F. (2023). ESG maturity: A software framework for the challenges of ESG data in investment. *Sustainability*, 15(3), 2610. <https://doi.org/10.3390/su15032610>
- Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal*, 74(3), 87–103. <https://doi.org/10.2469/faj.v74.n3.2>
- Andersen, J. V. (2010). Detecting anchoring in financial markets. *Journal of Behavioral Finance*, 11(2), 129–133. <https://doi.org/10.1080/15427560.2010.483186>
- Bancel, F., Glavas, D., & Karolyi, G. A. (2023). *Do ESG factors influence firm valuation? Evidence from the field*. SSRN. <https://doi.org/10.2139/ssrn.4365196>
- Benuzzi, M., Bax, K., Paterlini, S., & Taufer, E. (2025). Chasing ESG performance: How methodologies shape outcomes. *International Review of Financial Analysis*, 104(Part A), 104239. <https://doi.org/10.1016/j.irfa.2025.104239>
- Berg, F., Fabisik, K., & Sautner, Z. (2021). Is history repeating itself? The (un)predictable past of ESG ratings. *ECGI Finance Working Paper 708/2020*. <https://doi.org/10.2139/ssrn.3722087>
- Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6), 1315–1344. <https://doi.org/10.1093/rof/rfac033>
- Bhojnagarwala, V. (2025). When sustainability meets speculation: A critical review of investor overconfidence in ESG stocks and the market outcomes. *International Journal of Social Science and Economic Research*, 10(6), 2484. <https://doi.org/10.46609/IJSSER.2025.v10i06.036>
- Bissoondoyal-Bheenick, E., Bennett, S., Lehnerr, R., & Zhong, A. (2024). ESG rating disagreement: Implications and aggregation approaches. *International Review of*

- Economics & Finance*, 96(Part A), 103532.  
<https://doi.org/10.1016/j.iref.2024.103532>
- Bongermينو, G., & Romagnoli, S. (2025). ESG rating and ambiguity: An informative and distorted signal-based approach. *Decisions in Economics and Finance*.  
<https://doi.org/10.1007/s10203-025-00507-y>
- Brandon Gibson, R., Krueger, P., & Schmidt, P. S. (2021). ESG rating disagreement and stock returns. *Financial Analysts Journal*, 77(4), 104–127.  
<https://doi.org/10.1080/0015198X.2021.1963186>
- Bu, M., Liu, X., Zhang, B., Hazaea, S. A., Fan, R., & Wang, Z. (2024). Governance of corporate greenwashing through ESG assurance. *Systems*, 12(9), 365.  
<https://doi.org/10.3390/systems12090365>
- Cahan, S. F., De Villiers, C., Jeter, D. C., Naiker, V., & Van Staden, C. J. (2016). Are CSR disclosures value relevant? Cross-country evidence. *European Accounting Review*, 25(3), 579–611. <https://doi.org/10.1080/09638180.2015.1064009>
- Capizzi, V., Gioia, E., Giudici, G., & Tenca, F. (2021). The divergence of ESG ratings: An analysis of Italian listed companies. *Journal of Financial Management, Markets and Institutions*, 9(2), 2150006. <https://doi.org/10.1142/S2282717X21500067>
- Cauthorn, T., Dumrose, M., Eckert, J., Klein, C., & Zwergel, B. (2023). Rating changes revisited: New evidence on short-term ESG momentum. *Finance Research Letters*, 54, 103703. <https://doi.org/10.1016/j.frl.2023.103703>
- Chatterji, A. K., Durand, R., Levine, D. I., & Touboul, S. (2015). Do ratings of firms converge? Implications for managers, investors and strategy researchers. *Strategic Management Journal*, 37(8), 1597–1614. <https://doi.org/10.1002/smj.2407>
- Cherry, M. A., & Sneirson, J. F. (2011). Beyond profit: Rethinking corporate social responsibility and greenwashing after the BP oil disaster. *Tulane Law Review*, 85(4), 983.  
<https://doi.org/10.2139/ssrn.1670149>
- Chopra, S. S., Senadheera, S. S., Dissanayake, P. D., Withana, P. A., Chib, R., Rhee, J. H., & Ok, Y. S. (2024). Navigating the challenges of environmental, social, and governance (ESG) reporting: The path to Broader Sustainable Development. *Sustainability*, 16(2), 606. <https://doi.org/10.3390/su16020606>

- Christensen, H. B., Hail, L., & Leuz, C. (2021). Mandatory CSR and sustainability reporting: economic analysis and literature review. *Review of Accounting Studies*, 26, 1176–1248. <https://doi-org.proxy.uwasa.fi/10.1007/s11142-021-09609-5>
- Cort, T., & Esty, D. (2020). ESG standards: Looming challenges and pathways forward. *Organization & Environment*, 33(4), 491–510. <https://doi.org/10.1177/1086026620945342>
- Dale, S. (2015). Heuristics and biases: The science of decision-making. *Business Information Review*, 32(2), 93–99. <https://doi.org/10.1177/0266382115592536>
- Dell’Erba, M., & Doronzo, M. (2023). Sustainability gatekeepers: ESG ratings and data providers. *University of Pennsylvania Journal of Business Law*, 25, 355. Retrieved October 30th, 2025, from <https://scholarship.law.upenn.edu/jbl/vol25/iss2/2>
- Di Chiacchio, L., Vivian, B., Cegarra-Navarro, J., & Garcia-Perez, A. (2025). The evolution of non-financial report quality and visual content: information asymmetry and strategic signalling: a cross cultural perspective. *Environment, Development and Sustainability*, 27, 26427–26457. <https://doi.org/10.1007/s10668-024-04779-z>
- Ding, Z. (2025). The impact of behavioural biases on Attitudes and Intentions of Institutional and Retail Investors Towards ESG Investing. *Advances in Economics, Management and Political Sciences*, 168, 58–64. <https://doi.org/10.54254/2754-1169/2025.21513>
- Doğan, M., Chelery Komath, M. A., & Sayilir, Ö. (2025). Credit rating prediction with ESG data using data mining methods. *Future Business Journal*, 11, 79. <https://doi.org/10.1186/s43093-025-00490-1>
- Dobrick, J., Klein, C., & Zwergel, B. (2023). Size bias in Refinitiv ESG data. *Finance Research Letters*, 55(Part B), 104014. <https://doi.org/10.1016/j.frl.2023.104014>
- Doyle, T. M. (2018, July). *Ratings that don’t rate: The subjective world of ESG ratings agencies*. American Council for Capital Formation. Retrieved November 5th, 2024, from [https://accf.org/wp-content/uploads/2018/07/071818\\_ACCF\\_RatingsESGReport\\_PUB01.pdf](https://accf.org/wp-content/uploads/2018/07/071818_ACCF_RatingsESGReport_PUB01.pdf)

- Drempetic, S., Klein, C., & Zwergel, B. (2020). The influence of firm size on the ESG score: Corporate Sustainability Ratings Under Review. *Journal of Business Ethics*, 167, 333–360. <https://doi.org/10.1007/s10551-019-04164-1>
- Eccles, R. G., & Strohle, J. C. (2018). *Exploring social origins in the construction of ESG measures*. SSRN. <https://doi.org/10.2139/ssrn.3212685>
- Egorova, A., Pitenko, K., & Karminsky, A. (2024). Industry-specific characteristics of ESG components in company ratings. *Procedia Computer Science*, 242, 1206–1217. <https://doi.org/10.1016/j.procs.2024.08.156>
- ESG The Report. *What are ESG metrics?* (2024, December 31). Retrieved October 8th, 2025, from <https://esgthereport.com/what-are-esg-metrics/>
- Eskantar, A., Zopounidis, C., Doumpos, M., Galariotis, E., & Guesmi, K. (2024). Navigating ESG complexity: An indepth analysis of sustainability criteria, frameworks, and impact assessment. *International Review of Financial Analysis*, 95(Part A), 103380. <https://doi.org/10.1016/j.irfa.2024.103380>
- Escrig-Olmedo, E., Fernández-Izquierdo, M. Á., Ferrero-Ferrero, I., Rivera-Lirio, J. M., & Muñoz-Torres, M. J. (2019). Rating the raters: Evaluating how ESG Rating Agencies Integrate Sustainability Principles. *Sustainability*, 11(3), 915. <https://doi.org/10.3390/su11030915>
- Fagbemi, B. T., Saah, B. P., Nduka, A. I., & Aloke, E. M. (2025). The Evolution of ESG and Sustainability Reporting: A Review of Standards, Challenges, and Impacts on Corporate Transparency. *Journal of Economics, Business, and Commerce*, 2(2), 297–305. <https://doi.org/10.69739/jebc.v2i2.1239>
- Fama, E. F. (1970). Efficient capital markets: A review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417. <https://doi.org/10.2307/2325486>
- Gold, S., & Heikkurinen, P. (2018). Transparency fallacy: Unintended consequences of stakeholder claims on responsibility in supply chains. *Accounting, Auditing & Accountability Journal*, 31(1), 318–337. <https://doi.org/10.1108/AAAJ-06-2015-2088>
- González-Pozo, R., Arenas-Parra, M., Quiroga-García, R., & Bilbao-Terol, A. (2024). A proposal for refining ESG methodology used by rating agencies. *International*

- Transactions in Operational Research*, 32(4), 2003–2033.  
<https://doi.org/10.1111/itor.13550>
- Grewal, J., Riedl, E. J., & Serafeim, G. (2017). Market reaction to mandatory nonfinancial disclosure. *Management Science*, 65(7), 3061–3084.  
<http://dx.doi.org/10.2139/ssrn.2657712>
- Hanyu, W. (2023). The anchoring effect in ESG (Environmental, Social, Governance) investing. *Advances in Economics, Management and Political Sciences*, 54(1), 86–93. [10.54254/2754-1169/54/20230888](https://doi.org/10.54254/2754-1169/54/20230888)
- In, S. Y., Rook, D., & Monk, A. (2019). Integrating alternative data (also known as ESG data) in investment decision making. *Global Economic Review*, 48(3), 237–260.  
<https://doi-org.proxy.uwasa.fi/10.1080/1226508X.2019.1643059>
- Jain, J., Walia, N., Singla, H., Singh, S., Sood, K., & Grima, S. (2023). Heuristic biases as mental shortcuts to investment decision making: A meditation analysis of risk perception. *Risks*, 11(4), 72. <https://doi.org/10.3390/risks11040072>
- Jónsdóttir, B., Sigurjonsson, T. O., Jóhannsdóttir, L., & Wendt, S. (2022). Barriers to using ESG data for investment decisions. *Sustainability*, 14(9), 5157.  
<https://doi.org/10.3390/su14095157>
- Jung, J. C., & Sharon, E. (2019). The Volkswagen emissions scandal and its aftermath. *Global Business and Organizational Excellence*, 38(4), 6–15.  
<https://doi.org/10.1002/joe.21930>
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of Decision under Risk. *Econometrica*, 47(2), 263–292. <https://doi.org/10.2307/1914185>
- Khamisu, S. K., & Paluri, R. A. (2024). Emerging trends of environmental social and governance (ESG) disclosure research. *Cleaner Production Letters*, 7, 100079.  
<https://doi.org/10.1016/j.clpl.2024.100079>
- Kotsantonis, S., & Serafeim, G. (2019). Four things no one will tell you about ESG data. *Journal of Applied Corporate Finance*, 31(2), 50–58. Retrieved October 10th, 2025, from <https://ssrn.com/abstract=3420297>

- Kräussl, R., Oladiran, T., & Stefanova, D. (2023). A review on ESG investing: Investors' expectations beliefs and perception. *Journal of Economic Surveys*, 38(2), 476–502. <https://doi.org/10.1111/joes.12599>
- Lampinen, D. (2025). *Keva*. Retrieved October 21st, 2025, from [Restricted Availability]
- Lee, S. U., Perera, H., Liu, Y., Xia, B., Lu, Q., Zhu, L., Cairns, J., & Nottage, M. (2025). Integrating ESG and AI: A comprehensive responsible AI assesment framework. *AI Ethics*, 5, 5121–5148. <https://doi.org/10.1007/s43681-025-00741-5>
- Liang, H., & Renneboog, L. (2020). Corporate social responsibility and sustainable finance: A review of the literature. *European Corporate Governance Institute - Finance Working Paper 701/2020*. <http://dx.doi.org/10.2139/ssrn.3698631>
- Liu, M. (2022). Quantitative ESG disclosure and divergence of ESG ratings. *Frontiers in Psychology*, 13, Article 936798. <https://doi.org/10.3389/fpsyg.2022.936798>
- Liu, X., Dai, J., Dong, X., & Liu, J. (2024). ESG rating disagreement and analyst forecast quality. *International Review of Financial Analysis*, 95(Part B), 103446. <https://doi.org/10.1016/j.irfa.2024.103446>
- Liu, Y., Osterrieder, J., Hadji Misheva, B., Koenigstein, N., & Baals, L. (2023). Navigating the environmental, social and governance (ESG) landscape: Constructing a robust and reliable scoring engine-insights into data source selection, indicator determination, weighting and aggregation techniques and validation processes for comprehensive ESG scoring systems. *Open Research Europe*, 3, 119. (<https://doi.org/10.12688/openreseurope.16278.1>)
- Long, R. (2023). *The market for lemons and the regulator's signalling problem*. University of Chicago, Department of Economics. Retrieved October 15th, 2025, from <https://arxiv.org/html/2312.10896v1>
- Lukács, B., Molnár, P., & Rickards, R. C. (2024). Comparative assessment of ESG ratings methodology and results based XBRL. *Journal of Infrastructure Policy and Development*, 8(12), 8641. <https://doi.org/10.24294/jipd.v8i12.8641>
- Madison, N., & Schiehl, E. (2021). The effect of financial materiality on ESG performance assessment. *Sustainability*, 13(7), 3652. <https://doi.org/10.3390/su13073652>

- Mahmood, F., Arshad, R., Khan, S., Afzal, A., & Bashir, M. (2024). Impact of behavioral biases on investment decisions and the moderation effect of financial literacy; an evidence from Pakistan. *Acta Psychologica*, 247, 104303. <https://doi.org/10.1016/j.actpsy.2024.104303>
- Matakanye, R. M., van der Poll, H. M., & Muchara, B. (2021). Do companies in different industries respond differently to stakeholders' pressures when prioritising environmental, social and governance sustainability performance. *Sustainability*, 13(21), 12022. <https://doi.org/10.3390/su132112022>
- Mayer, R., & Reizingerné Ducsay, A. (2023). ESG: Credibility behind the scores – The reliability and transparency of ESG ratings. *Prosperitas*, 10(2). [https://doi.org/10.31570/prosp\\_2022\\_0041](https://doi.org/10.31570/prosp_2022_0041)
- Meng, Q., Knapp, D., Brecht, L., & Eckert, R. (2025). A comparative analysis of corporate sustainability reporting: A multi-method approach to China and the United States. *Sustainability*, 17(22), 10315. <https://doi.org/10.3390/su172210315>
- Oluwakemi, A. A., & Doorasamy, M. (2025). Effect of ESG Financial Materiality on Financial Performance of Firms: Does ESG Transparency Matter? *Journal of Risk and Financial Management*, 18(6), 315. <https://doi.org/10.3390/jrfm18060315>
- Park, J., Choi, W., & Jung, S. U. (2022). Exploring trends in environmental, social, and governance themes and their sentimental value over time. *Frontiers in Psychology*, 13, Article 890435. <https://doi.org/10.3389/fpsyg.2022.890435>
- Peon, D., & Antelo, M. (2021). The effect of behavioral biases on financial decisions. *Revista Estrategia Organizacional*, 10(2). <https://doi.org/10.22490/25392786.4963>
- Pinchot, A., & Christianson, G. (2019, February 12). *What investors want from sustainability data*. World Resources Institute. Retrieved October 31th, 2025, from <https://www.wri.org/insights/what-investors-want-sustainability-data>
- Richter, K. (2022). *Pain spots and opportunities regarding Environmental, social and governance (ESG) data: Imagine a future in which meaningful analysis of non-financial information is easy, accessible and real time*. SSRN. <https://doi.org/10.2139/ssrn.5340195>

- RobecoSAM. (2014, January). *RobecoSAM Sustainability Yearbook 2014*. Retrieved December 3rd, 2025, from [https://www.eticanews.it/wp-content/uploads/2014/02/RobecoSAM\\_Sustainability\\_Yearbook\\_2014.pdf](https://www.eticanews.it/wp-content/uploads/2014/02/RobecoSAM_Sustainability_Yearbook_2014.pdf)
- Saha, M. (2025, March 4). *Understanding ESG data and how to use it*. KnowESG. Retrieved October 30th, 2025, from <https://knowesg.com/featured-article/understanding-esg-data-and-how-to-use-it-05032025>
- SASB (Sustainability Accounting Standards Board). (2018). *Materiality map*. IFRS Foundation. Retrieved December 2nd, 2025, from <https://sasb.ifrs.org/standards/materiality-map/>
- Shi, Y., & Yao, T. (2025). ESG rating divergence: Existence, driving factors and impact effects. *Sustainability*, 17(10), 4717. <https://doi.org/10.3390/su17104717>
- Siew, R. Y. J., Balatbat, M. C. A., & Carmichael, D. G. (2016). The impact of ESG disclosures and institutional ownership on market information asymmetry. *Asia-Pacific Journal of Accounting & Economics*, 23(4), 432–448. <https://doi.org/10.1080/16081625.2016.1170100>
- Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, 87(3), 355–374. <https://doi.org/10.2307/1882010>
- Sustainability Directory. (2025, October 28). *What are key international ESG standards?* ESG Sustainability Directory. Retrieved November 15th, 2025, from <https://esg.sustainability-directory.com/question/what-are-key-international-esg-standards/>
- Świniarska, O. (2024). *ESG rating – Comparative analysis of methods used by selected rating organizations*. The Book of Articles, National Scientific Conferences 2024. Promovendi foundation. Retrieved November 17th, 2025, from <https://promovendi.pl/wp-content/uploads/2024/09/The-Book-of-Articles-2024.pdf>
- Trinks, P. J., & Scholtens, B. (2017). The opportunity cost of negative screening in socially responsible investing. *Journal of Business Ethics*, 140, 193–208. <https://doi.org/10.1007/s10551-015-2684-3>

- Tsang, A., Frost, T., & Cao, H. (2023). Environmental, Social and governance ESG disclosure: A literature review. *The British Accounting Review*, 55(1), 101149. <https://doi.org/10.1016/j.bar.2022.101149>
- Turker, D., & Altuntas, C. (2014). Sustainable supply chain management in fast fashion industry: An analysis of corporate reports. *European Management Journal*, 32(5), 837–849. <https://doi.org/10.1016/j.emj.2014.02.001>
- UniCredit Group. (2024, October). *What is ESG in banking*. Retrieved November 4th, 2025, from <https://www.unicreditgroup.eu/en/one-unicredit/articles/2024/october/what-is-esg-in-banking.html>
- Visalli, F., Patrizio, A., Lanza, A., Papaleo, P., Nautiyal, A., Pupo, M., Scilinguo, U., Oro, E., & Ruffolo, M. (2023). ESG data collection with adaptive AI. *In proceedings of the 25th International Conference on Enterprise Information Systems (ICEIS 2023), Volume 1* (pp. 468–475). <https://doi.org/10.5220/0011844500003467>
- Wang, Z., & Nishihara, M. (2025). Investment and information asymmetry in corporate sustainability: Incentive auditing contracts and policy insights. *International Review of Financial Analysis*, 105, 104435. <https://doi.org/10.1016/j.irfa.2025.104435>
- Yin, X.-N., Li, J.-P., & Su, C.-W. (2023). How does ESG performance affect stock returns? Empirical evidence from listed companies in China. *Heliyon*, 9(5), e16320. [10.1016/j.heliyon.2023.e16320](https://doi.org/10.1016/j.heliyon.2023.e16320)
- Zou, Y., Shi, M., Chen, Z., Deng, Z., Lei, Z., Zeng, Z., Yang, S., Tong, H., Xiao, L., & Zhou, W. (2025). ESGReveal: An LLM-based approach for extracting structured data from ESG reports. *Journal of Cleaner Production*, 489, 144572. <https://doi.org/10.1016/j.jclepro.2024.144572>
- Zumente, I., & Lāce, N. (2021). ESG rating—Necessity for investors and companies? *Sustainability*, 13(16), 8940. <https://doi.org/10.3390/su13168940>