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How Analysts Value ESG

An Empirical Analysis of the Impact of ESG Performance on the Price Target Bias

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Master's Thesis, Accounting[a]

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Executive summary

This thesis examines how firm ESG performance and ESG reporting affect the price target bias, a normalized and directional measure of how analysts' price targets predict the market price. To examine this relationship, we employ a data panel of 24 367 firm-quarter observations between 2001 to 2021 on the companies on the S&P 500 index. We test for the effect of ESG performance, scoring, and reporting on the price target bias employing controls for risk, firm performance, the information environment, and analyst expectations.

Using pooled OLS, we find ESG performance and the price target bias. Our results are driven by the Environmental and Social scores, while the Governance and Controversies scores mediate the price target bias. However, using within-estimators, we are not able to identify this relationship. We further test the interactive relationship between ESG performance and analyst following, finding that the BIAS of high ESG performers is less influenced by analyst following. We also find evidence for higher ESG performance for firms that issue ESG reporting and assure the reports. However, our results indicate that the ESG reporting does not influence the price target bias. Finally, using the within-estimator, we find that the price target bias is larger in the period after a firm receives an ESG score than before receiving the score.

Our main results provide evidence for a positive relationship between the price target bias and ESG performance. Furthermore, testing the price target accuracy indicates this relationship corresponds to a worsening of price targets, where analysts value ESG performance too high relative to the market outcome.

Keywords: ESG Performance, ESG Reporting, Corporate Social Responsibility, Price Target Accuracy, Price Target Bias

Preface

This master's thesis represents part of our degrees; Master of Science in Accounting[a] and Master of Science in Economics and Business Administration[b] at the Norwegian School of Economics.

This thesis aims to examine how firm ESG performance and ESG reporting affect the price target bias, a measure of analyst accuracy. This has been especially interesting as there is still a debate regarding the value effects of ESG. Furthermore, by comparing the relative pricing between the two groups, we believe to have gained additional insight into how analysts price ESG.

We extend our gratitude to our supervisor, Are Oust, for his valuable inputs, time, and feedback throughout the semester. His support has proven instrumental, and we are grateful to have been able to have him supervise our work. Additionally, we wish to thank Kjell Henry Knivsflå and Finn Kinserdal for aiding us in deriving our research topic.

Finally, we would like to thank each other for the excellent collaboration. Despite different study programs, our different backgrounds have proven to be complementary.

Bergen, December 20th, 2021

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1. Introduction

In the two decades following the United Nations Global Compact (2004) issuance of a report on Environmental, Social, and Governance factors, these considerations have become important to many. Companies face increasing demands by stakeholders to consider the non-financial aspects of their business. There are arguments for and against the potential value creation of ESG, and the debate of whether and how ESG performance might be value additive to the firm is ongoing. We, therefore, wish to further examine the value effect of ESG. To understand how these factors are valued, we focus on a group generally thought to provide high-quality, in-depth, short-term valuations of companies: financial analysts. As analysts collect, analyze, and disseminate information about the prospects of publicly listed firms (Brauer and Wiersema, 2018), financial analysts should be well suited to price such factors. Therefore, we propose that how sell-side analysts value such firms might provide valuable insights.

Many measures describe information asymmetry (i.e., Dechow & You, 2017). As we wish to examine the relationship between sell-side analysts and other market participants, we choose to examine the price target bias. The price target bias is defined as the relationship between price targets and the market price at horizon. We calculate this using data from the Institutional Brokers Estimate System (IBES) price target summary. We chose this measure as it is directional and therefore can provide insights into how analysts price ESG factors relative to the market. We, therefore, propose the following research question:

Do ESG performance and reporting influence the price target bias?

Previous studies have examined the relationship between analyst forecast accuracy and ESG factors. For example, Cui et al. (2018) find ESG performance to be correlated with lower forecast dispersion, while Dhaliwal et al. (2012) use CSR reporting as a proxy for the information environment finding lower analyst forecast errors for firms issuing CSR reporting. Regarding the value effect of ESG, Friede et al. (2015) find roughly 90 % of studies to exhibit a non-negative value effect regarding ESG. Pöyhiä (2017) finds, however, that analysts generally do not factor ESG metrics into their valuations.

This thesis considers the effect on analyst price target bias of ESG performance, reporting, and score availability. By employing a data panel of 24 367 firm-quarter observations of the companies on the S&P 500 index from 2001 to 2021, we analyze how the ESG performance and reporting affect the price target bias. Controlling for factors including risk, growth, firm performance, the information environment, and more, we use four models to estimate the relationship between ESG performance and the price target bias. We employ both pooled OLS and within-estimators to assess the relationships. First, we test, using Refinitiv ESG scores, for how ESG performance is related to the price target bias. We then test the interactive effect of analyst following and ESG performance by employing interaction terms. We also test if the relationship between ESG performance and the price target bias is stronger for higher levels of ESG reporting. Finally, as the scores are implemented gradually, we test if the price target bias changes after receiving an ESG score.

This thesis finds a positive relationship between analyst price target bias and firm ESG performance. We find the relationship to be driven by the Environmental and Social scores, while the Governance and Controversies score act as a mediating effect. We cannot find the same relationship between ESG performance and price target bias using the within transformation, either due to the relationship not existing or the failure of ESG scores to capture ESG performance. Analyzing how the analyst following influences the ESG-BIAS relationship, we find a higher but more stable BIAS (price target bias variable) for high ESG performers. We find the ESG reporting scope to have minimal impact on the ESG-BIAS relationship, but that ESG performance is higher for companies that issue and assure ESG reporting. Finally, we find the price target bias to be significantly higher when a Refinitiv ESG score is available for a firm.

This thesis contributes to the literature by analyzing how the price target bias is affected by ESG performance, reporting level, and the availability of performance scoring. We find the ESG performance and availability of scores to be positively related to the price target bias. Furthermore, testing the price target accuracy (BIAS absolute value) indicates the positive relationship is a worsening of price targets where analysts value ESG performance higher than the market outcome.

The structure of the rest of the thesis is as follows: In section 2, we will present relevant literature, motivate possible channels that might influence the price target bias, and detail the relationships we wish to examine. Section 3 will present the data and describe the sampling and variables. In section 4, we will present the methodology used in the thesis. In section 5, we will present the results of the thesis. Finally, we will discuss the results in section 6 before discussing limitations in section 7 and presenting the conclusion in section 8.

2. Background

2.1 ESG

Environmental, Social, and Governance (ESG) is a term closely related to Corporate Social responsibility (CSR) and refers to the extent a business takes on responsibility exceeding its legal requirements. The Environmental pillar measures resource use, emissions, and innovation. The Social pillar focuses on human rights aspects, while the Governance pillar considers shareholders' rights, company decision-making, and reporting (Refinitiv, 2021).

As the company is owned by its shareholders, and the investments for shareholders could be seen as a sunk cost, Milton Friedman (1970) stated that "The Social Responsibility of Business Is to Increase Its Profits." He argued that the management has a direct responsibility to the shareholders. If management engages in unnecessary CSR activities, this may act as a tax and reduce the economic surplus. Freeman et al. (2010), among others, however, argue that a firm has an additional social responsibility towards all stakeholders. They state that firms involved in activities not related to profit maximization will eventually be rewarded by its value creation resulting in a win-win-win situation for the firm, stakeholders, and the environment (Elkington, 1994).

Regardless of the effect of these factors on the firm, there is evidence that individual investors want their investments to do good, even at the cost of financial performance (Pedersen et al., 2021). For example, a Kiplinger – Domini Poll (2021) found that four in ten purchased stocks based on ESG issues and that 75% of millennial investors would be willing to sacrifice some level of return for ESG performance. Therefore, regardless of how the ESG performance impacts the firm, ESG factors are therefore likely important.

2.2 Analyst accuracy and bias

Price target accuracy is a measure used to analyze how precise analysts' price targets predict the market price at a specified future date. Common measures for analyst accuracy are hit rate, where the price target is assumed to be accurate if the market price reaches the price target within the specified horizon, price target bias a directional measurement by how far the price target is from the market price, and the price target accuracy (absolute value of the price target bias) measuring the same in absolute terms (Dechow & You, 2017). The relationship between analyst accuracy and financial disclosure has been the subject of intensive research (for a summary, see Ramnath et al., 2008). As analysts depend on quality inputs into their valuation models, reporting is essential. Dechow and Schrand (2004) find that a rich disclosure environment reduces information costs in stock markets, while Lang and Lundholm (1996) find that firm disclosure help analysts accurately predict forecasts. Additionally, Meek et al. (1995) and Byard et al. (2006) find that analysts can forecast earnings more accurately when the information is standardized. As analysts focus on short-term valuations (12 months in our data), Peek (1997) documents that analysts primarily focus on performance information.

2.3 ESG reporting and the firm information environment

Cui et al. (2018) find a link between the price target dispersion (normalized standard deviation of summarized price targets) and the CSR information environment, arguing that a firm's engagement in CSR activities might serve as a trust-building activity. Dhaliwal et al. (2012) find evidence for a decrease in analyst forecast errors when a company issues a separate CSR report and propose that non-financial reporting serves as a complementary addition to financial disclosure. However, as the reporting choices for ESG factors are not strongly regulated, firms may choose to report mostly positive aspects while failing to report negative aspects. Ashbaugh and Pincus (2001) find evidence for an improvement in analyst forecast predictions when variations in disclosure policies are reduced, and this might also apply to ESG reporting.

Del Giudice & Rigamonti (2020) find that measurement errors of ESG performance might be reduced by employing third-party assurance. In addition, a recent report published by the Center of Audit Quality (2021) found that over half of S&P 500 companies had some form of assurance of their ESG reporting compared to 29 % in 2019 (PWC). However, only 6 % of S&P 500 companies used a Certified Public Accounting firm to assure their ESG report, following stricter assurance standards and covering more areas of the ESG report. Other firms use other providers such as engineering and consulting firms to assure their report, with the assurance mainly covering greenhouse gas emissions.

Analysts are well suited to price information, including ESG factors. However, studies by Ernst and Young (1997) and Pöyhiä (2017) find that most analysts do not incorporate ESG factors, and if done, only by a minimal magnitude. The availability of such reporting might therefore have minimal impact on price targets.

2.4 Value additive channel

Several studies find a positive link between ESG performance and firm performance indicators. Most studies seem to find a positive relationship between ESG and firm financial performance (Friede et al., 2015; Ernst & Young, 1997). Although many studies identify a possible valuable link, the causal link is still debatable. Granskog et al. (2020) find environmental factors important to consumers, and Jiang et al. (2020) find that ESG performance is important for where people choose to work, indicating that ESG might be an important factor for revenue and talent acquisitions. Additionally, some studies find that high ESG performers might have a lower cost of capital as they can reduce ESG related risks (Dhaliwal et al., 2014). However, these factors should be priced by both the market and analysts and, unless valued differently, should not influence the price target bias.

2.5 Agency cost channel

Addressing firms with high institutional investor ownership, Cheng et al. (2013) find the marginal ESG investment is not profitable. They consider the supply curve of valuable investments and find that the marginal ESG investment, as a subset of all investments, cannot be greater than the marginal investment available to the firm. Building on the conjecture that the marginal ESG-investments may be an agency cost, Colak et al. (2020) conclude that negative ESG news increases the chances of CEO replacement, while Chen et al. (2019) finds that long-serving (i.e., with higher job security) CEOs tend to invest lower amounts in corporate social responsibility. Having a short-term approach to firm valuation, primarily valuing financial performance, analysts might not value ESG. Ioannou and Serafeim (2015) find that analysts view ESG investments as an agency cost. Flugum and Souther (2020) proposes that management sometimes promotes stakeholder value to compensate for failing to meet earnings expectations.

2.6 Sample bias channel

Bradshaw et al. (2012) find evidence for a general systematic overvaluation in price targets driven by analysts' conflicts of interest. Sell-side analysts focus on presenting buying opportunities, so recommendations are disproportionately distributed towards buy recommendations (Barber et al., 2002). Cowen et al. (2006) find that pure brokers issue more optimistic earnings forecasts to generate trading commissions. Analysts also depend on their relationships with firm managers to gain favorable inside access. Therefore, they might choose not to report negative information that might damage their relationships with management (Milian et al., 2017).

When issuing price targets, analysts can therefore be seen to be dually motivated. It is important that they provide accurate price targets to manage their reputation but must additionally provide interesting investment opportunities that might capture investor interest. ESG is an important factor to certain investors, and Pedersen et al. (2021) define a portfolio framework where investors maximize some combination of ESG performance and financial performance (Sharpe ratio). As ESG considerations become important to some investors, analysts might have two possible metrics to promote their recommendations. Similarly to management, as found by Flugum and Souther (2020), analysts might promote stakeholder value for firms that otherwise would not receive favorable recommendations. As Bradshaw (2002) finds that analysts use price targets to justify their recommendations, their dual motive might be reflected in the price target bias.

2.7 Study development

To address our research question if ESG factors impact the price target bias, we choose to look at four different models that might provide insight into the ESG-BIAS relationship.

Our main analysis will address how firm ESG performance influences the price target bias. The proposed channels for the relationship between firm value and ESG scores provide three possible explanations for the impact of ESG on price target bias. Analysts might recognize the ESG performance as either value additive or subtractive relative to the market pricing at the horizon through the value additive channel. If this is the case, analysts, market participants, or both fail to capture the firm's intrinsic value. The effect on the BIAS from this channel can either be positive or negative. If analysts see ESG as value subtractive, the ESG performance might be seen as an agency cost in accordance with Cheng et al. (2013).

As the group of analysts choosing to issue a price target for a firm is a self-selected sample, the effect can depend on the firm analyst’s choice to follow. For example, if analysts recommend firms they believe provide interesting investment opportunities and might exceed the general market return, the price targets should generally be more positive. However, Fama and French

(2010) finds evidence for that active investing does not generate excess returns. The higher price targets are thus more likely to reflect a worsening of price targets. Therefore, we propose to address how analyst price these factors relative to the market.

Relationship 1: ESG performance influences price target bias.

As the price target bias might be influenced by the group of analysts choosing to issue a price target for a firm, our sample is self-selected. As described through the selection bias channel, the relationship between ESG performance and bias might be influenced by the number of analysts following a firm. Therefore, we propose that it might provide important insights by addressing how the marginal analyst values ESG performance.

Relationship 2: The ESG-BIAS relationship is influenced by analyst following.

As the ESG performance in previous literature has been assumed to serve as a proxy for the information environment, we propose it might be useful to examine differences between ESG reporting levels. Furthermore, as the ESG information published by the firm can be seen as soft information, we will address how the relationship between ESG performance and price target bias might differ when the quality of ESG information is better. Therefore, we will analyze how ESG reporting influences the price target bias.

Relationship 3: The ESG-BIAS relationship differs for the ESG reporting levels.

Based on the increase in dual motive investors, we propose that ESG scores might either directly or be related to some effect that influences the price target bias. If the scores affect the price target bias, this might help explain if the ESG performance is the driver for our findings, or if the access to pre-analyzed summarized ESG information affects the BIAS.

Relationship 4: The availability of ESG metrics impacts the BIAS.

3. Data

3.1 Data sourcing

To answer our research question, we obtain data from the Refinitiv platform available to us through our institution, the Norwegian School of Economics. We source data by referencing the International Securities Identification Number (ISIN) to merge data from different providers. We chose to study the securities that made up the S&P 500 index on September 9th, 2021 ("List of S&P 500 companies", 2021). These companies should be closely followed, and the index was one of the first to have ESG scoring implemented. Our primary independent variable of interest, Refinitiv ESG scores, was implemented in 2002 for this index; we source data from 2000(Q1) to 2021(Q3), a data panel of 43 855 firm-quarter observations.

Additionally, for robustness, as ESG scores might fail to capture ESG performance (LaBella et al., 2019), we choose to source ESG performance data from two other providers available to us. We source ESG risk data from the Rep Risk Index (RRI) available through Wharton Research Data Services (WRDS) and RobecoSam ESG scores available through the Bloomberg Terminal.

3.2 Data handling

The variables used in this paper are constructed as described in appendix table A.1 from the data sourced from Refinitiv. Before constructing the variables, we remove any error values. As described in section 3.4.3 detailing ESG reporting variables, we remove observations for which the variables are not cumulatively defined. We drop all observations with missing controls or BIAS variable. Further, we Winsorize all continuous control variables and the BIAS variable at the 1 % and 99 % levels to reduce the impact of potential biases from outliers. Additionally, we drop values for the variables that we deem unreasonable, as described in table variables, resulting in a dataset of 24 367 firm-quarter observations. The variable constriction is further described in appendix table A.1. The correlation matrix of the variables can be found in appendix table B.1.

Table 3.1 - This table displays descriptive statistics of all main variables used in this thesis. The price target bias is defined as $\frac{\overline{Price\ Target_{q-4}}}{Price\ Close_q} - 1$, and the ESG, E, S, G, C variables are sourced from Refinitiv. The construction of the variables and data dropping is described in appendix table A.1. All continuous control variables and the BIAS are Winsorized at the 1% and 99% levels to reduce the potential impact of outliers.

	N	Min	Mean	Median	Max	Skew
BIAS	24367	-0.5302	0.0893	0.0028	3.2313	2.3575
ESG	20627	1.9040	49.5244	49.8579	94.9315	-0.0934
E	16508	0.0367	48.1860	50.7077	98.5458	-0.1486
S	20627	2.1897	51.5236	51.9124	98.1189	-0.0110
G	20627	0.4497	54.5186	56.0490	99.5175	-0.2412
C	20627	0.6173	80.9638	100.0000	100.0000	-1.4070
ROBECOSAM - ESG	5998	1.0000	47.9912	46.0000	100.0000	0.1925
RRI	15786	21.0000	83.4657	82.0000	100.0000	-0.7778
Analyst following	24367	1.3863	2.8826	2.9444	3.7136	-0.7799
Size	24367	19.7605	23.4014	23.3572	26.5187	0.0834
PB	24367	0.2795	4.3378	2.9936	43.4448	3.6280
LTG	24367	0.0157	12.2887	11.5400	49.9993	1.5695
RGROWTH	24367	-0.4741	0.0929	0.0697	1.3234	2.0358
Leverage	24367	1.0328	3.6690	2.5760	24.8997	2.6755
Momentum	24367	-0.4203	0.0334	0.0343	0.5495	0.0006
STD(RET)	24367	0.0221	0.1256	0.1095	0.5327	1.3694
Earn	24367	-0.0910	0.0626	0.0585	0.1949	0.8814
dEarn	24367	-2.6032	0.0510	-0.0024	3.0819	2.0201
STD(EARN)	24367	0.0001	0.0074	0.0054	0.1002	3.3351
Smoothing	24367	0.0041	0.2287	0.1603	0.9997	1.3638
Age	24087	0.0000	3.9733	4.1109	5.4681	-0.8606

3.3 Price target bias variable

To test how financial analysts value the ESG factors, we consider the relationship between analyst valuations and market price using the price target bias. The following section will explain the variable and its important factors.

Let F be the unobserved distribution function of all financial analysts' price targets, and the market price at the price target execution date is M_t. The price target bias can then be defined as:

$$BIAS = \frac{\bar{F_t}}{M_t} - \frac{M_t}{M_t} = \frac{\bar{F_t}}{M_t} - 1 \quad (3.1)$$

Where BIAS is the price target bias, $\overline{F_t}$ is the mean of the price target function, where the price target is assumed for period t, while M_t is the observed market price at the horizon.

If the true analyst bias diverges from the market valuation as defined by equation 3.1, either the market, financial analysts, or both must diverge in their estimations from the actual intrinsic value I, as shown in the expanded equation:

$$BIAS = \frac{\bar{F_t}}{M_t} - \frac{M_t}{M_t} = \frac{(I_t - M_t) - (I_t - \bar{F_t})}{M_t} \quad (3.2)$$

Where $\overline{F_t}$ is the mean of the price target function, M_t is the market price at the horizon, and I_t is the intrinsic value of the estimated security at the horizon.

3.3.1 Sample bias

As all analysts do not submit price targets for all companies, it is impossible to observe function F, detailing how analysts' pricing is relative to the market. We let g be the observed distribution found in the IBES summary data so that g ∈ F. If the sample is not proportional to F so that E[g] ≠ E[F] the sample g has a sampling bias, ε_r.

3.3.2 Stale price target bias

The above framework relies on the continuous sampling of price targets and that all price targets have the same horizon. Practically, the price targets will be lagged for up to a year until no longer is included in the sample (Sharief, 2021). The bias induced to the model due to this effect (stale price target bias), ε_h, can be defined by:

$$\varepsilon_h = \frac{\overline{F_h}}{M_t} - \frac{\overline{F_h}}{M_h} \quad (3.3)$$

Where $\overline{F_h}$ is the estimated price target mean for period h, M_h is the market price at h, and M_t is the market price at t.

The stale price target bias, ε_h, can be shown to be negative for increasing stock prices.[1] If this bias is systematically different for a variable, V, so that cov(V, ε_h) ≠ 0, this will cause endogeneity problems in the model as it cannot be controlled using price target summary data.

Based on the above inputs, we can define the variable of interest, the observed price target bias with its potential errors:

$$BIAS = \frac{\bar{g}}{M_t} - 1 = \frac{\overline{F_t}}{M_t} - 1 + \varepsilon_r + \varepsilon_h \quad (3.4)$$

Where BIAS is our variable of interest, $\bar{g}$ the observed price target mean, $\overline{F_t}$ is the true price target mean estimate for period t, M_t the market price at t, ε_h the stale price target bias, and ε_r the sampling bias.

3.3.3 Construction of the price target bias variable

This thesis use summarized IBES analyst recommendation data to assess how analysts value ESG performance per the proposed analytical framework. We create the variable as defined by Bradshaw et al. (2012) and Hutira (2016). As the price target horizon for the IBES summary in the Refinitiv dataset is 12 months (Sharief, 2021), we normalize the price target four quarters prior to the market value in the period of observation:

$$BIAS = \frac{\overline{Price\ Target_{q-4}}}{Price\ Close_q} - 1 \quad (3.5)$$

From table 3.1, we find the variable has a mean of 0.0893, median of 0.0028, and skew of 2.3575. These statistics are in accordance with the disproportionate recommendations found by Barber et al. (2002). From the visual representation of the variable distribution, shown in figure 3.1, we find the mode of the density function to be -0.0751 and that the distribution has a long right tail. However, the mode is unlikely only to represent the stale price target bias as its divergence from zero corresponds to an 8.12 % return, compared to the implied annualized return of 14 % in our sample[2]. Appendix figure C.1 details how the variable has varied across the time dimension in our data.

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[1] Let period h be a period before period t. If stock prices are systematically increasing so that E[M_h]<E[M_t] we find that $\frac{\overline{F_h}}{M_h} > \frac{\overline{F_h}}{M_t}$ so $\varepsilon_h = \frac{\overline{F_h}}{M_t} - \frac{\overline{F_h}}{M_h} < 0$.

[2] We find the implied return based on the mode: $\frac{1}{1-0.07510} - 1 = 0.0812$

From the momentum in table 3.1, we find the mean quarterly return to be 0.0334. The implied annual return is then: $1.0334^4 - 1 = 0.1404$

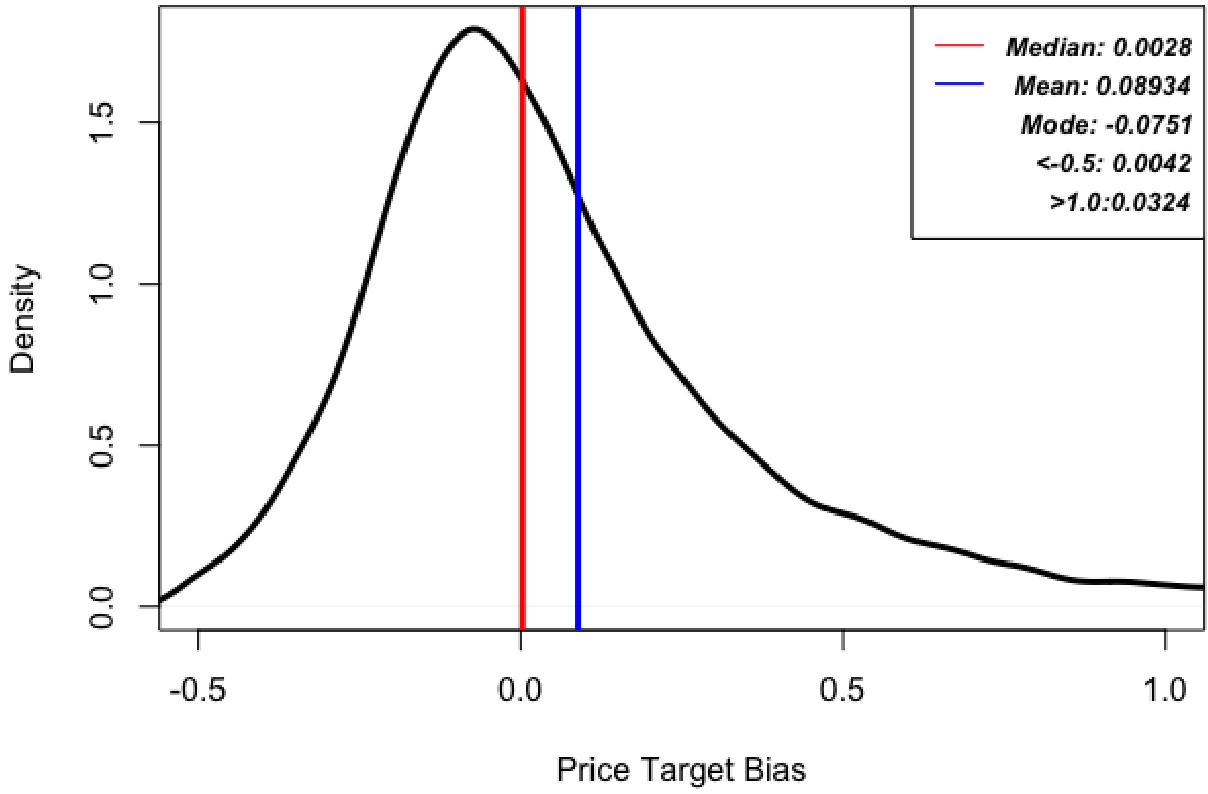

Figure 3.1 - This figure shows the distribution of the BIAS variable. The BIAS variable is normalized so that its expected value is zero, as described in equation 3.1. The mean [0.0893] of the variable is represented by the blue line, while the red line represents the median [0.0028]. As shown in the figure and described by (Barber et al., 2002), the variable has a larger proportion of optimistic biases. [Bias<-0.5 = 0.0042, Bias>1 = 0.0324]

3.4 ESG variables

3.4.1 Refinitiv ESG Scores

This thesis employs ESG performance variables from Refinitiv as our primary independent variable of interest. We source the ESG score and its four pillar scores, Environmental, Social, Governance, and Controversies. For a detailed description of the scoring methodology, we refer to Refinitiv (2021). These scores are sourced as both numerical scores and letter grades. The distribution of scores based on the letter grades are presented in appendix table C.1, while the change in ESG scores over the time dimension are presented in appendix figure C.2.

3.4.2 Score availability

To examine differences between the pre- and post-score implementation period, we construct dummies indicating if a score is available. For the instances where the dataset has no reported score, but both preceding and proceeding scores are observed, we assume a rating is available, and the dummy is set as 1. If no proceeding score is in the data, the value is set as NULL. The

Refinitiv ESG, S, G, and C scores are implemented simultaneously and perfectly correlated for our data. These are therefore combined into one variable. The cumulative sum of securities with an ESG score available is shown in figure 3.4.

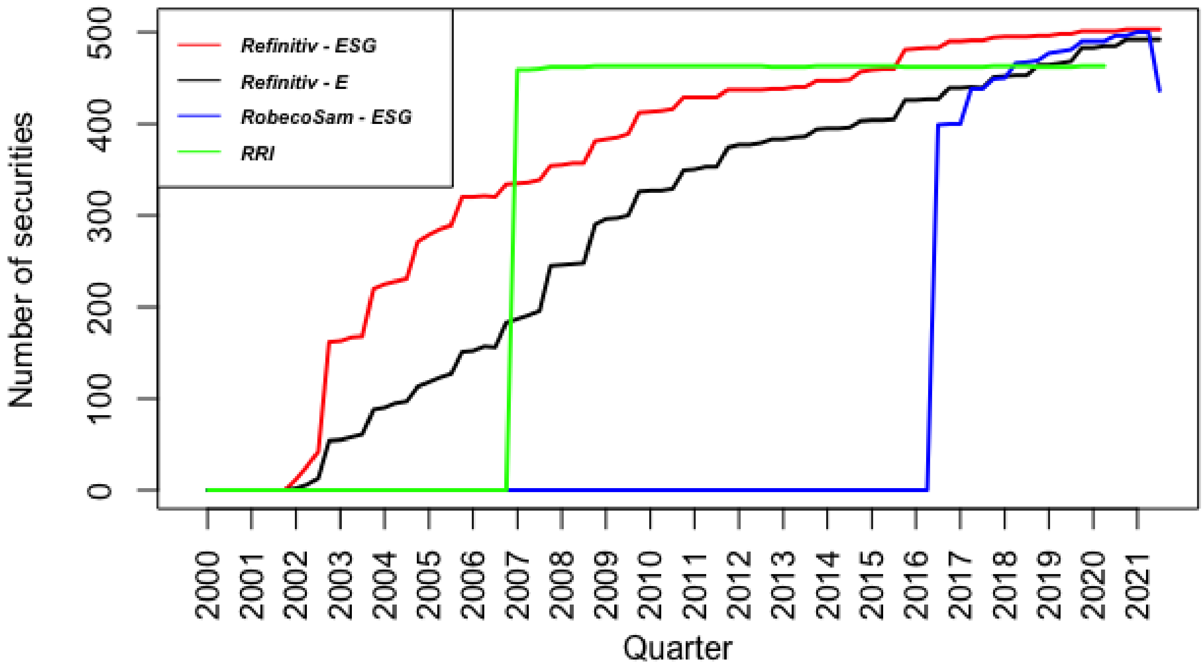

Figure 3.4 - This figure presents the cumulative sum of securities that had an ESG score available at or before the quarter of observation based on the raw data consisting of 43 855 observations. The decline of the cumulative sum of RobecoSam ESG scores at the end of the time series is caused by NULL values.

3.4.3 ESG reporting, assurance, and auditing

To test if the quality of the ESG information environment impacts the price target bias, we source information about the ESG reporting of the companies. The variable Reporting is defined as 1 if a company publishes a separate CSR report / CSR section. If this report has a named auditor, the dummy, Assurance, is assigned as 1. If the auditor is part of "the big four"[3], the third cumulative variable, BIG4, is 1[4]. These variables are made to be strictly cumulative. Companies must have issued a report to have it assured and must have an assured report if the BIG4 variable is applicable. Observations that do not follow this criterion are removed.

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[3] KPMG, EY, PWC, and Deloitte

[4] The Center for Audit Quality (2021) found that only a small percentage of firms receive at least some of their ESG audit from a public company auditing firm. Most of these audits are performed by engineering or consultancy firms and are done following different standards than AICPA certified firms. Although some other firms in our sample were AICPA certified, we chose only to define our variable as BIG4, as many of the AICPA certified firms did not have a substantial amount of their business as financial auditors.

From figure 3.5, presenting boxplots of the ESG scores for each reporting level, we find that firms with higher reporting levels have better ESG performance as measured by ESG scores. The number of firms reporting and assuring ESG information is shown across the time dimension in appendix figure C.3.

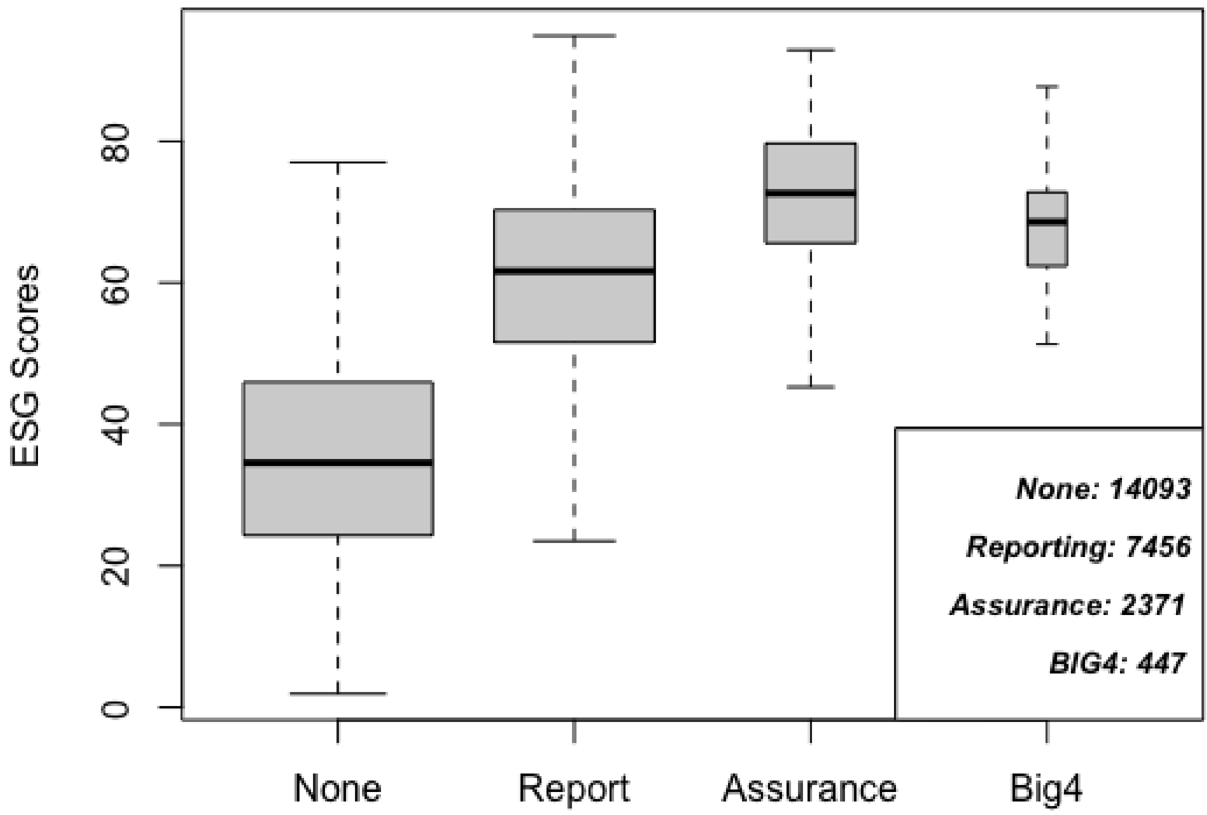

Figure 3.5 - This figure presents a boxplot of ESG scores for our sample's different ESG reporting levels. The box widths are sized by the square root of the number of observations. The boxes represent the middle 50 % of the data, while the whiskers represent the reasonable extremes in each quarter as defined by the default of the R boxplot function. The line in the box represents the median observation.

3.5 Control variables

Control variables for this study generally follow prior literature. Following Cui et al. (2018), we construct variables to control for risk, growth, earnings, financial information stability, and market pricing changes. As Peek (1997) finds firm performance measures to be most important to analysts, we include the following firm-level controls; EARN (Earnings per share/Share price), dEarn (yearly percentage change in EARN).

As previous studies find that ESG might serve as a proxy for the information environment, we construct variables to proxy these effects. The standard deviation of earnings in the last four quarters, STD(EARN), and earnings smoothing are defined by the relationship between reported and normalized earnings. We also control for revenue growth, book value leverage, and size measured by company market cap at the firm level. Stock market effects are also controlled in accordance with DeLisle et al. (2021). Momentum is defined as the change in stock price from q_{t-1} to q_t, the standard deviation of the momentum of the last four quarters, STD(MOM), and the price to book value, PB. As Hutira (2016) identifies a relationship between analyst following and bias, we employ the natural logarithm of analyst following as a variable to control for this effect. We also control for analyst growth expectations to ensure that our ESG variables do not proxy growth expectations.

In addition to these control variables, we control the sector fixed effects of the 11 GISC-sectors and quarter fixed effects to allow for differences in analyst optimism over time and sectors.

4. Empirical methodology

This section presents the models used to estimate the relationships we wish to examine as outlined in section 2.7. To assess the impact of ESG factors on BIAS, we utilize models inspired by Cui. et al. (2018) and DeLisle et al. (2021) used to test for ESG impact on information asymmetry. Importantly, we control for factors related to risk, growth, and earnings and the analyst following, an important determinant of the sample bias. A closer specification of the controls can be found in section 3.5.

4.1 Main model (1)

To test the effect of ESG scores on the observed analyst bias, we estimate the following regression model:

$$BIAS_{iq} = \alpha + \sum_j \beta_j ESG_{jiq} + \sum_k \beta_k R_{kiq} + \sum_l \beta_l C_{liq} + q + s + \varepsilon_{iq} \tag{4.1}$$

Where $BIAS_{iq}$ is the observation of the variable of interest, q the quarter fixed effects, and s the sector fixed effects. The notation q denotes the quarter, i denotes the firm, and j, k, and l denote the variable type. C denotes the control variables described in section 3.5 and appendix table A.1.

4.2 Within estimation (2)

The importance of ESG factors might vary between firms so that the observed estimators of the model in equation 4.1 capture this or some other firm-specific effect. To control for this, we also employ a difference in difference model, using the within transformation, controlling for firm fixed effects, and measuring the impact of variables' changes. To do this, we employ the following model:

$$\ddot{BIAS}_{iq} = \sum_j \beta_j \ddot{ESG}_{jiq} + \sum_k \beta_k \ddot{R}_{kiq} + \sum_l \beta_l \ddot{C}_{liq} + q + \ddot{\varepsilon}_{iq} \tag{4.2}$$

Where $BIAS_{iq}$ is the observation of the variable of interest, and q the quarter fixed effects. The notation q denotes the quarter, i denotes the firm and j, k and l denote the variable type. C denotes the control variables described in section 3.5 and appendix table A.1. The diaeresis diacritic, ¨, denotes the within transformation of the variable.

Gormley and Matsa (2014) describe how the estimate gets biased toward zero if the observed change across the time dimension for a variable is driven by measurement error. Labella et al. (2019) find a low correlation (not high) when comparing ESG performance scores from different providers. As these scores should be measuring the same performance, the low correlation might indicate the presence of large measurement errors, possibly resulting in the within estimators to be biased towards zero.

4.3 Interactive effect of analyst following (3)

The observed price target distribution in our sample has a relative area, defined by the number of analysts in the sample, in relation to the theoretical distribution consisting of all analysts, F. As the sample bias is dependent on the number of analysts, the interactive effect of analyst following on a variable might describe the marginal direction of the sample bias.[5] Therefore, the selection bias, ε_r, might increase or decrease as the number of analysts change. Hong and Kacperczyk (2009) find that high ESG performers attract a high baseline of analyst following. Alford and Berger (1999) argue that each additional analyst, at the margin, adds to the information environment. Hutira (2016) also finds that the price target bias increase with larger analyst following. The BIAS-ESG performance relationship might therefore be affected by analyst following. Consequently, we use the following model to test for this effect.

$$BIAS_{iq} = \alpha + \sum_j \beta_j ESG_{jiq} + \sum_j \beta_j [ESG_{jiq} * AF_{iq}] + \sum_k \beta_k R_{kiq} + \sum_l \beta_l C_{liq} + q + s + \varepsilon_{iq} \quad (4.3)$$

Where $BIAS_{iq}$ is the observation of the variable of interest, q the quarter fixed effects, and s the sector fixed effects. The notation q denotes the quarter, i denotes the firm, and j, k, and l denote the variable type. C denotes the control variables described in section 3.5 and appendix table A.1. AF_{iq} is part of the controls, C.

4.4 Interactive effect of reporting scope (4)

To test the effect of the different ESG reporting scopes, a regression model with interaction terms is deployed to test for differences in the BIAS-ESG performance relationship:

$$BIAS_{iq} = \alpha + \sum_j \beta_j ESG_{jiq} + \sum_k \beta_k R_{kiq} + \sum_{jk} \beta_{jk} [ESG_{jiq} * R_{kiq}] + \sum_l \beta_l C_{liq} + q + s + \varepsilon_{iq} \quad (4.4)$$

Where $BIAS_{iq}$ is the observation of the variable of interest, q the quarter fixed effects, and s the sector fixed effects. The notation q denotes the quarter, i denotes the firm, and j, k, and l denote the variable type. The variable for controls, C, denotes the variables described in section 3.5 and appendix table A.1.

[5] The absolute value function of $\varepsilon_r(a)$ must not be strictly decreasing, although it converges to 0 As g is a subsample of F, we know $\lim_{a \to A} \overline{g(a)} = \overline{F(A)}$, and the limit of $\varepsilon_r(a)$ must therefore be 0.

4.5 ESG Score availability (5)

We use the model from equation 4.2 to estimate the effect of the availability of ESG scores, applying score availability as a treatment effect, where the ESG variable is a dummy of value 1 if a score is available. The measured impact of the variable will then indicate the difference between the pre- and post-score availability period for a firm controlling for other factors described in section 3.5, including the quarter-fixed effects.

5. Empirical results

This section presents our results from the models defined in section 4. We first present the results of the main model using pooled OLS in section 5.1 and the within-transformation in section 5.2. In section 5.3, we present the interactive relationship on analyst following, while section 5.4 presents the interactive effect of the reporting scope. In section 5.5, we report the impact of ESG score availability. We additionally report the results of the price target accuracy, the absolute value of BIAS, in appendix table D.1. The discussion of the findings is presented in section 6.

5.1 Main model (1)

Table 5.1 reports the regression model's estimation results defined by equation 4.1. We find the ESG [0.0011, p-value<0.01], E [0.0003, p-value<0.01] and S 0.0006, p-value<0.01] scores to be of positive and statistically significant impact, while the G [-0.0004, p-value<0.01] and C [-0.0003, p-value<0.01] to exhibit a significant negative relationship when controlling interpillar covariance. For the reporting level dummies, we find a negative relationship for when companies publish a CSR report [-0.0137, p-value<0.01], a positive relationship for when the reports are audited [0.0236, p-value<0.01], and no significant relationship for when the audit is done by one of the BIG4 [0.0086, p-value>0.1].

5.1.1 Control variables

The control variables provide estimates mostly as expected. Noteworthy, we find the analyst following to provide a positive estimate indicating that firms with higher analyst followings have larger biases. In addition, we find the quarter-fixed effects to capture the difference in BIAS well.

Table 5.1 - This table reports the regression coefficients of the model in equation 4.1 on BIAS with time and sector fixed effects. The ESG score is used as the variable of interest column 1, the four pillar scores separately in columns 2-5, while column 6 includes all pillar scores controlling for interpillar covariance. Heteroskedastic robust standard errors in parenthesis. Significance levels (*: 0.01, **: 0.05, *, 0.10)**

	BIAS					
	1	2	3	4	5	6
ESG	0.0011***					
	(0.0002)					
E		0.0005***				0.0003**
		(0.0001)				(0.0001)
S			0.0010***			0.0006***
			(0.0001)			(0.0002)
G				-0.0001		-0.0004***
				(0.0001)		(0.0001)
C					-0.0004***	-0.0003***
					(0.0001)	(0.0001)
Reporting	-0.0137***	-0.0101*	-0.0113**	0.0062	0.0042	-0.0105*
	(0.0051)	(0.0054)	(0.0049)	(0.0046)	(0.0045)	(0.0055)
Assurance	0.0237***	0.0250***	0.0240***	0.0321***	0.0301***	0.0236***
	(0.0058)	(0.0059)	(0.0058)	(0.0059)	(0.0059)	(0.0059)
BIG4	0.0086	0.0094	0.0081	0.0033	0.0018	0.0091
	(0.0121)	(0.0122)	(0.0121)	(0.0122)	(0.0122)	(0.0122)
AF	0.1017***	0.1019***	0.1016***	0.1043***	0.1041***	0.1005***
	(0.0073)	(0.0082)	(0.0073)	(0.0073)	(0.0073)	(0.0082)
LTG	-0.0024***	-0.0033***	-0.0024***	-0.0026***	-0.0025***	-0.0033***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Size	-0.0313***	-0.0343***	-0.0318***	-0.0260***	-0.0318***	-0.0397***
	(0.0029)	(0.0032)	(0.0029)	(0.0028)	(0.0030)	(0.0035)
PB	-0.0050***	-0.0037***	-0.0050***	-0.0051***	-0.0049***	-0.0036***
	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
RGROWTH	-0.0126	-0.033298**	-0.0170	-0.0223	-0.0181	-0.0318*
	(0.0153)	(0.0170)	(0.0151)	(0.0152)	(0.0152)	(0.0170)
Leverage	-0.0027***	-0.0036***	-0.0028***	-0.0027***	-0.0028***	-0.0039***
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0010)
Momentum	-0.6187***	-0.6393***	-0.6186***	-0.6192***	-0.6197***	-0.6381***
	(0.0245)	(0.0274)	(0.0245)	(0.0245)	(0.0245)	(0.0273)
STD(RET)	0.0758	0.0590	0.0711	0.0716	0.0638	0.0503
	(0.0484)	(0.0539)	(0.0483)	(0.0484)	(0.0483)	(0.0537)
EARN	3.2253***	3.5621***	3.2347***	3.2589***	3.1945***	3.5258***
	(0.1744)	(0.1916)	(0.1738)	(0.1749)	(0.1747)	(0.1906)
dEarn	0.1681***	0.1381***	0.1678***	0.1674***	0.1676***	0.1382***
	(0.0123)	(0.0131)	(0.0123)	(0.0123)	(0.0123)	(0.0131)
STD(EARN)	5.6607***	5.1779***	5.7013***	5.7015***	5.7050***	5.2576***
	(0.7250)	(0.8035)	(0.7229)	(0.7266)	(0.7261)	(0.7997)
Smoothing	0.0331***	0.0409***	0.0330***	0.0329***	0.0303***	0.0384***
	(0.0114)	(0.0128)	(0.0113)	(0.0114)	(0.0114)	(0.0128)
AGE	-0.0125***	-0.0112***	-0.0129***	-0.0114***	-0.0111***	-0.0117***
	(0.0024)	(0.0026)	(0.0024)	(0.0024)	(0.0024)	(0.0026)
Constant	0.6005***	0.8149***	0.6228***	0.5049***	0.6741***	0.9867***
	(0.0704)	(0.1173)	(0.0711)	(0.0691)	(0.0768)	(0.1241)
Quarter FE	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES
Observations	20389	16340	20389	20389	20389	16340
R2	0.503	0.515	0.504	0.502	0.503	0.516
Adjusted R2	0.501	0.511	0.501	0.499	0.500	0.513
F Statistic	195.68	163.93	196.02	194.67	195.44	160.24

5.2 Within estimation (2)

Given our data's panel structure, we employ a within fixed effects model, as specified in equation 4.2, to control firm-specific time-invariant effects that might correlate with ESG performance. The fixed effects regression results for the BIAS variable are presented in Table 5.2.

When utilizing the within transformation, we find the independent variables of interest lose statistical significance, except for the G score that keeps significance on a 5 % level and the C score that keeps a significance on the 10% level when controlling for interpillar covariance. We also find the Leverage, Smoothing, and Age controls to lose statistical significance. The implications of these findings are further discussed in section 6.2.

Table 5.2 - This table presents the results from the model defined in equation 4.2. The ESG score is used as the variable of interest column 1, the four pillar scores separately in columns 2-5, while column 6 includes all pillar scores controlling for covariance. Heteroskedastic robust standard errors in parenthesis. Significance levels (*: 0.01, **: 0.05, *, 0.10)**

	BIAS					
	1	2	3	4	5	6
ESG	0.0006					
	(0.0004)					
E		0.0001				0.0000
		(0.0003)				(0.0003)
S			0.0006*			0.0006
			(0.0004)			(0.0004)
G				-0.0002		-0.0005**
				(0.0002)		(0.0002)
C					0.0002*	0.0003*
					(0.0001)	(0.0001)
Reporting	0.0144	0.0206*	0.0150	0.0229**	0.0208**	0.0210*
	(0.0109)	(0.0115)	(0.0101)	(0.0100)	(0.0095)	(0.0117)
Assurance	-0.0194	-0.0160	-0.0200	-0.0180	-0.0182	-0.0166
	(0.0176)	(0.0170)	(0.0175)	(0.0174)	(0.0173)	(0.0168)
BIG4	0.0436	0.0380	0.0442	0.0416	0.0417	0.0396
	(0.0321)	(0.0328)	(0.0319)	(0.0314)	(0.0313)	(0.0325)
AF	0.2285***	0.2444***	0.2286***	0.2295***	0.2286***	0.2442***
	(0.0196)	(0.0233)	(0.0196)	(0.0197)	(0.0196)	(0.0232)
LTG	-0.0055***	-0.0059***	-0.0055***	-0.0055***	-0.0055***	-0.0059***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Size	-0.1044***	-0.1298***	-0.1051***	-0.1042***	-0.1041***	-0.1323***
	(0.0177)	(0.0217)	(0.0177)	(0.0179)	(0.0177)	(0.0217)
PB	-0.0073***	-0.0053***	-0.0073***	-0.0073***	-0.0073***	-0.0054***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
RGROWTH	0.0315	0.0258	0.0302	0.0291	0.0293	0.0234
	(0.0250)	(0.0288)	(0.0250)	(0.0251)	(0.0250)	(0.0287)
Leverage	-0.0009	-0.0006	-0.0010	-0.0011	-0.0010	-0.0005
	(0.0035)	(0.0038)	(0.0035)	(0.0035)	(0.0035)	(0.0037)
Momentum	-0.5403***	-0.5414***	-0.5402***	-0.5395***	-0.5388***	-0.5374***
	(0.0242)	(0.0278)	(0.0242)	(0.0242)	(0.0241)	(0.0279)
STD(RET)	0.0928	0.0980	0.0908	0.0913	0.0939	0.0991
	(0.0617)	(0.0746)	(0.0619)	(0.0616)	(0.0615)	(0.0742)
EARN	2.8710***	3.1990***	2.8587***	2.8889***	2.9123***	3.2286***
	(0.4962)	(0.6164)	(0.4967)	(0.4980)	(0.4998)	(0.6203)
dEarn	0.1848***	0.1571***	0.1848***	0.1838***	0.1841***	0.1569***
	(0.0193)	(0.0213)	(0.0193)	(0.0193)	(0.0193)	(0.0212)
STD(EARN)	6.8829***	6.4898***	6.8885***	6.9232***	6.8853***	6.4568***
	(0.8774)	(1.0071)	(0.8753)	(0.8736)	(0.8732)	(0.9982)
Smoothing	-0.0254	-0.0293	-0.0259	-0.0257	-0.0245	-0.0281
	(0.0207)	(0.0234)	(0.0206)	(0.0208)	(0.0207)	(0.0233)
AGE	-0.0036	-0.0152	-0.0019	-0.0006	-0.0010	-0.0134
	(0.0445)	(0.0472)	(0.0441)	(0.0443)	(0.0441)	(0.0470)
Quarter FE	YES	YES	YES	YES	YES	YES
Observations	20389	16340	20389	20389	20389	16340
R2	0.560	0.566	0.560	0.560	0.560	0.567
Adjusted R2	0.547	0.551	0.548	0.547	0.547	0.552
F Statistic	265.55	217.06	265.73	265.44	265.62	211.25

5.3 Interactive effect of analyst following (3)

As the sample bias can be expressed as a function of the analyst following, we employ the interaction model defined in equation 4.3. From the results in table 5.3, we find the baseline estimators of the ESG score [0.0033, p-value<0.01] and analyst following [0.1334, p-value<0.01] to be of greater magnitude than the estimators in table 5.1, while the effect of the interaction is negative [-0.0008, p-value<0.01]. The variable analyst following is in log-form so that for marginal changes, the estimation can be interpreted as the percentage change. However, as the percentage difference of analyst following in our sample can be large, we caution against this interpretation following Thornton and Innes (1989).

Table 5.3 - This table displays the regression results using the model defined in equation 4.3 to estimate the interactive effect of analyst following. The ESG score is used as the variable of interest column 1, the four pillar scores separately in columns 2-5, while column 6 includes all pillar scores controlling for interpillar covariance. The controls load like the regressions in Table 5.1. Heteroskedastic robust standard errors in parenthesis. Significance levels (*: 0.01, **: 0.05, *, 0.10)**

	BIAS					
	1	2	3	4	5	6
ESG	0.0033***					
	(0.0008)					
E		0.0010				-0.0008
		(0.0007)				(0.0009)
S			0.0016**			0.0006
			(0.0007)			(0.0012)
G				0.0033***		0.0053***
				(0.0008)		(0.0010)
C					-0.0013**	-0.0007
					(0.0005)	(0.0006)
ESG*AF	-0.0008***					
	(0.0003)					
E*AF		-0.0001				0.0004
		(0.0002)				(0.0003)
S*AF			-0.0002			-0.00001
			(0.0002)			(0.0004)
G*AF				-0.0012***		-0.0019***
				(0.0003)		(0.0003)
C*AF					0.0003	0.0001
					(0.0002)	(0.0002)
AF	0.1334***	0.1077***	0.1111***	0.1618***	0.0799***	0.1786***
	(0.0145)	(0.0135)	(0.0135)	(0.0164)	(0.0174)	(0.0333)
Reporting	-0.0134***	-0.0103*	-0.0113**	0.0067	0.0041	-0.0106*
	(0.0051)	(0.0054)	(0.0049)	(0.0046)	(0.0045)	(0.0055)
Assurance	0.0246***	0.0251***	0.0243***	0.0326***	0.0299***	0.0227***
	(0.0059)	(0.0059)	(0.0058)	(0.0059)	(0.0058)	(0.0059)
BIG4	0.0110	0.0100	0.0087	0.0065	0.0034	0.0129
	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0123)	(0.0123)
Controls	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES
Observations	20389	16340	20389	20389	20389	16340
R2	0.503	0.515	0.504	0.503	0.503	0.517
Adjusted R2	0.501	0.511	0.501	0.500	0.500	0.514
F Statistic	194.02	162.38	194.18	193.38	193.64	155.36

5.4 Interactive effect of reporting scope (4)

As the ESG reporting is shown to increase the accuracy of ESG scores, we employ an interaction term between ESG reporting and performance using the model defined in equation 4.4. From the results in table 5.4, we find the estimator of the ESG score [0.0011, p-value<0.01], while the interactive effect of Reporting [-0.0006, p-value<0.05], Assurance [0.0030, p-value<0.01], and BIG4[-0.0051, p-value<0.01] provide significant estimators, but without a trend. The baseline reporting dummies also change to account for fitting the individual slopes. The cumulative regression slopes and coefficients are presented in table 5.6 and graphically in figure 5.1. The control variables load like the regressions in table 5.1.

Table 5.4 - This figure provides the regression coefficients of the interactive effect of ESG score and ESG reporting scope. The ESG reporting variables are defined cumulatively. The total effect of a reporting level is the sum of the base effect and interactive effects up to and including the reporting level. The summarized slopes and intercepts for the different reporting levels of column 1 are presented numerically in table 5.5 and graphically in figure 5.1. The ESG score is used as the variable of interest column 1, the four pillar scores separately in columns 2-5, while column 6 includes all pillar scores controlling for interpillar covariance. The controls load like the regressions in table 5.1. Heteroskedastic robust standard errors in parenthesis. Significance levels (*: 0.01, **: 0.05, *, 0.10)**

	BIAS					
	1	2	3	4	5	6
ESG	0.0011***					
	(0.0002)					
E		0.0005***				0.0005***
		(0.0002)				(0.0002)
S			0.0011***			0.0005**
			(0.0002)			(0.0002)
G				-0.0003**		-0.0009***
				(0.0001)		(0.0002)
C					-0.0007***	-0.0005***
					(0.0001)	(0.0001)
ESG*Reporting	-0.0006**					
	(0.0003)					
ESG*Assurance	0.0030***					
	(0.0005)					
ESG*BIG4	-0.0051***					
	(0.0020)					
E*Reporting		-0.0002				-0.0002
		(0.0002)				(0.0002)
E*Assurance		0.0010***				0.0001
		(0.0004)				(0.0004)
E*BIG4		-0.0011				0.0003
		(0.0008)				(0.0009)
S*Reporting			-0.0006***			-0.0003
			(0.0002)			(0.0003)
S*Assurance			0.0023***			0.0023***
			(0.0004)			(0.0005)
S*BIG4			-0.0034***			-0.0034***
			(0.0011)			(0.0010)
G*Reporting				0.0002		0.0007***
				(0.0002)		(0.0002)
G*Assurance				0.0009***		0.0007**
				(0.0003)		(0.0003)
G*BIG4				-0.0020		-0.0018
				(0.0012)		(0.0012)
C*Reporting					0.0004***	0.0001
					(0.0001)	(0.0002)
C*Assurance					0.0001	0.0002
					(0.0002)	(0.0002)
C*BIG4					-0.00005	-0.0002
					(0.0003)	(0.0003)
Reporting	0.0214	-0.0003	0.0253*	-0.0041	-0.0298**	-0.0297
	(0.0160)	(0.0107)	(0.0131)	(0.0123)	(0.0128)	(0.0266)
Assurance	-0.1855***	-0.0443*	-0.1388***	-0.0287	0.0227	-0.2104***
	(0.0374)	(0.0257)	(0.0305)	(0.0195)	(0.0146)	(0.0408)
BIG4	0.3658***	0.0856	0.2529***	0.1371	0.0062	0.3749***
	(0.1393)	(0.0536)	(0.0859)	(0.0861)	(0.0187)	(0.1413)
Controls	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES
Observations	20389	16340	20389	20389	20389	16340
R2	0.504	0.515	0.505	0.502	0.503	0.518
Adjusted R2	0.502	0.512	0.502	0.500	0.501	0.514
F Statistic	190.92	159.5	191.19	189.5	190.22	145.22

Table 5.5 - This table presents the cumulative effect of the four levels of ESG reporting from the regression in column 1 in table 5.4. The effect of the coefficients is displayed graphically in figure 5.1.

	BIAS	
	ESG intercept	ESG slope
Baseline	0.000	0.001
Reporting	0.021	0.000
Assurance	-0.165	0.003
BIG4	0.201	-0.002

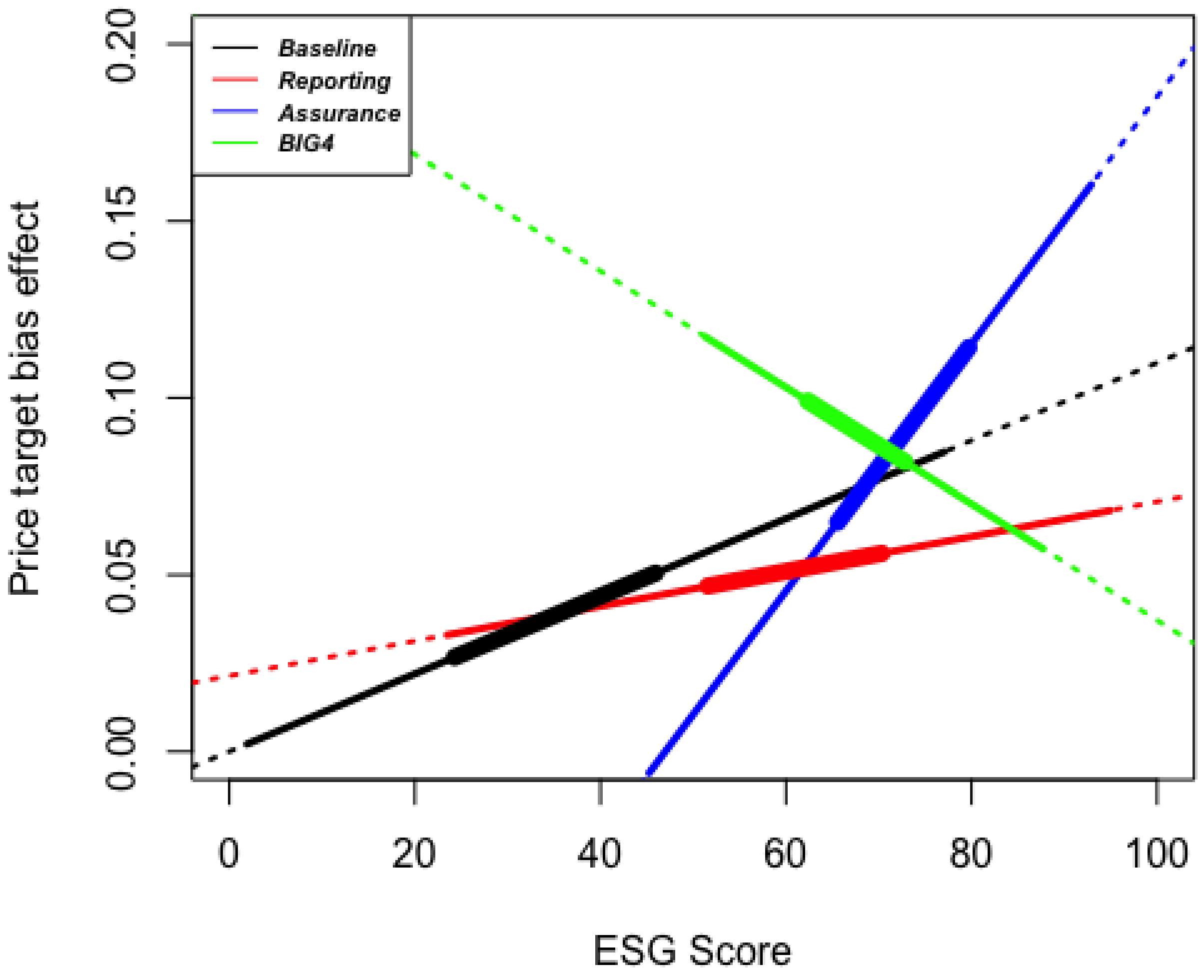

Figure 5.1 - This figure provides a graphical interpretation of the regression in column 1 in table 5.4 of the ESG scores for the different reporting variables explaining the ESG information environment. The thin solid line represents all observed variables excluding reasonable extremes, while the thick lines represent the middle 50 % of the data as shown in figure 3.5. The numerical values are presented in table 5.5.

5.5 ESG Score availability (5)

Using the within estimator model defined in equation 4.2, we estimate the effect of ESG score availability. Table 5.6 presents the estimates from the within-estimator regressions. The estimate for the availability of the Refinitiv ESG scores is positive [0.0579, p-value<0.01], while the estimate for the Refinitiv E score and RobecoSam ESG score is not significant. The effect on the RRI variable is significantly negative [0.0579, p-value<0.01]. The controls load similarly to the fixed effects regression estimating ESG performance as described in equation 4.2. We note that the effect of the reporting level variables, reflecting the availability of ESG information provided by the firm, is non-significant.

Table 5.6 - This figure displays the regression results from equation 4.2 regressing BIAS on the dummy variables indicating if an ESG score is available. The score tested for availability is named in each column. Heteroskedastic robust standard errors in parenthesis. Significance levels (*: 0.01, **: 0.05, *, 0.10)**

	BIAS			
	1	2	3	4
	Refinitiv ESG	Refinitiv E	RRI	ROBECO
Implemented	0.0579***	0.0067	-0.1655***	0.0061
	(0.0154)	(0.0117)	(0.0440)	(0.0204)
Reporting	0.0121	0.0108	0.0076	0.0106
	(0.0095)	(0.0096)	(0.0101)	(0.0096)
Assurance	-0.0233	-0.0245	-0.0265	-0.0257
	(0.0184)	(0.0184)	(0.0191)	(0.0186)
BIG4	0.0407	0.0422	0.0583*	0.0422
	(0.0303)	(0.0302)	(0.0304)	(0.0301)
AF	0.1881***	0.1920***	0.2044***	0.1924***
	(0.0194)	(0.0198)	(0.0210)	(0.0194)
LTG	-0.0044***	-0.0044***	-0.0039***	-0.0043***
	(0.0009)	(0.0009)	(0.0010)	(0.0009)
Size	-0.0759***	-0.0679***	-0.0747***	-0.0655***
	(0.0145)	(0.0142)	(0.0148)	(0.0139)
PB	-0.0090***	-0.0089***	-0.0091***	-0.0091***
	(0.0014)	(0.0015)	(0.0016)	(0.0015)
RGROWTH	0.0089	0.0061	-0.0055	0.0053
	(0.0240)	(0.0244)	(0.0259)	(0.0242)
Leverage	-0.0012	-0.0011	-0.0014	-0.0010
	(0.0029)	(0.0030)	(0.0030)	(0.0029)
Momentum	-0.5837***	-0.5882***	-0.5880***	-0.5873***
	(0.0221)	(0.0224)	(0.0239)	(0.0222)
STD(RET)	0.1903***	0.2062***	0.2876***	0.1906***
	(0.0665)	(0.0674)	(0.0709)	(0.0669)
EARN	2.2717***	2.3276***	2.3410***	2.3248***
	(0.4232)	(0.4316)	(0.4323)	(0.4276)
dEarn	0.1800***	0.1756***	0.1820***	0.1808***
	(0.0194)	(0.0196)	(0.0212)	(0.0197)
STD(EARN)	8.3111***	8.3737***	8.7717***	8.4792***
	(0.9673)	(0.9727)	(1.0420)	(0.9865)
Smoothing	-0.0368*	-0.0355*	-0.0376*	-0.0366*
	(0.0202)	(0.0204)	(0.0214)	(0.0202)
AGE	-0.0086	-0.0069	0.0150	-0.0060
	(0.0458)	(0.0457)	(0.0470)	(0.0456)
Quarter FE	YES	YES	YES	YES
Observations	24086	23689	21469	23914
R2	0.513	0.512	0.513	0.513
Adjusted R2	0.501	0.500	0.500	0.501
F Statistic	250.32	244.63	236.91	248.28

6. Discussion

In the above sections, we have presented relevant literature, outlined and tested different models using pooled OLS, and differences in differences methodology (within transformation). This section will discuss the results, their impact, and how they relate to the literature.

6.1 Main model (1)

The price target bias measures analysts' relative optimism or pessimism towards a particular firm. From the main cross-sectional regressions in table 5.1, we find the ESG performance to be positively related to the price target bias, implying that analysts' price targets are systematically higher than the realized market price regarding ESG performance. From the results in appendix table D.1, regressing the model on the absolute value of the BIAS, we note that the ESG-BIAS relationship indicates a worsening of the price target bias where the price target systematically deviates more from the realized market price.

Section 2.4-2.7 outlines three possible channels for ESG performance to impact the price target bias. Section 3.3 also outlines a fourth possible channel for how the summarized price target mean might be influenced by stale price targets. As we find the ESG score to have a positive estimator [0.0011, p-value<0.01], we find evidence that the price target bias, in total, does not reflect the ESG performance as either value subtractive or as an agency cost relative to the market. Three different explanations might therefore fit the positive results.

Firstly, ESG performance might proxy value additive effects, where analysts value its impact more than other market participants. This is especially relevant as the value creation of ESG is still debatable. This explanation implies that either the market, analysts, or both systematically fail to capture the actual intrinsic value as defined by equation 3.2.

Secondly, Cowen, et al. (2006) find that analysts' recommendations relate to their conflicts of interest. As Pedersen et al. (2021) propose that many (individual) investors are dual motive investors, investing both for financial gain and value their investments for social good, analysts may use ESG performance to compensate for lesser financial results and outlook. We find the results on ESG performance to be consistent with a worsening of price targets, as shown in appendix table D.1 column 1. If analysts use ESG performance to generate demand, and the price targets are constructed to justify their recommendation (Bradshaw, 2002), The observed difference should then be related to the sample bias.

Finally, systematic differences in the stale price target bias for high and low ESG performers might affect the observed coefficient. If the ESG performance is related to the age of the price targets, the estimate will be affected as stock prices are systematically increasing. We find high ESG performers to have higher BIAS. Therefore, if this is one of the influences, high ESG performers must have systematically newer price targets than low ESG performers. We are, however, not able to control for this effect.

6.1.1 ESG pillar scores

The positive BIAS is found in appendix table D.1 column 1 to correspond to a worsening of the price targets. When analyzing the effect based on the individual pillars, we find the positive estimation of the ESG score to be driven by the Environmental and Social pillars. In contrast, the Governance and Controversies pillars provide negative estimates when controlling for interpillar covariance, as shown in table 5.1 column 6.

The effect of Environmental and Social performance on the price target bias is positive. It indicates that price targets are systematically too high (appendix table D.1 column 2) for firms based on their Environmental and Social performance. Although Womak (1996) finds that optimistic price targets might benefit the firm by generating market interest, our results indicate that Environmental and Social performance seems to be related to overly optimistic price target means. Therefore, this finding has the same implications as the above discussion on the main ESG score.

The negative estimator for the Governance pillar indicates that Governance performance is related to more accurate price targets. This pillar, addressing firm reporting and how management considers shareholders long term interest, is by Cui et al. (2018), among others, assumed proxy the information environment. A better information environment should help alleviate uncertainty in the analyst valuation inputs, decreasing the price target dispersion. However, the expected value should not be influenced unless the uncertainty is disproportionate. The negative relationship with the Governance pillar reflects the relationship between price targets and market price. Therefore, the results might be related to one or both groups' valuations systematically improving or that Governance performance might reduce the price target bias, as there are less opportunities to issue to optimistic price targets when more information is available.

6.2 Within estimation (2)

Table 5.2 reports the regression results of the model defined in equation 4.2 using the within transformation. We find the ESG Score variable estimate not to be significantly different from zero [0.0006, p-value>0.10]. From our data and prior literature, we find two factors that might cause this. Firstly, analysts might not care about changes in ESG performance. If the ESG score proxies some other effect related to the firm, this firm fixed effect will be removed in this regression. This is a possible explanation as Pöyhiä (2017) finds that most financial analysts do not factor ESG performance into the price target.

Alternatively, the non-significance of the coefficients might be related to the failure of ESG scores to capture ESG performance. As mentioned in section 4.1.2, Gormley and Matsa (2014) find that large measurement errors cause the within estimators to be biased towards zero. The failure of ESG scores to capture ESG performance is supported by the low correlation seen between the different providers of ESG scores found by LaBella et al. (2019). We do, however, find the G score to remain significant at a similar magnitude [-0.0005, p-value<0.05], while the C score remains significant at the 10 % level [0.0003]. This might be caused by the information in these scores having smaller errors, as their impact is more definable, or there is a real relationship between BIAS and these measures.

6.3 Interactive effect of analyst following (3)

As the sample bias can be expressed as a function of the analyst following, we employ the interaction model defined in equation 4.3. Including the interaction term between ESG and analyst following, we find both the coefficient for analyst following and ESG score to increase, while the interaction term is negative. The BIAS for high ESG performers is relative to the main model in equation 4.1 higher for low analyst following, while it is also less affected by the number of analysts. In the range of analyst following in the sample, the interactive model is strictly higher than the results from table 5.1 column 1.

When performing regressions based on the four pillar scores, presented in table 5.3 column 6, we find the interactive ESG-BIAS relationship to be driven by the Governance pillar, while the effect of the other scores is non-significant. However, the non-significance of these scores might be caused by multicollinearity as we find the Variance Inflation Factor for these variables to be high [VIF>10]. The findings on firms with high Governance performance to have a more stable BIAS might indicate that information availability reduces the possibilities for analysts to interpret the information differently.

6.4 Interactive effect of reporting scope (4)

As the ESG performance by some is seen as a proxy for the information environment, we examine if the relationship between ESG performance and BIAS is affected by different levels of ESG reporting. The results of these regressions are presented in table 5.4, summarized in table 5.5, and presented graphically in figure 5.1. From these results, we find a statistically significant difference between the strengths of the relationships, although these relationships do not follow a trend.

Addressing the graphical representation of the estimators in figure 5.1, we find the estimated effect of the intervals for the different reporting scopes to not differ greatly from the baseline model. We find the middle 50 % of the data for all reporting scopes to be similar to the baseline regression slope. The deviations from the baseline slope in the relevant ESG performance intervals appear similar to the estimated coefficient of the ESG reporting dummies in the main model presented in table 5.1. From figure 3.5, we find that firms who issue and assure ESG reporting generally have higher ESG performance. The ESG performance intervals for the higher ESG reporting levels are smaller, while the ESG performance is generally greater. If the ESG reporting level truly influenced the relationship, we should expect the interactive relationship to follow a trend as these measures are supposed to proxy the ESG information environment. For this reason, we find overfitting of the model might be the cause of the interaction-effect of ESG reporting levels.

Unless related to some firm fixed effect or systematic errors calculating ESG scores, the ESG reporting should be expected not to influence the ESG-BIAS relationship. For example, Del Giudice & Rigamonti (2020) find assurance of ESG reporting reduce ESG performance measurement errors, but if these errors are not systematic the relationship should not be influenced.

6.5 ESG score availability (5)

We further examine if the effect of ESG performance on BIAS might be related to the availability of the scores. Table 5.6 reports the impact of the availability of ESG scores, seen as a treatment, estimated using the within-transformation model as defined in equation 4.2. We find that the availability of Refinitiv ESG scores, the earliest score available in our data, correlates with an increase in BIAS [0.0579, p-value<0.01] in the post-treatment period than for the pre-treatment period.

As we identify a significant increase of the BIAS between the pre- and post-period, the availability of the score might be, or be related to, some factor leading to too high price targets (controlled for in Appendix table D.1). The information contained in the ESG scores should already be available to analysts, either through published ESG reporting or firm following (DeLisle et al., 2021). We find the availability of the ESG information through reporting to, however, not significantly influence the BIAS. Therefore, the observed effect of the ESG performance on BIAS likely is not solely related to ESG performance but also some factors associated with the availability of the scores.

Apart from the RRI scores, we only identify a significant relationship between bias and the score availability for the Refinitiv ESG score. We do not identify a relationship for either the Refinitiv ESG score or the RobecoSam ESG score. As the RRI scores are implemented simultaneously, as shown in figure 3.4, the treatment effect occurs simultaneously for all companies. The differences in the pre- and post-period are therefore likely to capture the general difference in BIAS between periods.

6.6 ESG reporting level

Dhaliwal et al. (2012) find that firms that issue a separate CSR report have greater forecast accuracy. Similarly, we find firms that issue ESG reporting have lower BIAS, but contradictory that firms assuring the report have higher BIAS. However, using within estimators as reported in table 5.2 and figure table 5.6, we find no significant difference in price target bias related to the ESG reporting. The bias, however, seems to be mostly driven by ESG performance. As analysts can gather information through reporting, publicly available information, and direct monitoring of the company (DeLisle et al., 2021), analysts should generally be well suited to process such information. Pöyhiä (2017) finds that ESG information does not factor directly into analysts' price targets. Therefore, the finding that the reporting level of ESG information does not directly influence the price target bias is expected. Furthermore, the quality of the ESG information (fewer errors) will only impact the ESG-BIAS relationship if the errors are disproportionately distributed. Otherwise, the quality of information should only be associated with lower dispersion.

6.7 Robustness

This sub-section outlines the findings of the main additional testing performed to ensure the robustness of the results presented in this thesis.

6.7.1 Alternative ESG score providers

As the ESG scores might fail to capture ESG performance, we also employ ESG scores from two other providers available to us, RobecoSam and the Reputational Risk Index. We find the scores from these providers to provide results of approximately similar magnitude for ESG performance to Refinitiv, assuming the RRI is like the Refinitiv Controversies pillar.

6.7.2 ESG Ranking variables

Although found to be panel stationary, we have tested the quarter normalized ESG performance to ensure the increase in ESG performance, as shown in appendix figure C.2 does not drive our results. We find results similar to those presented in this thesis, using this variable transformation. The ranking variables are defined as:

$$rESG_{iq} = \frac{ESG_{iq}}{\overline{ESG_q}} - 1 \tag{6.1}$$

Where ESG is the ESG score, i denotes the firm, q denotes the quarter, and $rESG_{iq}$ *is the rank variable.*

6.7.3 ESG Score grades

We also test for the assumption of a linear relationship between ESG performance and price target bias. Using ESG Refinitiv grade scores, we find the estimated effect of ESG performance to be mostly linear, apart from the best(A+) and worst(D-) scores with estimators significantly greater than the linear estimate. There are, however, few observations with these scores, as shown in appendix table C.1, and the measured effect is likely is not representative.

6.7.4 Price target accuracy

We also test for the price target accuracy as a non-directional measure of the effect on price targets, defined as the absolute value of BIAS. A positive value indicates that the price target deviates more from the realized price. We find similar relationships as for the BIAS variable for all analyses as presented in Appendix table D.1. We find the positive relationships of our variables and the BIAS to generally correspond to a worsening of the price targets.

6.7.5 Robustness dependent variables

As our analysis uses summarized price target data, we employ additional dependent variables to test if our results might be influenced by changes in the observed price target bias distribution. Testing for the variables in table 6.1, we find the form of the price target distribution not to be practically impacted by our ESG factors. These robustness results provide evidence that our finding is not driven by a disproportional change in the price target summary distribution.

Table 6.1 – This table provides the formula for the variables used to test potential changes in the price target distribution function. The tilde denotes the median observation, i denotes the firm, and q denotes the quarter of observation.

Variable	Definition
Dispersion	$\frac{\sigma_{Price\ target_{iq}}}{\overline{Price\ target_{iq}}}$
Range	$\frac{\max\ [Price\ target_{iq}] - \min\ [Price\ target_{iq}]}{\overline{Price\ target_{iq}}}$
$\text{Range}_{\text{low}}$	$\frac{\lvert\min\ [Price\ target_{iq}] - \overline{Price\ target_{iq}}\rvert}{\overline{Price\ target_{iq}}}$
$\text{Range}_{\text{high}}$	$\frac{\lvert\max\ [Price\ target_{iq}] - \overline{Price\ target_{iq}}\rvert}{\overline{Price\ target_{iq}}}$
Skew	$\frac{\widetilde{Price\ target_{iq}} - \overline{Price\ target_{iq}}}{\overline{Price\ target_{iq}}}$

6.8 Further discussion and implication of findings

6.8.1 ESG performance

In the above subsections, we have discussed the effect of each model in our analysis. Our findings indicate a positive relationship between ESG performance and the price target bias. From the accuracy (BIAS absolute value) results presented in appendix table D.1, we find evidence that the positive coefficient represents a worsening of the price target bias. Looking at the individual pillars, we find the result to be driven by the Environmental and Social pillars.

In contrast, the Governance and Controversies pillar has a negative coefficient, acting as mediating effects.

We cannot test for the errors included in our dependent variable defined in equation 3.4 and are therefore not able to exclude any explanations for what is driving the observed correlation. The literature, however, outlines the existence of a sampling bias in analyst price targets, i.e., Bradshaw et al. (2012). It is, therefore, likely that the main driver of the results is related to this error, although other explanations cannot be excluded.

6.8.2 Information availability

We find the issuance or assurance of ESG reporting not to influence the price target bias. Therefore, the availability of such ESG information either does not influence the price target or equally influences analysts and market participants. We find small effects on the price target bias, cross-sectionally, but there is no clear trend in the relationships.

However, we find the bias to be larger in the period after a company receives an ESG score, indicating that ESG scoring availability is related to some factor that impacts the price target bias.

7. Limitations

The main limitation in this thesis is that we cannot exclude possible explanations for our findings as we cannot control for either the sample bias or the stale price target bias. Furthermore, the price target bias is also dependent on both analyst and market valuations, and deviations in either might cause the price target bias to be affected.

Firstly, as we use summarized IBES data to estimate the relationship between BIAS and ESG in this study, we cannot remove the effect of stale price targets. Thus, we cannot rule out the explanation that high ESG performers' price targets are systematically newer, and therefore more positive. Therefore, we recommend that future studies use detailed price target data to remove this potential error.

Secondly, as we use summarized IBES data to estimate the relationships, we cannot control for factors related to the specific analyst. For example, Dechow and You (2017) find differences between analysts, and by using summarized data, we cannot control for effects related to the individual analyst in the price target summary. Controlling for analyst effects might assist in isolating the factors that impact the ESG-BIAS relationship.

Thirdly, as we only source data from 2000-2021 and the Refinitiv ESG scores started to be implemented in 2002, the pre-treatment period for some of the firms in our sample might be too small. To add to the robustness of the results, data should be sourced for more years to ensure that the pre-treatment period is representative.

Finally, the failure of ESG scores to precisely capture ESG performance results in a failure to conclude if the non-significant effects of ESG performance on BIAS found using within estimators are caused by measurement error or because the proxied effect of ESG performance found in the cross-sectional regressions is due to some firm fixed effect.

8. Conclusion

In this thesis, we have studied the effect of ESG performance on the price target bias, a measure of analyst accuracy. ESG performance has been proposed to increase firm value and is important for "responsible-investors". Therefore, we have examined how analysts, a group providing in-depth research of companies, price ESG factors relative to other market participants.

To test the relationship between ESG performance and the price target bias, we designed and regressed models to control for factors known to influence the price target bias. We also tested for how the ESG-BIAS relationship was affected by analyst following and ESG reporting and the effect of ESG scoring availability.

Our final sample consisted of 24 367 firm-quarter observations in the period 2001-2021 based on the securities on the S&P 500, with data sourced from Refinitiv. In addition to sourcing ESG performance scoring from Refinitiv, we sourced ESG scoring data from RobecoSam and the Reputational Risk Index to add further robustness to our analysis.

Evaluating the relationship between ESG performance and BIAS in table 5.1, we find ESG performance to be positively correlated with the price target bias. The relationship is driven by the E and S scores, while the G and C scores act as a mediating effect. Analyzing the analyst accuracy, we find similar results, indicating that the measured positive relationship represents a worsening of the price targets. We do, however, not find this relationship to hold when estimating our model using the within transformation, except for the Governance pillar. We find the non-significance of the results to possibly be caused by ESG score measurement errors.

We also examine how the analyst following, an important determinant of the price target bias, affects the ESG-BIAS relationship reported in table 5.3. We find the baseline price target bias to be larger for high ESG performers, but also that the price target bias is more stable across analyst following. The results are driven by the Governance score and might indicate a link with the information environment.

We find that firms that issue and assure ESG reporting have higher ESG performance. Testing using the within estimator, we find the reporting to not significantly impact the BIAS. We additionally test for cross-sectional differences in the ESG-BIAS relationship in table 5.5, finding different ESG-BIAS relationships. However, by the inconsistency of the results, the relationship might be due to overfitting of the model.

In table 5.6, we test if the price target bias is different for the period before and after a company receives an ESG Score and find evidence for a larger BIAS after a company receives a Refinitiv ESG score. This result indicates that the observed effect on BIAS of ESG performance might be associated with the availability of ESG scoring information. Similar to the ESG performance, we find the increase in the price target bias to represent a worsening of the price targets.

Given our data, we cannot find if the ESG-BIAS relationship is caused by a sampling bias, stale price target bias, or real differences in analyst and/or market valuations. Our results indicate that analysts provide overly optimistic price targets for companies in relation to their ESG performance. We, therefore, propose that further research be done utilizing the IBES price target detail file to control for stale price targets and factors related to analysts.

9. References

Alford, A.W., Berger, P.G. (1999). A Simultaneous Equations Analysis of Forecast Accuracy, Analyst Following, and Trading Volume. *Journal of Accounting, Auditing & Finance, 14*(3), 219-240. https://doi.org/10.1177/0148558X9901400303

Ashbaugh, H., Pincus, M. (2002). Domestic Accounting Standards, International Accounting Standards, and the Predictability of Earnings. *Journal of Accounting Research, 39*(3), 417-434. https://doi.org/10.1111/1475-679X.00020

Barber, B.M., Lehavy, R., McNichols, M., Trueman, B. (2006). Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations. *Journal of Accounting and Economics, 41*(1), 87-117. https://doi.org/10.1016/j.jacceco.2005.10.001

Bradshaw, M., Huang, A., Tan, H. (2014). *Analyst Target Price Optimism Around the World.* (Working Paper). Boston College. https://www.fox.temple.edu/wp-content/uploads/2013/02/TP-20121228.pdf

Bradshaw, M.T. (2002). *The Use of Target Prices to Justify Sell-Side Analysts' Stock Recommendations* (Working Paper). Harvard Business School. https://dx.doi.org/10.2139/ssrn.303162

Brauer, M., Wiersema, M. (2018). Analyzing Analyst Research: A Review of Past Coverage and Recommendations for Future Research, *Journal of Management*, *44*(1), 218-248. https://doi.org/10.1177%2F0149206317734900

Byard, D., Li, Y., Weintrop, J. (2006). Corporate governance and the quality of financial analysts' information. *Journal of Accounting and Public Policy, 25*(5), 609-625. https://doi.org/10.1016/j.jaccpubpol.2006.07.003

Chen, W., Zhou, G., Zhu, X. (2019). CEO tenure and corporate social responsibility performance. *Journal of Business Research, 95*, 292-302. https://doi.org/10.1016/j.jbusres.2018.08.018

Cheng, I.-H., Hong, H., Shue, K. (2013). *Do Managers do Good with Other People's Money?* (Working Paper No. 19432). National Bureau of Economic Research. https://nber.org/papers/w19432

Colak, G., Korkeamaki, T., Meyer, N.O. (2020). ESG and CEO Turnover. *Proceedings of Paris December 2020 Finance Meeting EUROFIDAI – ESSEC.* https://dx.doi.org/10.2139/ssrn.3710538

Cowen, A., Groysberg, B., Healy, P. (2006). Which Types of Analyst Firms are More Optimistic? *Journal of Accounting and Economics, 41*(1), 119-146. https://doi.org/10.1016/j.jacceco.2005.09.001

Cui, J., Jo, H., Na, H. (2018). Does Corporate Social Responsibility Affect Information Asymmetry? *Journal of Business Ethics, 148*(3), 549-572. https://doi.org/10.1007/s10551-015-3003-8

Dechow, P. M., & Schrand, C. (2004). *Earnings quality*. Research Foundation of CFA Institute.

Dechow, P.M., You, H. (2017). *Determinants of Errors in Analysts' Target Price Implied Returns* (Working Paper). https://www.nhh.no/contentassets/0e2648f9e80c45a4835bf3a81e785eef/dechow-and-you-2017-1_4176.pdf?fbclid=IwAR3zcEMTS-IvejjKxMY6Vv5yq7jcwHidu2owCMw4Th_nHyg6qTXzWMACpRU

Del Guidice, A., Rigamonti, S. (2020). Does Audit Improve the Quality of ESG Scores? Evidence from Corporate Misconduct. *Sustainability, 12*(14), 5670. https://doi.org/10.3390/su12145670

DeLisle, R.J., Grant, A., Mao, R. (2021). *Does ESG Decrease Information Asymmetry? Evidence from Earnings Conference Call Tones and Subsequent Returns*.(Working Paper).https://www.efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/2021-Leeds/papers/EFMA%202021_stage-2049_question-Full%20Paper_id-330.pdf

Dhaliwal, D., Li, O.Z., Tsang, A., Yang, Y.G. (2014). Corporate social responsibility disclosure and the cost of equity capitals: The roles of stakeholder orientation and financial transparency. *Journal of Accounting and Public Policy, 33*(4), 328-355. https://doi.org/10.1016/j.jaccpubpol.2014.04.006

Dhaliwal, D.S., Radhakrishnan, S., Tsang, A., Yang, Y.G. (2012). Nonfinancial Disclosure and Analyst Forecast Accuracy: International Evidence on Corporate Social Responsibility Disclosure. *The Accounting Review, 87*(3), 723-759. http://jstor.org/stable/23245628.

Erns & Young. (1997). *Measures That Matter*. Ernst & Young Global Limited. http://valuementors.com/pdf/Measures%20that%20Matter.pdf

Fama, E.F., French, K.R. (2010). Luck versus Skill in the Cross-Section of Mutual Fund Returns. *The Journal of Finance, 65*(5), 1915-1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

Flugum, R., Souther, M.E. (2021). *Stakeholder Value: A convenient Excuse for Underperforming Managers?* https://dx.doi.org/10.2139/ssrn.3725828

Freeman, R. E., Harrison, J. S., Wicks, A. C., Parmar, B., & De Colle, S. (2010). Stakeholder theory: The state of the art. Cambridge University Press.

Friede, G., Busch, T., Bassen, A. (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210-233. https://doi.org/10.1080/20430795.2015.1118917

Friedman, M. (1970, September 13). A Friedman doctrine – The Social Responsibility of Business Is to Increase Its Profits. *The New York Times*. https://nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html

Gormley, T.A., Matsa, D.A. (2014). Common Errors: How to (and Not to) Control for Unobserved Heterogeneity. *The Review of Financial Studies*, *27*(2), 617-661. https://jstor.org/stable/24465367

Granskog, A., Lee, L., Magnus, K.-H., Sawers, C. (2020). *Survey: Consumer sentiment on sustainability in fashion*. (Report). McKinsey & Company. https://www.mckinsey.com/~/media/mckinsey/industries/retail/our%20insights/survey%20consumer%20sentiment%20on%20sustainability%20in%20fashion/survey-consumer-sentiment-on-sustainability-in-fashion-vf.pdf?shouldIndex=false

Hong, H., Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, *93*(1), 15-36. https://doi.org/10.1016/j.jfineco.2008.09.001

Hutira, S. (2016). *Determinants of Analyst Forecasting Accuracy* [Bachelor's thesis, University of Pennsylvania]. University of Pennsylvania Scholarly Commons. https://repository.upenn.edu/joseph_wharton_scholars/15

Ioannou, I., Serafeim, G. (2015). The impact of corporate social responsibility on investment recommendations: Analysts' perceptions and shifting institutional logics. *Strategic Management Journal*, *36*, 1053-1081. https://doi.org/10.1002/smj.2268

Jiang, L., Ferguson, A., Yeo, J., Bailey, R. (2020). *ESG as a Workforce Stategy. Part I: Overview and Results.* Marsh McLennan. https://www.marshmclennan.com/content/dam/mmc-web/insights/publications/2020/may/ESG-as-a-workforce-strategy_Part%20I.pdf

Kiplinger (2021, October 12). *Kiplinger – Domini Poll: ESG Investing Is Gaining Traction*. https://www.kiplinger.com/investing/esg/603503/esg-investing-is-gaining-traction

LaBella, M.J., Sullivan, L., Russel, J., Novikov, D. (2019). *The Devil is in the Details: Data and Implications for Responsible Investing* (Report No. QSCR 18884). QS Inverstors. https://leggmason.com/content/dam/legg-mason/documents/en/insights-and-education/whitepaper/lm-qs-the-devil-is-in-the-details-0919.pdf

Lang, M.H., Lundholm, R.J. (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review*, *71*(4), 467-492. http://jstor.org/stable/24856

List of S&P 500 Companies. (2021, September 9). In *Wikipedia*. https://en.wikipedia.org/w/index.php?title=List_of_S%26P_500_companies&oldid=1042268881

Meek, G.K., Roberts, C.B., Gray, S.J. (1995). Factors Influencing Voluntary Annual Report Disclosures by U.S., U.K. and Continental European Multinational Corporations. *Journal of International Business Studies*, *26*(3), 555-572. http://jstor.org/stable/155561

Millian, J.A., Smith, A.L., Alfonso, E. (2017). Does an Analyst's Access to Information Vary with the Favorableness of Their Language When Speaking to Management? *Accounting Horizons, 31*(4), 13-31. https://doi.org/10.2308/acch-51798

Pedersen, L.H., Fitzgibbons, S., Pomorski, L. (2021). Responsible investing: The ESG efficient frontier. *Journal of Financial Economics, 142*(2), 572-597. https://doi.org/10.1016/j.jfineco.2020.11.001

Peek, E. (1997). *Earnings Forecasting Research: An Overview and Critique* (Research Memorandum No. 1997-44). Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam. https://research.vu.nl/en/publications/earnings-forecasting-research-an-overview-and-critique

Pöyhiä, A.-M. (2017). *Sell-side analysts' valuation method choices and the role of ESG information in renewable energy valuations* [Master's thesis, Aalto University School of Business]. Aalto University Digital Archive. http://urn.fi/URN:NBN:fi:aalto-201708176709

PricewaterhouseCoopers. (2019). *Mind the gap: the continued divide between investors and corporates on ESG*. PwC Governance Insights Center. https://www.pwc.com/us/en/services/assets/pwc-esg-divide-investors-corporates.pdf

Ramnath, S., Rock, S., Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting, 24*(1), 34-75. https://doi.org/10.1016/j.ijforecast.2007.12.006

Refinitiv. (2021). *Environmental, Social and Governance Scores from Refinitiv* (Report No. RE1521154/10-21). https://refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

Sharief, M. (2020). *PriceTargets understanding* [Discussion post]. Refinitiv Developer Community. https://community.developers.refinitiv.com/questions/56149/pricetagets-understanding.html

Thronton, R.J., Innes, J.T. (1989). Interpreting Semilogarithmic Regression Coeficcients in Labor Research. *Journal of Labor Research, 10*(4), 443-447. https://doi.org/10.1007/BF02685335

UN Global Compact. (2004). *Who Cares Wins: Connecting Financial Markets To A Changing World*. UN environment program finance initiative. https://www.unepfi.org/fileadmin/events/2004/stocks/who_cares_wins_global_compact_2004.pdf

Womack, K.L. (1996). Do Brokerage Analysts' Recommendations Have Investment Value? *The Journal of Finance, 51*(1), 137-165. https://doi.org/10.2307/2329305

10. Appendicies

10.1 Appendix A – Variable construction

Table A.1 – This table describes the variable construction of the main variables in our sample. All continuous control variables and the BIAS variable is Winsorized at the 1 % and 99 % level to reduce the impact of outliers (denoted as W in data dropping). Further data dropping is described in column "Data dropping".

Variable	Description	Data dropping
BIAS	$\frac{\overline{Price\ target_{q-4}}}{Price\ Close_q} - 1$	W
ESG Score	Refinitiv ESG score	
ESG reporting	If separate ESG report/section	
ESG assurance	If named CSR report auditor	
Big 4 assurance	If CSR auditor is BIG4	
Analyst following	$ln(1 + \#of\ analysts)$	W
Long term growth	$Analyst\ estimated\ LTG$(FY2-FY5)	W, LTG < 0
RGROWTH	$\frac{Sales_q}{Sales_{q-4}} - 1$	W
EARN	$\frac{EPS}{Price\ Close}$	W
dEARN	$\frac{Earn_q}{Earn_{q-4}} - 1$	W
STD(EARN)	$sd(Momentum_q: Momentum_{q-4})$	W
Smooth	$\frac{\lvert Normalized\ EPS - EPS \rvert}{\lvert EPS \rvert} - 1$	W, Smooth > 1
Leverage	$\frac{Total\ assets}{Total\ equity}$	W, $Leverage < 1$
Size	ln(Market value)	W
Age	ln(first reported founding)	
PB	Price to book value	W, P/B < 1
Momentum	$\frac{Price\ Close_q}{Price\ Close_{q-1}} - 1$	W
STD(RET)	$sd(Momentum_q: Momentum_{q-4})$	W
GISC sector	Reported GISC sector	

10.2 Appendix B – Correlation matrix

Table B.1 - This table reports the correlation coefficients of the variables used in this paper. The variable construction is defined in table A.1 and table 6.1.

		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1	BIAS	1.0000									
2	ESG Score	0.0005	1.0000								
3	E	0.0016	0.8294	1.0000							
4	S	0.0079	0.8920	0.6711	1.0000						
5	G	-0.0176	0.6858	0.3343	0.3910	1.0000					
6	C	-0.0718	-0.2938	-0.2636	-0.2839	-0.1532	1.0000				
7	AF	0.0379	0.2721	0.1991	0.2848	0.0926	-0.2489	1.0000			
8	LTG	-0.0349	-0.1961	-0.1215	-0.1340	-0.1958	0.0598	0.0379	1.0000		
9	PB	-0.2189	0.0615	0.0912	0.0933	-0.0173	0.0437	0.0713	0.1704	1.0000	
10	Leverage	-0.0070	0.0848	0.0669	0.0811	0.0513	-0.0795	0.0734	-0.1321	0.1047	1.0000
11	Momentum	-0.3265	-0.0149	-0.0112	-0.0126	-0.0047	0.0158	-0.0199	0.0319	0.0967	-0.0220
12	STD(RET)	0.2017	-0.0839	-0.0827	-0.0576	-0.0820	0.0227	-0.0397	0.2075	0.0009	-0.0390
13	Earn	0.3981	0.1143	0.0664	0.0740	0.1053	-0.1630	0.0591	-0.2856	-0.3643	0.2417
14	dEarn	0.3694	-0.0580	-0.0382	-0.0433	-0.0479	-0.0081	0.0414	0.1849	-0.0703	-0.0103
15	STD(EARN)	0.3627	0.0088	-0.0193	0.0007	0.0161	-0.0567	-0.0016	-0.0102	-0.2145	0.1065
16	Smoothing	0.0602	-0.0983	-0.0812	-0.0795	-0.0711	0.0141	-0.0347	0.2141	-0.0355	-0.0203
17	Rgrowth	0.0383	-0.1973	-0.1484	-0.1439	-0.1554	0.0580	0.0019	0.2667	0.0397	-0.1042
18	Age	-0.0238	0.1981	0.1554	0.1715	0.1117	-0.0726	-0.0134	-0.2712	-0.0597	0.2300
19	Size	-0.0789	0.5131	0.4426	0.5037	0.2378	-0.4208	0.6270	-0.1148	0.1651	0.1347
20	Accuracy	0.8014	-0.0380	-0.0290	-0.0172	-0.0532	-0.0304	0.0087	0.1052	-0.1003	-0.0384
21	Dispersion	0.2975	-0.0848	-0.0639	-0.0596	-0.0804	-0.0322	0.0771	0.1508	-0.0113	-0.0304
22	Range	0.2803	-0.0018	-0.0013	0.0208	-0.0451	-0.0849	0.2968	0.1608	0.0090	-0.0213
23	Range_high	0.3399	-0.0099	-0.0083	0.0055	-0.0305	-0.0616	0.2245	0.1114	-0.0287	-0.0100
24	Range_low	0.1282	0.0079	0.0067	0.0318	-0.0478	-0.0855	0.2912	0.1695	0.0498	-0.0279
25	Skew	0.1923	-0.0108	-0.0057	-0.0128	0.0067	0.0056	-0.0307	-0.0423	-0.0453	0.0259
26	Robeco - ESG	-0.0023	0.6025	0.5632	0.5992	0.1809	-0.2730	0.1743	-0.0559	0.0418	0.0596
27	Robeco - G	0.0015	0.5349	0.4924	0.5445	0.1533	-0.2214	0.1487	-0.0290	0.0464	0.0539
28	Robeco – E	0.0092	0.6022	0.5818	0.5779	0.1934	-0.2891	0.1711	-0.0656	0.0301	0.0897
29	Robeco - S	-0.0098	0.5665	0.5211	0.5727	0.1646	-0.2658	0.1604	-0.0567	0.0259	0.0263
30	RRI	-0.0181	-0.4613	-0.4191	-0.4207	-0.2386	0.4682	-0.3148	0.1653	0.0089	-0.1566

		11	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*
11	Momentum	1.0000									
12	STD(RET)	0.0636	1.0000								
13	Earn	-0.2026	0.0211	1.0000							
14	dEarn	-0.3356	0.1011	0.2205	1.0000						
15	std(EARN)	0.0014	0.4438	0.4716	0.1496	1.0000					
16	Smoothing	0.0289	0.1499	-0.0336	0.0821	0.1725	1.0000				
17	Rgrowth	-0.0218	0.0985	-0.0452	0.1421	0.0246	0.0566	1.0000			
18	Age	-0.0385	-0.1797	0.1612	-0.0558	-0.0262	-0.1226	-0.2027	1.0000		
19	Size	0.0089	-0.2096	0.0210	-0.0549	-0.1250	-0.1308	-0.0883	0.1721	1.0000	
20	Accuracy	-0.1670	0.2572	0.2761	0.2492	0.3714	0.1200	0.0584	-0.0950	-0.1205	1.0000
21	Dispersion	-0.0704	0.3712	0.0733	0.1718	0.3067	0.1411	0.0577	-0.1426	-0.1189	0.3726
22	Range	-0.0641	0.3334	0.0806	0.1697	0.2824	0.1242	0.0589	-0.1425	0.0479	0.3458
23	Range_high	-0.0966	0.2912	0.1133	0.1992	0.2657	0.1004	0.0446	-0.1104	0.0093	0.3607
24	Range_low	-0.0077	0.2823	0.0191	0.0851	0.2172	0.1145	0.0577	-0.1368	0.0779	0.2255
25	Skew	-0.0810	0.0389	0.0801	0.1124	0.0745	-0.0008	-0.0174	0.0189	-0.0472	0.1444
26	Robeco - ESG	-0.0071	-0.0327	0.0908	-0.0194	0.0076	-0.0071	-0.1041	0.0918	0.3531	0.0004
27	Robeco - G	-0.0001	0.0045	0.0780	-0.0102	0.0277	0.0084	-0.0926	0.0604	0.2987	0.0184
28	Robeco – E	-0.0087	-0.0356	0.1162	-0.0274	0.0149	0.0010	-0.1083	0.0908	0.3550	0.0058
29	Robeco - S	-0.0131	-0.0546	0.0755	-0.0125	-0.0108	-0.0062	-0.1036	0.0959	0.3455	-0.0219
30	RRI	0.0289	0.1111	-0.1682	0.0299	-0.0153	0.1009	0.1405	-0.1974	-0.5694	0.0548

		21	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*
21	Dispersion	1.0000									
22	Range	0.9237	1.0000								
23	Range_high	0.8144	0.8805	1.0000							
24	Range_low	0.7734	0.8387	0.4803	1.0000						
25	Skew	0.1143	0.1004	0.3809	-0.2519	1.0000					
26	Robeco - ESG	-0.0070	0.0520	0.0432	0.0448	0.0249	1.0000				
27	Robeco - G	0.0019	0.0539	0.0382	0.0537	0.0163	0.9320	1.0000			
28	Robeco – E	-0.0091	0.0482	0.0376	0.0442	0.0297	0.9301	0.8271	1.0000		
29	Robeco - S	-0.0215	0.0397	0.0314	0.0358	0.0183	0.9471	0.8700	0.8605	1.0000	
30	RRI	0.0400	-0.0505	-0.0387	-0.0490	0.0050	-0.2842	-0.2456	-0.2982	-0.2689	1.0000

10.3 Appendix C – Additional data description

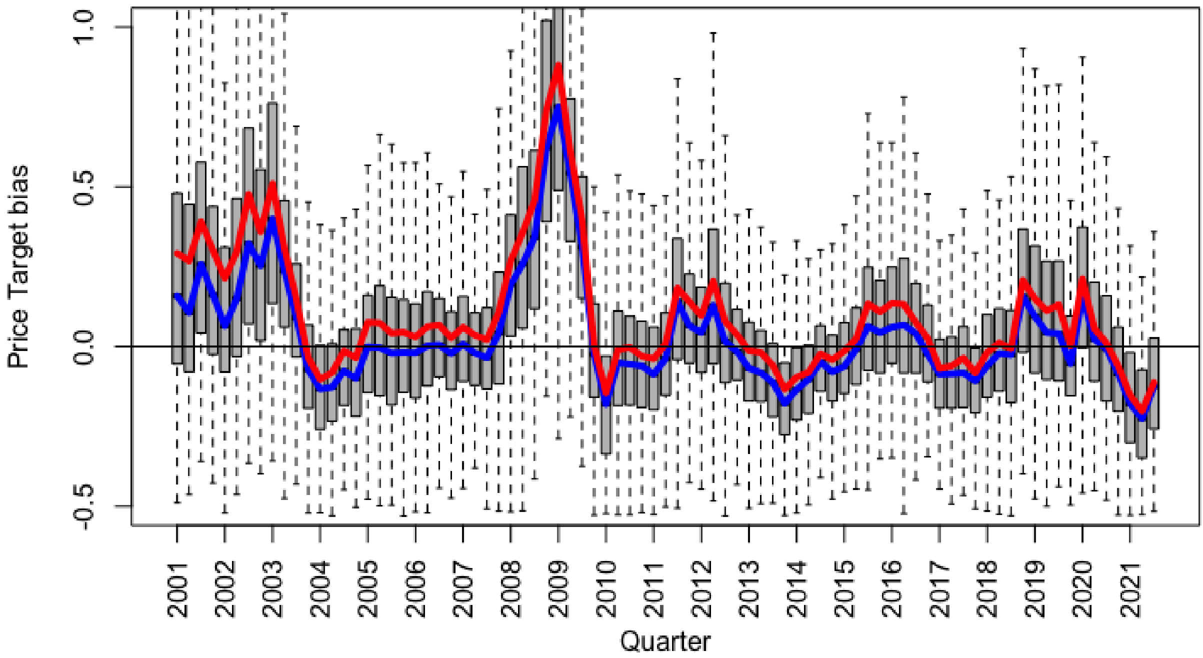

Figure C.1 - This figure provides a graphical representation of the price target bias over the time dimension in the sample. The boxes represent the middle 50 % of the data, while the whiskers represent the reasonable extremes in each quarter as defined by the default of the R boxplot function. The blue line represents the median observation, while the red line represents the mean.

Table C.1- This table shows the number of observations of each Refinitiv ESG score grade in the sample. The 12 grade scores are divided into 12 equally sized bins as described in the Refinitiv methodology (2021).

ESG Grade	Total	D-	D	D+	C-	C	C+	B-	B	B+	A-	A	A+
Observations	20627	177	864	1707	2277	2461	2887	2698	2647	2781	1450	640	39

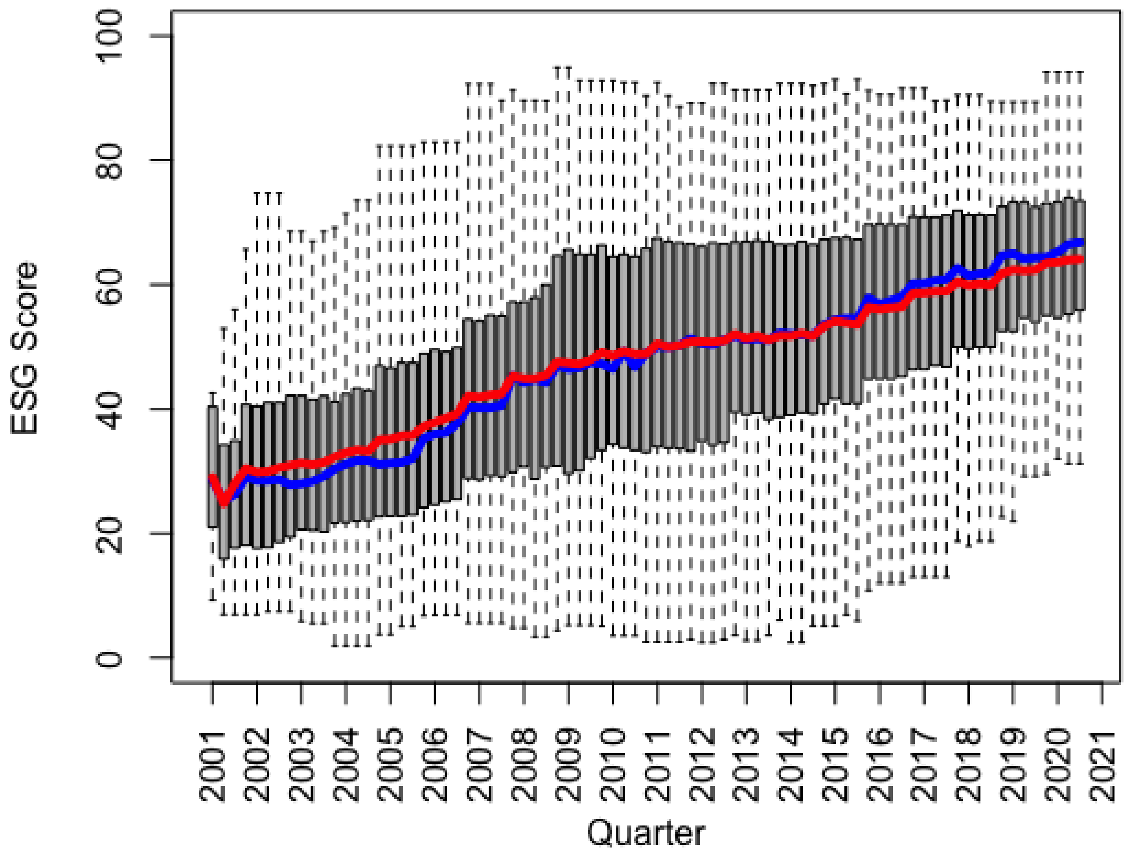

Figure C.2 - This figure displays the change across the time dimension for the Refinitiv ESG scores in our sample. The boxes represent the middle 50 % of the data, while the whiskers represent the reasonable extremes in each quarter as defined by the default of the R boxplot function. The blue line represents the median observation, while the red line represents the mean.

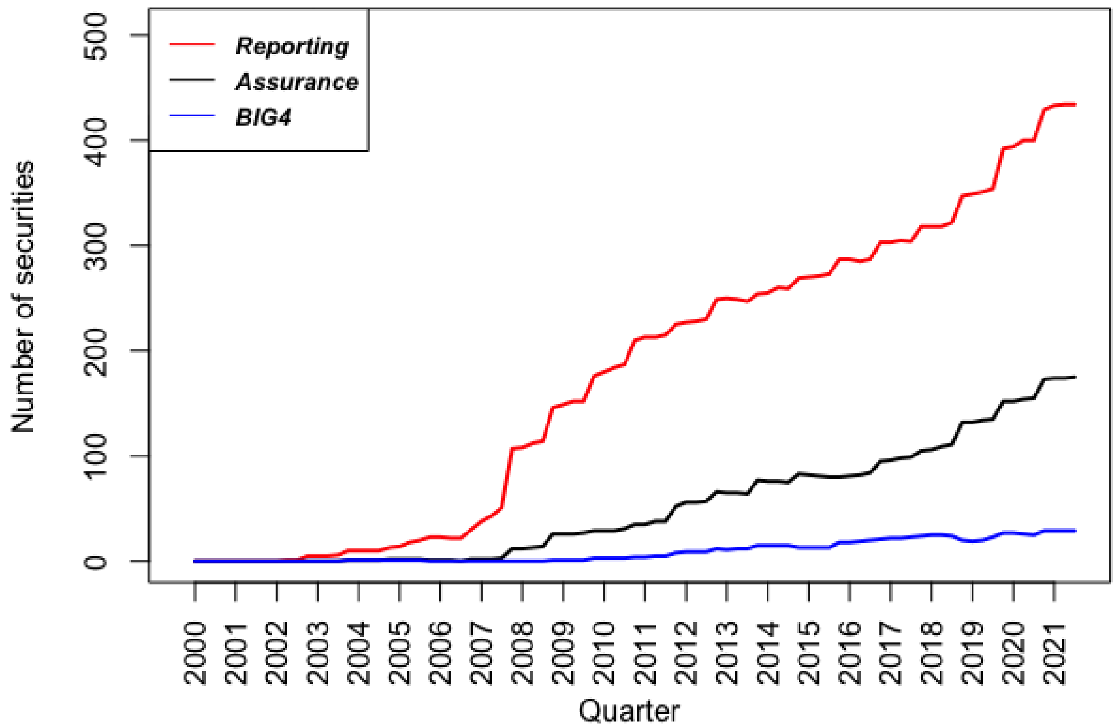

Figure C.3 - This figure displays the cumulative sum of the defined reporting levels for each quarter in the raw dataset consisting of 43 855 firm-quarter observations. The variables are not made to be strictly increasing.

10.4 Appendix D – Price target accuracy regressions

Table D.1 –This table reports robustness results based on the absolute value of BIAS. Columns 1 and 2 use the model in equation 4.1 and is comparable to table 5.1(1,6). Column 3 reports the effect of implementation (table 5.6 column 1). Column 4 uses model 4.2 similarly to table 5.2 column 1. Column 5 and 6 reports the effects on the interaction terms comparable to column 1 in table 5.3 and 5.4. Heteroskedastic robust standard errors in parenthesis. Significance levels (*: 0.01, **: 0.05, *, 0.10)**

	Accuracy					
	1	2	3	4	5	6
ESG	0.0009***			0.0004**	0.0033***	0.0007***
	(0.0001)			(0.0002)	(0.0006)	(0.0002)
E		0.0003***				
		(0.0001)				
S		0.0004***				
		(0.0001)				
G		-0.0002**				
		(0.0001)				
C		-0.0001**				
		(0.0001)				
ESG implemented			0.0434***			
			(0.0124)			
ESG*AF					-0.0008***	
					(0.0002)	
ESG*Reporting						0.0001
						(0.0002)
ESG*Assurance						0.0021***
						(0.0005)
ESG*BIG4						-0.0066***
						(0.0012)
AF	0.0605***	0.0618***	0.0591***	0.0782***	0.0950***	0.0615***
	(0.0056)	(0.0064)	(0.0159)	(0.0087)	(0.0105)	(0.0056)
Reporting	-0.0074	-0.0042	0.0074	0.0034	-0.0071	-0.0105
	(0.0047)	(0.0049)	(0.0078)	(0.0050)	(0.0047)	(0.0138)
Assurance	0.0134**	0.0148***	-0.0235	-0.0224***	0.0144***	-0.1393***
	(0.0055)	(0.0055)	(0.0158)	(0.0062)	(0.0055)	(0.0331)
BIG4	-0.0081	-0.0089	0.0386	0.0476***	-0.0055	0.4489***
	(0.0117)	(0.0115)	(0.0264)	(0.0132)	(0.0118)	(0.0807)
LTG	0.0031***	0.0023***	0.0009	0.0002	0.0031***	0.0031***
	(0.0003)	(0.0003)	(0.0007)	(0.0003)	(0.0003)	(0.0003)
Size	-0.0325***	-0.0391***	-0.0245**	-0.0470***	-0.0316***	-0.0323***
	(0.0022)	(0.0026)	(0.0122)	(0.0049)	(0.0022)	(0.0022)
P/B	0.0024***	0.0029***	0.0028***	0.0043***	0.0024***	0.0024***
	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0004)	(0.0004)
RGROWTH	-0.0025	-0.0184	-0.0188	-0.0011	-0.0043	-0.0032
	(0.0109)	(0.0123)	(0.0202)	(0.0106)	(0.0109)	(0.0109)
Leverage	-0.0055***	-0.0059***	-0.0073***	-0.0088***	-0.0056***	-0.0056***
	(0.0007)	(0.0008)	(0.0025)	(0.0012)	(0.0007)	(0.0007)
Momentum	-0.1650***	-0.1863***	-0.2045***	-0.1595***	-0.1652***	-0.1643***
	(0.0155)	(0.0173)	(0.0195)	(0.0140)	(0.0155)	(0.0154)
STD(RET)	0.1991***	0.1251***	0.1771***	0.0731**	0.2002***	0.2009***
	(0.0301)	(0.0341)	(0.0602)	(0.0287)	(0.0301)	(0.0301)
EARN	2.1607***	2.4155***	1.2894***	1.7978***	2.1766***	2.1707***
	(0.0851)	(0.0926)	(0.3990)	(0.1026)	(0.0852)	(0.0850)
dEarn	0.0401***	0.0182***	0.0712***	0.0534***	0.0399***	0.0402***
	(0.0061)	(0.0068)	(0.0149)	(0.0056)	(0.0061)	(0.0060)
STD(EARN)	6.6577***	6.2413***	8.8701***	7.6104***	6.6527***	6.7139***
	(0.3248)	(0.3528)	(0.9072)	(0.3052)	(0.3247)	(0.3246)
Smoothing	0.0585***	0.0673***	0.0047	0.0149*	0.0588***	0.0587***
	(0.0084)	(0.0093)	(0.0180)	(0.0085)	(0.0084)	(0.0084)
AGE	-0.0114***	-0.0110***	-0.0572*	-0.0473***	-0.0108***	-0.0118***
	(0.0021)	(0.0023)	(0.0335)	(0.0120)	(0.0021)	(0.0021)
Constant	0.7499***	1.0673***			0.6267***	0.7512***
	(0.0501)	(0.0690)			(0.0592)	(0.0502)
Sector FE	YES	YES			YES	YES
Quarter SE	YES	YES	YES	YES	YES	YES
Observations	20389	16340	24086	20389	20389	20389
R2	0.346	0.360	0.314	0.350	0.346	0.346
Adjusted R2	0.342	0.355	0.311	0.331	0.343	0.343
F Statistic	101.98	84.39	100.68	112.39	101.24	101.24