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Financial Analysts and Corporate Carbon Disclosure: Evidence from Asia Pacific Countries

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Abstract

Against the background of addressing climate change issues and reducing firms' carbon footprint, corporate carbon disclosure has become an important measurement for companies in fulfilling stakeholders' demands. This study examined the relationship between financial analysts and corporate carbon disclosure in Asia Pacific countries. Ordinal logit regression was employed for companies disclosing carbon information through the Carbon Disclosure Project (CDP) in 2019. The empirical result showed that financial analysts had significant positive effects on corporate carbon disclosure. This result is consistent with stakeholder theory. The finding is useful for governmental policymakers who are concerned about the effect of financial analysts on corporate carbon disclosure.

Keywords: financial analysts, carbon disclosure, ordinal logit model, Carbon Disclosure Project, Asia Pacific

1. INTRODUCTION

Financial analysts are important to the capital market as they provide brokers, money managers, and institutional investors with earnings forecasts, buy/sell recommendations, and other information (Lang & Lundholm, 1996). The firm provides much of the information used by analysts in their evaluations. Even in the case of mandatory disclosure, firms have considerable discretion in terms of the informativeness of their disclosures and the amount of detail they provide to the capital markets. For press releases and direct contact with analysts, discretion in disclosure is even more pronounced (Lang & Lundholm, 1996).

It is apparent that carbon emission is the primary source of global warming, posing a substantial threat to human living quality. Nonetheless, carbon emissions and disclosures remain largely voluntary in most countries. Hence, a number of firms have voluntarily agreed to take a proactive approach to emission reduction and transparency, whereas others have not. This situation motivates the researcher to identify and deeply understand incentives related to voluntary carbon disclosure. In this study, the researcher will examine whether financial analysts influence the level of corporate carbon disclosure.

2. LITERATURE REVIEW AND HYPOTHESIS

Stakeholder theory

According to stakeholder theory, the continuous existence of a firm is attached to the support of its stakeholders. To obtain that approval, the actions of that firm must be modified. Environmental data disclosure can be viewed as a kind of communication between an organization and its stakeholders. The stakeholder–organization power dynamic is unique to each entity (Deegan., 2000). The limited resources (e.g., finance and labor) or the ability to legislate against the organization are examples of power (Liu & Anbumozhi, 2009). As a result, stakeholder theory is concerned with how an organization manages its stakeholders in general. The strategic posture established, whether aggressive or passive, determines how a firm handles its stakeholders (Ullmann, 1985). An

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organization that takes an active posture may try to have an impact on its key stakeholders. Low levels of environmental disclosure are expected as a result of a lack of stakeholder engagement (Deegan, 2000).

The stakeholder theory has been widely applied in the agenda of corporate social responsibility (CSR) (Ullmann, 1985). The changing nature of the corporate environment compels businesses to recognize their responsibility to the broader public and assist in the resolution of significant environmental issues, particularly those caused by them. Unlike the institutional theory, which assumes that firms have the power to affect both society and its specific stakeholders, the stakeholder theory assumes that firms can influence both. Owners, customers, public organizations, and suppliers are among the conventional stakeholders identified for corporate strategy. The potential for opposing behavior among various stakeholders is viewed as a limitation on the firm's strategy for optimally matching its resources to the environment. Stakeholders in a CSR study should include external forces that could be harmful to the company. Regulators, environmentalists, analysts following, and/or special interest groups concerned with social issues are examples of these groups.

Financial analysts and corporate carbon disclosure

Analysts provide independent verification of information provided by companies, reducing information asymmetry between investors and companies and increasing corporate visibility (Chen, Harford, & Lin, 2015). According to Hong, Huseynov, & Zhang (2014), analysts fulfill the function of external monitors and put supervisory pressure on the choice of managers. Analyst following plays a key role in firms to attract outside investors and lower the cost of stock by expanding environmental information disclosure (Shen et al., 2014). As a result, analyst following can help raise the level of company environmental disclosure. Earlier studies have pointed out that analysts have significant advantages in identifying information (Yao & Liang, 2019). Analysts' Projections are based on more reliable data and scientific research methods than other sources of information, allowing them to deliver more relevant information (Brown & Rozeff, 1978). Analyst forecasts have become a significant medium for investors to get company information, according to Yao & Liang (2019). Investors and analysts are increasingly paying attention to environmental information as part of corporate social responsibility reporting, and analyst concerns might positively affect firms. In addition, the corporate information environment can be improved by analysts by using their professional abilities to collect, integrate, and evaluate data and then assist stakeholders in corporate information interpretation (Hu, Lin, & Wang, 2003).

Hypothesis of the study

Financial analysts can be thought of as gatekeepers of the financial markets, acquiring and analyzing data from a variety of sources before sending it to other stock market participants (Aerts et al., 2007). Given their exposure to stronger communication needs and/or greater ability to bear the costs associated with disclosure, firms that are more transparent than firms that a smaller group of financial analysts follows are expected to be more transparent. The increased informational asymmetry surrounding organizations that generate few recommendations could explain the influence of the number of analysts. In such circumstances, announcing private information has the potential to affect the market more deeply (Déjean & Martinez, 2009). Furthermore, according to the research, disclosure can reduce information asymmetry, lower financing costs, and boost the liquidation of stock (Healy & Palepu, 2001), so failing to give reliable information would be penalized by the market. Also, according to stakeholder theory, a bigger number of analysts monitoring firms are more likely to supply information about carbon risks and carbon management actions to meet this stakeholder's need. As a result of this conversation, the second hypothesis emerges:

H1: Firms that are followed by more financial analysts have a higher propensity to disclose more carbon information.

3. DATA, MODELS AND METHODS

Data

The sample consisted of companies from 6 countries, namely Australia, Japan, South Korea, India, Indonesia, and China, in Asia Pacific. This region is known as one of the most competitive regions in the world (WorldEconomicForum, 2019). The reason for choosing these countries is the availability of data. Most of the variables used in this research, as presented in the next section, were collected from many sources, including CDP, World Economic Forum, S&P Global, The World Bank, and United Nations Climate Change. It is a challenge to ensure that the chosen countries have all the needed data from various resources. The 2019 CDP reports were the most updated at the time the author started that project. Hence, the sample includes all firms submitting their 2019 reports to the CDP in the six countries. Accordingly, the sample consisted of 454 firms. According to Hair et al. (2019), in the case of the logistic regression used in this study, the sample size should be 400 to get the best results with maximum likelihood estimation. Accordingly, the sample size met this requirement.

Variables

Dependent variables

Carbon disclosure score measures whether and how well a firm responds to each question from the CDP questionnaire. Furthermore, the CDP offers the largest directory of climate-related corporate information. This provides a basis for comparisons of reporting practices and environmental performance across companies or industries (Carbon Disclosure Project, 2019). In addition, as long as the firms have voluntarily chosen to participate in CDP, they must follow a certain set of specific disclosure rules, which significantly improve the consistency and comparability of carbon information (Luo et al., 2013). The scoring methodology is a means to assess the responder's progress toward environmental stewardship as communicated through the company's CDP response (CDP, 2019). The methodology ultimately yields a score based on the evaluation. In the case of the sector-specific methodologies, the score will also be sector-specific, which will better enable responders for peer-to-peer benchmarking and comparison.

Responding companies will be assessed across four consecutive levels, which represent the steps a company will take as it progresses towards environmental stewardship. The levels are:

- Disclosure: Every question in the questionnaires is scored for disclosure
- Awareness: The awareness score measures the comprehensiveness of a company’s evaluation of how environmental issues intersect with its business. Companies’ evaluations should include the impacts of business activities on the environment, how these activities affect people and ecosystems, and the impact the environment may have on business activities. This will influence the degree of business risk that a particular company faces. The awareness score does not indicate that a company has taken any actions to address environmental issues beyond initial screenings or assessments. Action to address issues is measured in the next level of scoring - Management.
- Management: Management points are awarded for answers that provide evidence of actions associated with good environmental management, as determined by CDP and its partner organizations. Efforts can be made to mitigate risk, advance environmental accounting in at-risk sites, make risk assessments more robust and comprehensive, implement an environmental policy, and integrate environmental issues into business strategy. The management score rewards action in all these areas.
- Leadership: Companies who reached leadership status in the climate change program have shown high scores at all other levels and have disclosed particular actions that mark them as leaders. Their responses will show a thorough understanding of risks and opportunities related to climate change and will formulate and implement strategies to mitigate or capitalize on these risks and opportunities. These companies have verified GHG emissions statements and have implemented emissions reduction strategies to reach company-wide goals.

A minimum score and/or the presence of a minimum number of indicators on one level will be required in order to be assessed on the next level. If the minimum score threshold is not achieved, the company will not be scored on the next level. CDP provisionally sets the thresholds, and these will be reviewed during the scoring period to ensure that the distribution of responses among scoring levels is representative of the current level of progress in the responding population as a whole.

Table 1. CDP score band (Source: CDP Scoring Introduction 2019)

Level	Score	Score band
Disclosure	1-44%	D-
	45-79%	D
Awareness	1-44%	C-
	45-79%	C
Management	1-44%	B-
	45-79%	B
Leadership	1-79%	A-
	80-100%	A

Because the scoring methodology assesses the level of detail and comprehensiveness in response, as well as the company's awareness of carbon issues, its management methods, and progress toward environmental stewardship, the study chooses the CDP score as a proxy of the carbon disclosure score. Accordingly, in this study, if the corporation receives a score band that is A, B, C, and D, it will be coded as 1, 2, 3, and 4, respectively.

Independent variables
The number of financial analysts following for the year prior to the CDP disclosure (i.e., the year 2018) was chosen as a proxy of financial market pressure because financial analysts could be described as financial market's gatekeepers who gather and analyze information from different sources and pass it on other stock market participants (Aerts et al., 2007). The data is obtained from S&P Global.

Control variables
Firm size: It has been well documented that larger firms tend to receive more public scrutiny and media attention than smaller firms. Prior studies find environmental disclosures positively related to firm size (Clarkson et al., 2008; Stanny and Ely, 2008). We expected larger firms to be more likely to disclose more carbon information and predicted a positive sign on the proxy for firm size. In terms of the measurement, the logarithm of the stock market capitalization of the companies at the end of the fiscal year 2018 has been chosen as the firm size's surrogate measure in this study, being consistent with prior research, such as Luo et al. (2012). The measure for firm size is in natural logarithm to satisfy linearity and normal distribution (Tran and Ramachandran, 2006). The source of this data was from S&P Global.

Leverage: We expected that more highly leveraged firms would have stricter debt covenants to restrain shareholders' actions, and creditors would likely demand more information to monitor management behavior (Leftwich, Watts, and Zimmerman, 1981). Thus, highly leveraged firms may be motivated to make voluntary disclosures in order to reduce contracting costs. Clarkson et al. (2008) found a significant positive correlation between leverage and voluntary environmental disclosures. In this research, leverage was measured by the ratio of total debt to total assets at the end of fiscal year 2018, following the previous research, such as Luo et al., 2012. The source of this data was from S&P Global.

ROA: Profitable companies could more easily afford the expenditures needed to reduce carbon emissions and report carbon information (Bewley & Li, 2000). ROA is the proxy for the firm's profitability, calculated as net income divided by total assets at the end of fiscal year 2018. The source of this data was from S&P Global.

Industry type: Many research studies, such as those by Clarkson et al. (2008), suggest that firms in the same industry face similar regulatory and institutional pressure. Firms in carbon-intensive sectors are especially likely to utilize voluntary disclosure as a method to mitigate the negative impact of greenhouse gas legislation on their businesses. Therefore, we control for sector influences using sector dummies. Following the classification of CDP, firms will be scored one if they belong to the following high-impact sectors: electric utilities, cement, chemicals, metals & mining, steel, transport original equipment manufacturers, and transport services. Otherwise, firms will be scored zero if they belong to the remaining industries. The source of this data was from CDP.

Carbon emission: It could be argued that emissions increase with carbon-risk exposure, which refers to climate-change liabilities related to compliance and mitigation costs (such as carbon price or tax) imposed by current legislation (Al-Tuwaijri et al., 2004). As heavy emitters are likely to be the target of climate regulations (Patten, 2002) and are subject to intense scrutiny from environmental pressure groups (Brammer & Pavelin, 2008), they tend to disclose carbon information, both to fulfill the information demands of stakeholders and to reduce the potential compliance costs (Clarkson et al., 2011). The logarithm of carbon emissions of the companies in the fiscal year 2018, therefore, has been decided to be chosen as the carbon emission's surrogate measure in this study, being consistent with prior research, such as Luo et al. (2013). The source of this data was from CDP.

Model

Model 1 is used to examine the direct effect of external pressures on the level of corporate carbon disclosure.
$CDScore_t = \beta_0 + \beta_1$ analyst following$_{t-1} + \beta_2$ Size$_{t-1} + \beta_3$ Leverage$_{t-1} + \beta_4$ ROA $_{t-1} + \beta_5$ Industry type $+ \beta_6$ Carbon emission $_{t-1} + \varepsilon$ (1)

Methodology

The hypothesis is tested using ordinal logit regression analysis. The ordinal logistic method is a generalization of the linear regression method. The ordinal regression method is used to model the relationship between response (outcome) variables and a set of explanatory variables, which can be either categorical or numerical (Sentas et al., 2005). In this study, the outcome variable is categorical, as discussed above.

4. EMPIRICAL ANALYSIS

Descriptive analysis

Table 2 reports the descriptive statistics of the variables. As shown in Panel A, the most significant percentage went to "Management," accounting for 37.9 percent. The second largest group was from "Leadership" (28.6 percent), followed by "Awareness" (17.4 percent) and "Disclosure" (13.7 percent). Meanwhile, "Fail" only accounted for 2.4 percent of the sample, with 11 firms. Of the 454 companies, 298 (65.6 percent) belonged to the high-impact sectors, and 156 (34.4 percent) were in others. Panel B of the table indicates that the highest analyst following is 40.

Meanwhile, there are still some firms that have no analyst following. Firm size (natural logarithm of capitalization) aligned from 1.06 to 18.45, implying that the sample included many different sizes of firms. The firms had an average leverage of 0.27, indicating that the debt occupies a considerable proportion of the capital structure. Another noticeable point is that this variable has a wide range, as presented by the minimum and maximum values at 0.23 and 0.93, respectively. The highest ROA is 43.00, but the lowest one is -12.79. This points out that there is a high variation in the ROA variable of the sample. Also, carbon emission ranges from 2.52 to 2.93, with a mean of 2.49 for the whole sample. This might show that all firms in the sample with similarly high carbon emission levels tend to produce more carbon disclosures to CDP than the others.

Table 2. Descriptive statistics for the dependent and independent variables

Panel A: Categorical variables

	Number	Percent of sample
Carbon Disclosure Score		
Fail	11	2.4
Disclosure	62	13.7
Awareness	79	17.4
Management	172	37.9
Leadership	130	28.6
Industry type		
High impact sectors	298	65.6
Non – high impact sectors	156	34.4

Panel B: Continuous variables

Variables	N	Mean	Standard Deviation	Min	Median	Max
Analyst following	454	12.11	8.90	0	11.00	40
Size	454	8.88	1.77	1.06	8.79	18.45
Leverage	454	0.27	0.20	0.00	0.23	0.93
ROA	454	4.17	4.21	-12.79	3.50	43.00
Carbon emission	454	2.49	0.25	0.97	2.52	2.93

Ordinal logistic regression

According to Hair et al. (2019), logistic regression is distinct from multiple regression in that it does not necessitate the assumptions of normality and homoscedasticity. Instead, the primary assumption underlying logistic regression is the linearity of the relationship between the independent variables, particularly continuous variables, and the outcome variable.

Table 3. Test of Parallel Lines

Model	Likehood	Chi-square	df	Sig.
Null Hypothesis	1097.560			
General	1042.226	54.334	27	0.270

This tests the assumption of proportional odds, which we want to be greater than 0.05. This is the case here (p-value = 0.26). The main assumption of the ordinal regression is checked. Accordingly, the assumption of proportional odds was met, as assessed by a full likelihood ratio test comparing the fit of the proportional odds model to a model with varying location parameters, $\chi^2(27) = 55.334$, p=0.27.

Table 4. Goodness of Fit

	Chi-Square	**df**	**Sig.**
Pearson	1817.022	1767	0.205
Deviance	1097.560	1767	1.00

In the above table, the Pearson and deviance statistics test the same thing. These statistics test whether the observed data are consistent with the fitted model. The null hypothesis means that the fit is good. If this hypothesis is not rejected (i.e., if the p-value is large), then it could be concluded that the data and the model predictions are similar and that this is a good model. However, if the assumption of a good fit is rejected, conventionally, if $p<.05$, then the model does not fit the data well. Here, the Pearson and Deviance goodness of fit tests indicated that the model was a good fit to the observed data with p=0.204 and p=1.000, respectively.

Another method of assessing model fit is to look at the change in model fit when comparing the full model to the intercept-only model. The difference in the -2 log likelihood between these two models has a χ^2 distribution with degrees of freedom equal to the difference in the number of parameters. The likelihood-ratio test is presented in the Model Fitting Information table, as shown below:

Table 5. Model fitting information

Model	**-2 Log Likelihood**	**Chi-square**	**df**	**Sig.**
Intercept Only	1220.360			
Final	1096.660	123.700	9	0.000

Before looking at the effects of each explanatory variable in the model, it is necessary to determine whether the model improves our ability to predict the outcome. This is done by comparing a model without any explanatory variables (the baseline or 'Intercept Only' model) against the model with all the explanatory variables (the 'Final' model). The final model was compared against the baseline to see whether it significantly improved the fit of the data. The *Model fitting Information* table gives the -2 log-likelihood (-2LL) values, meaning the deviance, which is basically a measure of how much-unexplained variation there is in the logistic regression model – the higher the value, the less accurate the model. As can be seen, the model fit (the **"**-2 Log Likelihood" column) is 1220.260 for the intercept-only model (the **"**Intercept Only**"** row) compared to the model with the intercept and all independent variables (the "Final" row), which has a -2 log-likelihood of 1096.560. Remember that the smaller the -2 log-likelihood value, the better the fit.

As such, the greater the difference between the two models, the better the independent variables are at explaining the dependent variable. The difference between the two -2 log-likelihood values is presented in the "Chi-square" column (i.e., 1220.260 – 1096.560 = 123.700), which is chi-square distributed with 9 degrees of freedom ("df") and is statistically significant, $p < .001$ (the "Sig." column). In other words, the independent variables add statistically significantly to the model, or, put another way, at least one independent variable is statistically significant. It could be concluded that the Final model statistically significantly predicted the dependent variable over and above the baseline intercept-only model, $\chi^2(9) = 123.700$, $p < 0.001$. This shows that the model gives better predictions than if the researcher just guessed based on the marginal probabilities for the outcome categories.

Table 6. Variables in the Equation

	b (SE)		**95% CI for Odds Ratio**	
		Lower	**Odds Ratio (i.e. Exponential b values)**	**Upper**
Analysts following	0.062^{**} (0.015)	1.033	1.064	1.097
Size	0.068 (0.064)	0.945	1.071	1.213
Leverage	0.851 (0.510)	0.862	2.342	6.365
ROA	0.026 (0.024)	0.979	1.027	1.077
Industry type	-0.474^{*} (0.196)	0.424	0.622	0.913
Carbon emission	2.100^{**} (0.399)	3.739	8.170	17.852
Model summary				
Pseudo R squared				25.8%
Model fit χ^2				123.700^{**}
Note: * and **: significant at 0.05 and 0.01 level respectively				

As can be seen from Table 6, there is a statistically significant result for the variable "Analysts following" (p-value < 0.05). The value of the analyst following coefficient is positive (0.062), which suggests that as an analyst following increases, the likelihood of corporate carbon disclosure level will increase. The odds ratio is

1.064, meaning that a change in one unit of analyst following is associated with an odds ratio of 1.064; that is, for every analyst following an increase, the odds of the level of carbon information disclosed increases by 1.064 times. It could be concluded that an increase in analyst following was associated with an increase in the odds of the level of carbon information disclosure, with an odds ratio of 1.064, p-value < 0.05.

R^2 (the coefficient of determination) summarizes the proportion of variance in the outcome that can be explained by the explanatory variables in linear regression, with higher R^2 values indicating that more of the variation in the outcome can be explained up to a maximum of 1. Because the same R^2 statistic could not be computed for ordinal regression models, pseudo-R^2 was used instead. In this case, the pseudo-R^2 values (e.g., Nagelkerke = 25.8%) indicate a 25.8% variance in the outcome that the explanatory variables can make up. This explanatory power of the model is congruent with prior carbon disclosure literature (e.g., Luo, Lan, & Tang (2012) with the R^2 = 20.0% or Peters & Romi (2009) with the R^2 = 17.0%).

5. DISCUSSION AND CONCLUSION

Analysts found the following to have a significant impact on corporate carbon disclosure. This result is supported by the stakeholder theory that analysts following could be considered as a stakeholder group that may put pressure on companies and, thus, prompt these companies to use a proper strategy to manage carbon and consequently their disclosure in a bid to satisfy the analysts and pressures from stock markets. Disclosing information on their pollution-driven activities demonstrates that firms have a strong incentive to respond to the expectations of all stakeholders, including analysts. Yao & Liang (2019) also reported a positive relationship between analyst following and corporate environmental disclosure.

In reality, the analyst following can be viewed as an external monitor that exerts supervisory pressure on managers' decisions (Hong, Huseynov, & Zhang, 2014). Healy & Palepu (2001) also showed that besides information intermediation between corporate insiders and outsiders, analysts might act as managerial performance monitors. One effective monitoring by analysts could be presented by motivating firms to voluntarily disclose the underlying performance in an accurate and timely manner (Farber et al., 2018). As a result, as a third party, analyst following could force enterprises to boost impression control in disclosing carbon information to improve their carbon disclosure (Yao & Liang, 2019).

Previous research has pointed out that analysts have significant advantages in identifying information (Yao & Liang, 2019). Projections of analysts are backed by more substantial data and scientific research methodologies than other sources of information are, allowing them to deliver more relevant information (Brown & Rozeff, 1978). As a result, analyst following has a significant impact on investors' perceptions of corporate information. Meanwhile, a growing number of investors are interested in information on corporate social responsibility. Hence, environmental information has become a more important element of corporate social responsibility information for investors and analysts. Also, analyst concerns may have a significant impact on firms through information gathering, integration, and appraisal utilizing their professional abilities (Yao & Liang, 2019).

As can be seen from the findings on the sample of the six countries in the Asia Pacific, the following analysts can improve the extent of carbon disclosure. Hence, regulators and stakeholders can encourage more firms to disclose carbon information by enhancing the level of this external pressure. Although the thesis is limited to a cross-sectional one, this project supplies a base for future longitudinal research on corporate carbon disclosure, which could enable researchers to clarify the explanations for the results and shed further light on the process of evolution and gaining adoption of the disclosure practice.

REFERENCES

Aerts, W., Cormier, D., & Magnan, M. (2007). *Corporate environmental disclosure, financial markets and the media : An international perspective*.

Al-Tuwaijri, S. A., Christensen, T. E., & Hughes, K. . (2004). The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach. *Accounting, Organizations and Society*, *29*(5–6), 447–471.

Bewley, K., & Li, Y. (2000). *Disclosure of environmental information by Canadian manufacturing companies: A voluntary disclosure perspective* (pp. 201–226).

Brammer, S., & Pavelin, S. (2008). Factors influencing the quality of corporate environmental disclosure. *Business Strategy and the Environment*, *17*(2), 120–136.

Brown, L. D., & Rozeff, M. S. (1978). The superiority of analyst forecasts as measures of expectations: Evidence from earnings. *The Journal of Finance*, *33*(1), 1–16.

Carbon Disclosure Project. (2018). *About us - CDP*. https://www.cdp.net/en/info/about-us

CDP. (2019). *About us - CDP*. https://www.cdp.net/en/info/about-us

Chen, T., Harford, J., & Lin, C. (2015). Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics*, *115*(2), 383–410.

Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2008). Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. *Accounting, Organizations and Society*, *33*(4–5), 303–327.

Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2011). Does it really pay to be green? Determinants and consequences of proactive environmental strategies. *Journal of Accounting and Public Policy*, *30*(2), 122–144.

Deegan. C. (2000). *Financial Accounting Theory*. Sydney: McGraw Hill.

Déjean, F., & Martinez, I. (2009). Accounting in Europe Environmental Disclosure and the Cost of Equity : The French. *Accounting in Europe*, *6*(1), 57–80.

Farber, D. B., Huang, S. X., & Mauldin, E. (2018). Audit committee accounting expertise, analyst following, and market liquidity. *Journal of Accounting, Auditing and Finance*, *33*(2), 174–199.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (7th ed.). Prentice Hall.

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

Hong, Y., Huseynov, F., & Zhang, W. (2014). Earnings Management and Analyst Following: A Simultaneous Equations Analysis. *Financial Management*, *43*(2), 355–390.

Hu, Y.; Lin, W.; Wang, W. (2003). The Information Sources, Concerned Areas, and Analysis Tools of Financial Analyst. *Journal of Finance Research*, *12*.

Lang, M. H., & Lundholm, R. J. (1996). Corporate disclosure policy and analyst behavior. *The Accounting Review*, *71*(4).

Liu, X.; Anbumozhi, V. (2009). Determinant factors of corporate environmental information disclosure: an empirical study of Chinese listed companies. *Journal of Cleaner Production*, *17*, 593–600.

Luo, Le; Tang, Qingliang; Lan, Y.-C. (2013). Comparison of the propensity for carbon disclosure between developing and developed countries - A resource constraint perspective. *Accounting Research Journal*, *26*(1), 6–34.

Luo, L., Lan, Y. C., & Tang, Q. (2012). Corporate Incentives to Disclose Carbon Information: Evidence from the CDP Global 500 Report. *Journal of International Financial Management and Accounting*, *23*(2), 93–120.

Luo, L., Tang, Q., & Lan, Y. (2013). Comparison of propensity for carbon disclosure between developing and developed countries. *Accounting Research Journal*, *26*(1), 6–34.

Patten, D. (2002). Media exposure, public policy pressure, and environmental disclosure: an examination of the impact of tri data availability. *Accounting Forum*, *26*(2), 152–171.

Peters, G.; Romi, A. (2009). *Carbon disclosure incentives in a global setting: an empirical investigation*.

Sentas, P., Angelis, L., Stamelos, I., & Bleris, G. (2005). Software productivity and effort prediction with ordinal regression. *Information and Software Technology*, *47*(1), 17–29.

Shen, H., Huang, Z., & Guo, F. (2014). Confess or Defense? A Study on the Relationship between Environmental Performance and Environmental Disclosure. *Nankai Business Review*, *17*, 56–63.

Tran, D.K.N and Ramachandran, N. (2006). Capital Structure on Small and Medium–Sized Enterprises: The Case of Vietnam. *ASEAN Economic Bulletin*, *23*(2), 192–211.

Ullmann, A. A. (1985). Data in Search of a Theory: A Critical Examination of the Relationships Among Social Performance, Social Disclosure, and Economic Performance of U.S. Firms. *Academy of Management Review*, *10*(3), 540–557.

WorldEconomicForum. (2019). *The Global Competitiveness Report 2019*.

Yao, S., & Liang, H. (2019). Analyst following, environmental disclosure and cost of equity: Research based on industry classification. *Sustainability (Switzerland)*, *11*(2).