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How Does ESG Rating Disagreement Influence Analyst Forecast Dispersion?

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Abstract

The practice of responsible and sustainable investing has led to the incorporation of environmental, social and governance (ESG) information into investment decisions. The role of ESG rating agencies has been to facilitate decision-making by aggregating unstructured ESG information into a single rating. Market participants, such as financial analysts, rely on these ratings as part of their research. However, ESG rating agencies rarely agree in their assessment of a company's ESG performance, leading to divergent ESG ratings. This paper uses an OLS regression model based on a large sample of firm data to investigate whether ESG rating agency disagreement increases analysts' forecast dispersion. It builds on previous research by Kimbrough et al. (2022). The results do not provide sufficient evidence to support a significant relationship between ESG discrepancies and analyst forecast dispersion. This calls into question the importance of non-financial ESG information in analysts' assessment of a company‘s financial performance.

Keywords: analyst forecast; disagreement; ESG rating agencies; ESG score; intermediaries

1. Introduction

In the last ten years, the expanding practice of sustainable and responsible investing has resulted in the incorporation of environmental, social, and governance (ESG) information into investment decisions. An estimated US$ 35 trillion in assets under management are now invested with ESG information in mind (Global Sustainable Investment Alliance (GSIA), 2021, p. 9). Meanwhile, the parallel increase in demand from stakeholders for accurate information on firms' ESG performance, has led to the formation of ESG rating agencies. ESG rating agencies are third party information intermediaries that provide quantitative evaluations of a firm's ESG performance (Scalet & Kelly, 2010, p. 71). The concept of ESG performance intents to describe how well a firm manages its ESG risks and opportunities (MSCI, 2022b, p. 3). The final result of this evaluation is then compiled into an ESG rating score. In 2018 alone, investors spent $ 500 million on ESG ratings, highlighting their importance for guiding investment decisions (Gilbert, 2021).

However, there is considerable disagreement about what makes an investment sustainable and responsible. ESG rating agencies rarely agree in their assessment of a firm's ESG performance. This is remarkable considering how often credit rating agencies align in their assessment (Sindreu & Kent, 2018). Consequently, regulators and the media have raised concerns about whether ESG ratings can effectively guide investment decisions (Christensen et al., 2021, p. 147). If there is no agreement among rating agencies, ESG ratings might mislead market participants. Investors need to understand what the methodology chosen by ESG rating agencies actually measures and why. Otherwise, ESG ratings risk "creating a false sense of confidence among investors who don't really understand what lies behind the numbers – and therefore don't really understand what they're buying" (Allen, 2018).

One important group that relies on ESG ratings are financial analysts. Financial analysts are professionals who perform financial analyses on behalf of their clients to help them make investment decisions. To conduct those analyses, financial analysts use varous types of information about firms,

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including ESG information (Wansleben, 2012, p. 407-410). Non-financial ESG-related information are valuable because they provide insights into firm-related risks and opportunities. But, due to the inconsistencies in the way different firms report ESG information and a lack of standardization, financial analysts increasingly rely on ESG rating agencies to analyze ESG information (Kotsantonis and Serafeim 2019, p. 53; Doyle 2018, p. 8 f.).

Over the past five years, there has been considerable progress in the literature on why ESG rating agencies disagree that much. For instance, research shows that scope, weighting and measurement (Berg et al., 2022, p. 1335 f.), the use of different data imputation methods (Kotsantonis & Serafeim, 2019, p. 54), and greater ESG disclosure (Christensen et al., 2021, p. 34 f.) lead to greater ESG disagreement.

Though, there are few studies that examine the impact of ESG rating disagreement on analysts' forecast dispersion. Previous studies have examined the relationship between credit ratings and analyst forecast dispersion (Avramov et al., 2009, p. 101), or the empirical association between CSR and information asymmetry (Cho et al., 2013, p. 81 f.). Dispersion is often interpreted as a measure of uncertainty and information asymmetry (Barron et al., 2010, p. 333). Other studies have examined how mandatory ESG disclosure affects the accuracy and dispersion of analysts' earnings forecasts (Krueger et al., 2021, p. 35), or the relationship between ESG disagreement and analyst forecast dispersion for US firms (Kimbrough et al., 2022, p. 29 f.). However, no study has yet examined the relationship between ESG disagreement and analyst forecast dispersion globally.

With this thesis, I attempt to fill this research gap by empirically investigating the influence of ESG rating disagreement on analyst forecast dispersion in an international setting. Forecast dispersion might reflect the amount of information commonly available to analysts (Han & Manry, 2000, p. 119). When analysts share a common forecasting model and observe the same firm-provided disclosures but have different private information, they will place less weight on their private information as the informativeness of firm-provided disclosure increases, decreasing forecast dispersion. The more ESG-related information a firm is disclosing, the lower the dispersion of analysts' earnings forecast should be (Lang & Lundholm, 1996, p. 471). Contrary, a high dispersion might suggest a lack of public information and hence analysts rely more on their own private information. Alternatively, greater dispersion could also indicate less agreement among analysts due to the inability or unwillingness of some analysts to fully and objectively gather and process ESG-related information (Behn et al., 2008, p. 330). If analysts have the same firm-provided and private information but put different weights on the components of firm-provided disclosure in forecasting earnings, additional disclosure may increase the dispersion of analyst forecasts (Lang & Lundholm, 1996, p. 471 f.). I predict that the dispersion of analysts' forecasts is not due to a lack of ESG-related disclosure, but rather due to discrepancies in the evaluation of ESG information. However, analysts often rely on ESG rating agencies to make sense of ESG-related information. Rating agencies that differ in the scope, weighting, and measurement of ESG-related information (Kotsantonis & Serafeim, 2019, p. 53). Consequently, the disagreement between ESG rating agencies should increase analysts' forecast dispersion.

The remainder of this thesis is structured as follows: Chapter two describes the characteristics of financial analysts and their practices. Chapter three focuses on the integration of ESG criteria into investment decision making. Afterwards, chapter four investigates the ESG rating agencies and their disagreement. Chapter five develops the hypothesis for the association between ESG rating disagreement and analyst forecast dispersion. After that, chapter six outlines the empirical study. Chapter seven and eight interpret the empirical results. Chapter nine highlights the limitations of this study and future research opportunities. Finally, chapter ten concludes.

2. Financial Analysts

2.1. Historical Background of the Profession

This chapter briefly introduces the reader to the emergence of financial analysts as a profession. Before the twentieth century the practice of finance was not yet associated with professional status. Only after that the profession of financial analyst emerged (Wansleben, 2012, p. 408). A defining moment for the financial analyst profession was the introduction of the stock ticker in 1867 (Preda, 2006, p. 754). Prior to its introduction, price information would be delivered by messengers and stocks may trade using numerous ticker symbols and sometimes even different prices. Thus, the stock ticker enabled market participants to monitor firm prices more efficiently (Fisher, 2019). With the introduction of the stock ticker, a subset of financial analysts known as technical analysts emerged. Technical analysis rests on the assumption of repetitive price behavior than can be analyzed by focusing on trends in stock prices (Wansleben, 2012, p. 418 f.). The other subset of financial analysts known as fundamental analysts emerged much later in the 1930s. Their predecessors were statisticians and accountants in banks, not technical analysts. The reason for the late appearance of fundamental analysts was that they encountered serious obstacles, as neither firms nor financial insiders shared information about corporate fundamentals before 1929 (Knorr-Cetina, 2011, p. 429). Although analysts had developed practices to interpret firms before the 1930s, they simply lacked reliable data. This changed with the 1933 and 1934 Act in the US. While the 1933 Act established laws for new issuances, including registration and disclosure requirements, the 1934 Act focused on annual, biennial, and event-related reporting requirements for traded firms (Benston, 1973, p. 133). The disclosed information allowed fundamental analysts to accurately interpret firms' earnings power and value (Jacobson, 1997, p. 25).

Equally important for the rise of the financial analyst profession was the ongoing financialization of the US economy and public. During the 1950s share ownership doubled (Jacobson, 1997, p. 109). This surge in stock ownership not only created a demand for investment advice, but also fostered public legitimacy for analysts. This can be seen as a critical process in which financial analysts ultimately were in a position to ask questions and executives had to answer (Jacobson, 1997, p. 7). Another critical development has been the development of the certified financial analyst (CFA) examination as well as its worldwide acceptance. The standardized curriculum provided a source of legitimacy to the analyst practice. As Ketchum (1967, p. 35) points out, knowledge and its application builds the "keystone of a profession". (Wansleben, 2012, p. 411 f.)

The next chapter focuses on the practices of financial analysis and earnings forecasting commonly used by financial analysts. The purpose is to develop an understanding of how financial analysts evaluate the performance of firms and to show the reader what types of information are used in their evaluation.

2.2. Analyst Practices

2.2.1. Process of Financial Analysis

Collecting and Organizing Information

Financial analysis describes the process of collecting, processing, and evaluating fundamental information about firms and deriving investment recommendations for clients based on the analysis. Therefore, the first step is to collect and organize all relevant information about the firm.

The primary source of information is firm data. Such as financial statements, annual and quarterly result announcements, press releases, and other related news (Barker, 1998, p. 10). With these sources of information, though, analysts must always be cautious and question the reliability of the disclosed information. After all, firms are pursuing their own self-interest and may engage in creative accounting, window dressing or downright falsification of their books (B. Graham & Dodd, 2009, p. 68). Besides that, financial analysts attend analyst conferences, maintain intensive contact with investor relations representatives, and visit corporate headquarters and production facilities to fill the gaps left by disclosed firm information (Mars, 1998, p.86-111). In addition to firm information, analysts also draw on other sources of information for their analysis. In principle, any kind of information that can eventually affect future market developments is relevant. This can include all kinds of newspapers, business reports, books or studies, or other information sources on macroeconomic, political and social trends. In addition, personal contacts to sell-side analysts, external think tanks, firm representatives and people from academia as well as textbooks on financial analysis play an important role (Leins, 2018, p. 75-77). Hence, there is a wide range of financial information sources that analysts draw on.

In the last five years, non-financial ESG information has become an increasingly important source of information for analysts. According to the CFA Institute, 85% of their members now consider E, S, and/ or G factors when making investment decisions (CFA Institute, 2020, p. 4). This change is based on the view that integrating ESG factors into financial analysis allows for a more thorough assessment of both idiosyncratic and market-wide risk, as well as growth opportunities, which can improve long-term risk-adjusted returns (CFA Institute 2020, p. 27, MSCI 2022b, p. 2). Financial analysts draw from a mix of internal and external ESG information. On the one hand, they evaluate ESG information published directly by firms in their financial and statutory reporting. However, the consistency and comparability of ESG information from firms is poor because regulations on disclosure and reporting standards are still in development (CFA Institute, 2020, p. 37 f.). On the other hand, they draw on ESG ratings from rating agencies such as MSCI and Sustainalytics. 63% of financial analysts use them for their firm analysis. Still, a major problem with these ratings is that they vary widely across different rating providers. State Street Global Advisors reports a correlation of only 0.53 between the ratings of MSCI and Sustainalytics for firms in the MSCI World Index. These rating discrepancies result from differences in the collected data, conducted research, and models used to generate ratings, including valuation methodologies and weighting of various ESG information. (CFA Institute, 2020, p. 40)

Yet not all sources of information are equally valuable. Barker (1998, p. 11) surveyed analysts about their prioritized sources of information. He finds that personal contacts are particularly important to analysts (see Table 11 in the annex). By speaking to firm representatives, analysts seek to gain information advantages that goes beyond the disclosed information. These can be, for example, clarifications of financial statement notes, opinions on the firms' economic positioning relative to competitors or projections of next quarterly sales in a segment. Yet, the study does not include non-financial information. In addition to the source of information, there are four information attributes that matter to financial analysts. The information itself must be either timely, applicable, credible, or original to be of value (see Table 12 in the annex). First, the timeliness of the information matters. After financial analysts have analyzed a specific piece of information, and a widely accepted interpretation has taken hold among participants in the financial market, the data is deemed to be incorporated into the price. Consequently, the information loses its relevance for financial analysts. (Leins, 2018, p. 78 f.). Weekly newspapers, such as the Economist, serve as a good example. By the time the financial analyst reads the newspaper, the information has already been priced in for a few days. Consequently, weekly magazines are not really useful for the analyst in terms of the timeliness of their information (Leins, 2018, p. 80). Second, the applicability of the information also plays an important role. Applicability in this context means the usefulness of the information for the market forecasts. A highly applicable information often already contains information on how it could influence financial markets and links the information to specific firms, economic sectors or market regions. This is very helpful because identifying the potential impact of information on financial markets is one of the most challenging tasks for financial analysts (Leins, 2018, p. 84 f.). An example for an applicable information source is Barron's. The magazine evaluates market trends and draws up implications for firms and industries. The third criteria financial analysts use when evaluating information is credibility. Credible sources help financial analysts in crafting inventive narratives while concurrently strengthening their position as experts in finance. Academic research, in particular, is often considered a highly credible source of information (Leins, 2018, p. 88). The fourth criteria is originality. Analysts can promote their forecasts as unique and inventive if they employ information that has not already been used by other analysts. An seeming unique market perspective gives investors the impression that they have been provided resources to help them navigate the uncertainties of financial markets. This is important because investors have many ways of assessing financial market data. Within this context, analysts must generate unique statements to capture their audience's interest. (Leins, 2018, p. 91-94).

Forecasting and Valuation

After collecting and organizing all relevant information, the next step for financial analysts is to make projections and to evaluate whether a firm is a good or a bad investment based on its current share price. For this, financial analysts need to evaluate a firm in terms of its underlying intrinsic value. According to B. Graham and Dodd (1934) this intrinsic value "is understood to be that value which is justified by the facts, e.g., the assets, earnings, dividends, definitive prospects, as distinct, let us say, from market quotations established by artificial manipulation or distorted by psychological excesses" (B. Graham & Dodd, 2009, p. 64). Financial analysts estimate the intrinsic value of a firm after evaluating all relevant information at their disposal. Investors can profit from their evaluation when the intrinsic value deviates from the market value of a firm. This occasionally happens because the price of the shares is based on what investors believe those shares are worth (Koller et al., 2020, p. 80). Having said that, financial analysis is by nature not an exact science (B. Graham & Dodd, 2009, p. 61). Financial analysts can only calculate the intrinsic value of a firm to the best of their ability and the knowledge available to them.

To calculate intrinsic value, financial analysts need to know how value is created. The concept of value has been introduced by Alfred Marshall in 1890 and has proven to be both lasting in its validity and difficult in its application. In short, the two main drivers of value are growth and return on invested capital (ROIC). Growth can be achieved either organically through general market expansion or by gaining relative market share, or inorganically through mergers and acquisitions (Koller et al., 2020, p. 260). ROIC, by contrast, is the result of a competitive advantage that allows the firm to either command premium prices or to enhance the efficiency of its production process (Koller et al., 2020, p. 224). Firms create value when they grow, and earn a ROIC greater than their opportunity cost of capital (Koller et al., 2020, p. 53). Firms that invest in revenue growth and improving their ROIC will generate higher discounted values of future cash flows. However, there is one caveat. Growth alone is not enough to realize higher discounted future cash flows (see Figure 2 in the annex). In cases where the return on capital is below the firm's cost of capital, higher growth actually leads to a reduction in the discounted value of future cash flows (Koller et al., 2020, p. 94 f.). Hence, firms should try to find the combination of revenue growth and ROIC that produces the highest discounted value of future cash flows.

Non-financial factors such as ESG can also be a value driver for firms. According to Henisz et al. (2019), ESG creates value in five ways. First, it facilitates revenue growth. Regulators are more inclined to grant access, permits and licenses to firms with a strong ESG position. Hence creating new opportunities for growth. Customers are also willing to pay and additional 5% for a green product. Second, ESG reduces costs. Among others, a strong ESG position can help to increase resource efficiency and thus reduce operating expenses such as raw-material costs and the true cost of water or carbon. Resource efficiency can boost operating profits as much as 60%. Third, ESG reduces regulatory and legal interventions. A strong ESG position can reduce a firm's risk of harmful state intervention. According to the study, one-third of corporate profits are at risk from state interventions. Fourth, a strong ESG position may boost employee productivity. It allows firms to attract and keep talented staff, boost employee motivation by providing them a sense of purpose and enhance overall productivity. Fifth, ESG can improve long-term returns on investment and capital allocation. For example, by allocating capital to more sustainable investment opportunities, which reduces the risk of future write downs and divestments (Henisz et al., 2019, p. 3-8).

The next step for financial analysts is to use one of various valuation methods to estimate the value of a firm. The most commonly used valuation method is the discounted cash flow (DCF) method. This method discounts future cash flows by the opportunity cost of capital. The idea behind it is that future cash flows are worth less because of the time value of money and the riskiness of future cash flows and thus need to be adjusted (Koller et al., 2020, p. 86). The discounted present value of future cash flows in this case represents the intrinsic value of the firm. By capturing the future performance of a firm in a single number, financial analysts can determine whether a firm is undervalued or overvalued relative to its market price. They can also compare different firms with each other. The traditional DCF method includes only financial numbers. But, non-financial ESG factors can be integrated into the DCF method with little effort. This is because ESG factors are often material and influence the firm's long-term cash flows (Wild, 2017, p. 54 f.). One shortcoming of the DCF method, however, is that each year's cash flow provides little information about the firm's competitive position and economic performance. Declining free cash flow may indicate either poor performance or investment in the future (Koller et al., 2020, p. 305).

For the DCF method to work, financial analysts need to make projections about future cash flows. Yet, the further cash flows are in the future, the less accurate the projections become (Asquith & Weiss, 2016, p. 359). Graham and Dodd point out this problem in their book Security Analysis. They write, "some matters of vital significance, e.g., the determination of the future prospects of an enterprise, have received little space, because little of definite value can be said on the subject." (B. Graham & Dodd, 1934, p. vii). This leads to the problem of deciding how many years into the future to forecast and how detailed the forecast should be. Depending on the duration of the forecast, the financial analyst will arrive at different DCFs. In addition, there is also the problem of setting appropriate growth rates, interest rates, taxes, etc. Consequently, calculative approaches such as the DCF method can never produce precise results. They are always approximations of the future which are prone to errors (Leins, 2018, p. 72). To compensate for these uncertainties, some financial analysts create several cash flow scenarios (Winroth et al., 2010, p. 10). Others adjust their numbers according to the analyst consensus. Still others rely on their gut feeling or tweak the numbers to their liking (Leins 2018, p. 11 f. Wansleben 2012, p. 417 f.). As far as ESG factors are concerned, they usually have an impact over a longer period of time. Assessing ESG factors and their impact can therefore provide essential insights into future value drivers and thus improve long-term forecasting capabilities (Wild, 2017, p. 55 f.).

In the past, financial analysts and investors used earnings rather than DCF to calculate the intrinsic value of a firm. To use earnings as a measure of value creation is in principle not a bad idea, since firms that create value often also have attractive earnings and earnings growth. Moreover, earnings equals cash flow over the lifetime of the firm (Koller et al., 2020, p. 195 f.). However, practitioners have moved away from this method. The reason for this is that not all earnings create value. Margin improvements that come purely from cost cutting, e.g. research and marketing expenses, hurt value creating in the long term (Koller et al., 2020, p. 195). Furthermore, earnings can be accounting fiction (B. Graham & Dodd, 2009, p. xxx). Almost all firms need to invest in plant, equipment, or working capital. Free cash flow is what's left for investors once investments have been subtracted from earnings (Koller et al., 2020, p. 92). For simplicity, financial analysts and academics have sometimes assumed that all firms have the same ROIC. If this were the case, differences in the firms' cash flows would only result from differences in growth, making earnings growth a suitable measure of differentiation (Koller et al., 2020, p. 87 f.). Though, sometimes short-term earnings are the only reliable data available to financial analysts. In particular, when the uncertainty about the firm is so great that the cash flow cannot be accurately calculated. In this case, earnings are of great importance to the financial analyst (Koller et al., 2020, p. 204).

In addition to the DCF and earnings method, there are several other valuation methods worth mentioning. However, I will confine myself to valuation multiples and liquidation value, because I consider these to be the most important. Valuation multiples assume that similar assets should trade for a similar price. Firms in the same industry and with similar performance should trade at the same multiple. The most popular valuation multiple is the price-to-earnings (P/E) multiple, which is simply the equity value of the firm divided by its net income (Koller et al., 2020, p. 559). The advantage of these multiples is that they do not face the problem of inputs based on estimates, because only the market price and financial statements are needed for the calculation (Wansleben, 2012, p. 416). One major problem, nevertheless, is whether the firms are comparable at all. This requires a close look at the financial statements. For example, a firm with more debt relative to equity should trade at a lower P/E ratio than a firm with no debt, because more debt means higher risk for shareholders and a higher cost of equity (Koller et al., 2020, p. 559 f.). Also, comparisons of different ratios across different industries and among different firms might be misleading. Another problem is that the market valuation might be inflated by a speculative bubble or estimates of earnings, book value, and so forth can be wrong (Wansleben, 2012, p. 416 f.). Occasionally, DCF and valuation multiples may be inappropriate. This is the case, for instance, when the firm is expected to cease operations. Then it makes more sense to use the liquidation value (Asquith & Weiss, 2016, p. 354). The choice of the right valuation method therefore depends on the circumstances of the firm. In some cases, the use of several valuation methods may even have complementary benefits.

Investment Recommendation

After having determined the value of firm, financial analysts make investment recommendations to their clients based on their financial analysis. To underline their reports, financial analysts use persuasive charts, tables, and illustrations (Riles (2006, 2011) in Leins (2018, p. 12)). Analysts' recommendations are influential, as is evident from the changes in the price of a firm's stock after their release. Especially if the recommendations are widely publicized through the media or are issued by analysts with high credentials (Securities and Exchange Commission (SEC) 2010; Brown et al. 2009, p. 107). Ryan and Taffler (2004, p. 51) find that analyst activities such as issuing earnings forecasts and investment recommendations are associated with a 17% change in the market-adjusted price of stocks on the London Stock Exchange.

In general, one can distinguish between five different types of investment recommendations. These are Sell, Underperform, Hold, Buy and Strong Buy, whereby the in-between levels Underperform and Buy indicate a weaker conviction of the analyst. That said, not all recommendations carry the same weight. In fact, recommendation have to be assessed relative to the analyst's previous recommendation and the consensus opinion. For example, if a financial analyst just reiterates the same rating, it carries less weight. Or, if the analyst merely issues a recommendation in line with the consensus. Contrary, if the financial analysts releases a recommendation out of line with consensus, it carries more weight, because the analyst stands aside from the safety of the herd and takes a greater reputational risk (Brown et al., 2009, p. 92).

Ultimately, however, it is the customer who decides what to do with the information. The analysts' report only provides information regarding the cost or benefit of investing in a certain stock. Whether the customer can ultimately profit from this information is, nevertheless, an open question. After all, financial analysts often have a conflict of interest when it comes to their recommendation. Customers should therefore critically scrutinize and compare the information (Securities and Exchange Commission (SEC), 2010). According to Winroth et al. (2010), the more sophisticated financial clients are more interested in discussing facts, underlying assumptions and arguments than in recommendations themselves. This is because institutional investors typically use information from several analysts, comparing their assessments (Winroth et al., 2010, p. 10 f.).

The next chapter focuses on the practice of earnings forecasting and forecast dispersion. The aim of this chapter is to show the reader the differences between financial analysis and earnings forecasts. It also aims to build a theoretical foundation for the dependent variable of this master thesis.

2.2.2. Practice of Earnings Forecasting

Forecast Estimates

Earnings forecasts are ubiquitous in today's financial markets. Investors rely heavily on earnings forecasts when making investment decisions (Givoly & Lakonishok, 1980, p. 221). Givoly and Lakonishok (1983) mention that „Earnings per share emerge form various studies as the single most important account variable in the eyes of the investors" (Givoly and Lakonishok (1983) in Jennings (1985, p. 1)). This view contradicts sharply with the notion that the value of a firm is equal to its discounted long-term cash flows. However, due to the unpredictability of future cash flows, practitioners use earnings as a reasonable proxy for DCF. Accounting earnings are well defined, and public firms' earnings statements are subject to thorough audits before they are published. As a result, investors consider earnings to be fairly reliable and convenient measure to value public firms (McClure, 2022).

The economic importance of earnings forecasts can also be seen in the amount of resources devoted to the preparation and analysis of such information by the investment community. Large brokerage firms employ large amounts of financial analysts to produce earnings forecasts. These sell-side analysts disseminate their information to other market participant. In doing so, the brokerage firms hope to earn trading commissions. As a result, buy-side analysts face the potential conflicts of working for investment banking firms and the need to generate commissions. In addition to sell-side analysts, there are also buy-side analysts and independent analysts who prepare earnings forecasts. Independent analysts provide their research to a select group of individuals on a contract basis. Buy-side analysts typically work for mutual funds or pension funds or other non-brokerage firms and provide research exclusively for those firms (Gell, 2011, p. 10 f.). This raises the question of whether institutional investors have an information advantage over other investors. According to Groysberg et al. (2008), there is no such advantage. Groysberg et al. (2008) find that the forecasts of buy-side analysts are in fact more optimistic and less accurate than those of sell-side analysts. They attribute this to the higher retention rate for low-quality analysts and the fact that buy-side firms do not measure the performance of their analysts against each other and sell-side analysts (Groysberg et al., 2008, p. 37 f.). They further mention that buy-side analysts are less able to communicate directly with firm representatives (Groysberg et al., 2008, p. 26).

To forecast earnings, financial analysts build financial models that estimate prospective revenues and costs of firms. The model evaluates information about the general economy, the industry and the specific firm and then generates an estimate of the firm's earnings. The weighting of the three sources of information, however, differs between analysts. If the financial analyst believes that the firm is not able to accurately forecast earnings, he is more likely to rely on industry and economic data. (Jennings, 1985, p. 2).

When talking about earnings forecasts, what is meant is usually the consensus earnings estimate. The consensus earnings estimate refers to the mean or median of the forecasts of a group of financial analysts. Typically, financial analysts estimate a firm's quarterly or annual earnings per share (EPS). The more financial analysts provide a forecast estimate, the more accurate the consensus estimate becomes, as extreme and uninformed estimates carry less weight (Barron et al. (1998) in Byard et al. (2011, p. 94)). The accuracy of the forecast also increases with the amount of information available to analysts, their forecasting experience, and their reputation (Klettke, 2013, p. 2). At the beginning of the period, analysts have a higher forecast error compared to right before the earnings release (Capstaff et al., 1995, p. 74). Part of this change in forecast error is due to managers influencing analysts' forecasts by providing them with additional information. (Chopra, 1998, p. 36). Managers have an incentive to revise earnings estimates downward, because missing the consensus earning estimate is associated with a significant drop in stock price (J. R. Graham et al., 2005, p. 3f). Thus, the consensus earnings estimate varies over the year.

Forecast Biases

Financial analysts are consciously or unconsciously subject to biases when making their earnings forecasts. The two most prominent forecast biases in the literature are optimism and herding. Optimism describes the persistent tendency of financial analysts to issue overly positive earnings forecasts. It is measured as the difference between the consensus earnings forecast and the later realized earnings (Beckers et al., 2004, p. 75). The tendency for optimism has been documented as early as the 1970s and persists until today (McDonald 1973, p. 509; Barefield and Comiskey 1975, p. 244). Dreman and Berry (1995, p. 39) find that the optimism bias is persistent across industries and economic cycles. Financial analysts have incentives to issue more optimistic forecasts. Hong and Kubik (2003, p. 345 f.) note that financial analysts who are more optimistic than the consensus are more likely to experience positive career developments. The reason for this is that investment banks and brokerage houses want analysts to promote stocks in order to generate underwriting business and trading commissions. Athanassakos and Kalimipalli (2003, p. 59) further point out that forecast optimism is the largest at the beginning of the year. As more information becomes available during the year, financial analysts cannot afford to continue being overly optimistic without damaging their reputation.

Herding, on the other hand, describes the social phenomenon of financial analysts to conform and therefore not to deviate too much from the consensus. Scharfstein and Stein (1990) find that herding toward the consensus is less likely caused by fundamental information, but rather a lack of information. Financial analysts who have little or no information tend to herd more (Welch, 2000, p. 371). In addition, the reluctance to deviate from the consensus has been shown to increases with the number of estimates that are close to the consensus and the inaccuracy of analysts' previous estimates (J. R. Graham (1999) and Stickel (1990) in Beckers et al. (2004, p. 75)). This might be explained by the fact that investors view agreement with the consensus as an indication of forecast reliability (De Bondt & Forbes, 1999, p. 144 f.). By simply endorsing the consensus opinion, financial analysts take less reputational risk. As Keynes said, "worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally" (Keynes, 2018, p. 138). De Bondt and Forbes (1999, p. 146) further mentions that herding intensifies with the difficulty and ambiguity of the task. Herding may also be explained by career concerns. Hong et al. (2000, p. 123) find that older analysts are more likely to produce forecasts that deviate from the consensus, while younger analysts tend to be less bold. Similar, Zwiebel (1995, p 2 f.) note that younger financial analysts are more likely to function as opinion leaders due to lower reputational risks. Still, they also note that the earnings revisions from older financial analysts receive more weight due to higher reputational capital.

In the literature there are different explanations for forecast biases. Gell (2011) distinguishes six categories of explanations for biases: cognitive bias, strategic bias, selection bias, news bias, skewed earnings distribution bias and management bias explanation. First, under the cognitive bias explanation, financial analysts are supposed to be irrational and to systematically make mistakes when processing publicly available earnings information. Second, the strategic bias explanation assumes that financial analysts are rational, but produce biased forecasts due to strategic incentives. For example, financial analysts publish positive earnings reports to please a firm's management in order to maintain a good relationship with the firm. Third, the selection bias explanation states that financial analysts make optimistic forecasts only for those firms about which they are truly optimistic because these firms are more likely to bring in trading commissions. For firms that underperform, analysts stop making forecasts, resulting in outdated and hence biased forecasts. Fourth, the news bias explanation attributes forecast optimism to the asymmetric timeliness or earnings due to accounting conservatism. Good news are simply reflected in forecasts in a more timely manner than bad news. Fifth, the skewed earnings distribution bias explanation assumes that financial analysts are truthful, unselective, and rational. Though, they can choose whether to forecast the mean or median of an earnings distribution and thus bias earnings forecasts. Last, the management bias attributes forecast bias to the management practices of accounting discretion and guiding analysts' expectations (Gell, 2011, p. 13 f.).

Forecast Dispersion

Analyst forecast dispersion measures the variation in analysts' earnings forecast for a certain firm and period. Dispersion thus reflects the divergence in analysts' opinion about a firm's future earnings (Han & Manry, 2000, p. 99). Theoretical research shows that forecast dispersion may reflect both uncertainty and information asymmetry (Barry and Jennings 1992, p. 175 f. Barron et al. 1998, p. 422).

Uncertainty arises because financial analysts do not have the exact earnings numbers and instead need to estimate earnings. When earnings are announced, uncertainty decreases. As a result, the dispersion of analysts' earnings estimates typically decreases as well (Barron et al., 2010, p. 332). Likewise, Imhoff and Lobo (1992, p. 437) interpret forecast dispersion as a proxy for ex ante earnings uncertainty. Chopra (1998, p. 38) finds that the dispersion of earnings estimates declines over the year. He attributes the decline in dispersion to quarterly earnings releases and resulting improved visibility of the firm's prospects. Further, Ackert (1997, p. 264 f.) notes that financial analysts issue more optimistic forecasts when uncertainty around the firm is high. However, if the uncertainty is low, financial analysts may hesitate to issue optimistic forecasts due to reputational concerns. For the same reason, financial analysts may also avoid issuing contrarian forecasts when uncertainty is low.

Information asymmetry refers to the differences in information available to financial analysts. In this context, information can be divided into public and private information. On the one hand, public information comprises all firm-related information that is freely accessible to all financial analysts. Private information, on the other hand, is only available to the individual analyst. From the perspective of information asymmetry, forecast dispersion results from the different level of information available to financial analysts

(Barron et al., 2010, p. 332). Ajinkya et al. (1991, p. 393) argue that analyst forecast dispersion is in part due to differential information available to financial analysts at different times. Not all financial analysts prepare and submit their EPS updates at exactly the same time, so there may be a time lag between EPS estimates.

The relationship between public disclosure and forecast dispersion is thus not so obvious. The effect of disclosure depends on whether variations in forecasts are due to differences in information or differences in forecasting models. If analysts share a common forecasting model and observe the same firm-provided information but have different private information, they will attach less weight to their private information as the informativeness of the firm-provided information increases, thereby reducing forecast dispersion. Contrary, if analysts have the same firm-provided and private information, but assign different weights to the constituents of the firm-provided information when forecasting earnings, additional disclosure may increase financial analysts' forecast dispersion. Hence an observed positive association between earnings disclosure and forecast dispersion implies that financial analysts differ in their forecasting models, so that they draw different conclusions from the same observed disclosures. With more disclosures, their earnings forecasts become more dispersed. By contrast, an observed negative relationship between earnings disclosure and forecast dispersion implies that financial analysts vary primarily in their private information (Lang & Lundholm, 1996, p. 471 f.). In addition to the disclosure itself, its quality is also important. Earlier research has shown that poor quality disclosure of financial information is associated with high analyst forecast dispersion. Dechow et al. (1996, p. 27) find that forecast dispersion increases after the disclosure of alleged earnings manipulations. Swaminathan (1991, p. 40) shows that forecast dispersion decreased following the release of Securities and Exchange Commission (SEC)-mandated segment data.

Moreover, (Barron et al., 2010, p. 331) find that levels and changes in forecast dispersion reflect uncertainty and information asymmetry to varying degrees. According to them, levels of forecast dispersion before earnings announcements mainly reflects the variation in uncertainty and not in information asymmetry. Reciprocally, changes in dispersion around earnings announcements reflect variation in information asymmetry rather than variation in uncertainty. This means that when looking at levels of forecast dispersion, i.e. EPS estimates by analysts prior to earnings announcements, it is primarily uncertainty that is responsible for forecast dispersion. But, there is also research that disagrees with the proposition that forecast dispersion reflects uncertainty. Imhoff and Lobo (1992, p. 437) study the dispersion of analysts' forecasts prior to earnings announcements and suggest that the increased forecast dispersion is due to noise in financial statements rather than to uncertainty.

Last, firms with high forecast dispersion experience certain real effects. Han and Manry (2000, p. 119-121) find that firms with high forecast dispersion face high costs of capital and low earnings persistence. Also, Diether et al. (2002, p. 2135-2137) and Johnson (2004, p. 1975 f.) demonstrate that investors pay a premium for stocks with a high dispersion of analysts' forecasts, which leads to lower future stock returns, i.e., the degree of dispersion is negatively associated with future stock returns. Diether et al. (2002, p. 2137-2139) explain this negative association with market friction. In particular, higher dispersion induces a stronger optimistic bias in stock prices, as optimistic investors drive up prices, while pessimistic views are not reflected in stock prices due to short-selling restrictions, causing stocks with high dispersion to be overvalued.

2.3. Limits of Market Forecasting

Financial analysts analyze present firm information and make estimates about the future. These future forecasts are then used by market participants to outperform the overall stock market. It is therefore assumed that the activities of financial analysts add value to financial markets. Economic theory though expresses a great deal of skepticism about financial analysts' ability to forecast market developments. In 1933, Alfred Cowles empirically tested the attempt to predict the development of stock prices. After analyzing 7500 stock market forecasts from financial service providers, he concluded that "statistical tests of the best individual records failed to demonstrate that they exhibited skill, and indicated that they more probably were results of chance" (Cowles, 1933, p. 323). To test whether his results were due to a lack of skill, he repeated his test with the then editor of the Wall Street Journal. Cowles came to the same conclusion. Of 90 forecasts, half were successful, and half were not (Cowles, 1933, p. 323). Kendall and Hill (1953, p. 11) later validated Cowles' (1933) findings by showing that stock prices move randomly rather than predictably. According to economic theory, financial analysts should hence not be able to predict market movements.

The most well-known economic theory is Eugene Fama's efficient market hypothesis. The efficient market hypothesis states that all information that is publicly available about a firm is instantly reflected in a firm's stock price (Malkiel & Fama, 1970, p. 383), which makes long-term prediction of stock market movements impossible. According to Fama, "The Evidence in support of the efficient market model is extensive, and [...] contradictory evidence is sparse" (Malkiel & Fama, 1970, p. 416). For the work of financial analysts, this means that there is not a chance of systematically identifying unpriced information that will be reflected in the stock price at some point in the future. Otherwise, according to the logic of efficient markets, the share price would have already risen (Leins, 2018, p. 21). According to Fama, financial analysts can only predict stock price movement in an efficient market if they have access to insider information not accessible to the general public. Since financial analysts do not regularly possess insider information, the scope to predict market movements appears to be limited (Malkiel & Fama, 1970, p. 413).

Still, research suggests that the market is not always efficient. For example, Jones and Litzenberger (1970, p. 147

f.) find that prices do not respond immediately to the content of quarterly reports. In addition, McKibben (1972, p. 379) shows that publicly available information on sales returns, earnings changes, growth relative to price-earnings ratios, and payout ratios can be used to assemble a portfolio that produces superior returns. Moreover, Jennings (1985, p. 2 f.) argues that if the market were efficient, managerial EPS forecasts should present little new information to financial analysts. In reality, however, EPS estimates differ from those of managers, suggesting that they may not have all the information available. Therefore, the market is not always efficient. The practices of financial analysts thus add value.

2.4. Role of Analysts in Financial Markets

Financial analysts play an important role in financial markets. First of all, financial analysts function as information intermediaries (Beunza & Garud, 2007, p. 15). Market participants have limited attention and resources to analyze firm disclosures (Hirshleifer et al., 2009, p. 2323). By collecting, processing and evaluating information, financial analysts filter out the relevant information. The information is then disseminated either through research reports, recommendations, or earnings estimates. As a result, financial analysts reduce the time and resources market participants need to gather and analyze firm information before making an investment decision. Thus, reducing their transaction costs (Leins, 2018, p. 27). Further, financial analysts help reduce information asymmetry between disclosing firms and market participants (Frankel & Li, 2004, p. 256) and improve market efficiency by incorporating firm-specific information into share prices (Healy & Palepu, 2001, p. 417).

Yet, there are also critical voices in the literature that do not support the proposition that financial analysts are information intermediaries. The view of financial analysts as information intermediaries strongly contradicts with the efficient market theory of Eugene Fama. According to the efficient market theory all publicly available information are immediately reflected in the stock price (Malkiel & Fama, 1970, p. 413-416). Yet, Fama neglects that someone has to first incorporate new information into the market before it can be reflected in the stock price. Financial analysts integrate new information into the market and make sure that the market is efficient in the first place. By collecting, evaluating and distributing firm-related information they become enactors of market efficiency (Leins, 2018, p. 156). Moreover, Hou et al. (2020, p. 3) argues that, in general, financial analysts act as information intermediaries. But that they fail to act effectively as information intermediaries at times because they tend to be overoptimistic, underreact to negative news and overreact to positive news. Higgins and Saito (2007, p. 6) find little support for financial analysts acting as information intermediaries for intangible firms.

Second, financial analysts increase information quality by creating an external layer of scrutiny for financial reporting processes. They monitor firms on a regular basis and scrutinize management behavior and financial reporting irregularities. Thus, further reducing information asymmetry (Yu, 2008, p. 247). Healy and Palepu (2001, p. 408) argue that financial analysts as information intermediaries help to uncover managerial misconduct by engaging in private information production. Yu (2008, p. 268) finds that higher analyst coverage decreases the risk of earnings management. Dyck et al. (2006, p. 2214) suggest that financial analysts are the single most powerful third-party for detecting corporate fraud. Having said that, financial analysts are often under pressure from their employers to secure investment banking business, from competitors to maintain good relationships with managers in order to gain access to private information, and from major clients of their brokerage houses. All of which limits their ability to scrutinize bad firm behavior (Yu, 2008, p. 248).

Third, financial analysts play an important role in the allocation of capital (Wansleben, 2012, p. 421). Although usually portrayed as impartial observers and interpreters of the market, financial analysts actively contribute to the promotion of investments (Leins, 2018, p. 13). Their earnings estimates and investment recommendations generate, increase, reduce, or interrupt the flow of capital. If financial analysts are positive about a firm's future economic outlook, the firm can obtain additional financing on the capital market. However, if financial analysts are pessimistic about a firm's future, their evaluations deprive the firm of capital (Leins, 2018, p. 2 f.). Belnap (2022, p. 6 f.) mentions that reducing processing costs through information intermediaries affects price informativeness, price responsiveness, liquidity, volatility and trading volume.

Fourth, financial analysts perform a role as economic narrators. Through their market forecasts, they give meaning to economic activities in the market and provide a sense of agency for other market participants. This sense of agency allows other market participants to view market activities as predictable, that can be understood through the work of financial analysts, rather than as random. In this way, financial analysts influence the investment decisions of other market participants. Investors become active traders instead of investing passively because they feel they know how the market will develop. Although the market itself is unpredictable (Leins, 2018, p. 157-160).

The next chapter introduces the reader to the concept of ESG investing. The aim of this chapter is to show the reader the value proposition of ESG information and how market participants take it into account when making investment decisions. It theoretically addresses why ESG information matter to market participants. Or, in other words, why there ought to be a association between ESG information and analysts' estimates in the first place.

3. ESG Investing

3.1. ESG Integration in Investment Decision Making

ESG investing refers to the process of considering ESG factors when making investment decisions. ESG investments can be categorized within a broader spectrum of social and financial investing. On the one side, there is conventional financial investing which focuses on maximizing shareholder value through risk-adjusted financial returns. This investment approach assumes that the efficiency of capital markets will effectively allocate resources to those parts of the economy that maximize benefits, thus contributing to economic development. On the other side, there is pure social investing, such as philanthropy, which only aims at social returns, such as addressing social problems or protecting the environment. Within this spectrum, ESG investing focuses on maximizing financial returns by incorporating ESG factors to help assess long-term risks and opportunities (Boffo & Patalano, 2020, p. 14).

In the last ten years, there has been a growing demand for ESG investing. Bloomberg Intelligence estimates that total global ESG assets may surpass $ 41 trillion in 2022 and $ 50 trillion in 2025, equivalent to one-third of total global assets under management (Bloomberg, 2022). Indicative of this growth are also the more than 4900 signatories to the United Nations Principles for Responsible Investment, with over $ 121 trillion in collective assets under management (Principles for Responsible Investment (PRI), 2022, p. 35). According to one survey, this demand has been driven primarily due to end investors' desire to improve firms' alignment with social and moral considerations. Just about 20% of end investors pursue ESG investing for financial gain or the mitigation of investment risk (Boffo & Patalano, 2020, p. 17). However, institutional investors and asset managers integrate ESG in their investment decision making process primarily to improve long-term risk-adjusted returns and reputation. (BNP Paribas, 2019, p. 13)

ESG criteria can be integrated into the investment process in various ways, with the complexity and the level of integration increasing with each step. The first step, exclusion, simply excluded or avoided firms if their behavior is not aligned with fundamental societal values. Reasons for exclusion might include the manufacturing of controversial weapons or activities that are not aligned with ethical standards, such as tobacco, alcohol or gambling. The second step, standards-based or inclusive screening, aims to include or give greater representation to firms that meet international standards such as the UN Sustainable Development Goals. For instance, a firm may be included based on its ESG performance relative to its peers (best-in-class) or because it exceeds a certain ESG score. The third step is similar to the inclusive screening, in which ESG ratings are used to rebalance portfolio exposure to firms with higher ESG ratings and away from firms with lower ESG ratings. The fourth step is to focus on a particular E/S/G pillar and the underlying metrics. For example, a fund may focus on environmental issues and in particular on the carbon footprint and intensity of firms. The final step is full ESG integration, which means the systematic and explicit inclusion of ESG risks and opportunities in the investment process. ESG factors are continuously considered throughout the investment process (Boffo & Patalano, 2020, p. 32 f.)

With respect to ESG investing, one common question that arises, is whether there is a trade-off between ESG investing and traditional investing in terms of returns. On the one side, Berk and van Binsbergen (2021, p. 2) suggest that investors have non-financial preferences for green stocks and are therefore willing to accept lower returns for owning green stocks. Cornell (2020, p. 7) argues that investors buy green stocks as a hedge against ESG-related risks and are willing to accept lower expected returns in return. According to Cornell (2020, p. 6 f.), investors can only profit from green stocks if they are undervalued due to positive undisclosed ESG information. Raghunandan and Rajgopal (2022, p. 35) show that ESG funds appear to underperform financially relative to other funds within the same asset manager and year. On the other side, Kempf and Osthoff (2007, p. 13 f.) find that an investment strategy based on buying stocks with high socially responsible ratings and selling stocks with low socially responsible ratings leads to abnormal returns. Nagy et al. (2016, p. 121) find that portfolios that incorporate ESG into their decision making outperform the MSCI World Index over the sample period. Then again, Fish et al. (2019, p. 13) show that little difference existed between the returns of ESG-weighted and non-ESG-weighted portfolios. In addition, JP Morgan (2016) notes that the yearly net returns of the MSCI World Benchmark Index and the MSCI World ESG are not much different (JP Morgan (2016) in Boffo and Patalano (2020, p. 36)). Therefore, findings on ESG investment performance in the last 15 years are mixed.

3.2. Demand for ESG Information

The growth in ESG investing is accompanied by an increased demand for ESG information (see Figure 3 in the annex), research and ratings in order to make informed and meaningful investing decisions. Whether it be assessing a firm's economic long-term position or its impact on society. ESG refers to the three non-financial pillars that firms are expected to report in. The goal of ESG is to capture all non-financial risks and opportunities associated with a firm's daily operations. As mentioned earlier, investors increasingly demand ESG information to assess a firm's social impact or long-term risk-adjusted returns. But, it is not always clear what falls under these pillars. This is because there is no standard ESG reporting framework yet. For this reason, firms are typically applying one or more frameworks to determine how and what they want to report on. The most commonly used frameworks are the Global Reporting Initiative (GRI) and the Sustainable Accounting Standards Boards (SASB)' standards (Deloitte, 2022). The environmental pillar can include issues such as natural resource use, carbon emissions, energy efficiency, pollution, and sustainability initiatives. (Boffo & Patalano, 2020, p. 21). In terms of resource use, for example, a firm could report whether it uses new or recycled materials in its production and if it ensures that its products are recycled or end up in a landfill. A firm could also report on land use practices, such as deforestation and biodiversity disclosure, or water use. The social pillar can include issues regarding workforce-related practices, human rights, diversity and supply chain. For instance, a firm could report on how it manages their employee development and labor practices. They could also report on product liability related to the safety and quality of their products. Or a firm could report on supply chain labor, health and safety standards or controversial sourcing issues. The governance pillar can include issues such as board independence, board diversity, shareholder rights, management compensation and corporate ethics. For example, a firm could indicate whether management compensation is linked to the firm's sustainability performance or whether it has implemented measures to prevent anti-competitive practices and corruption (Deloitte 2022; Boffo and Patalano 2020, p. 21).

In a 2020 survey conducted by the SustainAbility Institute, investors were asked about their most important sources of ESG information. Investors indicated that corporate ESG ratings (55%), direct contact with firms (55%), corporate sustainability reports (50%) and internal research (41%) were the most useful sources of ESG information. Of the investors surveyed, 96% said they use ESG ratings, with 65% using them at least once a week (The SustainAbility Institute, 2020, p. 17 f.). Another survey conducted by Ninety One finds that 88% of professional fund managers currently use ESG ratings, with 92% expecting to increase their use (Ninety One, 2022). ESG rating agencies therefore play an important role in the ESG investment ecosystem, as investors rely on their assessment of ESG information.

The next chapter introduces the reader to ESG rating agencies. The chapter aims to inform the reader about the role ESG rating agencies play in the financial markets and to give him an overview of the ESG rating industry. In addition, this chapter intends to briefly introduce the three most important ESG rating agencies in this master thesis.

4. ESG Rating Agencies

4.1. Objectives and M&A activities

ESG rating agencies are third-party information intermediaries that assess a firm's ESG risks and opportunities based on public information and sometimes private surveys (Scalet & Kelly, 2010, p. 71). Due to the complexity and amount of information available, investors and other stakeholders rely on ESG rating providers for their assessments (The SustainAbility Institute, 2020, p. 6). The rating process is not always transparent, although ESG rating agencies attempt to be more transparent by disclosing their rating methodologies (Boffo & Patalano, 2020, p. 64 f.). The result is an ESG rating, often accompanied by a research report that provides additional information about the analysis. The ESG rating informs stakeholders about a firm's ESG performance. Investors usually pay to get access to these ratings. ESG ratings can be quit expensive, so that access tends to be limited to a select group of professional investors (The SustainAbility Institute, 2022, p. 10). Despite that, there are a number of ESG ratings that can be accessed online for free.

It is often misunderstood what ESG rating agencies actually measure. ESG rating agencies provide insights into a firm's ESG quality. Unfortunately, there is no single agreed upon definition of what is considered ESG quality. A common misperception is that ESG reflects the impact a firm has on the wellfare of its stakeholders, such as employees, suppliers, customers, local communities, and the environment. According to this view, firms can enhance their ESG rating by discontinuing activities that are harmful to stakeholders or by improving their business practices in affected areas for the benefit of stakeholders. This view therefore assumes that ESG quality measures the impact the firm has on societal and environmental factors In reality, however, the opposite is true. ESG quality measures the influence that social and environmental factors have on the firm and whether these factors are financially material. Through strategic planning, targeted investments or changes in operations, the firm can address these risks and opportunities. In the short term, this will lead to higher costs, but in the long term it will strengthen the firm's financial position (Larcker et al., 2022, p. 2).

ESG rating agencies have stated objectives. A common stated objective of ESG rating agencies is the reduction of investment risk. This objective assumes that ESG quality increases financial performance by reducing ESG factors that pose a risk to the firm's business model or operations. For this purpose, MSCI argues that its ratings "support ESG risk mitigation and long-term value creation". Likewise, Sustainalytics states that it measures "the degree to which a firm's economic value is at risk" due to ESG factors. If this is true, it would mean that firms with high ESG quality would face fewer regulatory violations, litigation, or bankruptcies in the future. Another stated objective of ESG rating agencies is that their ratings can predict returns. HIP contends that its ESG ratings "correlate with better returns for the same amount of risk". Arabesque asserts that their approach "is all about identifying firms that are better positioned to outperform over the long term" and that their algorithm for ESG ratings "will only use information that significantly helps explain risk adjusted performance". If this is true, an ESG rating upgrade should be associated with a subsequent change in stock price. Other stated objectives include measuring a firm's societal impact (ISS) and transparency and commitment to ESG (Refinitiv) (Larcker et al., 2022, p. 3).

In the last 15 years, there have been a large number of mergers and acquisitions (M&A) in the ESG rating market. As a result, the ESG ratings market has become increasingly consolidated. There are two main reasons for this surge in M&A activity. First, as the ESG ratings market matured, established rating providers entered the field and began acquiring smaller ESG firms to obtain expertise and market share. Recent examples include Moody's acquisition of a majority stake in Vigeo Eiris, S&P Global's purchase of RobecoSAM or Fitch's development of its sustainability platform. Second, increasing investor demand for broader and deeper information and the complexity of ESG reporting forced established ESG rating providers to expand their product offerings to remain competitive. Therefore, existing ESG ratings agencies merged or acquired smaller ESG firms (The SustainAbility Institute, 2020, p. 6). Currently the ESG rating market remains highly competitive, with the quality, range, scope, and frequency of ESG ratings increasing to the benefit of investors (The SustainAbility Institute, 2022, p. 3). Some of the most important ESG ratings agencies at present include Bloomberg, CDP, FTSE Russell's ESG Ratings, ISS, MSCI, Sustainalytics, Bloomberg, Refinitiv (formerly Thomson Reuters), RobecoSAM, which are used by investors primarily for their broad coverage of firms (The SustainAbility Institute, 2020, p. 33-35).

4.1.1. Sustainalytics

Sustainalytics is a leading independent ESG rating agency that evaluates and rates more than 20.000 firms worldwide based on their ESG performance. Sustainalytics is part of the Morningstar Group, which acquired the firm in 2020 (Cision, 2020). At present, Sustainalytics employs more than 1800 staff in 17 offices worldwide, including more than 800 research analysts with varied multidisciplinary expertise (Sustainalytics, 2022).

Sustainalytics has completed several key mergers and acquisitions over the past years. In 2008, the firm was formed from the consolidation of Analistas Internacionales en Sostenibilidad (Spain), Dutch Sustainability Research (Netherlands) and Scoris (Germany). In 2009, Sustainalytics merged with Jantzi Research, whose CEO Michael Jantzi serves as the current CEO (Novethic, 2014, p. 21). In 2012, Sustainalytics acquired Responsible Research, a ESG research firm based in Singapore and Share Dimension. In 2018, Sustainalytics acquired Solaron, another provider of ESG research and ratings, and in 2019 GES, a specialist in engagement, screening and fiduciary voting services for institutional investors. Last, in 2020, Sustainability acquired OMX, a supply chain data platform that tracks the socioeconomic impact of supply chains. As a result of these acquisitions, Sustainability is further strengthening its market position as a sustainability service provider (Sustainalytics, 2022).

Sustainalytics offers investors a wide range of products and services to help them navigate ESG-related risks and opportunities. Among others, Sustainalytics offers ESG Risk Ratings, Carbon Risk Ratings, Product involvement data, Controversy Research, Global Standards Screening data and an Impact Metrics (see Table 13 in the annex).

4.1.2. MSCI ESG Research

MSCI ESG Research is a provider of in-depth research, ratings, and analysis of ESG business practices of more than 10.000 firms. MSCI ESG Research is a fully-owned subsidiary of MSCI, a provider specializing in tools and services for investment decision support. The firm currently employs 600 ESG employees, including its foreign affiliates, with approximately 250 analysts and researchers worldwide (MSCI ESG Research, 2022, p. 3).

MSCI ESG Research was formed through the acquisition of RiskMetrics by MSCI in 2010. RiskMetrics has itself acquired the governance consulting agency ISS (US) in 2007 and the two rating agencies Innovest (US) and KLD (US) in 2009. In addition, MSCI acquired the governance service agency GMI ratings in 2014 and the climate change scenario analysis firm Carbon Delta in 2015 (MSCI 2019, p. 1; Novethic 2014, p. 14) . As a result, MSCI has further strengthened its focus on ESG analysis.

MSCI Research offers a wide range of ESG-related products and services to investors. These include the following products and services: MSCI ESG Ratings, MSCI ESG Controversies, MSCI ESG Global Norms Screening, MSCI Climate Value-at-Risk, MSCI ESG Business Involvement Screening Research, MSCI ESG Portfolio Analysis (see Table 14 in the annex; MSCI ESG Research 2022, p. 3 f.). MSCI has further set up a custom division to handle special client requests (Novethic, 2014, p. 14).

4.1.3. Refinitiv (formerly Thomson Reuters)

Refinitiv is a global provider of financial market data and infrastructure and offers ESG scores for more than 11800 firms worldwide. Refinitiv is a subsidiary of the London Stock Exchange Group (Refinitiv, 2022a). The firm currently employs over 350 content research analysts trained to collect ESG data (Refinitiv, 2022c).

Refinitiv in its current form is the result of several key mergers and acquisitions. In 2009, Thomson Reuters acquired Asset4, a Swiss firm that provides a global database of ESG information. Asset4 provides research on financial and non-financial information and was the first firm to provide raw ESG data that could by used by investors. In 2010, Thomson Reuters also acquired Point Carbon, an information provider specializing in energy and the carbon market (Novethic, 2014, p. 5 and 27). In 2018, Refinitiv was created through the acquisition of Thomson Reuters Group's Financial & Risk Division by investment firm Blackstone. Blackstone acquired a 55% stake in the newly formed firm, while Thomson Reuters retained a 45% stake (Reuters, 2018). In 2019, the London Stock Exchange Group acquired Refinitiv (The Economist, 2019).

The following chapter introduces the reader to the methodology of ESG rating agencies. The reader learns about the process of compiling ESG ratings. The purpose of this chapter is to make the reader aware of where ESG rating divergences may occur.

4.2. Methodologies of ESG Rating Agencies

4.2.1. Information Input and Firm Disclosure

ESG rating agencies collect a broad range of public and non-public information about the firm and its industry to assess a firm's ESG performance. The kind of information that is collected is important us, as it reveals what is factored into ESG ratings. As Dillenburg et al. (2003, p. 170) emphasize "what gets measured, gets managed".

In the case of ESG rating agencies, ESG data is collected in various ways, such as through corporate social responsibility reports, voluntary firm surveys and questionnaires, analysis of media reports, independent research, and active communication with the management of the rated firm and stakeholders (i.e. non-governmental organizations (NGOs), trade unions, governmental organizations, etc.) (Scalet & Kelly, 2010, p. 71). However, ESG rating agencies differ in what counts as relevant data, which makes it difficult to compare the results of different rating agencies. This is also the case with Sustainalystics, MSCI and Refinitiv. Sustainalytics collects data from firm's public disclosure, the media, and NGOs (Sustainalytics, 2020, p. 7). MSCI gathers macro data, firm disclosures and data from media, NGOs, and other stakeholders (MSCI, 2022b, p. 14). Refinitiv fully automatically collects publicly available data from annual reports, firm websites, NGO websites, stock market reports, CSR reports and news sources (Refinitiv, 2022b, p. 4). In comparison to financial disclosures, ESG data is largely unstandardized, frequently unstructured, difficult to compare, and tends to be more subjective than financial disclosures (Sipiczki, 2022, p. 6).

None of the investigated rating providers conduct surveys and questionnaires. Examples of ESG rating agencies that conduct subjective surveys or questionnaires are S&P Global, CDP and RobecoSAM (Deloitte, 2021). Surveys have the disadvantage compared to data-driven approaches that they are subjective in nature. What data is collected will depend on who is creating the survey. Also, responsibility for answering the questions truthfully resides with the firm. Self-reported survey data raises doubts regarding reliability (Sipiczki, 2022, p. 6). In addition, non-response rates are high (Chatterji & Levine, 2006, p. 30). Firms are understaffed to deal with the complexity and volume of ESG data requested. Managing a firm's ESG ratings can require hundreds of hours and several dedicated staff, something that even large organizations may struggle to accomplish. Small and mid-sized firms with fewer resources may risk not managing ESG ratings at all (The SustainAbility Institute, 2020, p. 7).

A major challenge for ESG rating agencies is data completeness. ESG rating agencies' models comprise of hundreds of material input variables for which data is required. As mentioned previously, corporate data is an important source of information for ESG rating agencies. In 2011, though, just under 20% of S&P 500 firms reported on their sustainability efforts, corporate social responsibility activities, and ESG performance. At the time corporate data on ESG was scarce. Since then, things have improved significantly. Last year, 96% of S&P 500 firms published a sustainability report. The number of non-reporters thus dropped to 4% (Governance & Accountability Institute, 2022, p. 5).

Another major challenge for ESG rating agencies is data consistency. A report by Deloitte that studied 4000 ESG reports finds a significant number of data omissions, groundless claims and inaccurate figures (Hespenheide & Koehler, 2013, p. 12). Firms may report on different ESG issues, because they consider different issues material to the firm's financial performance. This will lead to missing data in ESG rating agencies' models. Consequently, ESG ratings agencies face the challenge of determining how to address missing data. One approach would be to exclude data points with missing information. But, this would make it difficult to compare the ESG results of firms that report on certain ESG issues with those that do not. Another approach would be to make an assumption about what the data might be. ESG rating agencies fill data gaps by drawing on the opinions of industry peers, making assumptions, or obtaining missing information from third-party sources (Sipiczki, 2022, p. 7). For example, MSCI appears to assume that the firm's performance is in line with the industry average when no information is available. In contrast, FTSE makes the assumption that the firm's performance is the worst in the case of missing data to encourage information transparency. A third approach would be to use statistical methods to impute missing values (Larcker et al., 2022, p. 5). Still, all these approaches only reduce the problems of data inconsistencies, but do not eliminate them. Another issue that causes data inconsistencies is differences in reporting metrics and scales. When firms report on the same information but use different methods, scales or metrics, the information is not directly comparable. For example, one firm may report on workplace safety based on the number of incidents, while another may report the number of injuries over a period of time, and yet another may report how much time was lost due to workplace injuries (Larcker et al., 2022, p. 5). This short example illustrates the importance of standardized measurements. One way to eliminate data inconsistencies is to standardize corporate reporting on ESG issues. Firms and ESG rating agencies can increase data consistency by voluntary adopting or aligning themselves with sustainable reporting frameworks, such as the GRI and the SASB's standards (Boffo & Patalano, 2020, p. 20). Government disclosure mandates such as the EU Non-Financial Reporting Directive (NFRD) (EU-Directive Nr. 2014/95/EU) or the SEC's proposed ESG reporting mandate may also help to increase consistency in ESG reporting (Securities and Exchange Commission (SEC), 2022). Then again, the UN Principles for Responsible Investment (PRI) and International Corporate Governance Network (ICGN) suggest hat given the heterogeneity of users of ESG information, there is no one set of metrics or one framework that could satisfy all users. In their opinion, firms should disclose basic standardized ESG information and complement it with more customized ESG reporting (UN PRI and ICGN, 2018, p. 2).

Recent advances in artificial intelligence (AI) are contributing to changes in ESG rating agencies' data collection processes. ESG rating agencies are now deploying computer algorithms to automate data collection tasks and analyze information (Brackley et al., 2022). Repeatable tasks are carried out by bots in a fraction of the time, and algorithms can read information that otherwise might have been unusable due to its size or amount of low-quality data (S&P Global, 2020). While ESG rating analysts mostly draw on corporate ESG disclosures, algorithms also evaluate a wide range of media news (Nomura, 2022, p. 2). AI also enables ESG rating agencies to analyze data more efficiently. AI can help the agency exclude firm statements that mention ESG practices, which are not material to the business and hence unlikely to matter to investors (S&P Global, 2020). ESG ratings agencies that utilize AI technology can also update their data daily, reducing inaccuracies (Nomura, 2022, p. 2). Natural language processing is a particularly promising area. Sentiment analysis algorithms allow AI to detect the tone of a conversation. For example, a program trained to read transcripts of firm's quarterly earnings calls can use natural language processing to assess the tone of the CEO's words to gauge how engaged a firm appears on ESG issues. Using this approach, ratings agencies can deliver an in-depth overview of a firm's stance on ESG (S&P Global, 2020). In theory, AI gives ESG rating agencies access to a greater amount of higher quality data to incorporate into their ESG ratings. However, there are also challenges related to AI technology. For instance, it is difficult to substitute an ESG analyst who speaks directly to a firm or market participants and then makes a nuanced assessment. (Nomura, 2022). In addition, the opacity of the algorithms makes it difficult to assess the validity of the data. (Lu, 2021, p. 158). AI should therefore be viewed as useful tool to complement traditional data assessments and help to address human biases while im-proving understanding of evaluation results.

4.2.2. Information Processing and Transparency

For the most part, ESG raters are reluctant to reveal the inner workings of their ESG ratings. ESG rating agencies are reluctant to share their methodological process to ensure that firms cannot game the system. Yet, without some methodological openness, investors may lack confidence in the ESG rating process and doubt its usefulness for investment decisions. This is because analysts are unable to assess whether the rating truly reflects the firm's ESG performance (Brackley et al., 2022). Perhaps in response to recent regulatory scrutiny and increasing criticism of their role in the market, ESG rating agencies are moving towards greater methodological transparency (Brackley et al., 2022). While this move is commendable, ESG rating agencies do not currently disclose their methodologies in a fully transparent manner (Doyle, 2018, p. 8). Since the business model of ESG rating agencies is based on product differentiation, it is unlikely that the opacity of ESG rating agencies is going to change entirely unless there is a statutory mandate (Sipiczki, 2022, p. 6).

In the wake of increased transparency, it has become evident that ESG rating agencies' approaches to ESG ratings can vary widely. ESG rating agencies can differ in which input variables are relevant for measuring ESG performance, what constitutes as relevant data for these input variables, and how these input variables are weighted. Due to this differences between the methodologies used by ESG rating agencies, their ESG ratings could tell very different stories about firms‘ ESG performance (Scalet & Kelly, 2010, p. 72). Most often, however, institutional investors are less interested in the ratings itself than in the differences in methodology to form opinions on important issues for their own ESG analyses. The analysis of ESG rating agencies' methodological approaches is thus beneficial as it helps investors gain valuable insights into what factors determine the final ESG ratings (The SustainAbility Institute, 2020, p. 44 f.).

The process of creating an ESG rating usually looks something like this. First, certain key issues are defined and the corresponding data collected. After that, input variables that are not relevant for the business or the industry are removed. Next, the selected key issues are aggregated into subcategories and categories, then into E/S/G pillars, and finally into the rating itself. During this process, various weightings are applied as the discretion of the ESG rating agency (MSCI, 2022b, p. 2).

ESG rating agencies define the type and number of input variables they want to use for their ESG analysis. The number of input variables is usually very large, with hundreds and sometimes thousands of variables (Larcker et al., 2022, p. 4), with a wide variety of definitions due to a lack of regulation (Sipiczki, 2022, p. 6). Several ESG rating agencies use specific ESG framework providers such as GRI, SASB and Task Force on Climate-Related Financial Disclosure (TCFD) to select individual input variables (Boffo & Patalano, 2020, p 31). This way, they can increase the transparency and comparability of their ratings. But, Escrig-Olmedo et al. (2019, p. 14) find that ESG rating agencies are not fully integrating sustainability principles into their rating process. Input variables are also selected to some degree based on data availability to ensure that ESG rating agencies can measure can accurately measure each indicator over time. In addition, input variables can differ significantly across industries to reflect financial materiality or because ESG rating agencies simply consider different aspects of ESG to be financial material (Boffo & Patalano, 2020, p 31).

ESG rating agencies also change input variables in their ESG model over time to assess ESG performance in a more robust and accurate way. Escrig-Olmedo et al. (2019, p. 14) examine how the input variables of ESG rating agencies have changed between 2008 and 2018. They find that ESG rating agencies have mainly integrated new environmental and governance input variables. They further find that ESG rating agencies are now integrating more complex and integrated input variables such as data security and privacy as well as supply chain management (Escrig-Olmedo et al., 2019, p. 11).

The categories and subcategories of ESG rating agencies are quite similar (Boffo & Patalano, 2020, p 31). Occasionally however, there are slight differences between ESG rating agencies. These differences mostly result from different labels of categories and the different assignment of subcategories (see Table 15 and 16 in the annex). In some cases, though, ESG rating agencies also differentiate themselves from one another by including additional variables. MSCI, for example, includes social opportunities and stakeholder opposition in its rating process, while Refinitiv includes data privacy and CSR strategy. But, in most cases areas of interest are overlapping (see Table 15 and 16 in the annex).

To compile the input variables into subcategories, categories, pillars and finally ESG ratings, different weights are applied. One approach would be to simply apply equal weights to all input variables, subcategories, etc. This has the benefit of being simple, transparent and more comparable across industries (Nagy et al., 2020). Still, not all inputs may be equally material to firms' ESG performance. As a result, ESG rating agencies often apply different weights to different variables and categories and sometimes even to different pillars based on financial materiality (Larcker et al., 2022, p. 4). Those weightings are mostly based on subjective judgments, even though various ESG rating agencies rationalize their decisions (Boffo & Patalano, 2020, p 31). Another approach is to apply an optimized weighting based on historical data. In this approach, the weights are adjusted to mirror the best financial performance based on a collection of historical data. For example, a research report from MSCI finds that weights of 25% E pillar, 5% S pillar and 70% G pillar yield the best financial results. Yet another approach is to apply industry-specific weights. The advantage of this approach is that it more precisely reflects industry exposures to E, S, and G risks. But, the disadvantage of this approach is that it leads to more complexity and is less comparable across industries. The same research report from MSCI notes that the E pillar weighting varies from 5.8% for the communications services sector to 62.1% for utilities. The S pillar weighting varied between 16.3% for the energy sector and 59.8% for the financial sector. In the short term, Nagy et al. (2020) find that both equal-weighted and optimized approaches demonstrated superior performance, attributed to increased exposure to governance issues. In the longer term, however, the industry-specific weighted approach showed the strongest financial performance (Nagy et al., 2020). Because ESG measures the long-term risks and opportunities to a firm's financial performance, the industry-specific weighted approach hence appears superior.

ESG rating agencies sometimes also incorporate controversies surrounding rated firms into their ESG ratings. Controversies are events that cause reputational damage and demonstrate a firm's lack of preparedness and/or inability to deal with emerging events and risks. Having said that, not all ESG rating agencies include controversies into their ESG ratings. Some provide controversies as a stand-alone rating that exists alongside the pillars and contributes to a combined overall ESG rating, while others do not consider controversies at all (Boffo & Patalano, 2020, p 30). In summary, there are methodological parameters that allow ESG rating agencies to produce different ESG ratings. In addition, ESG rating agencies are not fully transparent about how their ratings are produced.

4.2.3. ESG Ratings and Rating Biases

A rating is an evaluation provided by a third party. It is an information product, a statement created with the explicit purpose of being communicated outward (Poon, 2012, p. 460). In the case of ESG ratings, ESG rating agencies provide an evaluation of a firm's ESG performance, which they communicate to investors and other stakeholders.

ESG ratings are usually expressed in the form of letters or numbers. Some ESG rating agencies use a seven-point scale from AAA to CCC. Others use a twelve-point scale from A+ to D, similar to grades in the Anglo-American education system. Yet others publish scores on a percentile basis using a scale of 1 to 100, where 100 can either represent high ESG quality (positive) or high ESG risk (negative). In addition, many ESG rating agencies claim to measure industry-relative ESG performance, while some claim to measure absolute ESG performance.

Industry-adjusted ratings enable investors to compare ESG performance among firms operating within the same industry. In this way, firms can be compared against their industry-peers in their ability to manage financial material ESG risks. However, ESG ratings based on industry criteria hinder the ability to compare firms across different industries and are highly dependent on the assigned industry. In contrast, absolute ESG ratings can be compared across industries. Although ratings may vary depending on the industry to which firms are assigned. Firms in more sustainable industries tend to receive higher ratings, while firms in less sustainable industries tend to receive lower ratings (Larcker et al., 2022, p. 3 f).

Moreover, ESG ratings are expensive. Institutional investors spend on average $ 487,000 per year on external ESG ratings, data, and consultants. Many use more than one ESG source in their investment process (The SustainAbility Institute, 2022, p. 5). A 2021 survey finds that more than half of institutional investors use more than one ESG data and research source, with 25% anticipating to use six or more sources in the next two to three years (Capital Group, 2021, p. 29). There has also been discussion about whether ESG performance can be distilled into a single rating. Some investors hide behind ESG ratings and use them as a substitute for in-depth ESG research and analysis. They may see ESG ratings as a quick fix. This happens because some investors may lack the resources for fundamental research or simply want to check a box (The SustainAbility Institute, 2020, p. 31). Other investors stress that ESG performance can not be aggregated into a single rating and that additional in-house research is needed to make sense of ESG ratings (The SustainAbility Institute, 2022, p. 30). These investors view ESG ratings as a starting point to help them understand the broader landscape and to benchmark firms against each other. For instance, a poor rating may signal the need for further research. They rely on their own thinking and use ESG ratings for the underlying data rather than the scores themselves. They develop a strong sense of which ESG factors are the most important for a particular industry and then perform their own evaluation of a firm's ESG performance (The SustainAbility Institute, 2022, p. 23 f.).

ESG ratings are also regularly biased. The most prevalent biases are firm size, geographical bias, and industry affiliation. One pattern is that ESG ratings are biased towards larger-sized firms. Firms with higher market capitalization or free float are more likely to be covered by raters, and their ratings are more likely to be reassessed. Recent initial public offerings are unlikely to be rated in their first year of listing (Brackley et al., 2022). Unlisted firms are often excluded from ESG ratings completely (Zhang, 2021). Larger firms also tend to receive higher average ratings compared to smaller firms (Giese et al., 2019, p. 77). The reason for this might be that larger firms disclose more ESG data due to more designated employees or the adoption of better sustainable management tools (Drempetic et al., 2020, p. 153). A second pattern is related to the firm's location. Firms listed on exchanges in North America and Europe are far more likely to get properly rated than those trading elsewhere, particularly in emerging markets (Brackley et al., 2022). Moreover, firms in Europe regularly achieve higher ratings on average than firms in the US. This pattern is not due to higher quality ESG practices by European firms, but rather to mandatory reporting requirements. Firms in the EU are required by law to report on various environmental and social topics under the Non-financial Reporting Directive and Corporate Sustainability Reporting Directive. As a result, there is greater availability of non-financial information (La-Bella et al., 2019, p. 5). The third pattern is industry-based. ESG ratings that are not industry-adjusted, i.e., do not assign scores based on industry peers, may assign higher average scores to certain industries (such as banking and telecommunications) and lower scores to others (such as tobacco and gambling) (Larcker et al., 2022, p. 5). Furthermore, industry-weighted ESG ratings assume that firms in the same industry have similar business models and are therefore exposed to similar ESG risks and opportunities. However, this approach can cause oversimplification in cases where firms are not comparable. While it is important to standardize methodologies, without individualized weightings, ESG ratings might be skewed (Sipiczki, 2022, p. 8).

In addition, research shows that ESG ratings have moved upward over time. D. E. Shaw (2022) analyze MSCI's aggregate ESG scores for all Russel 1000 firms between 2015 and 2021, and find that scores have improved by 18% over this period. Still, structural changes, such as changes in index composition, changes in component weighting, and greater disclosure by firms, account for only 6% of this improvement. The remaining 12 are not explained by MSCI. D. E. Shaw (2022) attribute this gap to grade inflation (D. E. Shaw, 2022, p. 6). Other research shows that low scoring firms have seen greater improvement in their ESG ratings than high-scoring firms. They attribute this greater score improvement to increased investors scrutiny (Boffo & Patalano, 2020, p. 43).

Furthermore there are a number of issues that affect the quality of ESG ratings. First, there is a conflict of interest arising from the provision of consulting services to rated firms. The practice of offering paid services to rated firms raises serious concerns about the independence of those ESG ratings (Larcker et al., 2022, p. 7). Tang et al. (2022, p. 29) find that firms affiliated with ESG rating agencies receive higher ESG ratings than firms not affiliated with them. Second, ESG ratings are mostly backward-looking, i.e., they evaluate past performance, while investors actually look for indicators of future performance (The SustainAbility Institute, 2020, p. 28). As a result, investors have stated that they would like to have more timely updates (The SustainAbility Institute, 2020, p. 43). Third, recent research claims that ESG ratings do not reliably predict future sustainability performance and do not correlate with ESG risk management capabilities (Brackley et al., 2022). Fourth, investors report that ESG rating agencies often do not respond to complaints about inaccurate information from rated firms. ESG rating agencies are often not sufficiently staffed to provide comprehensive support (The SustainAbility Institute, 2020, p. 28).

4.2.4. Comparison of ESG Rating Agencies' Methodologies

Sustainalytics

In terms of methodology of ESG ratings, Sustainalytics assesses a firm's ESG performance by measuring the extent to which a firm's economic value is exposed to unmanaged material ESG risks (Sustainalytics, 2021, p. 4). The analysis is based on data collected from a firm's public disclosure, the media, and NGO reports. The model includes between 70-90 ESG indicators for large and mid cap firms and between 20-30 for small cap firms. Indicators are selected based on their relevance to the assigned peer group and to the firm's particular business model. At the moment, Sustainalytics distinguishes between 138 peer groups, which are categorized into 42 distinct industries. Sustainalytics uses building blocks that start with corporate governance, consider material ESG issues, and then look for idiosyncratic ESG issues. Betas are then used by embedding the impact of events on financial performance into the process (Sustainalytics, 2021, p. 5-8). Once the analysis is done, firms have two weeks to provide feedback and submit additional information. The final result compiled into a score between 0 and 100, with a lower score being better as it means less exposure to unmanaged ESG risks (Sustainalytics, 2020, p. 7). The rating is absolute, meaning it is comparable across all peer groups covered. (Sustainalytics, 2021, p. 4). In addition, Sustainalytics provides individual E/S/G cluster scores and controversy research. Those are not used to calculate the ESG Risk Rating but provide investors with additional information on ESG performance (Sustainalytics, 2021, p. 12-14). The ratings are updated annually, while controversy research is updated as events occur (Sustainalytics, 2020, p. 5).

MSCI ESG Research

MSCI's rating methodology is as follows. First, MSCI collects macro data, firm disclosures and data from media, NGOs, and other stakeholders (MSCI, 2022b, p. 14). Then, MSCI measures a firm's exposure to material ESG risks and the quality of a firm's risk management (MSCI, 2022b, p. 6). This is done by analyzing the individual E/S/G pillars based on a selection of 35 key issues. Firm-specific exceptions are allowed for firms with diversified business model, facing controversies, or based on industry rules (MSCI, 2022b, p. 3 f.). Figure 4 in the annex shows an example of chosen key measures for the Coca Cola. Each environmental and social key issue typically accounts for 5% to 30% of the total ESG rating. The weightings take into account the industry's contribution, relative to all other industries, to negative or positive environmental or social impacts, as well as the timeframe in which the risk or opportunity is expected to materialize. The weight of the governance pillar is set at a minimum value of 33% (MSCI, 2022b, p. 5 f.). Controversies are directly included in the rating to indicate structural problems in a firm's risk management (MSCI, 2022b, p. 9). MSCI is proactively reaching out to firms for feedback. But, they do not issue surveys or questionnaires or conduct general interviews with firms. Neither are information that is not publicly available to stakeholders accepted and taken into account (MSCI, 2022b, p. 14).To arrive at the final ESG rating, the weighted average of the E/S/G pillar is computed and then normalized relative to industry peers. The best possible score is AAA and the worst CCC. The rating is intended to be interpreted relative to a firm's peers and not absolute (MSCI, 2022b, p. 10 f.). After the rating is published, firms are monitored on a systematic and ongoing basis. Controversies are monitored on a daily basis and new information is reflected in reports on a weekly basis. Significant changes to scores trigger a review and rerating (MSCI, 2022b, p. 14).

Refinitiv

Refinitiv ESG scores are designed to transparently and objectively measure a firm's relative ESG performance, commitment and effectiveness (Refinitiv, 2022b, p. 3). The methodology is as follows. Refinitiv's model is fully automated, datadriven, and transparent, making it free from subjectivity and hidden calculations and inputs (Refinitiv, 2022b, p. 6). The analysis is based exclusively on publicly available data from annual reports, firm websites, NGO websites, stock exchange filings, CSR reports and news sources (Refinitiv, 2022b, p. 4). The model captures and calculates over 630 firm level ESG measures, of which a subset of 186 of the most comparable and material are used for the firm valuation and scoring process (Refinitiv, 2022b, p. 6). Indicators that are irrelevant for a particular sector are excluded (Refinitiv, 2022b, p. 9). Not reporting on immaterial data points has no significant influence on a firm's rating, however, not reporting on highly material data points has a negative impact on a firm's rating (Refinitiv, 2022b, p. 3). The ESG measures are then aggregated into categories. Environmental and social categories are benchmarked against other firms in the same industry, whereas governance categories are benchmarked against other firms in the same country of incorporation. Categories are then compiled into weighted E/S/G pillars from which the final ESG score is calculated (Refinitiv, 2022b, p. 8 f.). Investigated firms are not asked for feedback, although they may request updates at any time (Deloitte, 2021). Refinitiv has two different scores. The regular ESG score and the ESGC score, which discounts for ESG controversies impacting the firm. The final rating is issued both in points from 0-100 and in letter grades from D- to A+, with a higher score or grade indicating better ESG performance. ESG data and scores are recalculated on an ongoing basis to align with corporate reporting patterns (Refinitiv, 2022b, p. 3 f.).

The next chapter delves into the issue of disagreement among ESG rating agencies. In particular, the extent to which ESG rating agencies disagree and the reasons for their disagreement. The chapter aims to build a theoretical foundation for the independent variable of this master thesis.

4.3. Disagreement among ESG Rating Agencies

ESG rating agencies can disagree significantly with respect to their ESG ratings. In a recent study, Berg et al. (2022) examine the disagreement between the ESG ratings of five major ESG rating agencies (KLD, Sustainalytics, Moody, Refinitiv and S&P Global). They find an average correlation of only 54% between the ESG ratings (see Table 1), which is surprising since these ESG ratings are supposed to measure the same risk construct. At the pillar level, the disagreement is even higher with correlations of 0.53, 0.42, and 0.30 for E, S, and G, respectively. ESG rating agencies appear to disagree the most on governance issues, with some ESG rating agencies even exhibiting negative correlations. The negative correlations indicate extreme disagreement among ESG rating agencies. Firms that were considered to have good ESG performance by one ESG rating agency, were considered to have bad ESG performance by the other ESG rating agency. The results indicate that the information investors receive from ESG rating agencies is relatively noisy.

Other studies support the notion that there is a significant disagreement among ESG rating agencies. Prall (2021) analyses the correlations between six major ESG rating agencies (MSCI, S&P, Sustainalytics, CDP, ISS and Bloomberg). He finds even lower correlations between those ESG rating agencies, with an average correlation of just 35%. MSCI's correlation with both Sustainalytics and S&P is below 50% (see Table 17 in the annex). The rest of the correlations range from 0.74 (between S&P and Bloomberg) to 0.07 (between ISS and CDP). State Street Global Advisors (2019, p. 2) assesses cross-sectional correlations between four major rating agencies (Sustainalytics, MSCI, RobeccoSAM and Bloomberg). The results show an average correlation of 60%. The correlation between Sustainalytics and MSCI is only 53% (see Table 18 in the annex), which is consistent with the findings of Prall (2021). Boffo and Patalano (2020, p. 28) examine the ESG rating variation among three major ESG rating agencies (Bloomberg, MSCI, and Refinitiv) for the components of the S&P 500 and STOXX 600 indices. They find large differences, with an average R-squared of 0.21 for the S&P 500 and 0.18 for the STOXX 600. From a correlation perspective, these values correspond to 46% and 42% for the two indices, respectively.

In another analysis, Boffo and Patalano (2020, p. 29) compare the disagreement between ESG rating agencies and credit rating issuers. For this purpose, they selected listed firms by largest market capitalization to represent various industries. The results show that ESG ratings agencies disagree significantly in their ESG ratings, while credit rating issuers mostly agree (see Figure 1). Berg et al. (2022, p. 6 f.) even report a correlation between credit ratings of 99%. Prall (2021) find that the credit ratings for the firms in their

Table 1: Correlations between ESG ratings (Source: Berg et al. (2022, p. 30))

	KL SA	KL MO	KL SP	KL RE	KL MS	SA MO	SA SP	SA RE	SA MS	MO SP	MO RE	MO MS	SP RE	SP MS	RE MS	Average
ESG	0.53	0.49	0.44	0.42	0.53	0.71	0.67	0.67	0.46	0.7	0.69	0.42	0.62	0.38	0.38	0.54
E	0.59	0.55	0.54	0.54	0.37	0.68	0.66	0.64	0.37	0.73	0.66	0.35	0.7	0.29	0.23	0.53
S	0.31	0.33	0.21	0.22	0.41	0.58	0.55	0.55	0.27	0.68	0.66	0.28	0.65	0.26	0.27	0.42
G	0.02	0.01	-0.01	-0.05	0.16	0.54	0.51	0.49	0.16	0.76	0.76	0.14	0.79	0.11	0.07	0.30

Note: Correlations between ESG ratings at the aggregate rating level (ESG) and at the level of the environmental dimension (E), the social dimension (S), and the governance dimension (G). SA, SP, MO, RE, KL, and MS are short for Sustainalytics, S&P Global, Moody's ESG, Refinitiv, KLD, and MSCI, respectively.

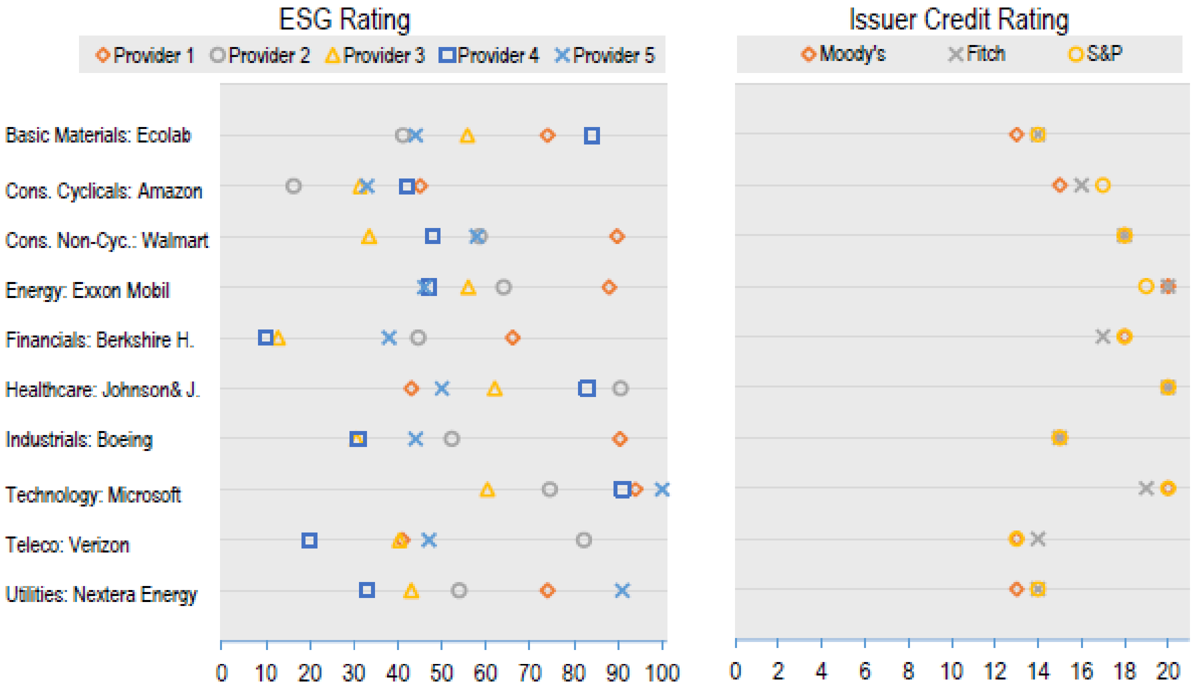
sample have a correlation between 94% and 96%. Therefore, the disagreement seems to be unique to non-financial rating agencies.

This raises the question why ESG rating agencies disagree that much. As mentioned in the previous chapter, ESG rating agencies use very different rating methodologies to collect, measure and analyze ESG information. The disagreement can be mostly attributed to different ESG rating methodologies. Because ESG rating agencies compete with each other for market share, there is no single approach to ESG rating methodologies. Each ESG rating agency uses its own proprietary methodology to differentiate itself from their peers and to meet investors' needs (Brackley et al., 2022). In addition, ESG rating methodologies are often not fully transparent (Doyle, 2018, p. 8). Berg et al. (2022) seek to understand which factors contribute to the disagreement among ESG rating agencies. They deconstruct ESG ratings into three factors: scope (the attributes that the ESG rating agencies attempt to measure), measurement (the measures used to assess the attributes), and weighting (the relative importance assigned to the attributes). They find that the majority of disagreement between ESG rating agencies can be attributed to differences in measurement (56%) and scope (38%), with weighting differences accounting for only 6% of the disagreement. The one exception to the study is MSCI, where the scope, rather than the measurement, accounts for most of the disagreement due to the firm-specific weights (Berg et al., 2022, p. 16 f.).

At the scope level, ESG rating agencies differ in the amount and type of input variables. While several ESG rating agencies use ESG frameworks, such as GRI, SASB, and TCFD to select input variables, others do not. Input variables are also selected to some degree based on data availability to ensure that each indicator can be accurately measured over time. In cases where firms do not provide direct information, approximations are used, which may or may not be accurate. Perhaps contrary to expectations, Christensen et al. (2021, p. 5 f.) find that increased firm disclosure does not lead to more consistent ESG ratings. Instead, they find that it actually increases the disagreement between ESG rating agencies. This is because the subjective nature of ESG information allows for different interpretations of the disclosed information, leading to greater disagreement among ESG rating agencies. Input variables can also differ significantly across industries or firms to account for financial materiality (Boffo & Patalano, 2020, p 31). ESG rating agencies may also replace input variables through time, making it difficult to compare ESG ratings over time or even leading to changes in past ESG ratings (Escrig-Olmedo et al., 2019, p. 14).

At the measurement level, disagreement between ESG rating agencies can arise due to differences in the interpretation of ESG information. For instance, ESG rating agencies use expert judgement to determine which input factors are material for various industries, how to interpret various input factors, or how to handle data gaps (Boffo and Patalano 2020, p. 31; Kotsantonis and Serafeim 2019, p. 54). Berg et al. (2022, p. 18) find that the ESG rating agencies' assessment of a firm in individual categories can influence their overall view of the firm, a phenomenon they called the rater effect. When a rater had a positive view of a firm's particular indicator, they were more likely to have a positive view of the firm's other indicators as well. Berg et al. (2022, p. 17) further find that certain categories are more prone to disagreement. ESG rating agencies mostly disagree on climate risk management, product safety, corporate governance, corruption and environmental management systems. Other categories, such as environmental fines, clinical trials, employee turnover, HIV programs and non-greenhouse gas air emissions are less prone to disagreement. Another factor that influences the interpretation of ESG information is experience. Many investors criticize the insufficient seniority and tenure of research analysts who develop ESG ratings, stating that research teams are stretched too thin and do not have a deep enough understanding of the issues and sectors (The SustainAbility Institute, 2020, p. 29). In any case, the level of experience affects the quality of ESG ratings and thus the disagreement between ESG rating agencies.

Finally, there are weights. ESG rating agencies often assign different weights to different input variables and categories. These weights can be either determined by expert judgment or based on quantitative data-driven approaches (Boffo & Patalano, 2020, p 31). Input variables and categories that have a greater impact on the firm's financial performance often receive a higher weighting (Larcker et al., 2022, p. 4). Since weights are assigned by the individual ESG rating agencies, there may be differences in weightings



Note: Sample of public companies selected by largest market capitalisation as to represent different industries in the United States. The issuer credit ratings are transformed using a projection to the scale from 0 to 20, where 0 represents the lowest rating (C/D) and 20 the highest rating (Aaa/AAA).

Figure 1: Comparison of disagreement between ESG ratings and credit ratings (Source: Boffo and Patalano (2020, p. 29))

that can lead to disagreement between ESG rating agencies.

The disagreement between ESG rating agencies can be both unintentionally and intentionally. Unintentional disagreement in ESG ratings often occurs at the level of specific input factors or data points. Unintentional divergence in ESG ratings may occur when different raters evaluating the same firm have different access to data or interpret the same information differently, resulting in divergent conclusions about the firm's ESG performance. Intentional disagreement in ESG ratings typically occurs at the composite ESG score level, and is the result of the rater's comprehensive analysis of the firm's ESG performance based on its own methodology. This disagreement reflects the differing perspectives and approaches used by the different ESG rating agencies in evaluating a firm's ESG performance (Brackley et al., 2022).

The disagreement between ESG rating agencies, which is often caused by the lack of consistency and standardization in rating methodologies, can limit the usefulness of ESG ratings in providing reliable and meaningful information about a firm's long-term resilience and non-financial performance (Brackley et al., 2022). Without a consistent and standardized approach to ESG ratings, it can be difficult to compare and evaluate the ESG performance of different firms, making it challenging to use ESG ratings as a tool for informed decision-making (Larcker et al., 2022, p. 6). However, while greater consistency in ESG ratings may be desirable in terms of providing more reliable and meaningful information about a firm's performance, it is not clear whether investors necessarily want greater consistency in rating methodologies. Greater regulation of ESG ratings may help to standardize the information input and rating process, resulting in more consistent ratings and reducing the disagreement between ESG rating agencies. On the one hand, greater consistency may reduce the amount of conflicting or contradictory ESG ratings, making it easier for investors to compare and evaluate the ESG performance of different firms. On the other hand, the inclusion of multiple perspectives and approaches in the ESG rating process may provide a more comprehensive and nuanced view of a firm's performance, and may be seen as a positive characteristic by some investors (Brackley et al. 2022; The SustainAbility Institute 2020, p. 44 f.).

The next chapter focuses on the development of the hypothesis. This chapter aims to provide a theoretical framework that can be used to make predictions about the association between ESG disagreement and the dispersion of analysts' forecasts.

5. Hypothesis Development: Influence of ESG Rating Disagreement on Analyst Forecast Dispersion

In this master thesis, I seek to understand the relationship between ESG rating disagreement and analyst forecast dispersion. ESG ratings are measures of a firm's performance in relation to ESG criteria. These ratings aim to measure a firm's exposure to ESG risks and opportunities, and how those risks and opportunities may impact the firm's financial performance (MSCI, 2022b, p. 3). ESG rating disagreement refers to the degree of variation in these ratings among different ESG rating agencies. Analyst forecast dispersion refers to the degree of disagreement among analysts in their forecasts of a firm's future EPS performance. In the accounting and finance literature, analyst forecast dispersion is widely recognized as an important measure, and is often used as a proxy for the uncertainty and the divergence in analysts' beliefs and the lack of consensus or agreement (Barry and Jennings 1992, p. 172; Abarbanell et al. 1995, p. 32; Barron et al. 2010, p. 422).

There is ongoing debate in the literature about why ESG rating agencies may disagree in their ratings of a firm's performance and how ESG information is relevant to market participants. Christensen et al. (2021, p. 4-6) examine whether a firm's ESG disclosure impacts the disagreement between ESG rating agencies. They find that greater ESG disclosure leads to greater ESG rating disagreement. They further find that ESG disagreement is associated with higher stock return volatility and larger absolute price movements, and is therefore relevant to market participants. Krueger et al. (2021, p. 35) study how mandatory ESG disclosure affects the dispersion of analysts' earnings forecasts. They find that as mandatory ESG disclosure improves, analyst earning forecasts become less dispersed. They also find that mandatory ESG disclosure significantly reduces the amount of negative ESG incidents in a firm-year (Krueger et al., 2021, p. 49). Cho et al. (2013, p. 81 f.) investigate whether CSR performance reduces the bid-ask spread, a proxy for information asymmetry. They find that both positive and negative CSR performance seem to reduce information asymmetry. Information asymmetry itself is often interpreted as a constituent of uncertainty (Barron et al., 2010, p. 333). Having said that, the literature on the relationship between ratings and analyst forecast dispersion is scarce. Avramov et al. (2009, p. 85) examine a dispersion-based trading strategy. They find that a portfolio strategy based on buying low dispersion stocks and selling high dispersion stocks yields a statistically significant return. They further find that recent credit rating downgrades lead to higher analyst forecast dispersion (Avramov et al., 2009, p. 99 f.). There are even fewer studies when it comes to the relationship between ESG rating disagreement and analyst forecast dispersion. In fact, during my research I were only able to find one study that addressed this relationship. Kimbrough et al. (2022, p. 48) examine whether ESG rating disagreement is associated with disagreement among market participants. They find that ESG rating disagreement is positively associated with analyst forecast dispersion, bid-ask spread and future stock return volatility. Though, the relationship between ESG rating disagreement and analyst forecast dispersion is only statistically significant at the 10% level, indicating a weak link between the two variables and that the relationship may not be causal. Also, Kimbrough et al. (2022) analyzed the relationship between ESG rating disagreement and analyst forecast dispersion in the US. Therefore, further research may be needed to confirm or refute the relationship between the two variables. This master thesis aims to fill this research gap by conducting an empirical analysis on the relationship between ESG rating disagreement and analyst forecast dispersion in an international setting (Kimbrough et al., 2022, p. 48). Since research on the association between ESG disagreement and analyst forecast dispersion is sparse, the hypothesis development is discussed in more detail. Different arguments for a positive, negative and no association are presented. A decision is then made in favor of one direction or the other based on the strongest arguments.

There are several arguments that could be made in favor of a positive relationship between ESG rating dispersion and analyst forecast dispersion. First, if analysts use different ESG ratings, this could lead to differences in their EPS forecasts, as each ESG rating agency provides different information and perspectives. The access to ESG ratings can be costly, with institutional investors on average spending on $ 487,000 per year on ESG ratings, data and consultants (The SustainAbility Institute, 2022, p. 5). This means that some analysts may not have the resources to access paid ESG ratings services or may choose to use fewer of them in their evaluations. This could lead to differences in the ESG ratings used by analysts, resulting in variations in their forecasts. Additionally, the selection of ESG ratings by individual analysts may be a factor, as some rating agencies are more likely to disagree with others (see Table 17 and 18 in the annex). According to Capital Group (2021, p. 29), the majority of investors use between two and five different ESG ratings (57%), while some use only one (24%) or none at all (7%). This means that it is possible that analysts are not using the same ESG rating agencies in their assessments, which could contribute to the dispersion in their forecasts. In the future, it is expected that the number of ESG ratings used by investors will increase, which may lead to a decrease in the effect of ESG disagreement on analyst forecast dispersion as the variations in ESG ratings are averaged out.

Second, even though analysts may use the same ESG ratings, their interpretations and resulting EPS forecasts can vary significantly. This is because some analysts may simply view ESG ratings as a form of box-checking exercise and do not delve deeper into how ESG rating agencies arrive at their ESG ratings (The SustainAbility Institute, 2020, p. 31). Others may use ESG ratings as a starting point for further research, scrutinizing the measurement, scope, and weights of the ratings in their analysis. High levels of disagreement among ESG rating agencies in particular can be seen as a reason for a more in-depth analysis (Boffo & Patalano, 2020, p. 29 f.). As a result, analysts may develop different private knowledge about ESG ratings, leading to dispersion in analyst EPS forecasts. This view is consistent with Lang and Lundholm (1996, p. 471 f.), who argues that that as public information becomes less informative, analysts place more emphasis on their private information. It is also consistent with Behn et al. (2008, p. 330) who argues that greater dispersion may reflect a lack of agreement among analysts, potentially due to some analysts' inability or reluctance to fully and objectively gather and interpret ESG-related information.

Third, analysts may disagree about whether ESG ratings actually reflect a firm's non-financial performance, as there seems to be no consensus even among ESG rating agencies. Assuming that ESG rating agencies observe the same firm-disclosed ESG information, and rate firms based on their non-financial risks and opportunities, there should be no dispersion in ESG ratings. But, ESG rating agencies seem to be not sure what constitutes as good or bad ESG performance, resulting in widely divergent ESG ratings (Boffo & Patalano, 2020, p. 64 f.). This raises questions about the credibility and reliability of these ratings as a measure of firms' non-financial performance (Larcker et al., 2022, p. 6). As a result, analysts rely more on private information in addition to ESG ratings (Lang & Lundholm, 1996, p. 471 f.), leading to divergent EPS forecasts.

There are also two arguments that could be made in favor of a negative relationship between ESG rating dispersion and analyst forecast dispersion. First, ESG rating dispersion could serve as a proxy for the disclosure of heterogenous ESG information, which in turn can lead to a reduction in analyst forecast dispersion. ESG rating agencies act as information intermediaries by gathering, aggregating and evaluating a firm's public non-financial information. Some ESG rating agencies even conduct their own surveys, therefore producing and facilitating their own disclosure of ESG information (Scalet & Kelly, 2010, p. 71). Under the premise that analyst forecast dispersion reflects the amount of information commonly available to analysts, forecast dispersion should decrease with more ESG information being available (Han & Manry, 2000, p. 119). This is because if analysts share a common forecasting model and observe the same ESG information but have different private information, they will attach less weight to their private information as the informativeness of ESG information increases, thereby reducing forecast dispersion (Lang & Lundholm, 1996, p. 471). This view is consistent with Krueger et al. (2021, p. 9) who argues that as more and better ESG information is made available, the diversity of opinions may decrease, and EPS forecast dispersion should decrease. Next to the quantity of disclosure, the quality also seems to be important. Swaminathan (1991, p. 40) find that forecast dispersion decreases following the release of newly mandated segment information by the SEC. Dechow et al. (1996, p. 3) find that forecast dispersion increases following alleged violation of generally accepted accounting principles. Because ESG information is largely unstandardized, frequently unstructured, difficult to compare and tends to be more subjective than financial disclosures (Sipiczki, 2022, p. 6), one could argue that through the aggregation and evaluation of unstandardized and unstructured ESG information, ESG rating agencies increase the quality of ESG disclosures, thereby reducing analyst forecast dispersion.

Second, ESG rating disagreement may reflects different perspectives and approaches of ESG rating agencies, allowing for a more comprehensive and nuanced understanding of a firm's ESG performance, and thus reducing the dispersion of analysts' forecasts. When ESG rating agencies have different perspectives and approaches to evaluating a firm's ESG performance, it leads to a more comprehensive and nuanced understanding of the firm. This is because the ESG ratings become more dispersed, meaning they reflect a wider range of viewpoints and a greater amount of underlying data (Scalet and Kelly 2010, p. 72; The SustainAbility Institute 2020, p. 44 f.). As a result, analysts have access to more information and can form a more informed opinion about a firm's financial prospects. This ultimately leads to a decrease in forecast dispersion and increased agreement among analysts. For this to hold true, though, analysts would have to have access to the same ESG ratings and interpret them in the same way (Lang & Lundholm, 1996, p. 471 f.).

In addition, there are several arguments why there may not be a significant relationship between ESG rating dispersion and analyst forecast dispersion. First, ESG disagreement may not have an effect on analyst forecast dispersion if ESG ratings reflect a firm's long-term ESG performance, while analyst forecasts reflect a firm's short-term profitability. In this view, ESG ratings provide analysts with information about a firm's long term risks and opportunities (Boffo & Patalano, 2020, p. 14). For example, a poor environmental performance can lead to negative consequences such as fines, legal action, and damage to a firm's reputation, which in turn can affect financial performance. Whereas, a good environmental performance can improve a firm's reputation and mitigates the risk of regulatory scrutiny (Henisz et al., 2019, p. 3-8). However, it is difficult to predict when these ESG risks will materialize in the future. In contrast, analyst EPS forecasts are projections of a firm's short-term financial performance, with a time horizon typically limited to the next quarter or fiscal year. Therefore, most ESG risks are unlikely to be relevant to analysts' EPS forecasts and may not be used when making EPS forecasts. Still, some ESG rating agencies include controversies into their ESG ratings. Controversies are short-term reputational risks that arise from negative media attention (Boffo & Patalano, 2020, p. 30). Because these controversies affect a firm's short-term performance, analyst may consider ESG ratings when making their EPS forecasts. As a result, the relationship between ESG rating disagreement and analyst forecast dispersion depends on whether ESG ratings reflect both short-term and long-term ESG performance.

Second, ESG ratings dispersion may not affect analyst forecast dispersion due to a lack in the transparency of ESG ratings. ESG rating agencies tend to not fully disclose their ESG rating methodologies. Investors lack an clear understanding about which metrics, inputs and weights ESG rating agencies use in their evaluation, as well as the degree of subjectivity that in their assessments (Brackley et al., 2022). This lack of transparency makes it difficult for analysts to use ESG ratings as a reliable source of information to inform their earnings forecasts. As a result, analysts may use other sources of ESG information beyond ESG ratings to inform their earnings forecasts such as firm-provided disclosures, market and industry trends and specific news and events.

This reliance on other sources of ESG information reduces the significance of ESG ratings and their disagreement, causing analysts to ignore ESG ratings.

Third, the dispersion of ESG ratings may not be relevant to analysts' forecasts because of the backward-looking data used in ESG ratings. ESG rating agencies mostly use publicly available information to access a firm's ESG performance. Therefore, they can produce an accurate assessment of a firm's past ESG performance. But, analysts are interested in forecasting a firm's future financial performance (The SustainAbility Institute, 2020, p. 28). Sheng and Thevenot (2012, p. 21) argue that analysts' EPS forecasts represent market participants' expectations of a firm's future earnings prior to the release of accounting data. Past ESG information may already be prized in by the market (Malkiel & Fama, 1970, p. 383). Also, past performance is not necessarily a reliable indicator of future performance, which is why analysts use estimates and correct their forecasts on an ongoing basis (Capstaff et al., 1995, p. 74). Thus, ESG ratings may be of limited use for future investment decisions and are therefore not considered by analysts in their forecasts. As a result, there would be no significant relationship between the dispersion of ESG ratings and the dispersion of analysts' forecasts.

Having considered all the arguments, I believe that analyst forecast dispersion is driven by differences in the interpretation and use of ESG ratings. Accordingly, a positive association between ESG rating dispersion and analyst forecast dispersion is considered the most likely hypothesis. Therefore, I hypothesize:

> **H1**: ESG rating disagreement is positively associated with analyst forecast dispersion

This means that as the dispersion between ESG ratings increases, the dispersion in analyst forecast also increases. To test whether there is a positive relationship between the dispersion of ESG ratings and the dispersion of analyst forecasts, I conduct an empirical analysis.

6. Empirical Study

6.1. Sample

I start with an initial sample of 7,186 global public firms obtained from Refinitiv Eikon. The firms are constituents of the Market WD index. The initial sample consists of 71,860 firm-year observations ranging from 2012 to 2022. The necessary firm data and the in-house ESG ratings were collected from Refinitiv Eikon. The time period of 10 years is chosen so that the earnings volatility of the last 5 years can be calculated correspondingly for each ESG rating observation. In a first step, I make sure that the sample does not contain duplicates, i.e., does not contain more than one observation belonging to the same firm-year. In a second step, I ensure that all firm-year observations are distinctly attributable to a single firm and a single fiscal year. Then, with the exception of the disagreement between ESG rating agencies, I calculate all variables required for the empirical analysis and remove missing observations from the dataset.

This subsample is then used to collect the respective other ESG ratings. In total, I hand-collect ESG ratings from 4 prominent ESG rating providers: MSCI, S&P, ISS, Sustainalytics. When a ESG rating agency released multiple ESG ratings for a given firm year, I collected the last ESG rating provided for a given year. The ESG ratings collected vary in data availability. For some ESG ratings, such as Sustainalytics and ISS, only the latest ESG ratings for 2022 are available, while MSCI and S&P, for example, provide ESG ratings covering a period from 2018 to 2022. Also, not all ESG rating agencies publish their corresponding E/S/G pillar scores to the ratings. In order to obtain a sufficiently large data basis, S&P and ISS were included in the empirical analysis. The initial intention was to include only MSCI, Sustainalytics and Refinitiv Eikon. However, the data basis would then have been too small. For the empirical analysis, a total of 9,577 ESG ratings from both MSCI and S&P were accessed, resulting in 3,785 and 3,888 ESG ratings respectively. In the case of Sustainalytics and ISS, 385 ESG ratings were accessed, resulting in 329 and 284 ratings, respectively. In addition, the pillar scores for S&P and Sustainalytics for the year 2022 were also collected.

After collecting the ESG ratings, the two datasets are merged and subsequently adjusted for missing values in the ESG disagreement calculation. The final sample consists of 3,968 firm-year observations ranging from 2018 to 2022. Table 19 in the annex shows the respective sample selection procedure. As mentioned previously, the sample is an international sample. All available country observations were collected, with the exception of the US. In fact, the final sample consists of 54 unique countries. The three largest positions are Japan, India and the United Kingdom, which account for 19.5%, 8.1% and 5.2% of the sample, respectively. Table 20 in the annex shows the composition of the sample by countries. The sample differs from the study by Kimbrough et al. (2022) in two important ways. First, Kimbrough et al. (2022, p. 5) focus only on firms in the US due to the voluntary nature of ESG information reporting, whereas our sample includes all countries excluding the US[1]. Second, Kimbrough et al. (2022, p. 2) collect ESG rating information from KLD (now MSCI), ASSET4 (now Refinitiv Eikon), and Vigeo Eiris (now Moody's). Therefore, this study differs from Kimbrough in that the type and quantity of different ESG ratings and the country choice differs. The next chapter addresses the research design of this empirical study.

6.2. Research Design

To test the hypothesis whether there is a positive association between analyst forecast dispersion and ESG disagreement, I perform an empirical analysis based on an OLS regression,

$$AF\_DISP_{i,t} = \beta_0 + \beta_1 ESG\_Disagreement_{i,t} + \beta_k Controls_{i,t} + \varepsilon_{i,t} \tag{1}$$

[1] All countries refers to all the countries included in the Market WD index.

where $AF\_DISP_{i,t}$ is the dependent variable, $ESG\_Disagreement_{i,t}$ the independent variable, $Controls_{i,t}$ the control variables and $\varepsilon_{i,t}$ the error term. Table 21 in the annex reports all variables used in the regression analysis. $AF\_DISP_{i,t}$ refers to the relative dispersion between analysts' forecasts. It is calculated as the natural logarithm of the standard deviation of analysts' forecast dispersion of annual EPS scaled by the absolute value of the mean analysts' forecast for firm i in year t. The absolute value is important to be mathematically correct since in a natural logarithm one cannot divide by a negative number. Otherwise, observations would be lost during the analysis. Kimbrough et al. (2022, p. 39) and Cui et al. (2018, p. 21) scale analyst dispersion using the absolute value of the mean. However, while Kimbrough et al. (2022) use the natural logarithm, Cui et al. (2018) do not. In addition, Krueger et al. (2021, p. 51) define analyst dispersion as the standard deviation of analysts' forecasts divided by the stock price for firm i in year t. Initially, I wanted to use the standard deviation of analysts' forecasts to calculate analyst dispersion ($AF\_Dispersion\_0_{i,t}$). But, as can be seen in the histogram in Figure 5 in the annex, the observations are not-normally distributed using this measure. For this reason, I used the natural logarithm to transform analyst forecast dispersion. After that, the sample observations for analyst dispersion are normally distributed as indicated by the bell curve (see Figure 6). $ESG\_Disagreement_{i,t}$ is the variable of interest. It is calculated as the natural logarithm of the standard deviation of ESG ratings scaled by the absolute value of the mean ESG forecast for firm i in year t. This measure is used to make $AF\_Dispersion_{i,t}$ and $ESG\_Disagreement_{i,t}$ comparable. In contrast, Kimbrough et al. (2022, p. 39) use the absolute value of the difference between the percentile rank of ESG ratings as a measure of ESG dispersion. They also use the standard deviation of the percentile ranks of ESG ratings as a measure of ESG dispersion in their study, but not when examining the influence on analyst forecast dispersion (Kimbrough et al., 2022, p. 48). Christensen et al. (2021, p. 39) use ESG disagreement as the dependent variable and calculate it using the standard deviation of ESG ratings. In the empirical analysis, the standard deviation of ESG ratings is calculated in such a way that if an ESG rating is missing, the standard deviation is still calculated for the available ESG ratings. Apart from this, at least three ESG ratings are required. To arrive at $ESG\_Disagreement_{i,t}$, ESG ratings themselves must first be made comparable. Each ESG rating provider uses its own rating scale, which makes it difficult to compare ESG ratings. Refinitiv (2022b, p. 3) and S&P Global (2022, p. 3) use a percentile rank scores between 0 and 100, where 100 represents the best score. Sustainalytics (2020, p. 7) also uses a percentile rank score. But, the percentile ranks range from 1 to 100, with 0 being the best and 100 the worst. MSCI (2022b, p. 12) uses a letter-based rating system with 12 categories, where AAA represents the best score and CCC the worst. ISS also uses a letter-based rating system. However, ISS ESG (2022, p. 2) uses only 7 letters, with D- representing the worst and A+ representing the best score .To make the ESG ratings of Refinitiv Eikon, MSCI, S&P, ISS and Sustainalytics comparable, I first change the direction of Sustainalytics' ESG score so that 100 represents the best and 1 the worst. Then I standardize Sustainalytics' ESG score so that 0 represents the worst score. Then I divide the ESG scores of the three ESG providers by 10 to arrive at a 10-point rating rank scale, which seems more appropriate given the lower number of score grades from MSCI and ISS. After that, I convert the letter-based scores from MSCI and ISS into numeric scores. Since one letter equals zero, I divide the highest possible score ten by $n-1$ to arrive at the respective numerical scores for MSCI and ISS (See Equation 2).

$$0 + \frac{10}{(n-1)} = numeric\ score\ rank \tag{2}$$

I also construct three alternative measures of ESG disagreement. The first alternative measure is $ESG\_Disagreement\_3$. Similar to $ESG\_Disagreement$, it is computed as the natural logarithm of the standard deviation of ESG ratings scaled by the absolute value of the mean ESG forecast for firm i in year t. The individual ESG ratings are also made comparable in the same way as for $ESG\_disagreement$. The difference is that for $ESG\_Disagreement\_3$ only the ESG ratings of Refinitiv Eikon, MSCI and S&P are used to calculate the standard deviation. Similarly, $ESG\_Disagreement\_4$ is calculated using the four ESG ratings from Refinitiv Eikon, MSCI, S&P and Sustainalytics. $ESG\_Disagreement\_5$ uses all five ESG ratings. If an ESG rating is not available in a particular firm year, the alternative measures are not calculated for this particular firm year. It is therefore required that all ESG ratings necessary for the calculation are available.

In addition, I construct three measures to analyse the disagreement among ESG rating agencies on the E/S/G pillar scores. The measures only include the pillar scores of Refinitiv Eikon, S&P and Sustainalytics, as the other pillar scores are not publicly available free of charge. Similar to ESG_Disagreement, E/S/G_disagreement it is computed as the natural logarithm of the standard deviation of the E/S/G pillar scores scaled by the absolute value of the mean E/S/G forecast for firm i in year t. E_Disagreement captures the disagreement among ESG rating agencies about environmental issues. S_Disagreement captures the disagreement While S_Disagreement captures the disagreement between ESG rating agencies on social issues and G_Disagreement on governance issues. One issue is to make the pillar scores comparable. Refinitiv and S&P create pillar scores and subsequently weight them to arrive at their ESG ratings. The pillar scores of Refinitiv and S&P are directly comparable. This is because the subsequent weighting does not affect the individual pillar scores. In the case of Sustainalytics, the sum of the individual pillar scores equals the final ESG rating. It is not entirely clear from Sustainalytics' rating methodology how the individual E/S/G pillars are weighted. To perform an empirical analysis, an equal weighting is assumed. The pillar scores from Sustainalytics are therefore multiplied by three to arrive at a comparable pillar score.

To control for the influence of other variables, I include several control variables in my empirical analysis. The control variables are chosen based on similar previous studies. Controls consists of firm size, book-to-market-ratio, analyst following, earnings surprise, forecast horizon, earnings volatility, indicator variable for negative earnings, leverage and Zmijewski financial distress score (Christensen et al. 2021, p. 40; Behn et al. 2008, p. 333 f. Hope 2003, p. 25; Kimbrough et al. 2022, p. 38). The calculations for the control variables are given in Table 21 in the annex. Firm size is included because large firms would be expected to have a smaller dispersion (Behn et al., 2008, p. 333). Analyst following is included based on Lang and Lundholm (1996, p. 482), who find a positive association between analyst following and forecast characteristics. Earnings surprise is also based on Lang and Lundholm (1996, p. 489), who find that larger changes in earnings are related to less accurate forecasts. Forecast horizon is considered based on Chopra (1998, p. 37), who finds that a forecast further away from to the actual earnings announcement date is less accurate and more dispersed than a forecast closer to the announcement date. However, because many firm-year observations are missing to calculate the variable, the control variable is ultimately not included in the study. Earnings volatility is included based on Kross et al. (1990, p. 465) who find that firms with large historical earnings variations have less accurate analyst's earnings forecasts. Variability in earnings should increase the difficulty of forecasting, resulting in larger dispersion. The indicator variable for negative earnings, leverage and Zmijewski financial distress score are included to control for uncertainties arising from strained financial conditions and bankruptcy risk. The indicator variable for negative earnings is included based on Hwang et al. (2014, p. 29) who find that analysts' forecasts for firms with negative earnings are on average less accurate than for firms with positive earnings. Leverage is included based on Hope (2003, p. 11) who mentions that highly levered firms tend to have more variable earnings. Zmijewski (1984, p. 65-69)'s financial distress score is included based on Behn et al. (2008, p. 333) who note that financially distressed firms tend to have less accurate forecasts. The book-to-market ratio is included based on the Kimbrough et al. (2022, p. 19) to control for growth opportunities related to ESG. In addition, I further include industry and year fixed effects. The variables are winzorized at both tails at the 1% level.

7. Empirical Results

7.1. Descriptive Statistics

Table 2 reports the descriptive statistics for the individual ESG ratings. As can be seen in Table 2, Refinitiv, MSCI and S&P are represented in the sample with around 4000 ESG ratings each, while ISS and Sustainalytics are only represented with just around 300 ratings.

Furthermore, it can be seen that the largest observation of ISS has a value of 6.36, and not close to ten. This is due to the fact that no ESG ratings better than B have been assigned to the firms in the sample. Accordingly, no ESG ratings from ISS for firms with excellent ESG performance are represented in the sample. In addition, it can be seen that the smallest observation for Sustainalytics has a value of 4.63, and not close to zero. Thus, Sustainalytics is distorted for firms with particularly poor ESG performance. This is because Sustainalytics assigns firms to the worst category at a value above 40. The assigned nominal value, though, goes beyond 40. To avoid distortions and make Sustainalytics comparable, one could set the maximum observed value as the upper limit and then adjust the other ESG ratings accordingly. But, due to the subordinate role of Sutainalytics in the sample and other robustness checks, this approach was not applied here. Still, it is important to be aware of this bias for the further course of this empirical analysis. It is also noticeable that the ESG ratings of S&P and ISS have a relatively low mean of 3.84 and 2.91. Together with the also low median values, this indicates that S&P and ISS generally assign lower ESG ratings than Refinitiv, MSCI and Sustainalytics. It is also worth noting that the standard deviation of MSCI and S&P with 2.68 and 2.48 are higher than those of the other ESG rating providers. This indicates that the ESG ratings of MSCI and S&P are more dispersed around the mean. Thus, a greater variability in ESG ratings.

Table 3 shows the correlation between the ESG ratings of different ESG rating providers. The correlations between the ESG ratings are low. This is consistent with the observations of Prall and State Street Global Advisors (see Table 18 and 19). Hence, ESG rating providers generally do not agree about the ESG performance of firms. Therefore, resulting in high levels of disagreement among ESG rating agencies. The highest levels of disagreement are found between Sustainalytics and other ESG rating providers. Yet, some of the correlations are not empirically significant at the 1% level. The highest levels of agreement are found between Refinitiv and S&P, and S&P and ISS with 0.55 and 0.55, respectively.

Table 4 and 5 present the descriptive statistics for the empirical analysis. Table 4 shows the descriptive statistics for analyst forecast dispersion and ESG disagreement before the transformation with the natural logarithm. Both variables are calculated as the standard deviation (See Table 21). The mean and median of AF_DISP_0 are 49.38 (0.43). The standard deviation of AF_DISP_0 is 342.99. These statistics indicate that there are substantial variations in forecasts made by financial analysts.

The reason why I transform analyst forecast dispersion is that the variable is highly dispersed around the mean, highly skewed, and exhibits a high positive kurtosis. All of this can be problematic for accuracy of the hypothesis test. First, the standard deviation is greater than the mean. Hence the coefficient of variation[2] is more than one. This means that analyst forecast dispersion exhibits a great degree of relative variability. A great degree of variability in the data set is

[2] The coefficient of variation is defined as the ratio of the standard deviation to the mean and is a standardized measure of dispersion.

Table 2: Descriptive Statistics of ESG ratings (Source: Own illustration)

Variable	N	Mean	SD	25%	Median	75%	Min	Max
Refinitiv	3,968	5.87	1.76	4.75	6.02	7.25	0.072	9.424
MSCI	3,785	5.65	2.68	3.33	6.67	8.33	0	10
S&P	3,888	3.84	2.48	1.8	3.2	6.0	0	9.3
ISS	284	2.91	1.26	1.82	2.73	3.64	0.91	6.36
Sustainalytics	329	7.59	0.84	7.07	7.68	8.26	4.63	9.39

Table 3: Correlations of ESG ratings (Source: Own illustration)

	(1)	(2)	(3)	(4)	(5)
(1) Refinitiv	1				
(2) MSCI	**0.40**	1			
(3) S&P	**0.55**	**0.37**	1		
(4) ISS	**0.49**	**0.38**	**0.55**	1	
(5) Sustainalytics	**0.14**	**0.49**	0.07	0.15	1

Note: Correlations with significance levels <0.01 are in bold.

Table 4: Descriptive statistics before transformation of variables (Source: Own illustration)

Variable	N	Mean	Standard Deviation	Median	Skewness	Kurtosis
AF_DISP_0	3,968	49.38	342.99	0.43	13.12	226.66
ESG_Disagreement_0	3,968	1.97	0.86	1.98	0.08	2.46

bad, because it reduces the power of the statistical test or in other word the probability that the test will detect a difference that actually exists. Second, forecast dispersion is highly positively skewed. In this case, the tail region may act as an outlier for the statistical model. This is bad, because the outliers adversely affect the regression model's performance. Third, analyst forecast dispersion exhibits a high level of kurtosis. This means that the distribution of values is much more peaked than the normal and has heavy tails. This heavier tails leads to a few large outliers which are problematic for tests which rely on normality. As a result, differences are obscured, resulting in lower statistical power of the empirical test. To solve all these problems, the natural logarithm is used to normalize analyst forecast dispersion. As can be seen in Table 5 and Figure 6 in the annex, the normalized measure of analyst forecast dispersion is less skewed, less dispersed, has less kurtosis and resembles a bell-shaped normal distribution.

Table 5 presents descriptive statistics for the main sample, which consists of 3,968 firm-year observations. The dataset in Table 5 is not directly interpretable due to its log transformation of some variables. One way to obtain information about the central tendency and variability of the data set is to back-transform the data using the exponential function. The mean (median) of $ESG\_Disagreement_{i,t}$ is then 0.36 (0.43). Because $ESG\_Disagreement_{i,t}$ tends to be left-skewed, interpretating the variable using the median seems more appropriate to describe the central tendency. Because the variable ESG disagreement is itself a coefficient of variation, I find it difficult to interpret it using a descriptive statistics. The back-transformed standard deviation of $ESG\_Disagreement_{i,t}$, is 2.10. Therfore, with normal data, most of the observations are spread within one-fifth on each side of the mean.

7.2. Univariate Analysis

Table 6 shows the correlation coefficients. Correlation is a statistical measure that describes how two variables are related and indicates that as one variable changes in value, the other variable tends to change in a specific direction. The Pearson correlations are below and the Spearman coefficients above the line. Of particular interest for the empirical analysis are the Pearson coefficients. All variables in the empirical analysis exhibit a statistically significant linear correlation with $AF\_DISP_{i,t}$ at the 5% level. Thus, there appears to be a linear relationship between the variables which, based on the significance level, also applies to the population and not only to the sample. There is only a small chance that the results from the sample occurred due to chance (random sampling error). But this does not imply that there necessary is a cause and effect relationship. $ESG\_Disagreement_{i,t}$ and $AF\_DISP_{i,t}$ are weakly positivly correlated, as expected, with a value of 0.04. Thus, providing preliminary support that ESG disagreement is associated with an increase in analyst forecast dispersion.

Table 5: Descriptive statistics after transformation of variables (Source: Own illustration)

Variable	N	Mean	Standard Deviation	25%	Median	75%	Skewness	Kurtosis
AF_DISP	3,968	-2.51	1.11	-3.19	-2.59	-1.92	0.53	3.97
ESG_Disagreement	3,968	-1.01	0.74	-1.39	-0.84	-0.52	-0.90	3.55
Size	3,968	25.42	2.37	23.50	25.01	27.30	0.44	2.35
NANA	3,968	2.67	0.56	2.40	2.71	3.09	-0.83	4.10
BTM	3,968	0.0007	0.0008	0.0002	0.0004	0.0008	2.78	12.52
Earnings_VOL	3,968	5.65e+07	4.54e+08	2438233.9	1419371	8731285	5.87	38.95
Earnings_Surprise	3,968	37.20	3789.78	-5.76	0.66	11.15	-0.36	20.66
Leverage	3,968	0.25	0.17	0.12	0.25	0.37	0.36	2.45
ZMIJ	3,968	-3.16	1.10	-3.18	-3.18	-2.38	2.93	2.43
LOSS	3,968	0.087	0.28	0	0	0		

Table 6: Pearson/Spearman Correlation Coefficients (Source: Own illustration)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) AF_DISP	1	**0.04**	**0.03**	**-0.05**	**0.28**	**0.17**	**-0.12**	**0.13**	**0.20**	**0.33**
(2) ESG_Disagreement	**0.04**	1	-0.01	**-0.18**	**-0.05**	-0.03	**0.03**	**-0.07**	**-0.07**	0.01
(3) Size	**0.05**	**-0.03**	1	**0.14**	-0.003	**0.87**	0.01	**-0.19**	**-0.19**	**-0.10**
(4) NANA	**-0.07**	**-0.18**	**0.16**	1	**-0.13**	**0.11**	0.01	**-0.07**	**-0.08**	0.003
(5) BTM	**0.23**	**0.08**	**-0.05**	**-0.07**	1	**0.32**	-0.03	**0.10**	**0.18**	**0.09**
(6) Earnings_VOL	**0.08**	-0.0005	**0.48**	**0.11**	**0.11**	1	0.007	**-0.11**	**-0.09**	-0.02
(7) Earnings_Surprise	**-0.08**	**0.04**	0.01	0.01	**-0.04**	**0.04**	1	-0.03	**-0.10**	**-0.28**
(8) Leverage	**0.13**	**-0.06**	**-0.19**	**-0.08**	**0.09**	0.01	-0.02	1	**0.97**	**0.13**
(9) ZMIJ	**0.21**	**-0.06**	**-0.19**	**-0.10**	**0.15**	-0.001	**-0.07**	**0.97**	1	**0.25**
(10) LOSS	**0.39**	0.006	**-0.10**	-0.005	**0.09**	**0.04**	**-0.22**	**0.14**	**0.26**	1

Note: Pearson (Spearman) coefficients are below (above). Correlations with significance levels <0.05 are in bold.

Furthermore, there is a very strong positive correlation between Leverage and ZMIJ with a value of 0.97 at the 5% significance level. This correlation exists because part of the calculation of the Zmijewski financial distress score includes a debt-to-assets ratio. The question is whether this correlation will lead to problems for the recession model due to multicollinearity. Multicollinearity occurs when independent variables in a regression model are correlated. This correlation is a problem because independent variables should be independent. If the degree of correlation between the two variables is high enough, it can cause problems when fitting the model and interpreting the results because it affects the coefficients and p-values. Therefore, it must be decided whether one of the two variables should be excluded or both should be kept in the model. However, multicollinearity only affects the specific variables that are correlated. A model can have severe multicollinearity and yet some variables in the model can be completely unaffected. Therefore if multicollinearity exists for the control variables but not the experimental variables, the experimental variables can be interpreted without problems. Because the multicollinearity is not present in $ESG\_Disagreement_{i,t}$, the variable of interest, the issue of multicollinearity does not need to be resolved and both variables are kept in the sample. AF_DISP and LOSS also show a moderate positive correlation with a value of 0.39 at the 5% significance level. But, there is no risk of multicollinearity as ESG_Disagreement and LOSS show almost no correlation with a value of 0.006. Nor is the correlation significant at the 5% significance level.

In some cases, however, the Pearson coefficient is not appropriate. In this case, the Spearman coefficient is used. The Spearman's rank correlation is used when Pearson's correlation cannot be run due to violations of normality, a non-linear relationship or when ordinal variables are being used. To analyze the data using the Spearman coefficient, two assumptions must be met. Otherwise, the Spearman correlation may not produce valid results. First, the two variables should be measured on an ordinal or continuous scale. Second, there needs to be a monotonic relationship between the two variables. In this empirical study, Earninngs_Vol and BTM have a non-normal distribution. Therefore, the Pearson coefficient is not appropriate and the Spearman coefficient is used instead. Earnings_VOL and Size show a very strong positive correlation with a value of 0.87, which is significant at the 5% level. BTM and Earnings_VOL exhibit a weak positive correlation with a value of 0.32, which is also significant at the 5% level. In both cases, multicollinearity is not an issue.

7.3. Multivariate Analyses

Table 7 reports the OLS regression results. To test the goodness of fit of the regression model, R-squared is used. The R-squared value indicates how well the model explains the dependent variable's variance. The first model has a R-squared value of 0.001. Therefore, the model does not produce predictions that are reasonably precise. But, because the predictor of ESG_Disagreement is statistically significant, it can still be concluded that changes in ESG_Disagreement are associated with changes in AF_DISP. One limitation of R-squared is that it is invalid for nonlinear regression. To test whether the regression is linear, I examine the residuals plot (see Figure 7 in the annex). The residuals plot shows no signs of nonlinearity. I also examine the Significance F of the overall regression model. The Significance F represents the p-value for the overall regression model. This test shows whether a model with all its independent variables explains the variability of the dependent variable better than a model without any independent variables. The Significance of F for the first model is 0.019. Because 0.019 is lower than the 5% significance level, the regression model as a whole is statistically significant, i.e. the model fits the data better than the model with no predictor variables. The coefficient of ESG_Disagreement is 0.0557. Thus, the results suggest that ESG_Disagreement is positively associated with AF_Dispersion, supporting the hypothesis. Because both variables were transformed with the natural logarithm, changes cannot be expressed in absolute numbers, but only as percentages. Hence, the results suggest that when ESG disagreement increases by 1%, analyst forecast dispersion also increases by 5.57%.

The second model controls for the influence of other factors on analysts' forecast dispersion. I use only three control variables to address the problem of underspecification of the first model. An underspecified model, i.e., a model that is too simple, can lead to biased estimates. The second model also avoids the problem of overspecification caused by too many variables. A model that contains to many variables, i.e. is too complex, tends to reduce the precision of coefficient estimates and predicted values. Furthermore, I use the adjusted R-square to test the goodness of fit of the regression model. The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. It takes into account whether R-squared is higher because the predictors are better or just because the model has more predictors. The second model has an adjusted R-squared of 0.091. It is therefore compared to the first model better at explaining the variability in analyst forecast dispersion. The coefficient of ESG_Disagreement is 0.0534. The association between ESG disagreement and analyst forecast dispersion remains positive and significant at the 5% level. The third model adds additional control variables. It has an adjusted R-squared value of 0.223. Figures 8 and 9 in the annex show the residual plots for models two and three, respectively. Both residual plots show no sign of a nonlinear regression. The coefficient of ESG_Disagreement is 0.0408 and is statistically significant at the 10% level. To control for heteroskedasticity, I include robust standard errors in all three models. Heteroscedasticity refers to the unequal scatter of residuals. When heteroscedasticity is present in a regression analysis, the results of the analysis become hard to trust. Heteroscedasticity increases the variance of the regression coefficient estimates, but the regression model does not take this into account. As a result, a regression model is more likely to declare a parameter in the model to be statistically significant when it is in fact not. The fourth model controls for year-fixed and country-fixed effects. Fixed effects are commonly used in panel data analysis, to account for unobserved heterogeneity. By including fixed effects, individual-specific factors (e.g. individual attitudes, preferences and abilities) that remain constant over time are controlled for, ensuring that the regression results are not distorted by these unobserved factors. Fixed effects models thus help to mitigate the problem of omitted variable bias, which arises when important variables are excluded from the analysis (Collischon & Eberl, 2020, p. 291 f.). The fourth model has an adjusted R-squared value of 0.375. The coefficient of ESG_Disagreement is 0.0131. However, the coefficient is no longer statistically significant at the 10% level. Therefore, after removing the time-constant error term, there is no longer a significant positive relationship between ESG disagreement and analyst forecast dispersion. Hence, after accounting for unobserved heterogeneity, it is not possible to reach a conclusion about whether ESG disagreement is associated with the dispersion of analysts' forecasts.

8. Robustness Checks

One concern is the impact of outliers on the regression model. As discussed in Chapter 7.1, outliers or those treated as outliers (i.e., fat tails) can reduce the power of the regression model. In my regression model, there are several control variables that might affect its performance. First, the book-to-market-ratio is skewed. Second, earnings volatility and earnings surprise exhibit outliers (see Table 5). To test whether these control variables reduce the statistical power of the regression model, I transform all three variables with the natural logarithm and repeat the main analysis (see Table 22 in the annex). The first model uses only size, ln(BTM), and ZMIJ as control variables. It has an adjusted R-squared value of 0.091. The coefficient for ESG_Disagreement is 0.084. A 1% increase in ESG disagreement is associated with an 8.47% increase in analyst forecast dispersion. The coefficient is statistically significant at the 0.1% level, making it very unlikely that the result is due to chance. Next, I use all control variables. The second model has an adjusted R-squared value of 0.199. The coefficient of ESG_Disagreement is 0.042. The result is not statistically significant at the 10% level anymore. The third model again includes year-fixed and industry-fixed effects. It has an adjusted R-squared value of 0.379. The coefficient for ESG_Disagreement is 0.019. However, the result is also not statistically significant at the 10% level. The results are consistent with the main analysis.

Table 7: Regression results of the main analysis (Source: Own illustration)

	(1) AF_DISP	(2) AF_DISP	(3) AF_DISP	(4) AF_DISP
ESG_Disagreement	0.0557**	0.0534**	0.0408*	0.0131
	(0.019)	(0.020)	(0.060)	(0.540)
Size		0.0387***	0.0450***	-0.106***
		(0.000)	(0.000)	(0.000)
NANA			-0.086***	0.0804**
			(0.006)	(0.015)
BTM		305.9***	225.3***	231.4***
		(0.000)	(0.000)	(0.000)
Earnings_VOL			05.64e-11	3.47e-10**
			(0.563)	(0.036)
Earnings_Surprise			0.00014*	0.00012*
			(0.067)	(0.054)
Leverage			-3.717***	-4.064***
			(0.000)	(0.000)
ZMIJ		0.197***	0.684***	0.729***
		(0.000)	(0.000)	(0.000)
LOSS			1.085***	0.926***
			(0.000)	(0.000)
Year-Fixed Effects	No	No	No	Yes
Country-Fixed Effects	No	No	No	Yes
N	3,968	3,968	3,968	3,968
R-Square	0.001	0.092	0.225	0.385
Adjusted R-Square	0.001	0.091	0.223	0.375
F-Statistic	0.019	0.000	.	0.000

Note: P-values are below the coefficients in brackets. The significance levels are market with stars: * p<0.10, ** p<0.05, *** p<0.01.

Another concern is the influence of financial firms and utilities on the empirical results. It is a common approach in empirical finance to exclude financial firms. This is because their business model is highly different from other firms. Fama and French (1992, p. 429) state: "We exclude financial firms because the high leverage that is normal for these firms probably does not have the same meaning as for non-financial firms, where high leverage more likely indicates distress." Utilities are excluded due to their association with the state. State-owned firms are often not profit-oriented and are highly affected by governmental decisions. Their business model also differs from that of private firms in that they perform public functions. Utilities also have a very high leverage and an unusually high book-to-market ratios, which makes them highly sensitive to interest rate changes. For these reasons, utilities are usually excluded from empirical studies (Stack Exchange, 2023). Table 23 in the annex reports the empirical results without financials. The first model without control variables has an adjusted R-squared value of 0.001. The coefficient for ESG_Disagreement is 0.0606. The coefficient is statistically significant at the 5% level with a value of 0.010. The second model with three control variables has an adjusted R-squared value of 0.090. The coefficient for ESG_Disagreement is 0.0578. The coefficient is statistically significant at the 5% level with a value of 0.011. The third model with control variables has an adjusted R-squared value of 0.224. The coefficient for ESG_Disagreement is 0.0455. The coefficient is also statistically significant at the 5% level with a value of 0.034. The fourth model with fixed-effects has an adjusted R-squared value of 0.376. The coefficient for ESG_Disagreement is 0.0198. The coefficient is not statistically significant at the 10% level. Table 24 reports the empirical results without financial, utilities and real estate firms. Real estate firms are excluded due to their unusual high leverage. The first model has an adjusted R-squared value of 0.001. The coefficient for ESG_Disagreement is 0.0623. The coefficient is statistically significant at the 5% level with a value of 0.012. The second model has an adjusted R-squared value of 0.103. The coefficient for ESG_Disagreement is 0.0675. The coefficient is statistically significant at the 1% level with a value of 0.004. The third model has an adjusted R-squared value of 0.235. The coefficient for ESG_Disagreement is 0.0507. The coefficient is statistically significant at the 5% level with a value of 0.024. The fourth model has an adjusted R-squared value of 0.383. The coefficient for ESG_Disagreement is 0.0179. The coefficient is not statistically significant at the 10% level. The results of the main analysis are thus robust to the influence of financial firms, utilities, and real estate firms.

Afterwards, I test whether the relationship between ESG disagreement and analyst forecast dispersion is consistent over time. Table 8 shows the results. In 2018, the coefficient of ESG_Disagreement is 0.143. The coefficient is highly statistically significant at the 0.1% level. As a result, it is unlikely that the result is due to chance. A 1% increase in ESG disagreement leads to a 14.3% increase in analyst forecast dispersion. In 2019, the coefficient of ESG_Disagreement is 0.0938. The coefficient remains statistically significant at the 5% level with a value of 0.016. In 2020, the coefficient of ESG_Disagreement is 0.0281. However, the results are not significant at the 10% level. Accordingly, it cannot be ruled out that the results are due to chance. In 2021, the relationship between ESG_Disagreement and AF_DISP turns negative with a value of -0.02263. The result is also not statistically significant at the 10% level. In 2022, there is an even stronger negative association between ESG_Disagreement and AF_DISP with a coefficient of -0.0930. The results remain not statistically significant at the 10% level. When examining the coefficients, it is evident that the relationship between ESG_Disagreement and AF_DISP is at first positive, but becomes negative over time. Also, with the exception of 2022, the strength of the relationship decreases over time. Moreover, the relationship between ESG_Disagreement AF_DISP is highly statistically significant in the years 2018 and 2019, but not significant in the last three years. Thus, the relationship between ESG disagreement and analyst forecast dispersion does not appear to be consistent over time. Next, I incorporate fixed effects and repeat the regression model. Table 25 in the appendix shows the results. Across all years, the coefficient for ESG disagreement remains statistically insignificant. The results remain robust to the main analysis.

Another concern is whether the association between ESG disagreement and the dispersion of analysts' forecasts is robust for different measures of ESG Disagreements. For this reason, I use three additional measures of ESG Disagreement that differ from ESG_Disagreement in their calculation (see Table 9). ESG_Disagreement_3 includes three ESG ratings, while ESG_Disagreement_4 and ESG_Disagreement_5 include four and five ESG ratings, respectively. In the first model without control variables, the coefficient for ESG_disagreement_3 is 0.0517 and significant at the 5% level. The second model with three control variables has a coefficient of 0.0440 and is significant at the 10% level. The third model with all control variables, ESG_Disagreement has a coefficient of 0.0349. The result is not significant at the 10% level. The fourth model with year fixed and country fixed effects has a coefficient for ESG_Disagreement_3 of 0.0180. It is not statistically significant at the 10% level with a value of 0.391, so there is a high chance that the result is due to chance.

The results for ESG_disagreement_4 and ESG_disagreement_5 are both highly not statistically significant. Thus, there is a high probability that the results are due to chance. The results with control variables are tabulated in model five and six in Table 9. As can be seen, the number of observations for both models is rather low. A larger sample may provide more precise estimates and more significant results.

Next, I disaggregate ESG ratings into its pillar scores to examine the extent to which environmental, social, and governmental issues account for the influence of ESG disagreement on analyst forecast dispersion. As can be seen in Table 10, all results for the influence of the pillar scores are highly non-significant. Thus, there is a high probability that the results are due to chance. Consequently, no conclusive statement can be made about which issues are driving the positive association between ESG_Disagreement and analyst forecast dispersion.

In total, the findings of this master thesis do not provide sufficient evidence to support a significant association between ESG disagreement and analyst forecast dispersion. Thus, it cannot be concluded with confidence that the disagreement among ESG rating agencies influences the dispersion of analyst EPS forecasts. In other words, the disagreement between ESG rating agencies regarding a firm's non-financial ESG performance does not seem to have a discernible impact on analysts' uncertainty about the firm's future earnings. These results have important implications for practitioners, suggesting that non-financial ESG criteria may not play a substantial role in analysts' evaluation of a firm's financial performance.

9. Limitations and Future Research Opportunities

9.1. Limitations

There are several limitations that may affect the validity and reliability of the results of this empirical study. One limitation is that the results are biased by the selection of ESG rating providers. In this empirical study, ESG ratings from Refinitiv Eikon, MSCI, S&P, ISS and Sustainalytics were used. The results may not be reproducible with ESG ratings from other ESG rating providers, as the degree of disagreement between ESG rating providers varies. Another limitation is the omitted variable bias caused by confounding variables. Omitted variable bias refers to the bias that can occur in regression analysis when an important independent variable is left out of the model. The omitted variable bias occurs because cofounding variables are still affecting the dependent variable, but their effects are absorbed by the error term in the regression model. For example, analyst forecast dispersion could be influenced by the forecast horizon. The further away a forecast is from a firm's actual earnings announcement, the more uncertain the forecast (Chopra, 1998, p. 37). Although the inclusion of fixed effects helps to mitigate endogeneity concerns and control for time-constant factors, it can not completely eliminate the possibility of omitted variable bias. Fixed effects models assume that the unobserved heterogeneity across firms and time periods is adequately captured by the fixed effects variables. However, if there are additional unobserved variables that are correlated with both

Table 8: ESG Disagreement over time (Source: Own illustration)

	(1) AF_DISP -2018-	(2) AF_DISP -2019-	(3) AF_DISP -2020-	(4) AF_DISP -2021-	(5) AF_DISP -2022-
ESG_Disagreement	0.143***	0.0938**	0.0281	-0.0263	-0.0930
	(0.000)	(0.016)	(0.533)	(0.569)	(0.441)
Size	0.0242	0.0534***	0.0909***	-0.0216	0.00126
	(0.117)	(0.000)	(0.000)	(0.169)	(0.957)
NANA	-0.0420	0.0606	-0.204***	-0.126	0.0465
	(0.524)	(0.338)	(0.002)	(0.169)	(0.602)
BTM	245.8***	208.6***	213.5***	159.4***	237.3**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)
Earnings_VOL	3.75e-10*	1.79e-11	-3.55e-10**	4.11e-10*	-2.28e-10
	(0.067)	(0.924)	(0.040)	(0.072)	(0.742)
Earnings_Surprise	0.00005	-0.0002	0.00003	0.0005***	0.0005***
	(0.760)	(0.145)	(0.841)	(0.000)	(0.006)
Leverage	-6.121***	-6.641***	-3.976***	-1.691*	-0.602
	(0.000)	(0.000)	(0.000)	(0.055)	(0.650)
ZMIJ	1.051***	1.148***	0.792***	0.309**	0.133
	(0.000)	(0.000)	(0.000)	(0.026)	(0.520)
LOSS	0.665***	0.971	0.982***	1.224***	1.591***
	(0.001)	(0.262)	(0.000)	(0.000)	(0.000)
N	785	1,048	1,053	752	330
R-Square	0.228	0.213	0.277	0.232	0.257
Adjusted R-Square	0.219	0.206	0.270	0.222	0.236

Note: P-values are below the coefficients in brackets. The significance levels are market with stars: * p<0.10, ** p<0.05, *** p<0.01.

ESG disagreement and analyst forecast dispersion, the estimated coefficients may still be biased by time-varying heterogeneity (Collischon & Eberl, 2020, p. 292 f.). There is also the problem of endogeneity. Endogeneity refers to the situation in which the independent variables in a regression model are affected by the dependent variable. This can create a circular relationship between the variables, causing a bias in the estimates of the model parameters. Financial analysts use financial and non-financial information to evaluate a firm's financial performance. ESG rating providers may use financial analysts' non-financial assessment as an input for their own ESG performance assessment. Another problem is the opaqueness of ESG rating agencies' methodologies. ESG rating agencies attach different weights to their pillar scores. This makes it difficult to compare the pillar scores of different ESG rating providers if they are not directly comparable, as is the case with Sustainalytics. The assumption that the pillar scores are equally weighted distorts the results if the true weightings vary. Another problem of this empirical study is the data availability for the E/S/G pillar scores. The small sample size resulting from the lack of freely available pillar scores leads to inaccurate conclusions and reduces the generalizability of the results.

9.2. Future Research Opportunities

Future researchers could address some of the limitations mentioned in the previous chapter. They could address the selection bias by using different ESG rating providers in their study to see if the results remain consistent as the level of disagreement between ESG rating providers changes. They could also use different control variables in their empirical study that could better reflect changes in the dispersion of analyst forecasts and thus reduce the risk of variable omission. They further could address endogeneity concerns by controlling for prior disclosed nonfinancial information from financial analysts. In addition, future researchers could use pillar scores that are directly comparable or find a way to make pillar scores more comparable. To some extent, improved transparency in ESG rating providers' methodologies should also help. Or, they could examine whether environmental, social, or governance issues are responsible for the positive association between ESG disagreement and analyst forecast dispersion. Another interesting research direction would be to examine how changes in ESG disagreement affect the dispersion of analysts' forecasts. In this study, the levels of ESG disagreement were analyzed. However, certain information from the previous ESG ratings may already available be to financial analyst. Therefore, changes in ESG information in particular may be responsible for variations in analysts' forecasts. Yet another interesting research direction would be to

Table 9: Alternative measures of ESG disagreement (Source: Own illustration)

	(1) AF_DISP	(2) AF_DISP	(3) AF_DISP	(4) AF_DISP	(5) AF_DISP	(6) AF_DISP
ESG_Disagreement_3	0.0517**	0.0440*	0.0349	0.0180		
	(0.029)	(0.053)	(0.107)	(0.391)		
ESG_Disagreement_4					-0.0227	
					(0.823)	
ESG_Disagreement_5						-0.0548
						(0.799)
Size		0.0458***	0.0515***	-0.106***	-0.0641	-0.0805
		(0.000)	(0.000)	(0.000)	(0.446)	(0.385)
NANA			-0.0832**	0.0790**	0.139	0.107
			(0.012)	(0.021)	(0.415)	(0.642)
BTM		307.6***	223.4***	232.0***	292.1*	251.8
		(0.000)	(0.000)	(0.000)	(0.105)	(0.213)
Earnings_VOL			1.14e-11	3.34e-10**	2.35e-10	3.52e-11
			(0.906)	(0.041)	(0.856)	(0.981)
Earnings_Surprise			1.27e-4	1.09e-4*	7.16e-4*	6.60e-4
			(0.111)	(0.085)	(0.063)	(0.138)
Leverage			-4.078***	-4.495***	-1.987	-2.247
			(0.000)	(0.000)	(0.256)	(0.268)
ZMIJ		0.202***	0.746***	0.799***	0.445*	0.468
		(0.000)	(0.000)	(0.000)	(0.100)	(0.138)
LOSS			1.054***	0.882***	1.155***	1.114***
			(0.000)	(0.000)	(0.000)	(0.001)
Year-Fixed Effects	No	No	No	Yes	Yes	Yes
Country Fixed Effects	No	No	No	Yes	Yes	Yes
N	3,783	3,783	3,783	3,783	141	127
R-Square	0.001	0.096	0.228	0.392	0.428	0.405
Adjusted R-Square	0.001	0.095	0.227	0.382	0.344	0.303

Note: P-values are below the coefficients in brackets. The significance levels are market with stars: * p<0.10, ** p<0.05, *** p<0.01.

investigate the influence of non-financial disclosure regulations on the association between ESG disagreement and analyst forecast dispersion. Researchers could use a difference-in-difference design to control whether the introduction of a non-disclosure regulation is associated with greater analyst forecast dispersion. There are two non-financial disclosure regulations that are of particular interest. On is the European Union's NFRD, which requires all firms covered by the directive to report for the first time for the 2017 financial year on non-financial issues (Hankamper-Vandebulcke, 2021, p. 4). The other is an amendment to the Financial Instruments Exchange Act of Japan, which requires listed firms in Japan with a current fiscal year-end to report on ESG issues by March 2023 (Tomoko & Kyoko, 2022). Both are of interest for a difference-in-difference design. Unfortunately, due to the chosen time period of this sample, it is not possible to apply such a difference-in-difference design to this empirical study.

10. Conclusion

Non-financial ESG information has become an increasingly important source of information for the investment community, as it allows for a more thorough assessment of a firm's long-term risks and opportunities. One important group that relies on non-financial ESG information are financial analysts. Financial analysts use non-financial information alongside traditional financial information to inform their forecasts. However, ESG information often lack standardization and are difficult to compare. For this reason, financial analysts increasingly rely on ESG rating agencies as third-party information intermediaries to make sense of available ESG information. ESG rating agencies aggregate the available ESG information and produce ESG ratings by assessing a firm's ESG performance. Those ESG ratings intend to inform investors about a firm's ability to cope with long-term risks and opportunities. However, ESG rating agencies disagree on what constitutes as good ESG performance. This leads to sometimes widely divergent ESG ratings. The reason ESG rating agencies tend to disagree is

Table 10: E/S/G Disagreement (Source: Own illustration)

	(1) AF_DISP	(2) AF_DISP	(3) AF_DISP	(4) DISP	(5) DISP	(6) AF_DISP
E_Disagreement	-0.0340	0.0224				
	(0.734)	(0.839)				
S_Disagreement			-0.0813	-0.0308		
			(0.536)	(0.777)		
G_Disagreement					-0.0893	-0.0206
					(0.465)	(0.862)
Size	0.0436	-0.00984	0.0360	-0.0187	0.0336	-0.0137
	(0.441)	(0.931)	(0.541)	(0.872)	(0.552)	(0.904)
NANA	-0.277	-0.381	-0.282	-0.403	-0.281	-0.403
	(0.441)	(0.343)	(0.248)	(0.306)	(0.250)	(0.306)
BTM	467.1***	386.8	423.8**	351.9	438.5***	367.1
	(0.001)	(0.105)	(0.014)	(0.165)	(0.004)	(0.133)
Earnings_VOL	-6.58e-10	-3.84e-10	-4.29e-10	-2.65e-10	-4.54e-10	-3.05e-10
	(0.319)	(0.796)	(0.541)	(0.862)	(0.525)	(0.842)
Earnings_Surprise	0.0004**	0.0003	0.0004**	0.0003	0.0004**	0.0003
	(0.024)	(0.155)	(0.019)	(0.151)	(0.029)	(0.157)
Leverage	-2.142	-1.314	-2.356	-1.390	-2.238	-1.350
	(0.470)	(0.585)	(0.432)	(0.565)	(0.444)	(0.575)
ZMIJ	0.322	0.328	0.354	0.329	0.327	0.322
	(0.479)	(0.389)	(0.443)	(0.387)	(0.465)	(0.398)
LOSS	0.926***	0.968*	0.929***	0.984*	0.910***	0.977**
	(0.006)	(0.093)	(0.004)	(0.088)	(0.008)	(0.090)
Year-Fixed Effects	No	Yes	No	Yes	No	Yes
Country Fixed Effects	No	Yes	No	Yes	No	Yes
N	83	79	83	79	83	79
R-Square	0.236	0.413	0.241	0.414	0.241	0.413
Adjusted R-Square	0.142	0.262	0.148	0.262	0.148	0.262

Note: P-values are below the coefficients in brackets. The significance levels are market with stars: * p<0.10, ** p<0.05, *** p<0.01.

because they differ in scope, weighting, and measurement of ESG information. Because ESG rating agencies compete with each other for market share, there is no single approach to ESG rating methodologies. In addition, ESG rating methodologies are not fully transparent. As financial analysts seek to understand ESG ratings and their underlying data, they obtain their own private information, leading to divergent opinions about a firm's long-term risks and opportunities.

The objective of this master thesis was to empirically investigate the influence of ESG rating disagreement on analyst forecast dispersion in an international setting. Prior research based on Kimbrough et al. (2022) found a positive association between ESG rating disagreement and analyst forecast dispersion for firms in the US. The first regression model without control variables shows that there is indeed a statistically significant relationship between ESG disagreement and analyst forecast dispersion. The coefficient of ESG disagreement is 0.0557 and is statistically significant at the 5% level. Because both ESG disagreement and analyst forecast dispersion were transformed with the natural logarithm, a 1% increase in ESG disagreement is associated with a 5.57% increase in analyst forecast dispersion. However, the first model has a low R-squared value and therefore does not produce predictions that are reasonably precise. The introduction of control variables increases the predictability of the empirical model. The second (third) model with three (eight) control variables are also statistically significant at the 5% (10%) level. A 1% increase in ESG disagreement is associated with a 5,34% (4,08%) increase in analyst forecast dispersion. However, the inclusion of year and country fixed effects within the regression model leads to a notable shift in the nature of the obtained results, yielding statistically non-significant findings. To ensure the validity and reliability of these findings, I employ several robustness checks. First, I address the presence of skewed distributions in some of the control variables by applying a natural logarithm transformation. This transformation helps to control for outliers that might influence the regression model. After implementing this adjustment, the results remain consistent with the main findings, providing additional confidence in the robustness of the findings. Second, I exclude financial firms and utilities from the analysis due to their fundamentally distinct nature from private firms. Additionally, real estate firms are excluded due to their unusually high levels of leverage. Despite these exclusions, the results remain consistent with the main findings, reinforcing the stability of the observed relationships. Third, I examine the time consistency of the relationship between ESG disagreement and analyst forecast dispersion. However, there is a deviation from the main results in the years 2018 and 2019. This incon-sistency prompts further investigation into the potential factors driving the variation and underscores the need for cautious interpretation of the more distant results. Fourth, alternative measures of ESG disagreement are employed to assess their impact on the results. Despite these variations in measurement, the main findings remain unchanged, indicating robustness in the relationship between ESG disagreement and analyst forecast dispersion. Fifth, I explore the individual influence of environmental, social, and governance factors on analyst forecast dispersion. However, due to the small sample size, the results are not statistically significant and cannot be considered representative. Overall, the empirical results remain robust after performing several robustness checks. Hence, no definitive conclusion can be drawn regarding the influence of ESG disagreement on the dispersion of analysts' forecasts.

These findings hold significant implications for practitioners, particularly those involved in the investment industry, as they challenge the relevance of non-financial ESG information provided by ESG rating agencies in informing financial analysts' forecasts. This master thesis also presents opportunities for further research in the field. Potential avenues include investigating the influence of environmental, social, and governance (ESG) criteria on analyst forecast dispersion, or employing a difference-in-difference design to study the effects of new non-financial disclosure requirements. For instance, researchers could explore the impact of regulatory frameworks like the European Non-Financial Reporting Directive (NFRD), which predates the sample period covered in this study, or the recent amendment to the Financial Instruments Exchange Act of Japan which mandates listed firms in Japan to include ESG information in their current fiscal year reporting by March 2023.

References

Abarbanell, J. S., Lanen, W. N., & Verrecchia, R. E. (1995). Analysts' forecasts as proxies for investor beliefs in empirical research. *Journal of Accounting and Economics*, *20*(1), 31–60.

Ackert, L. F. (1997). Prior Uncertainty, Analyst Bias, and Subsequent Abnormal Returns. *The Journal of Financial Research*, *20*(2), 263–273.

Ajinkya, B. B., Atiase, R. K., & Gift, M. J. (1991). Volume of Trading and the Dispersion in Financial Analysts' Earnings Forecasts. *The Accounting Review*, *66*(2), 389–401.

Allen, K. (2018). Lies, damned lies and ESG rating methodologies. Financial Times. Retrieved September 30, 2022, from https://www.ft.com/content/2e49171b-a018-3c3b-b66b-81fd7a170ab5

Asquith, P., & Weiss, L. A. (2016). *Lessons in Corporate Finance*. New Jersey.

Athanassakos, G., & Kalimipalli, M. (2003). Analyst Forecast Dispersion and Future Stock Return Volatility. *Quarterly Journal of Business and Economics*, *42*(1 & 2), 57–78.

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2009). Dispersion in analysts' earnings forecasts and credit rating. *Journal of Financial Economics*, *91*(1), 83–101.

Barefield, R. M., & Comiskey, E. E. (1975). The Accuracy of Analysts' Forecasts of Earnings per Share. *Journal of Business Research*, *3*(3), 241–252.

Barker, R. G. (1998). The market for information—evidence from finance directors, analysts and fund managers. *Accounting and Business Research*, *29*(1), 3–20.

Barron, O. E., Kim, O., Lim, S. C., & Douglas, E. S. (1998). Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment. *The Accounting Review*, *73*(4), 421–433.

Barron, O. E., Standford, M. H., & Yu, Y. (2010). Further Evidence on the Relation between Analysts' Forecast Dispersion and Stock Returns. *Contemporary Accounting Research*, *26*(2), 329–357.

Barry, C. B., & Jennings, R. H. (1992). Information and Diversity of Analyst Opinion. *The Journal of Financial and Quantitative Analysis*, *27*(2), 169–183.

Beckers, S., Steliaros, M., & Thomson, A. (2004). Bias in European Analysts' Earnings Forecasts. *Financial Analysts Journal*, *60*(2), 74–85.

Behn, B. K., Choi, J.-H., & Kang, T. (2008). Audit Quality and Properties of Analyst Earnings Forecasts. *The Accounting Review*, *83*(2), 327–349.

Belnap, A. (2022). The effect of intermediary coverage on disclosure: Evidence from a randomized field experiment [Corrected proof in press]. *Journal of Accounting and Economics*.

Benston, G. J. (1973). AssociationRequired Disclosure and the Stock Market: An Evaluation of the Securities Exchange Act of 1934. *The American Economic Review*, *63*(1), 132–155.

Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings. *Review of Finance*, *26*(6), 1315–1344.

Berk, J., & van Binsbergen, J. H. (2021). *The Impact of Impact Investing* [Working Paper No. 3981, Stanford University Graduate School of Business].

Beunza, D., & Garud, R. (2007). Calculators, Lemmings or Frame-Makers? The Intermediary Role of Securities Analysts. *The Sociological Review*, *55*(2), 13–39.

Bloomberg. (2022). ESG May Surpass $41 Trillion Assets in 2022, But Not Without Challenges, Finds Bloomberg Intelligence. Press Release. Retrieved December 6, 2022, from https://www.bloomberg.com/company/press/esg-may-surpass-41-trillion-assets-in-2022-but-not-without-challenges-finds-bloomberg-intelligence/

BNP Paribas. (2019). The ESG Global Survey 2019. Retrieved December 5, 2022, from https://securities.cib.bnpparibas/app/uploads/sites/3/2019/08/esg-global-survey-en-2019.pdf

Boffo, R., & Patalano, R. (2020). ESG Investing: Practices, Progress and Challenges. Retrieved December 5, 2022, from www.oecd.org/finance/ESG-Investing-Practices-Progress-and-Challenges.pdf

Brackley, A., Brock, E. K., & Nelson, J. (2022). Rating the Raters Yet Again: Increasing ESG Scrutiny Makes Current Rate the Raters Study Even More Crucial. Sustainability. Retrieved December 15, 2022, from https://www.sustainability.com/thinking/rating-the-raters-yet-again-increasing-esg-scrutiny-makes-current-rate-the-raters-study-even-more-crucial/

Brown, R., Chan, H. W. H., & Ho, Y. K. (2009). Analysts' recommendations: from which signal does the market take its lead? *Review of Quantitative Finance and Accounting*, *33*, 91–111.

Byard, D., Li, Y., & Yu, Y. (2011). The Effect of Mandatory IFRS Adoption on Financial Analysts' Information Environment. *Journal of Accounting Research*, *49*(1), 69–96.

Capital Group. (2021). ESG Global Study 2021. Retrieved January 12, 2023, from https://www.capitalgroup.com/content/dam/cgc/tenants/eacg/esg/global-study/esg-global-study-full-report(en).pdf

Capstaff, J., Paudyal, K., & Rees, W. (1995). The Accuracy and Rationality of Earnings Forecasts by UK Analysts. *Journal of Business Finance & Accounting*, *22*(1), 67–85.

CFA Institute. (2020). Future of Sustainability in Investment Management: From Ideas to Reality. Retrieved November 5, 2022, from https://www.cfainstitute.org/-/media/documents/survey/future-of-sustainability.pdf

Chatterji, A., & Levine, D. (2006). Breaking Down the Wall of Codes: Evaluating Non-Financial Performance Measurement. *California Management Review*, *48*(2), 29–51.

Cho, S.-Y., Lee, C., & Pfeiffer, R. J. (2013). Corporate Social Responsibility Performance Information and Information Asymmetry. *Journal of Accounting and Public Policy*, *32*(1), 71–83.

Chopra, V. K. (1998). Why So Much Error in Analysts' Earnings Forecasts? *Financial Analysts Journal*, *54*(6), 35–42.

Christensen, D., Serafeim, G., & Sikochi, A. (2021). Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings. *Accounting Review*, *97*(1), 147–175.

Cision. (2020). Morningstar to Acquire Sustainalytics and Expand Access to ESG Research, Data, and Analytics for Investors Worldwide. PR Newswire. Retrieved November 25, 2022, from https://www.prnewswire.com/news-releases/morningstar-to-acquire-sustainalytics-and-expand-access-to-esg-research-data-and-analytics-for-investors-worldwide-301044196.html

Collischon, M., & Eberl, A. (2020). Let's Talk About Fixed Effects: Let's Talk About All the Good Things and the Bad Things. *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*, *72*(2), 290–299.

Cornell, B. (2020). ESG preferences, risk and return. *European Financial Management*, *27*(1), 12–19.

Cowles, A. (1933). Can Stock Market Forecasters Forecast? *Econometrica*, *1*(3), 309–324.

Cui, J., Jo, H., & Na, H. (2018). Does Corporate Social Responsibility Affect Information Asymmetry? *Journal of Business Ethics*, *148*(3), 549–572.

D. E. Shaw. (2022). Keep the Change: Analyzing the Increase in ESG Ratings for U.S. Equities. Retrieved January 3, 2023, from https://www.deshaw.com/assets/articles/DESCO_Market_Insights_ESG_Ratings_20220408.pdf

De Bondt, W. F. M., & Forbes, W. P. (1999). Herding in analyst earnings forecasts: evidence from the United Kingdom. *European Financial Management*, *5*(2), 143–163.

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1996). Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC. *Contemporary Accounting Research*, *13*(1), 1–36.

Deloitte. (2021). ESG Ratings: do they add value? How to get prepared? Deloitte. Retrieved November 28, 2022, from https://www2.deloitte.com/ce/en/pages/about-deloitte/articles/esg-ratings-do-they-add-value.html

Deloitte. (2022). What is ESG? Deloitte. Retrieved December 5, 2022, from https://www2.deloitte.com/hu/en/pages/energy-and-resources/articles/e.html

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance*, *57*(5), 2113–2141.

Dillenburg, S., Greene, T., & Erekson, H. (2003). Approaching Socially Responsible Investment with a Comprehensive Ratings Scheme: Total Social Impact. *Journal of Business Ethics*, *43*(3), 167–177.

Doyle, T. M. (2018). Ratings That Don't Rate. Washington D.C. Retrieved November 4, 2022, from https://accfcorpgov.org/wp-content/uploads/2018/07/ACCF_RatingsESGReport.pdf

Dreman, D. N., & Berry, M. A. (1995). Analyst Forecasting Errors and Their Implications for Security Analysis. *Financial Analysts Journal*, *51*(3), 30–41.

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*(2), 333–360.

Dyck, A., Morse, A., & Zingales, L. (2006). Who Blows the Whistle on Corporate Fraud? *The Journal of Finance*, *65*(6), 2213–2253.

Escrig-Olmedo, E., Fernández-Izquierdo, M. A., 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), 1–16.

European Parliament and of the Council. (2014). Directive 2014/95/EU of the European Parliament and of the Council of 22 October 2014. *L 330*, 1–9. Official Journal of the European Union.

Fama, F. E., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465.

Fish, A. J. M., Kim, D. H., & Venkatraman, S. (2019). The ESG Sacrifice. Retrieved December 5, 2022, from http://dx.doi.org/10.2139/ssrn.3488475

Fisher, K. (2019). November 1867: The Invention of the Stock Ticker. Ken Fisher. Retrieved November 4, 2022, from https://www.kenfisher.com/market-history/november-1867-the-invention-of-the-stock-ticker

Frankel, R., & Li, X. (2004). Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders. *Journal of Accounting and Economics*, *37*(2), 229–259.

Gell, S. (2011). *Determinants of Earnings Forecast Error, Earnings Forecast Revision and Earnings Forecast Accuracy* [Doctoral dissertation, University of Cologne].

Giese, G., Lee, L.-E., Melas, D., Nagy, Z., & Nishikawa, L. (2019). Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance. *The Journal of Portfolio Management*, *45*(5), 69–83.

Gilbert, M. (2021). The Rising Cost of Investing Responsibly. Bloomberg Opinion. Retrieved November 4, 2022, from https://www.bloomberg.com/opinion/articles/2019-01-11/the-rising-cost-of-esg-and-socially-responsible-investing?leadSource=uverify%20wall

Givoly, D., & Lakonishok, J. (1980). Financial Analysts' Forecasts of Earnings. *Journal of Banking and Finance*, *4*(2), 221–233.

Global Sustainable Investment Alliance (GSIA). (2021). Global Sustainable Investment Review 2020. Retrieved November 4, 2022, from http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf

Google Trends. (2022). ESG. Google Trends. Retrieved December 10, 2022, from https://trends.google.com/trends/explore?date=today%205-y&q=esg

Governance & Accountability Institute. (2022). Sustainability Reporting in Focus. Governance & Accountability Institute. Retrieved December 12, 2022, from http://www.ga-institute.com/fileadmin/ga_institute/images/FlashReports/2022/G_A-2022-Sustainability_Trends_Report.pdf?vgo_ee=fmIveivJ13fn9Ym%2FtP4nyNSYFmrMikCwlKFARSZoYAo%3D

Graham, B., & Dodd, D. L. (1934). *Security Analysis* (1st).

Graham, B., & Dodd, D. L. (2009). *Security Analysis* (6th).

Graham, J. R. (1999). Herding among investment newsletters: Theory and evidence. *The Journal of Finance*, *54*(1), 237–268.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The Economic Implications of Corporate Financial Reporting. *Journal of Accounting and Economics*, *40*(1-3), 3–73.

Groysberg, B., Healy, P., & Chapman, C. (2008). Buy-Side vs. Sell-Side Analysts' Earnings Forecasts. *Financial Analysts Journal*, *64*(4), 25–39.

Han, B. H., & Manry, D. (2000). The Implications of Dispersion in Analysts' Earnings Forecasts for Future ROE and Future Returns. *Journal of Business Finance & Accounting*, *27*(1-2), 99–125.

Hankamper-Vandebulcke, N. (2021). Non-financial Reporting Directive. Retrieved February 3, 2023, from https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/654213/EPRS_BRI(2021)654213_EN.pdf

Healy, P. M., & Palepu, K. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, *31*(1-3), 405–440.

Henisz, W., Koller, T., & Nuttall, R. (2019). Five ways that ESG creates value. Retrieved November 5, 2022, from http://dln.jaipuria.ac.in:8080/jspui/bitstream/123456789/2319/1/Five-ways-that-ESG-creates-value.pdf

Hespenheide, E. J., & Koehler, D. A. (2013). Disclosure of long-term business value – What matters? Retrieved December 15, 2022, from https://www2.deloitte.com/content/dam/insights/us/articles/disclosure-of-long-term-business-value/DUP150_Reporting_What_Matters.pdf

Higgins, H. N., & Saito, Y. (2007). Do Analysts Play an Information Intermediary Role? Evidence from High and Low Intangible Firms. *SSRN*, 1–28.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, *64*(5), 2289–2325.

Hong, H., & Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *Journal of Finance*, *58*(1), 313–351.

Hong, H., Kubik, J. D., & Solomon, A. (2000). Security Analysts' Career Concerns and Herding of Earnings Forecasts. *The RAND Journal of Economics*, *31*(1), 121–144.

Hope, O.-K. (2003). Accounting Policy Disclosures and Analysts' Forecasts. *Contemporary Accounting Research*, *20*(2), 295–321.

Hou, J., Zhao, S., & Yang, H. (2020). Individual analysts, stock return synchronicity and information efficiency. *International Review of Financial Analysis*, *71*, 1–39.

Hwang, L. S., Jan, C.-L., & Basu, S. (2014). Loss Firms and Analysts's Earnings Forecast Errors. *The Journal of Financial Statement Analysis*, *1*(2), 18–30.

Imhoff, E. A., & Lobo, G. J. (1992). The Effect of Ex Ante Earnings Uncertainty on Earnings Response Coefficients. *The Accounting Review*, *67*(2), 427–439.

ISS ESG. (2022). ESG Corporate Rating. Retrieved January 22, 2023, from bit.ly/3QYAfiL

Jacobson, T. C. (1997). *From Practice to Profession: A History of the Financial Analysts Federation and the Investment Profession*.

Jennings, R. H. (1985). *Reaction of Financial Analysts to Management Earnings Forecasts*.

Johnson, T. C. (2004). Forecast Dispersion and the Cross Section of Expected Returns. *The Journal of Finance*, *59*(5), 1957–1978.

Jones, C. P., & Litzenberger, R. H. (1970). Quarterly Earnings Reports and Intermediate Stock Price Trends. *The Journal of Finance*, *25*(1), 143–148.

Kempf, A., & Osthoff, P. (2007). The effect of socially responsible investing on portfolio performance. *European Financial Management*, *13*(5), 908–922.

Kendall, M. G., & Hill, A. B. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society*, *116*(1), 11–34.

Ketchum, M. D. (1967). Is financial analysis a profession? *Financial Analysts Journal*, *23*(6), 33–37.

Keynes, J. M. (2018). *The General Theory of Employment, Interest, and Money*.

Kimbrough, M., Wang, X., Wei, S., & Zhang, J. (2022). Does voluntary ESG reporting resolve disagreement among ESG rating agencies? [Forthcoming]. *European Accounting Review*.

Klettke, T. (2013). *New Determinants of Analysts' Earnings Forecast Accuracy* [Doctoral dissertation, University of Cologne].

Knorr-Cetina, K. (2011). Financial Analysis. In C. Camic, N. Gross, & M. Lamont (Eds.), *Social Knowledge in the Making* (pp. 405–441).

Koller, T., Goedhart, M., & Wessels, D. (2020). *Valuation: Measuring and Managing the Value of Companies* (7th).

Kotsantonis, S., & Serafeim, G. (2019). Four Things No One Will Tell You About ESG Data. *Journal of Applied Corporate Finance*, *31*(2), 50–58.

Kross, W., Ro, B., & Schroeder, D. (1990). Earnings Expectations: The Analysts' Information Advantage. *The Accounting Review*, *65*(2), 461–476.

Krueger, P., Sautner, Z., Tang, D. Y., & Zhong, R. (2021). The Effects of Mandatory ESG Disclosure Around the World. (754), 1–66.

LaBella, M. J., Sullivan, L., Russel, J., & Novikov, D. (2019). The Devil is in the Details: The Divergence in ESG Data and Implications for Responsible Investing. Retrieved January 2, 2023, from https://bit.ly/3WY6n7N

Lang, M. H., & Lundholm, R. J. (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review*, *71*(4), 467–492.

Larcker, D. F., Pomorski, L., Tayan, B., & Watts, E. M. (2022). ESG Ratings: A Compass without Direction [Forthcoming].

Leins, S. (2018). *Stories of Capitalism: Inside the Role of Financial Analysts*.

Lu, S. (2021). Algorithmic Opacity, Private Accountability, and Corporate Social Disclosure in the Age of Artificial Intelligence. *Vanderbilt Journal of Entertainment & Technology Law*, *23*(1), 99–159.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417.

Mars, F. (1998). *Wir sind alle Seher: Die Praxis der Aktienanalyse*.

McClure, B. (2022). Earnings Forecasts: A Primer. Investopedia. Retrieved December 18, 2022, from https://www.investopedia.com/articles/stocks/06/earningsforecasts.asp

McDonald, C. L. (1973). An Empirical Examination of the Reliability of Published Predictions of Future Earnings. *The Accounting Review*, *48*(3), 502–510.

McKibben, W. (1972). Econometric Forecasting of Common Stock Investment Returns: A New Methodology using Fundamental Operating Data. *The Journal of Finance*, *27*(2), 371–380.

Morningstar. (2021). Enterprise Sustainability Report. Retrieved November 25, 2022, from https://assets.contentstack.io/v3/assets/blt4eb669caa7dc65b2/blt3ad3261518bad875/2021_Enterprise_Sustainability_Report.pdf

MSCI. (2019). MSCI to Strengthen Climate Risk Capability with Acquisition of Carbon Delta. Retrieved November 26, 2022, from https://ir.msci.com/node/15706/pdf

MSCI. (2022a). ESG Ratings Key Issue Framework. Retrieved November 26, 2022, from https://www.msci.com/ousolutions/esg-investing/esg-ratings/esg-ratings-key-issue-framework

MSCI. (2022b). MSCI ESG Ratings Methodology. Retrieved November 4, 2022, from https://www.msci.com/documents/1296102/21901542/ESG-Ratings-Methodology-Exec-Summary.pdf

MSCI ESG Research. (2022). SEC Investment Adviser Firm Summary - Part 2 Brochures. Retrieved November 26, 2022, from https://files.adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=762070

Nagy, Z., Kassam, A., & Lee, L.-E. (2016). Can ESG Add Alpha? An Analysis of ESG Tilt and Momentum Strategies. *The Journal of Investing*, *25*(2), 113–124.

Nagy, Z., Lee, L.-E., & Giese, G. (2020). ESG Ratings: How the Weighting Scheme Affected Performance. MSCI Blog. Retrieved December 18, 2022, from https://www.msci.com/www/blog-posts/esg-ratings-how-the-weighting/01944696204

Ninety One. (2022). Ninety One survey finds European fund industry overly reliant on ESG scores. Ninety One. Retrieved December 7, 2022, from https://ninetyone.com/en/united-states/newsroom/ninety-one-survey-finds-european-fund-industry-overly-reliant-on-esg-scores

Nomura. (2022). How Artificial Intelligence is Reshaping ESG Ratings. Retrieved December 16, 2022, from https://d1qfwzw6aggd4h.cloudfront.net/about/ESG-Evaluation-using-AI-A4.pdf

Novethic. (2014). Overview of ESG Rating Agencies. Retrieved November 25, 2022, from https://www.novethic.fr/fileadmin/user_upload/tx_ausynovethicetudes/pdf_complets/2014_Overview-of-ESG-rating-agencies.pdf

Poon, M. (2012). Rating Agencies. In K. K. Cetina & A. Preda (Eds.), *The Oxford Handbook of The Sociology of Finance* (pp. 407–459). Oxford University Press.

Prall, K. (2021). ESG Ratings: Navigating Through the Haze. CFA Institute Blogs. Retrieved January 4, 2023, from https://blogs.cfainstitute.org/investor/2021/08/10/esg-ratings-navigating-through-the-haze/

Preda, A. (2006). Socio-Technical Agency in Financial Markets: The Case of the Stock Ticker. *Social Studies of Science*, *36*(5), 753–782.

Principles for Responsible Investment (PRI). (2022). Annual Report. Retrieved December 5, 2022, from https://dwtyzx6upklss.cloudfront.net/Uploads/b/f/m/pri_annual_report_2022_689047.pdf

Raghunandan, A., & Rajgopal, S. (2022). Do ESG funds make stakeholder-friendly investments? *Review of Accounting Studies*, *27*, 822–863.

Refinitiv. (2022a). About Us. Refinitiv. Retrieved November 28, 2022, from https://www.refinitiv.com/en/about-us#what-we-do

Refinitiv. (2022b). Environmental, Social and Governance Scores from Refinitiv. Retrieved November 28, 2022, from https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Refinitiv. (2022c). Refinitiv ESG company scores. Refinitiv. Retrieved November 28, 2022, from https://www.refinitiv.com/en/sustainable-finance/esg-scores

Reuters. (2018). Thomson Reuters closes deal with Blackstone. Reuters. Retrieved November 28, 2022, from https://www.reuters.com/

article / us - thomsonreuters - m - a - blackstone / thomson - reuters - closes-deal-with-blackstone-idUSKCN1MB3PY
Riles, A. (2006). *Documents: Artifacts of modern knowledge*. University of Michigan Press.
Riles, A. (2011). *Collateral knowledge: Legal reasoning in the global financial markets*. University of Chicago Press.
Ryan, P., & Taffler, R. J. (2004). Are Economically Significant Stock Returns and Trading Volumes Driven by Firm-specific News Releases? *Journal of Business Finance & Accounting*, *31*(1& 2), 49–82.
Scalet, S., & Kelly, T. F. (2010). CSR Rating Agencies: What is Their Global Impact? *Journal of Business Ethics*, *94*, 69–88.
Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American economic review*, 465–479.
Securities and Exchange Commission (SEC). (2010). Analyzing Analyst Recommendations. SEC. Retrieved November 5, 2022, from https://www.sec.gov/tm/reportspubs/investor-publications/investorpubsanalystshtm.html
Securities and Exchange Commission (SEC). (2022). SEC Proposes to Enhance Disclosures by Certain Investment Advisers and Investment Companies About ESG Investment Practices. Retrieved December 12, 2022, from https://www.sec.gov/news/press-release/2022-92
Sheng, X., & Thevenot, M. (2012). A new measure of earnings forecast uncertainty. *Journal of Accounting and Economics*, *53*(1-2), 21–33.
Sindreu, J., & Kent, S. (2018). Why It's So Hard to Be an 'Ethical' Investor. The Wall Street Journal. Retrieved November 4, 2022, from https://www.wsj.com/articles/why-its-so-hard-to-be-an-ethical-investor-1535799601
Sipiczki, A. (2022). A critical look at the ESG market. Retrieved December 16, 2022, from https://www.ceps.eu/wp-content/uploads/2022/04/PI2022-15_A-critical-look-at-the-ESG-market.pdf
S&P Global. (2020). How can AI help ESG investing? S&P Global. Retrieved December 16, 2022, from https://www.spglobal.com/en/research-insights/articles/how-can-ai-help-esg-investing
S&P Global. (2022). S&P Global ESG Scores – Methodology. Retrieved January 22, 2023, from https://www.spglobal.com/esg/documents/sp-global-esg-scores-methodology-2022.pdf
Stack Exchange. (2023). Exclusion of Utilities and Financials in Magic Formula. Quantitative Finance Stack Exchange. Retrieved January 30, 2023, from https://quant.stackexchange.com/questions/41192/exclusion-of-utilites-and-financials-in-magic-formula
State Street Global Advisors. (2019). The ESG Data Challenge. Retrieved January 4, 2023, from https://www.ssga.com/investment-topics/environmental-social-governance/2019/03/esg-data-challenge.pdf
Stickel, S. E. (1990). Predicting individual analyst earnings forecasts. *Journal of Accounting Research*, *28*(2), 409–417.
Sustainalytics. (2020). The ESG Risk Rating: Frequently Asked Questions – For Companies. Retrieved November 25, 2022, from shorturl.at/kopX3
Sustainalytics. (2021). ESG Risk Ratings – Methodology Abstract. Retrieved November 25, 2022, from https://connect.sustainalytics.com/esg-risk-ratings-methodology
Sustainalytics. (2022). About Us. Sustainalytics. Retrieved November 25, 2022, from https://www.sustainalytics.com/about-us
Swaminathan, S. (1991). The Impact of SEC Mandated Segment Data on Price Variability and Divergence of Beliefs. *The Accounting Review*, *66*(1), 23–41.
Tang, D. Y., Yan, J., & Yao, C. Y. (2022). The Determinants of ESG Ratings: Rater Ownership Matters. *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI – ESSEC*.
The Economist. (2019). The London Stock Exchange buys Refinitiv. The Economist. Retrieved November 28, 2022, from https://www.economist.com/finance-and-economics/2019/08/01/the-london-stock-exchange-buys-refinitiv
The SustainAbility Institute. (2020). Rate the Raters 2020: Investor Survey and Interview Results. Retrieved December 7, 2022, from https://www.sustainability.com/globalassets/sustainability.com/thinking/pdfs/sustainability-ratetheraters2020-report.pdf
The SustainAbility Institute. (2022). Costs and Benefits of Climate-Related Disclosure Activities by Corporate Issuers and Institutional Investors. Retrieved January 2, 2023, from https://www.sustainability.com/globalassets/sustainability.com/thinking/pdfs/2022/costs-and-benefits-of-climate-related-disclosure-activities-by-corporate-issuers-and-institutional-investors-17-may-22.pdf
Tomoko, F., & Kyoko, N. (2022). Japan Introduces Mandatory ESG Disclosures For Public Companies. Morgan Lewis. Retrieved February 3, 2023, from https://www.morganlewis.com/pubs/2022/12/japan-introduces-mandatory-esg-disclosures-for-public-companies
UN PRI and ICGN. (2018). Investor Agenda For Corporate Esg Reporting. Retrieved December 12, 2022, from https://www.unpri.org/download?ac=6181
Wansleben, L. (2012). Financial Analysts. In K. K. Cetina & A. Preda (Eds.), *The Oxford Handbook of The Sociology of Finance* (pp. 407–459). Oxford.
Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics*, *58*(3), 369–396.
Wild, D. (2017). ESG Integration Approach. In C. Institute, C. S. Switzerland, & S. S. Finance (Eds.), *Handbook on Sustainable Investments* (pp. 54–59).
Winroth, K., Blomberg, J., & Kjellberg, H. (2010). Enacting Overlapping Markets. *Journal of Cultural Economy*, *3*(1), 3–18.
Yu, F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics*, *88*(2), 245–271.
Zhang, H. (2021). It's Time for Private Companies to Come Clean on ESG. Institutional Investor. Retrieved January 2, 2023, from https://www.institutionalinvestor.com/article/b1v8zb72tjzcy3/It-s-Time-for-Private-Companies-to-Come-Clean-on-ESG
Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research*, *22*, 59–82.
Zwiebel, J. (1995). Corporate Conservatism and Relative Compensation. *Journal of Political Economy*, *103*(1), 1–25.