The impact of CSR reporting quality on analyst forecast accuracy*

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ABSTRACT

We investigate the impact of the quality of corporate social responsibility (CSR) reports on sell-side analyst forecast accuracy. The sample comprises 506 large companies that were selected according to the CSR-Sustainability Monitor, which was used to measure the quality of CSR reports issued in 2012 by the members listed in Fortune 500 US and the Global Index. Forecast error is calculated for the forecast horizons of the same fiscal year and one fiscal year ahead. A multiple-regression model showed a negative correlation of CSR quality and forecast accuracy in both forecast horizons, which was significant for companies domiciled in the stakeholders' region of Western Europe. A probit regression model showed that the probability of overestimating earnings and thus making overly optimistic forecasts was higher in companies that issued CSR reports of better quality, which was significant for the one year ahead forecast horizons of both Western European companies and companies domiciled in the shareholder-oriented region of North America.

Key Words: CSR, analyst forecast, disclosure quality

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1 Introduction

In their widely recognized study of the impact of corporate social responsibility (CSR) performance scores on sell-side analysts' investment recommendations, Ioannou and Serafeim (2015) observed, "organizational policies achieve legitimacy to the extent that they are consistent with prevailing institutional logics" (p. 1054). In their social constructionist, neo-institutional perspective, the institutional logic of CSR, which has predominated for forty years, has shifted from an agency cost that privileges managerial objectives over shareholders' interests to a stakeholder-oriented view in which CSR functions as insurance and thus is risk reducing. This shift is accompanied by analyst investment recommendations. According to Ioannou and Serafeim, the old logic is rooted in Milton Friedman's famous assertion, "the social responsibility of the firm is to increase its profits." According to the old logic, high CSR scores implied that the expectations of non-shareholding stakeholders were met in transfer payments, which were an unnecessary cost. This arrangement yielded lower earnings and lowered shareholder value, leading to pessimistic investment recommendations. However, as analysts follow the new logic, they acknowledge that higher CSR scores preserve value and even increase profit because they indicate risk mitigation or the preservation of relationship-based intangible assets. Following the socially responsible investment movement, Ioannou and Serafeim observed a change in investor behavior, in which investment decisions were based on CSR scores, the high growth in assets under the management of strategies, and the establishment of CSR indices. In their social constructionist view, investor`s language shifted to

express corporate sustainability rather than CSR necessities and the institutionalization of CSR in companies through the emergence of sustainability officers in C-level executive positions.

To test their hypothesis, they used a sample comprised of publically traded American firms in the US in the period 1993 to 2007. Using a model based upon Thomson Reuters` I/B/E/S recorded investment recommendations and the CSR scores in the Kinder, Lydenberg, Domini Research and Analytics (KLD) database, they investigated 16,064 observations. They found evidence of the change in institutional logics during the study period when higher CSR scores indicated less pessimistic and more optimistic recommendations. From the negative coefficient of 0.08 in 1993, the coefficient of total CSR strength as the independent variable increased, overtaking the zero-barrier in 2003 and growing to the positive correlation of 0.004 in 2007. Increasing the robustness of their model, they investigated the learning effects on sell-side analysts by including a long-term forecast error, which they used as a dependent variable in a related analysis. Throughout the study period 1993 to 2007, they did not find a statistically significant association between total CSR strength and analysts' long-term forecast errors.

While researchers such as Ioannou and Serafeim examined CSR performance scores in CSR reports, other researchers directly investigated the impact of a firm's CSR reports on analysts' behavior. Dhaliwal, Li, Tsang, and Yang (2011) examined the impact of the initiation of stand-alone CSR reports on the cost of equity capital. In the second step of their investigation, they followed the assumption that firms with broader analyst coverage (i.e., a higher number of analysts following), produced more accurate earnings forecasts and lower dispersion of the former yield lower cost of equity capital. They then tested the impact of the initiation of CSR

reporting on the three. Their sample comprised US-American firms from 1993 to 2007. They examined 1,190 CSR reports of which 213 were issued by firms that had reported CSR for the first time. They found that initiating firms had more covering analysts than non-initiating firms did (26.08 versus 15.72 analysts). In addition, in the initiating firms, the delta of the forecast error was negative, whereas it was positive in the non-initiating firms, indicating that when the firms initiated CSR reports, the analysts' forecasts were more precise compared to the previous year, whereas the non-initiating firms had higher errors in the subsequent year. Similar results were obtained for forecast dispersion, in which the initiating firms showed improvement in dispersion, whereas the non-initiating firms showed a decrease in dispersion. In the regression results, the observed firms were separated into two groups of high and low performers regarding their KLD CSR score industry sector median. The results showed that the initiation of CSR reports in the high performing group was statistically significantly associated with broader analyst coverage, lower forecast dispersion, and more accurate forecasts. Dhaliwal et al. (2011) explained these results as due to the reduction in information asymmetry between managers and shareholders and among shareholders. In firms with a high CSR performance, the initiation of CSR reporting would reduce uncertainty and risk. However, their argument implies the contrary. The information provided low CSR performers would be useless, or some firms would issue non-value relevant information. If low performers disclosed their actual low-performance on CSR, this information would also reduce information asymmetry, hence improving forecast accuracy and lowering forecast dispersion.

Dhaliwal, Radhakrishnan, Tsang, and Yang (2012) investigated the connection between CSR disclosure and forecast accuracy. Their hypotheses were as follows: 1) There is a positive relationship between CSR disclosure and forecast accuracy; 2) There is a stronger positive relationship in countries that have a higher level of stakeholder-orientation; 3) There is a stronger positive relationship in companies with high levels of financial opacity. They tested these hypotheses in a sample comprised of 1,297 companies in 31 countries, which issued 7,108 stand-alone CSR reports from 1994 to 2007. For forecasted earnings for the same year, one year, and two years ahead, they found an average improvement in forecast accuracy of 10 percent when stand-alone CSR reports were disclosed. The results of investigating the interaction term of CSR reporting disclosure in stakeholder-oriented countries were significant, as were the interaction term of CSR reporting by financially opaque firms. These results supported all three hypotheses: CSR disclosure has a positive influence on forecast accuracy, which is stronger in stakeholder-oriented countries and in firms with high levels of financial opacity.

While Dhaliwal et al. (2011, 2012) addressed the topic of CSR reporting and analysts' forecasts by testing whether the mere issuance of a report would affect analysts' precision, Muslu, Mutlu, Tsang, Radhakrishnan, and Tsang (2015) investigated the impact of CSR reporting quality on analysts' forecasts. They hypothesized that a higher quality of disclosure would be more informative for investors and hence improve analyst forecast accuracy. In the first step, they developed a CSR disclosure score based on a computational linguistics approach and analyzed aspects of the narratives in the reports, which included the number of optimistic, pessimistic, numerical, and horizon-related keywords, as well as the readability and length of

the respective reports. They then categorized three groups according to high, middle, and low disclosure scores. They controlled for a benchmark group that did not disclose a CSR report, and following Dhaliwal et al. (2012), they regressed against forecast errors in the same year, one year ahead, and two years ahead. In testing their model on US-American firms across 24,020 firm-year observations of which 2,462 were of firms that issued CSR reports, they found a significant positive influence of disclosure scores on forecast accuracy in the two groups of middle (significant at 5% to 10%) and high (significant at 1%) disclosure scores, whereas the low disclosure score group was insignificant. Interestingly, their descriptive statistics showed that the mean forecast errors in the middle disclosure group were higher than in the low group. However, they fell under the level of the low disclosure group when they were scored high, indicating the relationship of a reversed U-shaped curve between disclosure scores and forecast errors.

In investigating their mode of scoring the quality of CSR report disclosure, their attempt to operationalize the scoring process should be taken into account. Although a vast number of reports can be measured through a computer-based analysis, risk is involved. The use of optimistic or pessimistic keywords alone cannot sufficiently indicate the quality of disclosure. The reason is that in merely counting the number of words, the context of human language is ignored, which is especially important in the complex topic of CSR reporting.

Cormier and Magnan (2014) further explored the relationship between CSR reporting and analysts' forecasts based on the actual corporate governance present in a firm. They theorized that effective corporate governance could do two things: first, it could have a positive

influence on analysts' forecasts; second it could have a mediating effect on social and environmental disclosure, which would then influence analysts' forecasts. They built their model around three scores. The first two were environmental disclosure and social disclosure, which comprised 40 and 35 items, respectively. These items were used to measure quality in terms of the ratio of occurrence and information usefulness, awarding financial and quantitative information. Their third score, corporate governance, was included in *The Globe and Mail`s Annual Report* on corporate governance, inherited board composition, shareholding and compensation, and shareholders' rights and disclosure. The variables used to measure forecast accuracy were forecast dispersion and consensus. While forecast dispersion is the commonly used standard deviation of earnings per share, the term "consensus" needs explanation. Developed by Barron, Kim, Lim and Stevens (1998), consensus is the degree to which analysts share a common belief, or the ratio of common information to the sum of common and private information, which implies the existence of such private information. The closer the score is to 1, the more that analysts share a common belief and hence there is less information asymmetry among them. According to Cormier and Magnan (2014), the quality of CSR disclosure should be positively correlated with consensus, thereby pushing it towards 1. Their hand-made analysis of CSR disclosure, such as reports, news and websites, explains the sample size of 192 of the largest Canadian firms listed on the Toronto Stock Exchange in 2008. The three-stage least squares regression analysis showed a positive influence of corporate governance and CSR disclosure on forecast dispersion and analyst consensus, whereas the impact of social and environmental disclosure tended to substitute each other, and their effect was substituted by corporate

governance. The results also suggested the mediating effect of corporate governance on social and environmental disclosure. Higher governance scores lead to a better quality of disclosure, both of which attract more analysts to follow a stock, which in turn lowers dispersion and improves consensus.

As shown above, recent studies examined the connection between CSR reporting and analyst forecasts, first examining the initiation and mere issuance of CSR reports and then investigating the effects of different qualities of disclosure. We aim to contribute to this stream of the literature by adding evidence for the impact of the quality of CSR reporting on forecast accuracy.

2 Hypotheses

Following Dhaliwal et al. (2012), we hypothesize that CSR disclosure is associated with the quality of a firm's information environment. The accuracy of forecasts was found to be positively correlated with the greater transparency of value-relevant information (Lang and Lundholm 1996). Hence, CSR disclosure should have a positive impact on forecast accuracy. If so, then a higher quality of disclosure should be accompanied by a better information environment and thus fewer forecast errors, which indicates the value relevance of the CSR-related information disclosed. Consistent with Cormier and Magnam's (2014) findings of this positive influence, we state our first hypothesis:

Hypothesis 1: *A higher quality of CSR reporting is associated with higher forecast accuracy.*

Dhaliwal et al. (2012) found a stronger impact of CSR disclosure on forecast accuracy in firms domiciled in stakeholder-related countries than in those based in shareholder-related countries. Ioannou and Serafeim (2015) argued that between 1993 and 2007, there was a general shift in institutional logics, even within countries. They also identified different states of institutional logics in different geographical regions: Western Europe was stakeholder-oriented and North America was shareholder-oriented. Dhaliwal et al. (2012) ranked countries according to their stakeholder orientation and found that Western European countries ranked ahead of the US-American market, and Asian countries were in the bottom quartile. These findings indicate that the quality of CSR reporting has a stronger impact in Western Europe than in North America and East Asia. Therefore, the second hypothesis is as follows:

Hypothesis 2: *The impact of the quality of CSR reporting on forecast accuracy is stronger in firms domiciled in Western Europe than in firms domiciled in North America and East Asia.*

In general, analysts' forecasts were found to be overly optimistic. One explanation is the bias inherent in analysts who have worked for firms they have become familiar with over time. When Ioannou and Serafeim (2015) found that the institutional logic was shifting, analysts' recommendations for higher CSR performances tended to be optimistic. Analysts could interpret that a higher quality of CSR reporting by a firm could indicate increased sensitivity regarding

CSR topics and thus the integration of the institutional shift towards stakeholder-oriented policies. In their optimism regarding actual CSR performance, analysts' perceptions of disclosure quality could lead to biased forecasts. Therefore, the third hypothesis is as follows:

Hypothesis 3: *Analysts' forecasts tend to be optimistic regarding the high quality of CSR reporting.*

Hypothesis 2 states that the impact of the quality of CSR disclosure on forecast accuracy is higher in Western Europe. The same hypothesis could be stated regarding the impact of the quality of CSR disclosure on optimistic forecasts. The shift in institutional logic towards stakeholder orientation in Western Europe influences analysts' perceptions, increasing their sensitivity to CSR-related topics. Hypothesis 3 states that disclosure quality is associated with the higher probability of a forecast being optimistic. The combination of both hypotheses yields the fourth hypothesis:

Hypothesis 4: *The impact of the quality of CSR reporting on the probability of analysts' forecasts being optimistic is stronger in firms domiciled in Western Europe than in firms domiciled in North America and East Asia.*

3 Regression models

The first equation explores the effect of the quality of CSR reporting on forecast accuracy in a linear multiple-regression by estimating an ordinary least squares model. The second equation identifies the influence, if any, of CSR reporting quality on the probability of analysts being overly optimistic in their forecasts by using a non-linear regression and estimating a probit model. The regression models are as follows:

$$(1) \quad lnFE_{c,t}\,(Y) = \beta_0 + \beta_1 CSRQ_c + \beta_2 lnSTDEV_{c,Y} + \beta_3 lnMCAP_c + \beta_4 LOSS_{c,Y} + D\_SECTOR + D\_REGION + \varepsilon_{c,Y}$$

$$(2) \quad \Pr\left[OVE_{c,t}\,(Y)\right] = \Phi\,(\beta_0 + \beta_1 CSRQ_c + \beta_2 lnMCAP_c + D\_SECTOR + D\_REGION + \varepsilon_{c,Y})$$

<< INSERT TABLE 1 >>

Table 1 presents the variables used in the regression models expressed in equations (1) and (2). They serve as the basis for the empirical analysis, which will be conducted to support or reject the hypotheses. The dependent and independent variables included in the regression models are described in the following two subsections.

3.1 Dependent variables

Forecast accuracy

$$(3) \quad FE(Y)_{c,t} = \frac{|foreEPS^{Y}_{c,t} - EPS^{Y}_{c,t}|}{Stock\ Price_c}$$

$$(4) \quad RFE(Y)_{c,t} = \frac{foreEPS^{Y}_{c,t} - EPS^{Y}_{c,t}}{Stock\ Price_c}$$

As suggested in the literature, we use the absolute relative error of mean forecasts to actual earnings per share as the inverse measure of forecast accuracy. The difference between the analyst consensus forecasted EPS (foreEPS) and the actual EPS (EPS) in absolute terms shows the forecast error (FE) for company c. To compare different companies, the forecast error needs to be deflated. The literature suggests using either the actual EPS or the stock price of the company (Dhaliwal et al. 2012). In using actual EPS, the forecast error becomes a percentage measure, but it is also vulnerable to very low actual EPS, which would result in extreme forecast errors. If the stock price is used, the percentage measure is lost, but the risk of extreme values is mitigated. The forecast error is then dependent on stock prices, which poses a risk if a longer time series were investigated. Since this sample includes only forecasts made in the fiscal year 2012, using the stock price is not a risk. In addition, the use of the actual EPS would indeed result in extreme values of FE and thus outliers, which would shrink the sample unnecessarily. For these reasons, we use the stock price of the respective company c at the end of fiscal year 2011 as a deflator (i.e., Stock Price).

The direction of deviation between the forecasted and actual earnings is irrelevant in measuring an error term. Hence, the nominator is in absolute terms and yields values of FE greater or equal to zero, where zero indicates perfectly forecasted earnings and thus the best accuracy. The larger FE becomes, the worse is the accuracy of the analysts' forecasts. However, for the purpose of descriptive statistics, we also calculate the relative forecast error (RFE). Unlike the forecast error, the relative forecast error does not use absolute values in the nominator and thus shows the direction of the forecast error. If it is positive, the forecasted earnings are above actual earnings and thus are overestimated and vice versa.

Longer forecast horizons have been shown to have a negative influence on accuracy. Following Dhalwil et al. (2012) and referring to De Bondt and Thaler (1990), the indicator Y is used to distinguish between forecast horizons, that is, Y = 0 is fiscal year 2012 and Y = 1 is fiscal year 2013. While they include the horizon of two fiscal years ahead, we do not include it because of the scope of this analysis. We rely on the expressiveness of the short and middle term to answer the specific research questions posed in this paper.

Instead of using the mean of absolute forecast errors for the fiscal year and controlling for the age of the individual forecasts, we use only one single mean forecast per firm per forecast horizon. This is in accordance with the efficient market hypothesis (Fama 1970), which states that information can assumed to be incorporated by market participants quickly after disclosure and not over the period of the fiscal year. The reporting period, as given by the Thomson Reuters I/B/E/S database, serves as the reference point of disclosure. We use the mean forecast of one month after the end of the reporting period. It is therefore assumed that firms issue their CSR

reports with their annual reports. However, controlling for a potential biasing effect caused by both assumptions in estimating the regression model with the mean of monthly absolute forecast errors for the fiscal year yielded similar results. Thus, our approach is valid.

As suggested by the tests for the fit of the model and the assumptions of ordinary least squares regression, we performed a logarithmic transformation to the variable FE because it was skewed to the right, which could lead to a violation of the assumption of ordinary least squares regression of normal-distributed residuals. However, it can be mitigated through the transformation (Backhaus, Erichson, Plinke, and Weiber 2016). The following example shows how to read the variable:

$$FE(1)_{Barrick\ Gold} = \frac{|foreEPS^{1}_{Barrick\ Gold} - EPS^{1}_{Barrick\ Gold}|}{Stock\ Price_{Barrick\ Gold}}$$

In this example, the forecast error is for the company Barrick Gold as the absolute difference of the mean forecast for fiscal year 2013 earnings made one month after the end of the reporting period of fiscal year 2012 and the actual reported earnings for fiscal year 2013 divided by Barrick Gold`s stock price at the end of fiscal year 2011.

We introduce the binary variable OVE to measure analysts' forecasts that are overly optimistic. It equals 1 if the mean forecast by analysts was optimistic for company c and the forecast horizon Y; it equals 0 otherwise. Because c and Y follow their definitions in FE, good readability is conveyed. Optimism is the case if the actual reported earnings are smaller than the

forecasted earnings; hence, the mean of the analysts' forecasts is seen as overestimating earnings. In other words, OVE equals 1 if RFE > 0. For the purpose of descriptive statistics, we also introduce UND to indicate the underestimation of earnings, which is the case if OVE equals 0, or in other words, if RFE < 0.

3.2 Independent variables

As the literature review revealed, researchers have used different methods to measure the equality of CSR reporting. However, most approaches have used f content analysis to identify items according to the GRI guidelines, assuming that they are value relevant and favor quantitative and monetary above qualitative information. but demanding strategy- and risk relating and hence managerial narrative. The assurance of the disclosed information also was found to be a measure of quality. Country and region affect both forecast accuracy and CSR reporting quality, which led to a hypothesis concerning stakeholder- versus shareholder-oriented regions. In addition, firm size was found to influence both, but CSR reporting quality became independent at a certain threshold.

The CSR-Sustainability Monitor (CSR-S) was chosen (Sethi, Martell, and Skou 2014; Sethi, Martell, and Demir 2015) by merging the above summarized results with the requirements of the independent variable of CSR reporting quality and adding the claim for a preferably large and contemporary sample with available data. It was conducted by the Weissman Center for International Business at the Baruch College of the City University of New York, and it provided

a better fit to the requirements described above than other possible measures did. It specifically examined CSR reports issued at a certain point in time instead of throughout the year, as well as information disclosed on the internet, which was measured by the Pacific Sustainability Index (PSI). Furthermore, the PSI does not exclusively assess the quality of reporting but includes CSR performance measures. Another possibility would have been to use the disclosure scores provided by Bloomberg, which has the advantage of a large number of available data points. Nevertheless, we decided not to use those disclosure scores because they are based on only the quantity of disclosed information and not its quality (Ioannou and Serafeim 2015). The following table will describe the CSR-S and illustrate the fit to the requirements of the CSR quality variable needed in the regression models.

<< INSERT TABLE 2 >>

The individual components of the CSR-S are presented in Table 2. A list of the sub-elements and a detailed definition of each component are provided in the Appendix. The eleven items are weighted with 15, 10, or 5 points, which comprise a potential total score of 100. Because the items indicate the most common areas of CSR reporting, they should provide insights into the current state of disclosure. Each component is assessed by a content-based analysis with attention to the depth and scope of coverage. Depth refers to the level of specificity and type of detail included. Strong depth means that a managerial narrative is combined with quantitative data. The scope of coverage refers to the range of topics and locations included. A strong scope

means that the relevant topics are both domestic and international. To guarantee objectivity and the consistent application of the framework, each report is analyzed by more than one analyst, and the results are randomly reviewed. We conclude that the CSR-S is a suitable dependent variable. Therefore, it is used as the CSRQ for company c in the regression analysis ranging from 0 to 100.

We base our control variables on Hope's (2003) models, which were used in recent research. The control variables include earnings volatility, firm size, loss, industry, and region. Historical earnings volatility can be used as a proxy for the complexity of the task to predict future earnings (Dhaliwal et al. 2011, 2012). Following Dhaliwal et al. (2012), we use the natural logarithm of the standard deviation of EPS (lnSTDEV) in the five years before the fiscal year Y for which the EPS are forecasted for company c. The variable is included only in the regression model estimated for forecast error because prior research did not identify the complexity of analysts' task as affecting the probability of overestimating earnings.

Firm size is measured as market capitalization and is a proxy for the richness of a firm's general information environment based on the assumption that the bigger the company, the more information that is available. Moreover, the more likely it is that investment banking and brokerages follow this information, the more precise the accuracy of forecasts (Dhaliwal et al. 2011; Bhushan 1989). Similarly, the incentives for analysts to predict optimistic earnings are higher in large firms. Thus, firm size is implemented in the probit model. Three measures of firm size are commonly used: total sales, market capitalization, and total assets. Following Dhaliwal et al. (2011), Lang and Lundholm (1996) and Hope (2003), we use the natural logarithm of market

capitalization (lnMCAP) for company c at the end of the previous fiscal year, which in the present case is fiscal year 2011. For the purpose of this study, which concerns analyst behavior and the search for a proxy of investment banking and brokerage following, the market value of equity is the better measure because it indicates the size traded. Even if a firm is large in terms of total assets, only a small portion of these assets is traded as equity on markets. Analysts' following should be lower for firms with a high market capitalization. The number of analysts that follow a stock could be added, and they could be proxied by the number of forecasts included in the mean forecast. However, as Bhushan (1989) showed, firm size attracts analysts' coverage and thus both already inherit collinearity. To prevent multi-collinearity, which would violate the assumptions of ordinary least squares regressions, only one of both variables can be retained in the model (Backhaus et al. 2016). We retain firm size because it has been identified in the literature as the cause of analyst coverage. Thus, firm size potentially captures more effects than does the number of analysts providing the mean forecast.

We include an indicator variable for losses (LOSS) that equal 1 if company c reports negative earnings in the fiscal year indicated by Y because research showed that losses are harder to predict than earnings are (Dhaliwal et al. 2013; Hope 2003).

Finally, we include the dummy variables of geographical region and sector, which are presented in Table 3. We do not use country as a dummy variable for two reasons. First is the risk of overfitting the model, which, with more than forty countries in the sample, would have been too high. Second, the statistical power of the model would be constrained because less than five observations were made for twenty-five countries. The geographical regions are depicted

according to the CSR-S, but the small sample sizes from specific regions are grouped as Rest World. An estimation of the regression using each country yielded similar results; thus, our approach is credible.

To account for the effects of sector, we include ten dummy variables following the Global Industry Classification Standard framework. Although these sectors could include industry groups, industries, and sub-industries, we assume that the main effects are captured by following the Global Industry Classification Standard framework. Other classification frameworks, such as the North American Industry Classification System or the International Standard Industrial Classification, could have been used, but they did not provide a reasonable advantage.

<< INSERT TABLE 3 >>

4 Sample and data

The sample used in this study is comprised of companies on which the CSR-S was conducted. The CSR-S was used to score the CSR reports issued in 2012 on 614 companies in 42 countries, which were selected from the Fortune 500 US index, the Fortune 500 Global index, and the previous CSR-S survey. Thus, the CSR reporting of the world`s largest companies is covered in the sample. Because the data in the previous edition are not available, we include only the recent study. A detailed list of the companies included in the CSR-S is provided in the Appendix.

The data on forecast error, including actual and forecasted EPS, were obtained from the Thomson Reuters I/B/E/S database. Because this database has been used widely in previous research on forecast accuracy, it is used in the present study. Although the data collection was focused on forecasts by sell-side analysts since 1976 for US-American firms and since 1986 for non-US-American firms, other data, such as actual EPS, market capitalization, and cash flows were included consecutively. The data were detailed, showing each forecast made by a specific analyst for a company. However, because in this study, forecast error is computed from the mean of forecasts, only the summarized mean of the number of forecasts conducted in a month is used. The Thomson Reuters I/B/E/S database provides data sets of estimates made in different currencies, which are normalized and adjusted to one default currency in which the company reports, adjusting for stock splits. Because forecast error is deflated by stock price, no further actions regarding currency need to be taken. To achieve data coherency, the control variables also were obtained from or calculated based on the Thomson Reuters I/B/E/S-database.

In matching the CSR-S monitor companies to the Thomson Reuters I/B/E/S database, 108 companies were excluded because of data availability. Because the Thomson Reuters I/B/E/S covers companies only if sell-side analysts conduct forecasts for them, private companies could not be investigated in this study (e.g., IKEA International and Bacardi). Other reasons for the lack of available data were capital market transactions in which actual EPS were not comparable to forecasts or not available (e.g., Dell). A list of the excluded companies is provided in the Appendix (p. 62). All calculations are made using STATA.

5 Results

5.1 Descriptive statistics

<<INSERT TABLE 4>>

<<INSERT FIGUTRE 4>>

<<INSERT FIGUTRE 5>>

The distribution statistics of the forecast error in the full sample are shown in Table 3. The results showed a difference in accuracy between the forecast horizons. The means of FE (0) < FE (1) indicated that the forecasts made for the same year were more precise than those made for the next year were. Also as expected, the relative forecast error was positive in both forecast horizons: RFE (0) and RFE (1) > 0. The histograms of the forecast errors shown in Figure 2 and Figure 3 illustrate the distribution of forecast errors showing a right skew: Skew. FE (0) = 3.438 and Skew. FE (1) = 4.349. The logarithmic transformation was used to correct for a normal distribution: lnFE (0) and lnFE(1).

<<INSERT TABLE 5>>

The results for the other dependent variable, OVE, are shown in Table 5, including the number of companies for which earnings were overestimated by the mean analysts' forecast and the findings for relative forecast errors. Of the companies in the sample, 57.91% were overestimated when earnings were forecasted for the same year, whereas 65.61% were

overestimated when earnings were forecasted for a longer forecast horizon. The mean absolute deviation of earnings forecasted from actual EPS, as captured by FE, was higher in the overestimated companies, which explains the results of RFE (0) and RFE (1) > 0.

CSR reporting quality

<< INSERT TABLE 6 >>

<< INSERT FIGURE 4 >>

As shown in Table 6 and Figure 4, the results for the quality of the CSR reports were near normally distributed. The delta between the mean and median was just 0.487 and the Skew of the distribution was close to zero with -0.009, which further supports this finding. Because the excess kurtosis of a normal distribution is 3, the results - 2.237 = 0.763 > 0 indicate a light-tailed distribution, which is also observed in the histogram. Because the results showed a Min. score of 10.5 and a Max. score of 88.5, no company rated the potential low and high scores of 0 and 100.

Control variables

<< INSERT TABLE 7 >>

<< INSERT TABLE 8 >>

Table 7 and Table 8 show the distribution statistics for the control variables. The mean market capitalization and thus the mean size of the observed firms was $31.48bn at the end of the fiscal year 2011. The largest firm, Exxon Mobil, displayed a market capitalization of $406.27bn. The logarithmic transformation normalized the values and fit them to the regression model. The actual EPS reported in the fiscal years 2012 and 2013 were negative for twenty companies, yet different ones. As expected, in both forecast horizons, losses were harder to predict and hence showed a forecast error that was larger than positive earnings.

<< INSERT TABLE 9 >>

<< INSERT TABLE 8 >>

<< INSERT TABLE 10 >>

The correlation matrixes presented in Table 9 and Table 10 indicate the effects on forecast error that were expected in the results of the regression analysis. Firm size had a negative sign and hence a positive influence on forecast accuracy, as predicted based on the literature review. Also consistent with the findings of previous research, higher volatility in earnings and losses were negatively correlated with forecast accuracy, which was indicated by their positive signs. The variable of the utmost interest in this study, CSRQ, showed a positive sign, which contradicts the previous research because it indicated a negative relationship between CSR reporting quality and forecast accuracy. Thus, H1 is rejected. However, whether

these findings are significant and robust could only be determined through the application of statistical methods that are more sophisticated than the regression analysis conducted in the present study. The main purpose of the correlation matrixes is to prevent multicollinearity among the predictor variables. Because they violate the assumptions of ordinary least squares regression, high correlations among the independent variables could indicate multicollinearity, which would cause the regression coefficients to be unreliable. As previously explained, in establishing the control variables, the number of analysts involved in a specific mean forecast was omitted because of its correlation to firm size. However, both matrixes seem valid because the correlation coefficients of their independent variables were smaller than 0.23, excluding lnFE.

<< INSERT TABLE 11 >>

As predicted by the literature, the results showed differences in forecast errors among regions (Table 11).. The North American firms were predicted to be the most precise, and the East Asian firms were predicted to be the least precise. Interestingly, the results showed that the overestimation of earnings confirmed these predictions. Affirming their stakeholder-orientation, the Western European region scored higher in the mean of CSR reporting quality than the North American and East Asian regions. However, the Eastern European regions scored slightly less than the Rest World residual region. In all regions, forecast errors were larger in longer forecast horizons, consistently at FE (0) < FE (1). The positive relative forecast errors matched the theory with the exception of East Asia, where the earnings forecast in the horizon of one-year ahead were slightly negative. However, the number of firms that were overestimated was greater than

50% in every region and forecast horizon, thus indicating that an optimistic bias is inherent in earnings forecasts.

<< INSERT TABLE 12 >>

As shown in Table 12, the split in data according to the sector dummies showed a differentiated perspective. Consumer sectors, health care, and information technology were more precise in the one-year ahead forecasted earnings than in the present year´s earnings. In addition, overestimation showed the wide range of 41% to 80% for OVE (0) and 45% to 88% for OVE (1). It fell below 50% in five of twenty sector observations. With regard to the quality of CSR reporting, the results showed differences between sectors. Industrials and financials were at the lower boundary with means of 42.60 and 43.06, respectively. The highest scores were observed in the information technology and telecommunication sectors with means of 55.08 and 54.21, respectively. These findings support the inclusion of sector dummy variables in the regression models.

5.2 Regression analysis

The results of the multiple and probit regression models are presented in Table 13 and Table 14. Dhaliwal et al. (2012) performed a country-by-country analysis in addition to their total sample analysis to mitigate the risk of results that were potentially misleading because of the data on certain countries. However, because their small samples forced them to group the

countries, we formed the same groups and computed regressions on each of the four regions according to regional dummy variables. Another side effect of this grouping is that it offered the opportunity to observe the effects of the quality of CSR reporting on different regions, thereby testing H, which stated that stakeholder- and shareholder-orientation influenced. The indicator variables used to control for sector effects were included in all regressions.

Multiple-regression: forecast error

$$(1) \quad lnFE_{c,t}\,(Y) = \beta_0 + \beta_1 CSRQ_c + \beta_2 lnSTDEV_{c,Y} + \beta_3 lnMCAP_c + \beta_4 LOSS_{c,Y} + D\_SECTOR + D\_REGION + \varepsilon_{c,Y}$$

Investigating the correlation coefficient of the main variable of interest in this study yielded surprising results, which were signaled by the correlation matrixes in descriptive statistics. The sign of CSR reporting quality was significantly positive in the total sample for both forecast horizons, which indicated that higher qualities of CSR reporting were correlated with higher errors in the forecasts made for the same fiscal year and one fiscal year ahead. Although the signs were positive, because the total sample was split into regions, only Western Europe showed significant correlation coefficients for CSRQ. Hence, the findings for the total sample regarding the impact of CSR reporting quality seemed to be driven by the Western European region.

The control variables largely showed expected relationships in the forecast errors across the sample. lnSTDEV was used to measure earnings volatility and proxying for the complexity to predict earnings. The results showed a significant positive sign for every sample except Western Europe. The control variables of a firm's information environment and size, expressed in lnMCAP, were negative and significant in most of the sample selections. The indicator variable LOSS, which was used to capture the impact of negative earnings, was positive and significant in seven of ten sample selections. Hence, these results indicated that the ability of analysts to forecast earnings accurately was impaired by the complexity of the task and was positively influenced by a better information environment.

The R^2 was adjusted between 17.94% and 26.30% for overall significant models, which is in line with the previous research, showing a good fit of the models to the data. Consistent with the previous research, these results support the validity of the applied model, which is also expressed in F-statistics. The results of the calculations on the Rest World sample and the one fiscal year-ahead forecasted earnings in East Asia were not reliable, which was indicated by the low overall significance levels and the adjusted R^2.

Probit-regression: Overestimation

$$(2) \quad \Pr\left[OVE_{c,t}\,(Y)\right] = \Phi\,(\beta_0 + \beta_1 CSRQ_c + \beta_2 lnMCAP_c + D\_SECTOR + D\_REGION + \varepsilon_{c,Y})$$

Because the coefficients in probit models are not easily interpreted, the predicted probabilities of overestimating earnings in CSRQ margins are presented in the lower rows. The margins of 10.5 and 88.5 were set according to the minimum and maximum CSRQ scores observed in the total sample. Each column presents the probit estimations for a specific sample selection and forecast horizon. The positive relationship between CSR reporting quality and the likelihood of overestimating earnings are easily observed. Because this relationship is significant for the total sample in the one fiscal year ahead forecasted earnings, the split among the regions again proved to be useful. The Western European region showed a significant and positive effect of CSRQ on overestimation, and results similar to the multiple-regression model on forecast error were found. However, the results for the total sample were not only influenced by Western Europe but also by North America in the forecast horizon of one fiscal year ahead.

The control variable lnMCAP was used to measure a firm`s potential incentives for investment banking services. The results were not significant in any model although its sign was positive as predicted in eight of ten regressions. This result indicates the need for an improved model in further research, particularly one that could not only identify potential confounders but also control for the factors that influence overestimation.

The pseudo R^2 was McFadden`s R^2, which tends to be "considerably lower" (McFadden 1978, 207) than the adjusted R^2. The results of the models were 9.73% and 11.4%, which were significant in showing that CSRQ was a good but not an excellent fit. The number of observations was lower in some sample selections. Specific sectors predicted the outcome perfectly, and thus they were omitted by STATA. Revision of hypotheses

Hypothesis 1

A higher quality of CSR reporting is associated with higher forecast accuracy.

As the correlation matrixes indicated and the results of the multiple-regression model indicated, higher qualities of CSR reporting showed a statistically significant relation to higher forecast errors. Indeed, the higher quality of CSR reporting is associated with less accurate forecasts in short- and middle-term forecast horizons. However, the results for the total sample were driven mainly by the Western European region. Thus, H1 is rejected.

Hypothesis 2

The impact of CSR reporting quality on forecast accuracy is stronger on firms domiciled in Western Europe than it is on firms domiciled in North America and East Asia.

The multiple-regression estimations showed a significant negative correlation of CSR reporting quality with forecast accuracy in Western European firms and in both forecast horizons. However, the results for the sample firms in North America and East Asia did not show significant correlations in either direction. These results showed that CSR reporting quality was more important in the Western European and thus in the stakeholder-oriented region. Hence, H2 is supported.

Hypothesis 3

Analysts' forecasts tend to be optimistic when the quality of CSR reporting is high.

The results of the probit-regression models showed a positive relationship between CSR reporting quality and the likelihood of overestimating earnings. This finding was statistically significant for one-year ahead forecasted earnings in the total sample, which was driven by specific regions, namely Western Europe and North America. Thus, H3 is supported.

Hypothesis 4

The impact of the quality of CSR reporting on the probability of analysts' forecasts being optimistic is stronger on firms domiciled in Western Europe than on firms domiciled in North America and East Asia.

The results showed differences in the impact of the quality of CSR reporting on the likelihood of overestimating earnings but not coherently across the stakeholder- versus the shareholder-oriented regions, which were proxied by Western Europe, North America, and East Asia. Instead, the results showed that the relationship was present in Western Europe for earnings forecasted for the same year and one fiscal year ahead and in North America for one fiscal year ahead. East Asian firms showed no significance in either direction. Thus, the results are mixed. Hence, H4 is supported with regard to the overestimation of earnings forecasted for the same fiscal year, but it is rejected with regard to one fiscal-year ahead forecasts.

5.3 Robustness

Several measures were applied to increase the robustness of the results. First, the total sample was split into four regions, which revealed the robustness of the results in specific regions regarding both the forecast error and the overestimation model. Second, different measures of forecast error were tested by calculating the twelve-month mean of forecasts and using the mean forecast six months after the end of the reporting period. In general, these calculations had similar results, except the one fiscal-year ahead forecast horizon in the North

American region. There, as in the results of the probit-regressions, CSRQ showed a significant positive sign, which provided evidence that the quality of CSR reporting negatively influenced forecast accuracy. However, the t-tests that were conducted to determine differences in the coefficients revealed that Western Europe was significantly higher. Thus, the impact was stronger, and the results confirmed that H2 was valid. Finally, all forecast error regression models were calculated using robust standard errors to mitigate the risk that heteroscedasticity would influence the outcomes. By setting the forecast horizon to the same fiscal year, the coefficients for CSRQ remained significant in the total sample and in the Western European region although the level of significance decreased to 5%. In the forecast horizon of one fiscal year ahead, the results remain consistent with those obtained from the calculations of non-robust standard errors. When the probit model was tested for heteroscedasticity, only the Western European region in the same fiscal year, without sector dummy variables, indicated the need to use a heteroscedastic probit model. This model obtained similar results but with 25 percent reduction in significance . Keeping this in mind, adding the insignificance of the control variable firm size and the character of the model not being used in research like this before sets clear limitations to its findings. Nevertheless, it helped in interpreting the increasing number of forecast errors and showed a good fit with the data, which was indicated by the pseudo R^2 scores, thus validating their inclusion in this study.

6 Conclusion

The results of the empirical analysis indicate that the higher quality of CSR reporting is associated with higher forecast errors in the stakeholder-oriented Western European region. Indeed, not only the number of forecast errors but also the likelihood of overestimating earnings increases with CSR reporting quality. On one hand, these findings indicate the negative influence of the quality of CSR reporting on a firm's information environment. On the other hand, they provide evidence for the shift in institutional logics theorized by Ioannou and Serafeim (2015), rendering the perception of analysts regarding CSR-related topics more sensitive. That is, analysts could be biased in overestimating the earnings of firms that show a high quality of CSR disclosure. The finding that the North American region's earnings were likely to be overestimated could also be a sign that shifting institutional logics provoke bias in the perceptions of analysts.

Thinking the impact on forecast error further, it could add evidence to the accusation of CSR reporting being more a marketing-trick, manipulating stakeholders´ perception (Michelon et al. 2015) rather than disclosing value-relevant information. Although analysts might not be able to interpret the information disclosed correctly, they are indeed value relevant in terms of conveying information that affects earnings, growth, and cost of capital. This would not render CSR disclosure obsolete but would trigger a call for the improved analysis of the former.

The findings of the present study do not necessarily contradict the results of prior research. Dhaliwal et al. (2012) found evidence that analysts' forecasts were positively influenced

by the issuance of CSR reports. Because Dhaliwal et al. (2012) investigated US-American firms, their findings need to be compared to the present study's findings on the North American region. Although no significant impact of disclosure quality was found on forecast accuracy, a significant impact was indicated on overestimating the next fiscal year`s earnings. Following Dhaliwal et al.'s (2012) examination of the issuance of CSR reports, we investigated the impact of their quality, and our research questions differed. Cormier and Magnan (2014) investigated Canadian firms in 2008. They investigated forecast dispersion and analyst consensus, but they did not investigate forecast error. The extent to which analysts shared a common belief was investigated. The scatter plots of forecasts were analyzed and found to be positively influenced by CSR disclosure quality. Our findings did not contradict these previous findings because higher forecast errors can be accompanied by lower dispersion and higher consensus. This would be the case if all analysts were imprecise in their forecasts. Muslu et al. (2014) examined a sample of US-American firms and a time horizon prior to that used in the present study. Their results showed a significant positive influence of CSR reporting quality on forecast accuracy. Thus, Muslu et al. (2014) is the only previous study that contradicts our findings. The most likely explanation is the difference in the variable used to measure quality. Muslu et al. used the experimental approach of computer linguistics to derive their scores, which was not in line with the academic practice of using content analysis to investigate the quality of CSR reports. CSR-S scores that are based upon content analysis, which is the measure used in our study, have higher credibility.

Several points need to be investigated in future research. Regarding the regression models used in the present study, additional control variables, especially in the probit regression analysis, need to be added. Bradshaw's (2011) advice not only to investigate forecast errors but also to incorporate more measures, such as investment recommendations and target prices, could also be taken into account. In the present study, the sample was restricted to the CSR reports issued in 2012. In future research, the study period could be extended, which would also help to expand the sample size in specific countries, thus addressing the limitation of a regional split. The forecast horizons of the same fiscal year and one fiscal year ahead also could be extended. The limitation of the sample's bias in favor of large companies could be mitigated through the inclusion of small- and medium-sized businesses.

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Tables and Figures

lnFE:	The natural logarithm of the forecast error for company *c* and forecast horizon *Y*, based on mean forecast made at *t*. Forecast horizon *Y* is 0 or 1, with 0 indicating mean forecast for fiscal year 2012 and 1 for fiscal year 2013. *t* is equal to 1, indicating mean forecast at 1 month after the end of the reporting period.
OVE:	An indicator variable that equals 1 if the mean forecast made at *t* was optimistic for company *c* and the forecast horizon *Y*. *t* is equal to 1, indicating mean forecast at 1 month after the end of the reporting period.
CSRQ:	Quality of the CSR report of company *c* issued in fiscal year 2012.
lnSTDEV:	The natural logarithm of the standard deviation of earnings reported for the last five years for company *c* on a rolling basis for forecast horizon *Y*.
lnMCAP:	The natural logarithm of the market capitalization of company *c* in US dollars at the end of fiscal year 2011.
LOSS:	An indicator variable that equals 1 if company *c* reported negative earnings for the fiscal year indicated by *Y*.
D_SECTOR:	A dummy variable controlling for sector effects.
D_REGION:	A dummy variable controlling for regional effects.

Table 1: Variable definitions

15 points each	10 points each	5 points each
Integrity assurance	Environment	Corporate governance
Codes of conduct	Corporate citizenship	Bribery & corruption
	Stakeholder engagement	Human rights
	Supply-chain management	Executive message
	Labor relations	

Table 2: Composition of the CSR-S (Own table based on Sethi et al., 2015)

Geographical region (D_Region)	Sector (D_Sector)
East Asia	Consumer Discretionary
North America	Consumer Staples
Western Europe	Energy
Rest World	Financials
Eastern Europe & Central Asia	Health Care
Latin America & The Caribbean	Industrials
Middle East & North Africa	Information Technology
Oceania	Materials
South Asia	Telecommunication Services
Sub-Saharan Africa	Utilities

Table 3: Dummy variables (Own table based on Sethi et al., 2014)

All (n=506)	Mean	Median	SD	Min.	Max.	Kurt.	Skew.
FE (0)	0.021	0.008	0.036	0.000	0.282	17.861	3.438
lnFE (0)	-4.943	-4.805	1.666	-10.345	-1.264	3.067	-0.433
RFE (0)	0.009	0.002	0.041	-0.199	0.282	15.082	1.767
FE (1)	0.034	0.016	0.055	0.000	0.577	30.531	4.349
lnFE (1)	-4.304	-4.108	1.578	-9.605	-0.550	3.377	-0.651
RFE (1)	0.017	0.008	0.062	-0.336	0.577	23.622	1.784

Table 4: Forecast error, distribution statistics

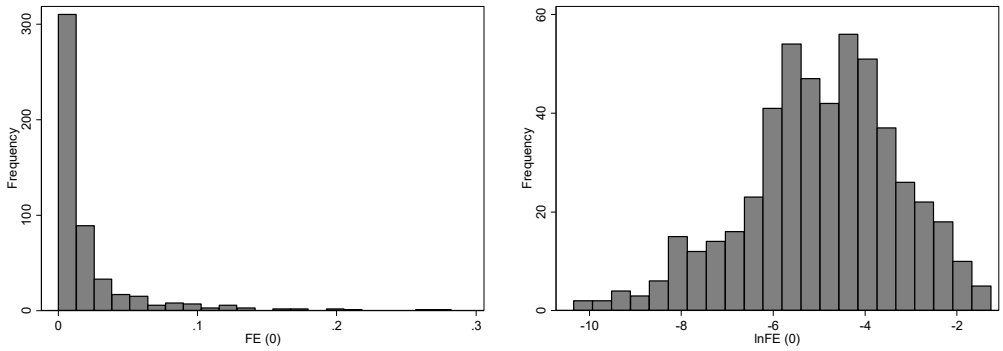

Figure 1: Forecast error to forecast horizon Y = 0, histogram

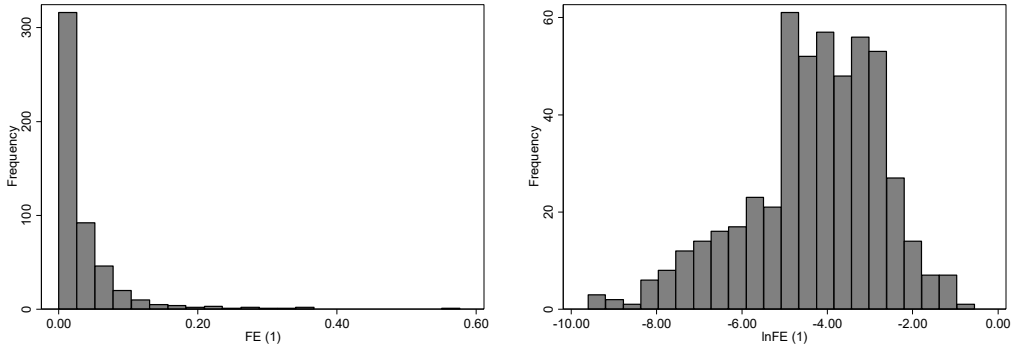

Figure 2: Forecast error to forecast horizon Y = 1, histogram

All (n=506)	n	%	FE
OVE (0)	293	57.91	0.026
UND (0)	213	42.09	0.015
OVE (1)	332	65.61	0.039
UND (1)	174	34.39	0.025

Table 5: Overestimation, distribution statistics

CSR reporting quality

All (n=506)	Mean	Median	SD	Min.	Max.	Kurt.	Skew.
CSRQ	47.263	47.750	15.709	10.500	88.500	2.237	-0.009

Table 6: CSR reporting quality, distribution statistics

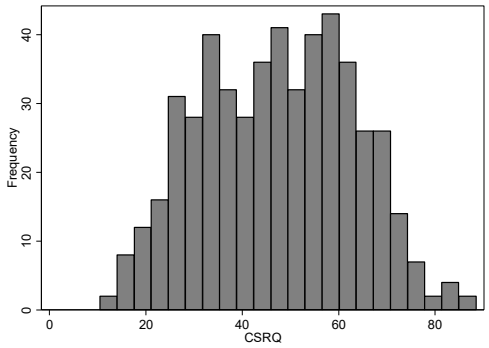

Figure 3: CSR reporting quality, histogram

Control variables

All (n=506)	Mean	Median	SD	Min.	Max.	Kurt.	Skew.
MCAP ($ bn)	31.475	16.715	44.207	0.274	406.272	23.183	3.730
lnMCAP ($)	23.517	23.540	1.180	19.430	26.730	3.225	-0.163
lnSTDEV (0)	0.566	0.054	2.240	-3.947	10.237	5.008	1.207
lnSTDEV (1)	0.520	0.017	2.210	-4.148	10.688	5.464	1.289

Table 7: Control variables firm-size and earnings volatility, distribution statistics

All (n=506)	n	%	FE
LOSS (0)	20	3.95	0.129
WIN (0)	486	96.05	0.016
LOSS (1)	20	3.95	0.180
WIN (1)	486	96.05	0.028

Table 8: Control variable loss, distribution statistics

All (n=506)	lnFE (0)	CSRQ	lnMCAP	lnSTDEV (0)	LOSS (0)
lnFE (0)	1.000				
CSRQ	0.072	1.000			
lnMCAP	-0.226	0.230	1.000		
lnSTDEV(0)	0.283	-0.008	-0.118	1.000	
LOSS (0)	0.334	0.047	-0.225	0.130	1.000

Table 9: Correlation matrix to forecast horizon Y = 0

All (n=506)	lnFE (1)	CSRQ	lnMCAP	lnSTDEV (1)	LOSS (1)
lnFE (1)	1.000				
CSRQ	0.097	1.000			
lnMCAP	-0.215	0.230	1.000		
lnSTDEV(1)	0.277	-0.012	-0.098	1.000	
LOSS (1)	0.258	0.129	-0.205	0.077	1.000

Table 10: Correlation matrix to forecast horizon Y = 1

Fixed effects

	n	CSRQ	FE (0)	RFE (0)	OVE (0)	FE (1)	RFE (1)	OVE (1)
East Asia	90	45.74	0.032	0.014	58 (64%)	0.051	-0.002	51 (57%)
North America	198	43.58	0.013	0.005	107 (54%)	0.021	0.012	123 (62%)
Western Europe	174	51.12	0.025	0.010	106 (61%)	0.041	0.031	133 (76%)
Rest World	40	51.82	0.021	0.011	22 (55%)	0.031	0.025	25 (63%)

Table 11: Means of CSR reporting quality, forecast error and overestimation along regions

	n	CSRQ	FE (0)	RFE (0)	OVE (0)	FE (1)	RFE (1)	OVE (1)
Consumer Disc.	66	45.05	0.184	-0.003	28 (42%)	0.038	0.005	39 (59%)
Consumer Staples	49	50.92	0.129	0.003	20 (41%)	0.017	0.011	30 (61%)
Energy	42	47.79	0.026	0.006	28 (67%)	0.044	0.039	37 (88%)
Financials	92	43.06	0.026	0.006	45 (49%)	0.041	0.018	50 (54%)
Health Care	26	49.01	0.015	0.010	11 (42%)	0.019	0.005	13 (50%)
Industrials	90	42.60	0.016	0.007	63 (70%)	0.029	0.013	60 (67%)
Information Tech.	35	55.08	0.029	0.024	24 (69%)	0.046	0.012	24 (69%)
Materials	53	53.73	0.034	0.031	42 (80%)	0.048	0.039	45 (85%)
Telecommunication	20	54.21	0.010	0.003	14 (70%)	0.040	0.017	9 (45%)
Utilities	33	45.76	0.019	0.008	18 (55%)	0.015	0.010	20 (61%)

Table 12: Means of CSR reporting quality, forecast error and overestimation along sectors

.

		Total sample		**East Asia**		**North America**		**Western Europe**		**Rest World**	
Independent	Pred. sign	lnFE (0)	lnFE (1)	lnFE (0)	lnFE (1)	lnFE (0)	lnFE (1)	lnFE (0)	lnFE (1)	lnFE (0)	lnFE (1)
CSRQ	-	.0121*** (2.63)	.0103** (2.33)	.0144 (1.43)	.0005 (-.05)	.0034 (.48)	.0092 (1.32)	.0238*** (2.78)	.0236*** (3.00)	.0158 (.67)	-.0012 (-.06)
lnSTDEV	+	.0808** (2.16)	.0888** (2.46)	.0852* (1.96)	.0923* (1.96)	.3568*** (2.81)	.3562*** (2.79)	-.0396 (-.52)	.0372 (.51)	.0288 (.14)	-.0795 (-.44)
lnMCAP	-	-.2638*** (-4.30)	-.2681*** (-4.61)	-.0886 (-.69)	-.2873** (-2.05)	-.2406** (-2.56)	-.3021*** (-3.21)	-.4321*** (-3.71)	-.3288*** (-3.24)	-.1550 (-.58)	-.0795 (-.34)
LOSS	+	2.2300*** (6.30)	1.4125*** (4.26)	2.1359*** (4.00)	.2962 (.39)	2.6296** (2.58)	2.4080*** (2.87)	1.8603*** (3.01)	1.659*** (3.42)	1.9116 (1.21)	1.7160 (1.47)
Intercept		.3740 (.27)	.6627 (.50)	-3.5376 (-1.13)	2.0884 (.63)	-.3076 (-.14)	1.9729 (.89)	3.9927 (1.44)	1.9380 (.82)	-3.0837 (-.5)	-4.1697 (-.76)
Sector Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Effect		Yes	Yes	No	No	No	No	No	No	No	No
Adj. R^2		23.93%	24.04%	25.02%	8.44%	22.56%	26.30%	20.75%	17.97%	-0.01%	7.04%
n		506	506	94	94	198	198	174	174	40	40

F statistic	10.29***	9.66***	3.39***	1.66*	5.41***	6.41***	4.48***	3.92***	0.96	1.27

Table 13: Forecast error multiple-regression results

This table presents the multiple-regression outputs for sample selections along regional dummy variables. The numbers in brackets show t-values for the respective coefficients, whereas stars indicate the level of significance with *, **, *** indicating a 15%, 5% and 1% significance-level.

		Total sample		**East Asia**		**North America**		**Western Europe**		**Rest World**	
Independent	Pred. sign	OVE (0)	OVE (1)	OVE (0)	OVE (1)	OVE (0)	OVE (1)	OVE (0)	OVE (1)	OVE (0)	OVE (1)
CSRQ	+	.0046 (1.13)	.0166*** (3.84)	-.0109 (-.96)	.0058 (.56)	.0031 (.46)	.0190*** (2.68)	.0137* (1.89)	.0194** (2.44)	.0107 (.65)	.0218 (1.17)
lnMCAP	+	.0207 (.39)	.0248 (.44)	.1891 (1.24)	.1514 (1.04)	.0074 (.09)	-.0105 (-.12)	-.0266 (-.28)	.0217 (.20)	.0765 (.40)	.1850 (.88)
Intercept		-.1631 (-.13)	-.5503 (-.42)	-3.1387 (-.90)	-3.6606 (-1.09)	-.2129 (-.1)	-.2193 (-.10)	4.8610 (.03)	4.0834 (.01)	-7.7873 (-.01)	-11.3468 (-.01)
Sector Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Effect		Yes	Yes	No	No	No	No	No	No	No	No
Predicted probability to overestimate earnings at CSRQ margin											
10.5		51.73%	44.52%	71.88%	44.13%	50.59%	40.30%	41.17%	50.93%	42.39%	38.86%
30		55.05%	56.28%	65.55%	48.28%	52.65%	53.38%	50.77%	64.06%	49.17%	53.02%
49.5		58.34%	67.55%	58.71%	52.47%	54.70%	66.20%	60.41%	75.97%	56.00%	66.59%
69		61.57%	77.44%	51.54%	56.66%	56.74%	77.45%	69.48%	85.44%	62.69%	78.02%
88.5		64.72%	85.38%	44.43%	60.78%	58.76%	86.26%	77.51%	92.06%	69.02%	86.45%

Pseudo R^2	6.40%	11.10%	13.32%	4.32%	9.61%	11.09%	9.73%	11.40%	18.72%	22.02%
n	506	506	90	86	198	198	174	168	39	37
LR statistic	43.83***	72.28***	16.14*	5.15	26.24***	29.12***	22.65**	17.35**	10	10.27

Table 14: Overestimation probit-regression results

This table presents the probit-regression outputs for sample selections along regional dummy variables and predicted probabilities along CSRQ margins. The numbers in brackets show t-values for the respective coefficients, whereas stars indicate the level of significance with *, **, *** indicating a 15%, 5% and 1% significance-level.

Appendix

Appendix 1: Detailed composition CSR-S (Own table based on Sethi et al., 2015)

Contextual element	Definition	Sub-elements
Chair/executive message	The chair/executive message contextual element measures the quality of information provided by the company in the introductory statement of their CSR report about their management commitment and effectiveness across all CSR subjects, in terms of current achievements and future targets	• Message signatory • CSR key topics • Current achievements • Future targets
Environment	The environment contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding environmental issues such as waste management, climate change, and biodiversity, as well as disclosure about product or process innovation opportunities, reducing the	• Waste management • Climate change • Water management • Biodiversity • Sourcing • Accidents/spills/fines • Environmental opportunities • Packaging materials

	firm's environmental impact through their supply chain, and any environmental accidents	
Philanthropy and community involvement	The philanthropy and community involvement contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding their charitable activities, including the type (cash, in-kind, employee engagement), purpose, and geographic scope of contributions, and how their philanthropy is tied to their business	• Cash donations • In-kind donations • Employee engagement • Donation matching • Purpose of activities • Geographic scope of activities • Integration with business
External stakeholder engagement	The external stakeholder engagement contextual element measures the quality of information provided by the company about their management commitment and effectiveness toward integrating the advice of external stakeholders in their business operations, including CSR-related projects. Engagement at both the	• Engagement for business operations • Engagement for CSR-related projects • Engagement for governance/oversight • Engagement for field-level and corporate-level projects and policies

	field level (single-site) and corporate level (company-wide) is examined	
Supply chain	The supply chain contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding the CSR aspects of their relationship with suppliers, including the procurement process, contract terms, and monitoring/auditing of suppliers (including contractors, sub-suppliers, joint- venture partners, or other major business associates)	• Union relations • Employee health and safety • Supply-chain labor standards • Child labor • Women and minority contracting Supply-chain certifications • Local/global sourcing
Labor relations	The labor relations contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding its treatment of employees, both direct (employed by the company) and indirect (employed by a partner, such as a supplier). Areas covered include compensation and benefits, health and safety, professional	• Union relations • Cash profit sharing • Employee involvement (in ownership, stocks) • Employee health and safety • Supply-chain labor standards • Compensation and benefits • Professional development • Child labor • Employment of underrepresented groups • Workforce diversity/ equal opportunity

	development opportunities, commitment to diversity and equal opportunity, and union relations	
Governance	The governance contextual element measures the quality of information provided by the company about their management commitment and effectiveness toward following the best practice governance principles in areas including the composition and level of independence of their board of directors, compensation of top management, commitment to relevant governance codes, and shareholder engagement	• Board composition • Top management compensation • Governance codes/policies • Shareholder engagement
Anti-corruption	The anti-corruption contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding the prevention of bribery and corruption, through policies and procedures for monitoring activities which are vulnerable, as well as describing any investigation currently	• Policies for preventing corruption • Discussion of publicized cases of corruption • Political instability

	underway by regulatory authorities and the steps the company is taking to address the situation	
Human rights	The human rights contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding their impacts on local communities and the rights of indigenous peoples, support for any controversial regimes, and their commitment to protecting freedom of expression and preventing censorship. Note that human rights topics tied to labor issues are covered under the labor relations and/or supply-chain contextual elements	• Community impact • Indigenous peoples relations • Support for controversial regimes • Freedom of expression/censorship • Discussion of publicized cases of human rights violations
Codes of conduct	The codes of conduct contextual element measures the quality of information provided by the company about their management commitment and implementation of internal and external codes of conduct in the CSR area,	• Individual company codes of conduct • Industry codes of conduct • Universal codes of conduct • Involvement in code governance structure

	including an individual company code of conduct, industry codes of conduct (such as the International Council on Mining and Metals), and universal codes of conduct (such as the UN Global Compact)	
Integrity assurance	The integrity assurance contextual element measures the quality of information provided by the company about their management commitment and effectiveness regarding independent verification of the CSR report, either in its entirety or for specific contextual elements.	• Independent third-party verification statement • Internal assessment • External assessment • Specific contextual element assurance

Appendix 2: Total sample companies (Own table based on Sethi et al., 2014)

3i Group
3M
AB Electrolux
AB Volvo
ABB
Abbott Laboratories
Abertis Infraestructuras
Acciona
Accor
Acer
ACS, Actividades de Constuccion y Servicios
Adecco
adidas
Adobe Systems
Advanced Micro Devices
AECOM Technology
AEGON
AEON
Aetna
Aflac
Agfa-Gevaert
Agilent Technologies
Agricultural Bank of China
Air France KLM Group
Air Products & Chemicals
Aisin Seiki
Akzo Nobel
Alcoa
Alfa
Allergan
Allianz
Alstom
Apple
Applied Materials
Arcelor Mittal
Areva
Asahi Glass
Asahi Group
Asahi Kasei
Ashland
ASML Holding
Assicurazioni Generali
Associated British Foods
AT&T
Australia & New Zealand Banking Group
Aviva
Avnet
AXA
BAE Systems
Baker Hughes
Baloise Holding
Banca Monte die Pasci di Siena
Banco Bilbao Vizcaya Argentaria
Banco Santander
Bancp Bradesco
Bangkok Bank Public Company
Bank of America
Bank of Montreal
Baosteel Group
Barclays
Barrick Gold
BASF
Baxter International
Bayer

Altria Group
American Electric Power
American Express
Amgen
Anadarko Petroleum
Anglo American
AngloGold Ashanti
Anheuser-Busch InBev
Aon
Apache
British Sky Broadcasting Group
Brown-Forman
BT Group
Bunge
Caja de Ahorros y Pensiones de Barcelona
Campbell Soup Company
Canadian Imperial Bank of Commerce
Canon
Carnival
Caterpillar
Celanes
Cemex
Centrica
Chesapeake Energy
Chevron
China Construction Bank
China Mobile Communications
China Petrochemical
China Railway Construction
China Railway Group
China State Construction Engineering
China Telecommunications
Chubu Electric Power
CIGNA
Cisco Systems
BCE
Becton, Dickinson & Company
BHP Billiton
BNP Paribas
Bombardier
Bouygues
British Petroleum
Brambles
Bristol Myers Squibb Company
British American Tobacco
Credit Suisse Group
CRH
CSX
Cummins.
CVS Caremark
Daikin Industries
Daimler
Daiwa House Industry
Danske Bank
Dassault Aviation
Dean Foods Company
Deere & Company
Delhaize Group
Delta Air Lines
Deutsche Bank
Deutsche Boerse
Deutsche Lufthansa
Deutsche Post
Deutsche Telekom
Devon Energy
Diageo
Dongfeng Motor Group
Duke Energy
E.I. du Pont de Nemours & Company
E.ON

Citigroup
CNP Assurances
Coca Cola Enterprises
Colgate Palmolive Company
Comcast
Commonwealth Bank of Australia
Community Health Systems
Compagnie de Saint-Gobain
Compass Group
Computer Sciences
ConAgra Foods
ConocoPhillips
Consolidated Edison
Constellation Brands
Contact Energy
Continental
Credit Agricole
Fibria Celulose
Fifth Third
FirstEnergy
FirstGroup
Fletcher Building
Fluor
Fomento Economico Mexicano,
Ford Motor Company
Fortum
Freeport-McMoRan Copper & Gold
Fuji Electric
Fuji Heavy Industries
FUJIFILM Holdings
Fujitsu
Gas Natural SDG
GDF Suez
General Dynamics
General Electric
East Japan Railway Company
Eaton
Ecolab
Ecopetrol
Electricite de France
Eli Lilly & Company
EMC
Enbridge
EnCana
Endesa
Enel
Eni
EADS Company
Exelon
Exxon Mobil
FedEx
Ferrovial
Iberdroida
Idemitsu Kosan
Illinois Tool Works
Impala Platinum Holding
Imperial Tobacco Group
Indian Oil
Industrial & Commercial Bank of China
Infosys
ING Group
Ingersoll-Rand
Intel
International Business Machines
International Paper Company
Intesa Sanpaolo
Isuzu Motors
ITOCHU
ITV
J. Sainsbury

General Mills
General Motors
GlaxoSmithKline
Gold Fields
GPT Group
Group Danone
Grupa Lotos
GS Holding
Halliburton
Hammerson
Heineken Holding
Hellenic Telecommunication Organization
Henkel
Hess
Hitachi
Home Retail
Hon Hai Precision Industry
Honda Motor
Hormel Foods
HSBC Holdings
Huntsman
Husky Energy
Hyundai Heavy Industries
Hyundai Motor
Ladbrokes
Lagardere
Land Securities Group
Legal & General Group
LG Electronics
Linde
Lloyds Banking Group
Lockheed Martin
Lomin
Lowe's Companies
LVMH Moet Hennessy Louis Vuitton
J.C. Penney Company
Jacobs Engineering Group
Japan Tobacco
Johnson & Johnson
Johnson Controls
JPMorgan Chase & Co.
JX Holdings
KB Financial Group
KB Home
KBC Group
Kellogg
Kesko
Kimberly-Clark
Kingfisher
Kobe Steel
Koc Holding
Kohl's
Komatsu
Koninklijke Ahold
Koninklijke KPN
Koninklijke Philips
Korea Electric Power
KT
L'Oreal
MTR
Muenchner Rueck
National Australia Bank
National Bank of Abu Dhabi
National Oilwell Varco
NEC
Nedbank Group
Nestle
Newmont Mining
NEXTERA ENERGY
Nike

LYONDELLBASELL Industries
Macy's
MAN SE
MANPOWERGROUP
Manulife Financial
Marathon Oil
Marks and Spencer Group
Marsh & McLennan Companies
Marubeni
Mazda Motor
McDonald's
McKesson
Medtronic
Merck & Co.
MetLife
Microsoft
Mitsubishi Chemical Holdings
Mitsubishi Electric
Mitsubishi Heavy Industries
Mitsubishi Materials
Mitsubishi Motors
Mitsubishi UFJ Financial Group
Mitsui & Co
Mizuho Financial Group
MOL Magyar Olaj es Gazipari Nyrt.
Molson Coors Brewing Company
Mondi
Monsanto Company
Morgan Stanley
Motorola Solutions
MS&AD Insurance Group Holdings
Owens Corning
OZ Minerals
Peabody Energy
Pearson
Nippon Express
Nippon Steel & Metal
Nippon Telegraph
Nippon Yusen Kabushiki Kaisha
Nirthrop Gunman
NiSource
Nissan Motor
Nokia
Nomura Holdings
Nordea Bank
Nordstrom,
Norfolk Southern
Norsk Hydro
NORTHEAST UTILITIES
Northern Trust
Novartis
Novo Nordisk
Novozymes
Nucor
OAO Gazprom
OAO Lukoil
OAO Rosneft Oil Company
Obayashi
Occidental Petroleum
Office Depot
Old Mutual
Omnicom Group
OMV
ONEOK
Orange
Outokumpu
Samsung Electronics
Sanofi
SAP
Sasol

Pepco Holdings
Perusahaan Perseroan Telekomunikasi Indonesia
Petroleo Brasileiro
Pfizer
PG&E Corp
Pinnacle West Capital
Pitney Bowes
POSCO
Potash of Saskatchewan
PPG Industries
PPL
PPR
Praxair
Prudential Financial
PT Bank Mandiri (Persero)
PTT
Public Service Enterprise Group
Puma
PVH
Qualcomm
Quanta Computer
Quest Diagnostics
Raytheon Company
Reed Elsevier
Regions Financial
Renault
Rentokil Initial
Repsol
Ricoh Company
Rio Tinto
Roche
Rockwell Automation
Royal Bank of Canada
Royal DSM
Royal Dutch Shell
Saudi Basic Industries
Saudi Telecom Company
Schneider Electric
Segro
Seiko Epson
Sekisui House
Seven & I
Shimizu
Siemens
Singapore Airlines
Sinochem
Skanska
SKF
Societe Generale
Sodexo
Sony
Southwest Airlines
SSE
Standard Bank Group
Standard Life
Staples
Starbucks
Statestreet
Statoil
STMicroelectronics
Stora Enso
Strauss Group
Sulzer
Sumitomo Chemical
Sumitomo
Sumitomo Electric Industries
Sumitomo Mitsui Financial
Sun Life Financial
SUPERVALU
Suzuki Motor

RSA Insurance Group
RWE
Ryder System
Symantec
Syngenta
Sysco
T&D Holdings
Taisei
Taiwan Semiconductor Manufacturing Company
Target
Technip
Teck Resources
Telecom Italia
Telefonaktiebolaget LM Ericsson
Telefonica
Telekom Austria
Telstra
Telus
Tesco
Tesoro
Texas Instruments
Textron
Thales
The AES
The Allstate
The Bank of New York Mellon
The Bank of Nova Scotia
The Boeing Company
The British Land Company
The Clorox Company
The Dai-ichi Life Insurance Company
The Dow Chemical Company
The Go-Ahead Group
The Goldman Sachs Group
The Goodyear Tire & Rubber Company
Svenska Cellulosa
Swiss Reinsurance Company
Swisscom
Tokio Marine Holdings
Tomra Systems
Toppan Printing
Toshiba
Total
Toto
Toyota Motor
TRW Automotive Holdings
U.S. Bancorp
UBS
UniCredit
Unilever
Union Pacific
United Parcel Service
United Technologies
UnitedHealth Group
Unum Group
Vaisala
Vale
Veolia Environment
Verizon Communications
Viacom,
Vivendi
Vodafone Group
Volkswagen
Wal-Mart Stores
Waste Management
Wellf Fargo & Compnay
WellPoint,
Wesfarmers
Westpac Banking
Whirlpool

The Hartford Financial Services Group
The Home Depot
The Kroger Company
The PNC Financial Services Group
The Procter and Gamble Company
The Royal Bank of Scotland Group
The Siam Cement Public Company
The Toronto Dominion Bank
Tiffany & Co.
Time Warner
Xerox
Wienerberger
William Hill
Wilmar Internaitonal
WM Morrison Supermarket
Wolseley
Woodside Petroleum
Woolworth
WPP
Wyndham Worldwide
Xcel Energy
Zurich Insurance Group

Appendix 3: Excluded companies (Own table based on Sethi et al., 2014)

A.P. Moller-Maersk	Hawlett-Packard Company
ACE	Hayleys
AGL Energy	Hibu
Aker ASA	Hitachi Chemical
Alcatel-Lucent	Humana
Alliance Boots	Hydro-Quebec
Aramark	IKEA International
AstraZeneca	Integrys Energy Group
Auchan	Investa Property Group
Bacardi	Irish Bank Resolution
Bechtel Group,	Japan Post Holdings
Bertelsmann	John Lewis Partnership
Best Buy & Co.	KDDI
BG Group	Kraft Foods Group
BPCE	Lafarge
British Airways	Land O'Lakes
C&S Wholesale Grocers	Landesbank Baden Wuertemberg
Camelot UK Lotteries	Marathon Petroleum
Carrefour	Marriott International
China Communications Construction Company	Mars
China Huaneng Group	Massachusetts Mutual Life Company
China Minmetals	MCI Group Holding
China National Offshore Oil	MeadWestvaco
China National Petroleum	Metro
China Resources	Mitsui O.S.K. Lines
China Southern Power Grid	Motorola Mobility Holdings
City Lodge Hotels	Navistar International
Cooperative Centrale Raiffeisen-Boerenleenbank	Nexen
De Beers Consolidated Mines	Pall
Dell	Panasonic
Deutsche Bahn	Petroliam Nasional Berhad
Dialog Axiata	Pirelli

Dominion Resources

DZ BANK Deutsche Zentral-Genossenschaftsbank

Entergy

Experian

Fiat

First Data

Freescale Semiconductor

Georgia-Pacific

Glencore Internaitonal

H&M Hennes & Mauritz

PricewaterhouseCoopers

Progress Energy

Prudential

PSA Peugeot Citroen

PT Astra International

PTT Global

PUBLIX SUPER MARKETS,

R.R. Donnelley & Sons Company

Robert Bosch

SABMiller

Safeway

Saudi Arabian Oil Company

Science Applications International

Scottish Power

Sharp

Sigma-Aldrich

Smith & Nephew

Smithfield Foods

Societe Nationale des Chemins de Fer Francais

Sprint

Standard Chartered

The Bidvest Group

The Coca Cola Company

The Emirates Group

The Federation of Migros Cooperatives

The Hillshire Brands Company

The Mosaic Company

TNT Express

United States Postal Service

US Airways Group

Vattenfall

Walgreen

Xstrata