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Mestrado em Administração

Fernando Cortezi

Knowledge Disclosure as a Weapon in Technological Change Battles – Straight Shot or Backfire?

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Dissertação de Mestrado, apresentada ao Programa de Pós-Graduação em Administração da Escola de Administração Pública e de Empresas da Fundação Getulio Vargas como requisito para a obtenção do título de Mestre em Administração.

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FERNANDO CARLOS RODRIGUES CORTEZI

"KNOWLEDGE DISCLOSURE AS A WEAPON IN TECHNOLOGICAL CHANGE BATTLES — STRAIGHT SHOT OR BACKFIRE?"

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Dedicatória

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Knowledge Disclosure as a Weapon in Technological Change Battles – Straight Shot or Backfire?

Fernando Cortezi

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Abstract

This work aims at evaluating how effective is knowledge disclosure in attenuating institutional negative reactions caused by uncertainties brought by firms' new strategies that respond to novel technologies. The empirical setting is from an era of technological ferment, the period of the introduction of the voice over internet protocol (VoIP) in the USA in the early 2000's. This technology led to the convergence of the wireline telecommunications and cable television industries. The Institutional Brokers' Estimate System (also known as the I/B/E/S system) was used to capture reactions of securities analysts, a revealed important source of institutional pressure on firms' strategies. For assessing knowledge disclosure, a coding technique and a established content analysis framework were used to quantitatively measure the non-numerical and unstructured data of transcripts of business events occurred at that time. Eventually, several binary response models were tested in order to assess the effect of knowledge disclosure on the probability of institutional positive reactions. The findings are that the odds of favorable institutional reactions increase when a specific kind of knowledge is disclosed. It can be concluded that knowledge disclosure can be considered as a weapon in technological changes situations, attenuating adverse institutional reactions to the companies' strategies in environments of technological changes.

1 Introduction

Understanding the causes of firm's failures in environments of technological changes have attracted the interest of numerous researchers. Christensen (1997) highlighted some of the common reasons incumbent firms fail when facing technological changes: bureaucracy, short-term focus, arrogance, inadequate skills and resources, or even bad luck. Many other researchers studying technological change have been diving into searching alternative reasons underlying incumbents' lacking, delayed or ineffective responses. Institutions may exert pressures that can determine firms' fortunes. However, fewer studies have shown the effects of institutional influences on firms' strategies in contexts of technological change.

One of the important sources of institutional pressures on firms is the financial analysts. As intermediaries between the stock market and investors, securities analysts interpret and disseminate information about corporate finances, strategic decisions and industry trends of the firms they follow. Analysts periodically issue reports with assessments and judgements on firms' current performance and their future prospects, recommending investors to buy, hold or sell firms' stocks. There are abounding evidences that analysts recommendations have impact on stock prices (e.g. Zuckerman, 1999; Westphal and Clement, 2008; Litov et al., 2012). Firms with capital dependency that make use of stock markets are object of institutional pressures coming from financial analysts.

The literature has shown that the stock market strongly influences firms' strategic decisions. One of the mechanisms that make securities analysts influent agents are their reactions to business' strategies. When analysts oppose the firms' course of action, they downgrade their recommendations about investing in the firms' shares. Downgraded recommendations lead to discounts in stock's prices (Zuckerman, 1999). These stock price pressures trigger changes in firms' strategies toward greater alignment with analysts' view (Zuckerman, 2000). In addition to the indirect pressures that the stock prices exert on firms, financial analysts wield direct influences on corporations in earnings conference calls and investor meetings. Benner and Ranganathan (2012) found that analysts recommendations trigger changes in strategic investments during periods of uncertain technological change.

Notwithstanding, there are indications in the literature suggesting circumstances through which the financial analysts' negative reactions are attenuated. Theeke et al. (forthcoming) showed that if there is knowledge overlap between the companies that are covered by brokerage firms, the institutional negative reaction against a new knowledge is attenuated. According to those researchers, one of the reasons why the negative reactions are attenuated is familiarity about the knowledge that the overlap brings to financial analysts. The attenuation of the tension between new knowledge and negative institutional reaction is important because it can potentially safeguard firms' strategies from institutional interferences.

The classical view in competitive strategy defends that existing knowledge must be protected. Nevertheless, there is a growing stream of research defending that innovators may share even proprietary knowledge with the market, consequently being relatively opened to their rivals in order to reduce uncertainty and slowing down competition. Pacheco-de Almeida and Zemsky (2012) argue that by disclosing Intelectual Propriety, innovators indirectly induce rivals to wait and imitate instead of concurrently investing in innovation, which alleviates competitive pressure. Those researchers showed that leader firms may want to allow some knowledge spillovers when followers have a choice between concurrent and imitative technology development. According to those authors, the consequence of that more open approach reduces development costs.

Thus, there are evidences in the literature that if on the one hand the stock market influences firms' strategies, on the other hand knowledge overlap has the power of attenuating adverse reactions of the stock market. If firms undergoing technological change disclose new knowledge, they will increase the financial analysts' familiarity with the new knowledge. Furthermore, disclosure reduce information asymmetry between firms and the stock market, enhancing understanding about the strategy logic, and then diminishing uncertainties. Hence, divergent reactions to those firms' strategies are expected to be attenuated when firms manage knowledge disclosure. This possibility is considered in this study, which investigates the following question: How effective is knowledge disclosure to reduce institutional pressures from the stock market on firms' strategic decisions, under an environment of technological change?

Undoubtedly, having less external pressures is important to firms because it isolates opposing tensions between technological pressures for survival and institutional pressures for predictable earnings and cash flows (Benner and Ranganathan, 2012). While surviving should be the fundamental objective of the firms, predicting earnings and cash flows not only enables financial analysts to evaluate business and securities in a rational way, but also provides legitimacy to managers course of action. Achieving successful recognition from securities analysts will lead to "a significant impact on a firm's fate in financial markets" (Zuckerman, 1999). Indeed, getting positive coverage from financial analysts brings a number of advantages to companies such as obtaining an important form of recognition (Mola et al., 2013), increasing their market values (Zuckerman, 1999), lowering their cost of capital (Bowen et al., 2008) and enhancing their ability to form alliances (Pollock and Gulati, 2007). Therefore, under environments of technological change, solving this tension between strategic choices and its reflection in the firm's influential external world is paramount.

The contribution of this research is aligned with Christensen (1997) observation, proposing that the logical, competent decisions of management that are critical to the success of their companies are also the reasons why they lose their positions of leadership. Decisions favoring knowledge disclosure are commonly considered as detrimental to innovators but beneficial to imitators. The unique aspect of this article, however, is to show that knowledge disclosure, especially business knowledge can moderate adverse reactions of institutional pressures under environments of technological changes. As a result, the strategy outcome can be eventually positive. Thus, what seems to be a phenomenon that functions ineffectively as a means for the attainment of a strategy can be in reality a phenomenon that functions effectively. The contribution of this work turns the field of strategy even more intriguing because if empirical evidences support, knowledge disclosure that seemed to deter innovation would in fact sustain firms' propositions of change, the strategies for their survival.

2 Literature Review and Theoretical Development

2.1 External influences on firms' internal decisions

Some innovations have the potential of shifting the underlying base of technological knowledge (Dosi, 1982; Tushman and Anderson, 1986; Gatignon et al., 2002). Those changes on technological knowledge base and the corresponding accommodation of firms' resources to fit into the new competitive environment are crucial to firms' long term health and survival (Teece et al., 1997). Implementing the organizational adjustment, however, is a different story. The challenges that firms face in environments of technological change are linked to the difficulties in changing structures and routines (Dosi, 1988; Leonard-Barton, 1992; Levinthal and March, 1993; Tripsas, 1997; Benner and Tushman, 2002). Researchers have explored the inabilities of organizations to transfer capabilities between them (Prahalad and Hamel, 1990; Grant, 1991) and within them (Szulanski, 1996; Toh and Polidoro Jr., 2013). Other studies focused on limits of learning capabilities (Levinthal and March, 1993). This work, however, gets a different perspective on the problem. It considers the forces that come from outside the boundaries of the firms and affect their decision making processes, the forces that come from institutions.

The institutional forces that exert pressure on firms' strategic management may come from many sources, such as customers (Christensen and Bower, 1996; Danneels, 2003), networks of suppliers (Glasmeier, 1991), competitors (Sull, 2001), professional associations (Greenwood et al., 2002) or other regulatory bodies (Tolbert and Zucker, 1983). In particular, pressures may also come from stock markets (Baker et al., 2003), through brokerage firms and financial analysts (Benner and Ranganathan, 2012). Analysts directly interact with management through earnings calls, road shows and other ways of communication promoted by public firms. In these occasions, analysts are given opportunity to make questions to firms' executives regarding finance, strategy and operational aspects of the businesses. Financial analysts provide information and recommend investors to buy, hold or sell stocks, which eventually influence stock prices.

Strategy in this work is defined as decisions that will influence the long-term welfare of the organization, often involving major organizational changes and large resource commitments that are difficult to reverse once they are implemented. However, strategy changes also bring uncertainty and information asymmetry between managers and analysts. In the face of an emergent technology, incumbent firms suffer pressures for adaptation. Those firms need to invest in new strategies, knowledge and capabilities in order to survive (Agarwal and Helfat, 2009). Managers need to face uncertainties, investing on new strategies that they believe have more chances to succeed in the long run.

Benner (2010) found that securities analysts are more attentive and positive toward incumbents' strategies that extend and preserve the existing technology than toward strategies that respond directly to an emergent technology. Securities analysts generally specialize in covering firms from the same industry (Zuckerman, 1999). The financial models used for evaluating firms of the same industry are usually shared and reflect taken-for-granted ideas about the suitable strategies for generating profits, cash flows and other performance measures. Strategies that deviate from what is established in the industry turn the evaluative task more difficult to the analysts. Similarly, strategies that are unique or complex require more levels of information processing by analysts. By facing higher costs of information and analysis, financial analysts make pressure to firms to alter their strategy so as to reduce the information costs that accompany it.

Litov et al. (2012) observed that there are managerial incentives for adopting unique, value-creating strategies only to the point that the capital market is efficient in accurately assessing the values of the strategies selected. On the one hand, that authors found that the capital markets systematically discount uniqueness in the strategy choices of firms. On the other hand, they also obtained empirical support to assert that strategic uniqueness is positively associated with firm value. They called this puzzle "the uniqueness paradox", as the unique strategy that brings value to firms proves to concurrently be a hindrance to financial analysts carry out assessments, analyses and valuations of those firms.

Greater cost of information to perform evaluations discourage analysts to collect data and analyze firms. During periods of technological change, financial analysts face uncertainties about the future value of the firm. The changing environment turns predictions more difficult and uncertain, imposing to analysts a higher cost of performing valuations. Moreover, with uncertainty, it is not possible for financial analysts to accurately assess future cash flows. New strategies impose to analysts extra costs to collect information about firms' new approaches and to acquire new knowledge. Consequently securities analysts negatively react to firms that are trying to react to a challenging environment with innovation because they do not understand their strategies. As a result, financial analysts provide reports opposing to firms' strategy, discount valuations, downgrade recommendations or simply drop covering those firms.

In addition to pushing up costs of information and rising uncertainties to financial analysts, technological changes potentially deteriorate the short term financial performance of firms responding to this environment. Firms implementing new strategies are expected to financially underperform in the short term because of the lack of experience with the novel technology, which leads to higher operational costs, and the absence of economy of scale. Expectations of poor results in the short run and inability of making forecasts minimally accurate for the long term, also make analysts to become reacting negatively to the company's management.

Thus, by facing uncertainties brought by new strategies that respond to novel technologies, stock investors tend to diversify their portfolio, reducing risks by shifting investments away from firms that are challenged by technological changes. The outcome of this investors' behavior is a decline on stock prices of the firms under uncertainties brought by environment and strategy changes. The decline on stock prices led to further negative reactions from the part of financial analysts. Those negative reactions are reflected in the reports prepared by the analysts, certainly downgrading their recommendations to buy the shares of the companies in question.

Hypothesis 1 (H1): The probability of stock market's positive reaction diminishes as firms implement new strategies responding to technological changes.

2.2 Corporate external reporting

In the last section, arguments found in the body of literature were offered suggesting that the stock market's reaction tends to be negative as firms implement new strategies responding to technological changes. One of the intents of the first part of this theoretical approach was to show a particular and relevant challenge that firms face, under an environment of technological change – the external reactions to firms' decisions that eventually can be reconsidered due to the pressure exerted by institutions. The novel contribution aimed by this work, however, is to evaluate the effect of firms disclosing information so that negative reactions to strategic changes in an environment of technological change is attenuated.

In this section, the role of corporate external communication is reviewed because it is relevant to assess not only the quantity of information disclosed by firms to the market, but also the kind of topics and the quality of the narratives that are being delivered by the firms. In the next section, arguments will be provided predicting that some characteristics of the firms' narratives positively influence market reactions in technological changes circumstances. Prior to that, however, it is necessary to define what characteristics should be assessed in transcripts of all sorts of corporate external communications and what are the methods that support this assessment.

It is common knowledge that the capital market requires transparency from public firms, who in the present day should disclose more than the traditional backward-looking, quantified financial information (Beattie et al., 2004). There are considerable benefits to firms, derived from disclosure of information. However, there are also costs and disadvantages. On the one hand, increasing transparency leads to a reduction in asymmetry of information between firms and market participants, which in turn reduces information risk, lowers cost of capital, increases share price, increases stock liquidity and alleviate agency problems (Beyer et al., 2010). On the other hand, in addition to the costs of developing and presenting reports, there are other disincentives to full disclosure, such as loss of competitive advantage and litigation costs (Elliot and Jacobson, 1994).

Early papers in report narratives focused on evaluating the readability of reports and their role of communication or manipulation. Some of the characteristics of the research approaches at that earlier times were the use of binary or ordinal measures trying to capture quality aspects of reporting items and whether each item was weighted or unweighted. Currently, many aspects of even great amount of texts are critically examined, such as topic, futurity, readability, tone, certainty, attribution, vividness, deception and self-references. Those various linguistic attributes have been associated with outcomes such as market returns, trading volume, financial distress, financial statement irregularities and corporate environmental performance (Beattie, 2014).

Research on contents of corporate external communications has evolved due to the application of a variety of knowledge fields, along with the development of methods and softwares. Theories on this topic have drawn upon the literature in literary theory, sociology, cultural studies, linguistics, philosophy and psychology. Given such a wealth of knowledge as well as the large amount of texts that research in this area usually need to evaluate, the development of methods and computer softwares has been an important ally of the development of this field. Natural Language Processing (NLP), Corpus Linguistics (CL), Data Mining (DM) and Artificial Intelligence (AI) are some of the methods used in those softwares. "Big Data" (BD) is defined by the capacity of searching, aggregating, and cross-referencing large data sets. This unprecedented capacity of analyzing big data has transformed natural and social sciences and its evolution makes narrative assessment more productive and efficient, although is not disentangled of inbuilt limitations and restrictions (danah Boyd and Crawford, 2012).

In 1994, the American Institute of Certified Public Accountants (AICPA), the national professional organization for Certified Public Accountants (CPAs) in the United States proposed a model of business reporting with eight main topics: financial data, operating data, management analysis, forward-looking information, information about management and shareholders, objectives and strategy and description of business and industry structure. Known as the Jenkins Report (AICPA, 1994), this report has influenced both companies and regulators to provide voluntary or, in some cases, mandatory disclosures quantitatively and qualitatively more extensive than in older times. Based on this report, researchers have developed a number of methods for evaluating the level and the quality of disclosure. Among those researchers, Beattie et al. (2004) proposed the method for collecting knowledge disclosure adopted in this work.

The method consists of using a coding instrument for gathering information within topic classifications based on the Jenkins report, yet extra categories were included. The categories, showed on Figure 1, are organized into four code stages. The first stage – time orientation – is concerned with narratives related to the past (historical), future (forward-looking) or non-time specific. The second stage has connections with the narratives related to financial or non-financial topics. The third stage has significance for measures, changes and other quantitative topics or non-quantitative contents, being facts, judgements or others. Finally, the fourth stage

of coding bear upon the original Jenkins' topics, compounded by nine categories. The method makes possible to quantitatively analyze non-numerical and unstructured data in a rich manner, based on general principles of content (or thematic) analysis, a well known method in social science. The adopted procedure can be thought of as a bridge between the worlds of qualitative and quantitative research. More information about this method can be found on the subsection 3.3. For a comprehensive review on the methods for assessing disclosure see Beattie et al. (2004). This framework has been widely accepted and extensively used by researchers for analyzing and evaluating narratives in finance reporting and disclosure index studies.

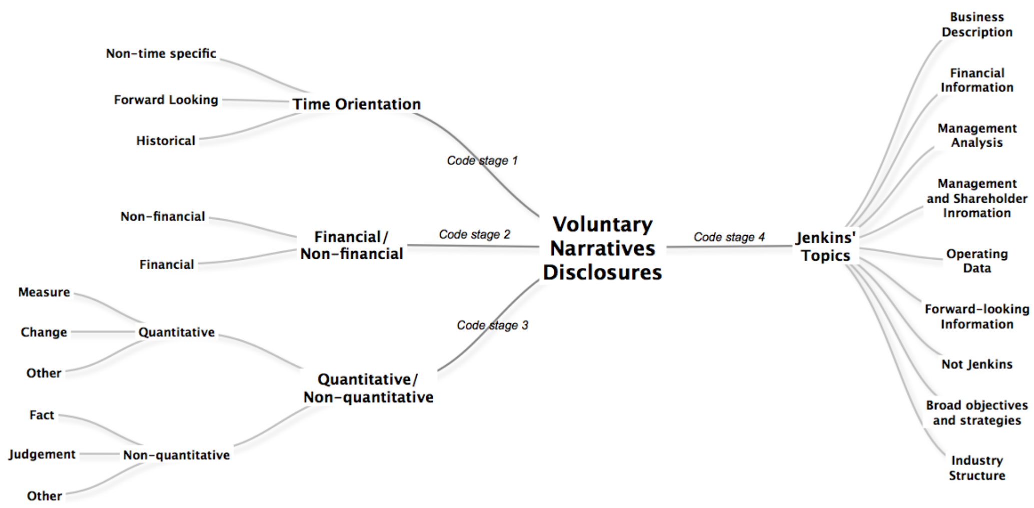

Figure 1: Architecture of coding scheme for voluntary disclosures.

2.3 Attenuation of external influences

Securities analysts become not attentive and positive to incumbent companies that decide to shift their strategies because they do not fully understand firms' new course of action. Analysts are not able to dully assess future earnings of the firms they cover because of the uncertainty posed from incumbent firms when they propose and put in action new strategies. Asymmetry of information contributes for the hardship that analysts face to evaluate firms. As already observed by other researchers (e.g. Benner, 2010; Litov et al., 2012), by attempting to reduce high costs of information, financial analysts make pressure to firms to alter its strategy. Actors external to the firms can only respond to what they know rather than what is knowable (Teece et al., 1997). Analysts cannot recommend investors to buy firms' shares if strategies are not known and duly understood.

The evaluative challenges posed to brokerage firms associated with companies' new knowledge reduce when there is greater knowledge overlap. Theeke et al. (forthcoming) observed that greater knowledge overlap between a company and other companies that a brokerage firm covers diminishes the difficulty in understanding a company's use of new knowledge. Knowledge

overlap was measured by those authors as common patent citations made by a focal company and the other companies that the brokerage firm covers. Knowledge overlap in upstream enables brokerage firms to provide more reliable estimates, and increases its propensity to cover a company that builds its strategy on a new knowledge. Those authors found that a higher knowledge overlap increases the probability of brokerage firms to cover the firm. Thus, greater upstream knowledge overlap between brokerage firms and companies attenuate the negative relationship between the companies' use of new knowledge and coverage.

Coverage is a way for firms to obtain an important form of recognition (Mola et al., 2013), resulting in an increase in the market value. In contrast, an absence of coverage by securities analysts leads to discounts in the stocks price (Zuckerman, 1999). Thus, the effect of being covered by financial analysts is paramount for firms operating in the capital market. In consequence, knowledge overlap is central for those firms. Figure 2 shows the effect of knowledge overlap on the probability of coverage.

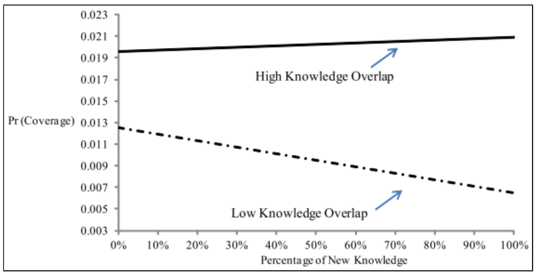

Figure 2: Knowledge Overlap Effect on Probability of Coverage. Source: *Theeke et al. (forthcoming)*

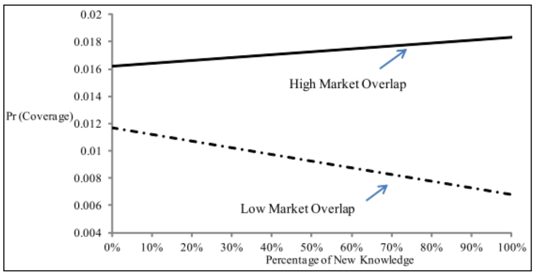

Figure 3: Market Overlap Effect on Probability of Coverage. Source: *Theeke et al. (forthcoming)*

Similarly, Theeke et al. (forthcoming) showed evidences that market overlap also exerts similar effect on the probability of coverage. According to their studies, market overlap between a company and other companies that a brokerage firm covers positively affect that brokerage firms confidence in accurately evaluating the value that such company will likely create. Thus, market overlap will also attenuate the negative effect that a companys use of new knowledge produces on its ability to attract brokerage firm coverage. Figure 3 shows this effect.

Knowledge is a critical and direct route for financial analysts carry out adequate assessments and evaluations of firms that are going through technological changes. Familiarity with knowledge and reduction of information asymmetry are the cornerstones that diminish uncertainty and enable brokerage firms to provide more reliable estimates, and increase its propensity to cover a company that builds its strategy on a new knowledge. Both the upstream knowledge and market overlaps increase familiarity and reduces information asymmetry. Both are essentially two sides of the same coin – business knowledge. It is fundamental that financial analysts understand the business about which they will evaluate, produce reports and provide recom-

mendations. Therefore, in a broader sense, it is business knowledge that attenuates the negative external reactions to firms' strategic responses in a technological change environment. It is, then, possible to say that providing financial analysts with knowledge increases firms' chances of being duly covered by brokerage firms.

It is only conceivable to actively provide the market with knowledge through disclosure. In general terms knowledge disclosure is the key for companies to attract coverage from brokerage firms. Eventually, just as coverage results in a number of benefits to firms, we can say that knowledge disclosure potentially has similar effects in specific conditions. The proposition of this paper is that an adequate knowledge disclosure will increase firms' chances of success when they redesign their strategies responding to technological changes.

Hypothesis 2 (H2): Other factors being equal, the probability of stock markets positive reaction increases as firms duly disclose knowledge.

3 Empirical Analysis

3.1 Sample Data

The setting is convergence between the wireline telecommunications and cable television industries in the USA in the period from first quarter of 2001 to the fourth quarter of 2008. This empirical setting was selected because at that time, those industries were experiencing a business environment surrounded with uncertainty, innovation changes, imitation, knowledge development and disclosure. The industry change occurred when Voice Over Internet Protocol technology (VoIP) was first commercialized in 2002. VoIP is a radical technological change that allows phone calls to be transmitted digitally using the Internet. Although early VoIP deployments were tormented with quality problems, continued improvements in the performance and price of the new technology led to rapid commercialization. In addition, VoIP technology provided a way for cable television firms to offer telephone services. Cable firms subsequently offered bundles of services that included telephone, video, and high-speed Internet. The telecommunications firms responded by offering stand-alone VoIP telephony products on existing copper-based wireline networks as well as similar bundles of Internet, video, and telephone services, often on upgraded fiber-optic networks.

A panel data with 106 observations was set. The access to the database (Reuters-Datastream) that reliably contains most of the information needed for this research. Two companies from each industry were considered – Verizon Communications Inc. (VZN) and AT&T Inc. (ATT) from telecommunications – Cablevision Systems Corporation (CVC) and Comcast Corporation (CMC), representing the Cable industry. The difference between the institution reactions (originally measured by the analysts' recommendations) in the period of study can be observed on figure 4. Observing the figure, it seems that the pessimism about the telecommunication industry is more prominent compared with the cable segment. In fact, Table 1 shows that the

difference of means between the two segments is significant. Nevertheless, just seeing what the data shows and using this simple statistics is not sufficient for understanding the nature of the relationship between the institutional reaction and knowledge disclosure. Thus, a more robust model was developed. The variables of the model and its specifications are described below.

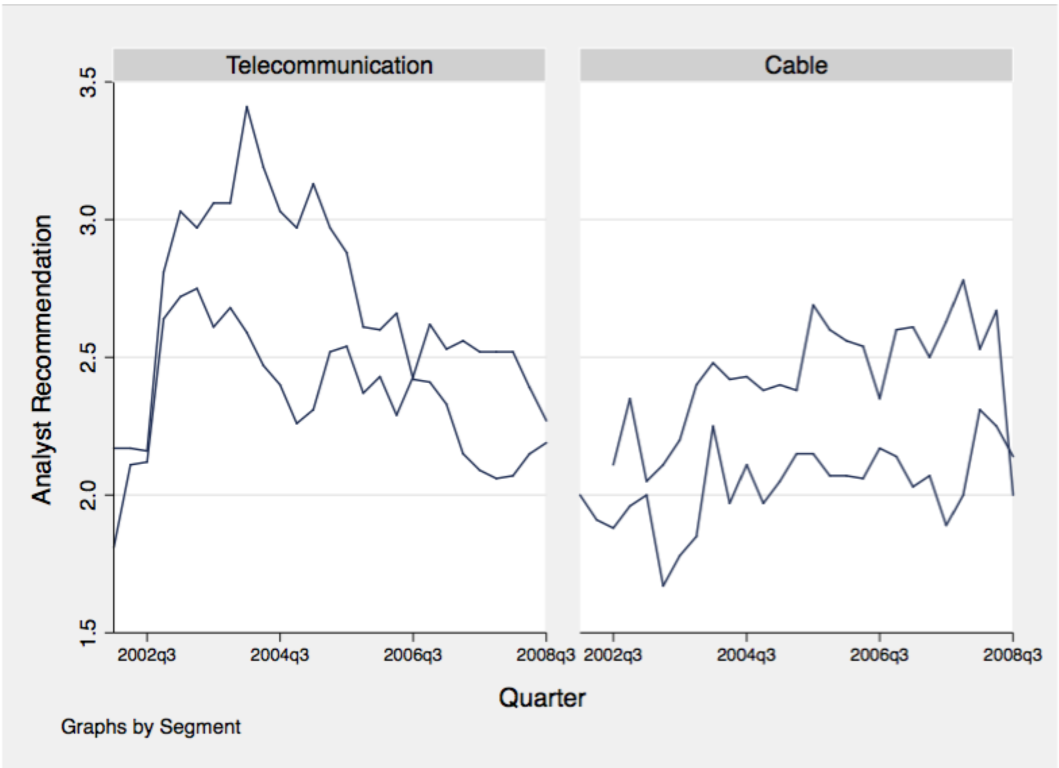

Figure 4: Analyst Recommendation By Segment

Table 1: **Difference of Analyst Recommendations Means Between Segments**

	Telecom firms	Cable firms	diff	se	t	p_value
analyst recommendation	2.53	2.22	.31	.0597	5.15	<0.001

3.2 Dependent Variable

The dependent variable is *institutional reactions* and to assess it, the Institutional Brokers Estimate System (I/B/E/S) was used, as widely applied in research of this genre. As many brokers have different ratings, the I/B/E/S maintains a standard set of analysts' recommendations, each with an assignment numeric value. The consensus recommendation is the mean of the assigned values. The consensus texts are the following: Strong Buy, Buy, Hold, Under Perform and Sell and they are respectively related to the following range of *analyst recommendation*: between 1 and 1.49, between 1.5 and 2.49, between 2.5 and 3.49, between 3.5 and 4.49 and between

4.5 and 5. Positive reactions were considered when a company holds a recommendation value lower or equal than the median and negative reaction if it is higher than the median in the period of study. The variable *institutional reactions* then received an 1 if the firm earns a positive evaluation in quarter t, and 0 otherwise.

3.3 Independent Variables

The first of the four-dimensions structure developed by Beattie et al. (2004) was used for assessing *knowledge disclosure*. The object of investigation for obtaining was the companies' narrative disclosures. Mandatory report sections greatly subject to regulatory requirements or fairly standard in nature are not focus of analysis. For that reason, the following report sections are not targeted: auditor's report, the directors' report, corporate governance statements, directors' remuneration reports, tables of contents, information for shareholders, historical summary tables and lists of principal operating companies. Narratives to be analyzed are voluntary disclosures, including: highlights, chairman's statement, CEO's review, operating financial review (OFR), people, community, directors and advisors and captions from pictorial material.

A computer software was used for assisting the analysis. The use of software helps ensuring rigor in the analysis process, providing a more complete set of data for interpretation than might occur when working manually. There are many softwares that offer this sort of technique in the market. The software used was *MAXQDA*, produced and distributed by VERBI GmbH, based in Berlin. This software supports the processes of coding data in order to set up the voluntary disclosure architecture. Table A3, located on the appendix of this work, shows a detailed documentation of the coding instrument, including its category, definition, flags, qualifications, exclusions and examples. Initially, 364 documents were collected, being 106 transcripts of Earnings Conference Calls, which were chosen to be the priority and exclusive focus at the current stage of the research, as they constitute a rich source of voluntary narrative disclosure. The method allows only one code for each dimension (stage) and the area of text coded is measured by the software. These measurements were exported to *Stata*, where the final models were run.

Strategic Decisions are choices that will influence the long-term welfare of the organization. These decisions often involve major organizational changes and large resource commitments that are difficult to reverse once they are implemented. New products, services, alliances and partnerships introduced into the market are consequences of strategic decisions and will be used as a proxy of them. The strategic events occurred during the time frame of this study can be found in the work of Benner and Ranganathan (2012). Those data were used in this research and a summary can be seen on Table 2.

Table 2: **Timeline of Firms New Products/Services During the Study**

date	**firm**	**event description**
Telecom firms		
May 2003	ATT, VZN	Announce common technical requirements for fiber initiatives
Dec 2003	ATT	Announces alliance with Alcatel for fiber initiative
Apr 2004	ATT	CallVantage launch complete-expanded to more than 100 U.S. markets
Jul 2004	ATT	Launches Voicewing VoIP services to residential customers
Oct 2004	VZN	Announces rollout plans for FiOS in northeastern United States
Nov 2004	ATT	Announces launch of residential VoIP service for its DSL customers
Apr 2005	VZN	Introduces FiOS broadband in trial markets
Sep 2005	VZN	Rolls out fiber-optic TV service as part of FiOS triple-play
Feb 2006	ATT	Trials U-verse (fiber-based bundle) in Nevada
Cable firms		
May 2003	CVC	Trials residential VoIP product
Nov 2003	CVC	Launches Optimum Voiceresidential VoIP product
May 2004	CMC	Announces Digital Voice residential VoIP product rollout for 2005/2006
Jun 2004	CVC	Announces bundling of Internet and phone product
Dec 2004	CVC	Announces expansion of VoIP service
Jan 2005	CMC	First rollouts of Digital Voice

Source: Benner and Ranganathan (2013)

3.4 Control Variables

It is necessary to control for several factors that are likely to affect institutional reactions, such as the company's level of financial performance and company's size (Bhushan, 1989). Examples of those controls are firm's *log of total assets, return on assets (ROA), log of revenue, log of net income, log of earnings per share, and log of stock price*. A company's use of debt can influence the level of coverage it receives (Barth et al., 2001), and it also may affect its innovation strategy. Therefore, the company's *debt-to-equity ratio* should be taken into account as a control variable.

3.5 Descriptive Statistics

The descriptive statistics are shown below on Table 3 and a more detailed documentation of the data can be seen on the Appendix A.

Table 3: **Descriptive Statistics**

variable	N	min	p25	p50	p75	max	mean	sd
institutional reactions	106.0	0.0	0.0	1.0	1.0	1.0	0.5	0.5
analyst recommendation	106.0	1.7	2.1	2.4	2.6	3.4	2.4	0.3
knowledge disclosure	106.0	9.9	10.4	10.6	10.7	12.0	10.5	0.3
historical	106.0	9.5	10.0	10.2	10.3	11.3	10.2	0.3
forward looking	106.0	8.1	9.0	9.3	9.6	11.3	9.3	0.5
strategic decision	106.0	0.0	0.0	0.0	0.0	1.0	0.2	0.4
log of total assets	106.0	16.0	17.4	18.5	18.9	19.5	18.1	1.2
return on assets	106.0	-3.9	2.3	4.5	5.7	11.9	4.2	2.8
log of revenue	106.0	13.8	14.8	16.1	16.7	17.3	15.8	1.1
log of net income	106.0	-6.9	14.6	14.9	15.2	15.7	14.7	2.1
earnings per share	106.0	-1.1	0.0	0.3	0.6	1.5	0.2	0.4
stock price	106.0	4.0	18.0	24.2	32.1	41.3	24.7	8.8
log of debt-to-equity	106.0	5.8	6.8	6.8	6.8	7.0	6.7	0.3

3.6 Model

This research project needed a model that estimates the probability of an event occurring – the probability of institutional reaction being positive. By presenting this characteristic, the *logistic model* was chosen for testing the hypotheses. The advantages of choosing this model are:

i. It allows properties of a linear regression model to be exploited,

ii. The logit itself can take values between $-\infty$ and $+\infty$, depending on the range of x.

iii. Probability remains constrained between 0 and 1

iv. The logit can be directly related to the odds of an event (e.g. the odds of positive institutional reaction)

As a binary response, the interest of this model lies primarily in the response probability. For estimating this model with the guarantee that the dependent variable, represented by a probability will range between 0 and 1, with the characteristic of gradually approaching the extremes. The curve of this model is s-shaped and resembles a plot of the cumulative distribution of a continuous variable. Thus, it is not a surprise that some well-known cumulative distributions have been used to provide the model for dichotomous dependent variables.

Being the quantity $\pi(\boldsymbol{x})$ a representation of the conditional mean of the outcome variable $E(Y|x)$. Y denotes the outcome variable and $\boldsymbol{x}$ denotes a collection of independent variables. $\pi(\boldsymbol{x})$ can be also be defined as the probability of the outcome, given $\boldsymbol{x}$.

$$\pi(\boldsymbol{x}) = \frac{e^{(\beta_0+\boldsymbol{\beta_1 x})}}{1+e^{(\beta_0+\boldsymbol{\beta_1 x})}} \tag{1}$$

Where β_0 and $\boldsymbol{\beta_1}x$ are the parameters of the model.

$\pi(\boldsymbol{x})$ is the **cumulative distribution function (cdf)** for a standard logistic random variable, which can be seen on Figure 5.

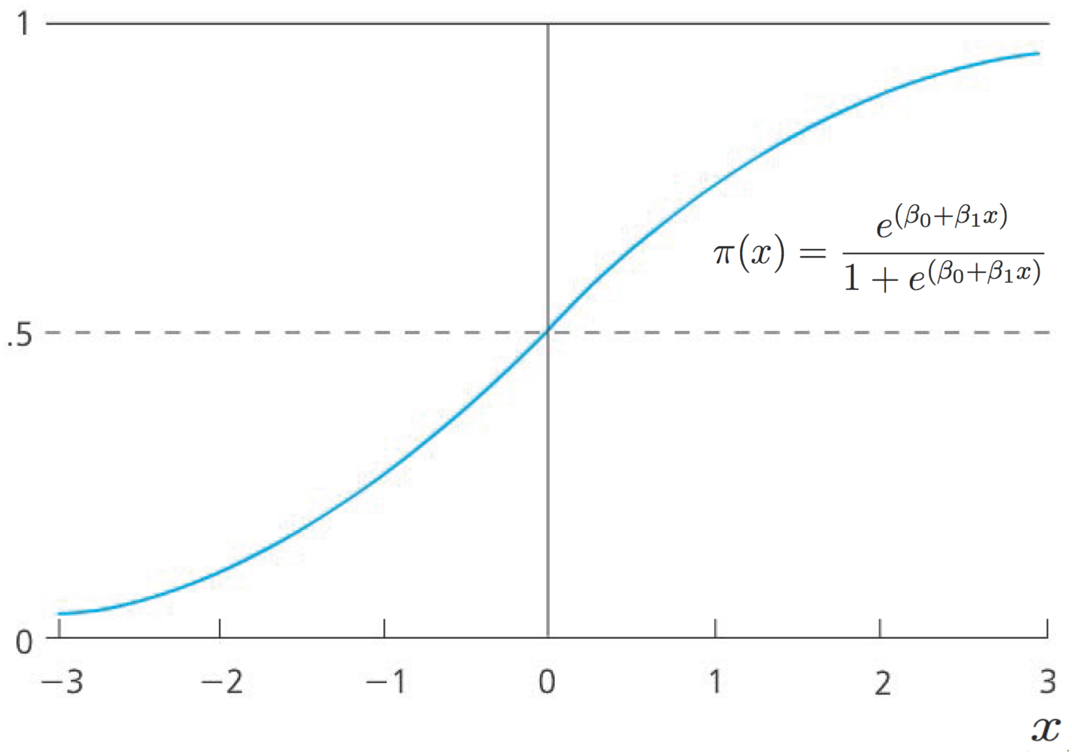

Figure 5: Graph of the logistic function - *Source*: Adapted fromWooldridge (2013)

The **odds** of an event occurring, represented by $G(\boldsymbol{x})$, can be expressed as the following:

$$G(x) = \frac{\pi(\boldsymbol{x})}{[1-\pi(\boldsymbol{x})]} \tag{2}$$

Taking the logarithm of expression (2), **the log of odds** or simply the **log odds** is obtained. It is possible to show that the log odds is equal to $\beta_0 + \beta_1 x$. The following form of the logistic regression model takes place:

$$g(x) = \ln\left\{\frac{\pi(\boldsymbol{x})}{1-\pi(\boldsymbol{x})}\right\} = \beta_0 + \boldsymbol{\beta_1 x} \tag{3}$$

The density of y_i given $\mathbf{x_i}$ is needed in order to obtain the Maximum Likelihood Estimation (MLE), which is an indispensable method to estimate this kind of model. It can be written as:

$$f(y|\mathbf{x_i};\beta) = [G(\mathbf{x_i}\beta)]^y[1-G(\mathbf{x_i}\beta)]^{1-y}, y = 0,1 \tag{4}$$

Taking the log of equation 4, the **log-likelihood function** is obtained:

$$l_i(\beta) = y_i log[G(\mathbf{x_i}\beta)] + (1-y_i)log[1-G(\mathbf{x_i}\beta)] \tag{5}$$

The log-likelihood for a sample size of n is obtained by summing this equation across all observations. The MLE of β maximizes this log-likelihood. To find the logit estimator, the value of $\hat{\beta}$ that maximizes the $L(\beta)$, we differentiate $L(\beta)$ with respect to β_0, β_1 and so forth and set the resulting expressions equal to zero. According to Wooldridge (2013), under very general conditions, the MLE is consistent, asymptotically normal, and asymptotically efficient.

This transformation of $\pi(x)$ is central because $g(x)$ has many of the desirable properties of a linear regression model. It may be continuous and is linear in the parameters with the potential for a range between $-\infty$ and $+\infty$ depending on the range of x. Contrary to linear models, the statistical distribution of errors in the logit is the binomial with mean zero. Its variance is not constant and it can be estimated by the following equation:

$$\widehat{Var}(\hat{g}(\boldsymbol{x})) = x'[\widehat{Var}(\hat{\boldsymbol{\beta}})]\boldsymbol{x} \tag{6}$$

The confidence interval for the *logit* can be computed by $\hat{g}(\boldsymbol{x}) \pm z_{1-\alpha/2}\widehat{SE}(\hat{g}(\boldsymbol{x}))$, where $\widehat{SE}$ is the $\sqrt{\widehat{Var}}$, and finally, the confidence interval for the estimated logistic probability is the following:

$$\frac{e^{\hat{g}(\boldsymbol{x}) \pm z_{1-\alpha/2}\widehat{SE}(\hat{g}(\boldsymbol{x}))}}{1+e^{\hat{g}(\boldsymbol{x}) \pm z_{1-\alpha/2}\widehat{SE}(\hat{g}(\boldsymbol{x}))}} \tag{7}$$

Thus, with all those proprieties, the following logit model was used in order to test the hypotheses:

$$\boxed{\begin{gathered} Pr(Institutional\ Reaction \mid x) = \alpha_0 + \beta_1 Strategic\ Decision\ + \beta_2 Knowledge\ Disclosure \\ + \boldsymbol{\beta_3} Control\ Variables\ + \varepsilon \end{gathered}}$$

3.7 Results

The proposed model and a number of variants were estimated and presented on table 4. On the appendix of this work, alternative models were tested. The results were in general consistent with the ones presented below. All models presented on table 4 are statistically significant, according to either the likelihood ratio or the Wald test. This can be observed through the p-values for the chi-squared statistics tests as well as throughout the significances of the co-

efficients reported on that table. A brief summary on how the likelihood ratio and Wald tests works for checking the significance of logistic models can be seen on the Appendix B. Model one and two are of particular interest because the former reinforce evidences showed by Benner (2007, 2010), which is also the focus of the first formulated hypothesis one of this work. Benner showed that analysts are more focused and positive toward incumbents strategies that extend and preserve the existing technology, rather than toward fresh strategies that respond a new environment. Models two and three show statistical significance for the *Strategic Decision* variable on its lag three, as reported on table 4. Model two not only shows a significant impact of new strategic decisions ($p<0.05$), but also indicates a negative sign of this variable. Thus, according to this model the more new strategics are developed, the more negative is the institutional reaction. Other lags for the *Strategic Decision* variable were tested and reported on table A14 of the appendix. The major focus and novelty brought by this piece of research, however, is the role of corporate disclosure on institutional reactions. The model one addresses this issue.

Model one not only is the most parsimonious among the four reported, but it also has the lowest Bayesian (BIC) and Akaike (AIC) information criteria. It is known that given two or more models fit on the same data, the model with the smaller value of the information criterion is considered to be better. Therefore, among the options reported, model one is the best according to both information criteria. Model one was run with the option of robust standard errors, which yields variances for the MLE that are asymptotically correct even when the model is misspecified. According to Wooldridge (2010), in a binary response model it is not possible to correctly specify $E(y=1|\boldsymbol{x})$ but to misspecify $Var(y|\boldsymbol{x})$. Still in accordance with the author and econometrician, once $P(y=1|\boldsymbol{x})$ was specified, all conditional moments of y given x were specified. Although not reported, model one was also run without this error correction option and, as expected, all coefficients were exactly the same and its standard errors were nearly the same. Nevertheless, with the robust standard errors option, the control variable *net income* had its standard error reduced by 60% and turned to be significant. Thus, model one is a parsimonious, significant and robust logit model that shows statistical significance on all variables, including the key ones related to knowledge disclosure. Model one results were analyzed in detail for addressing the research question of this work and hereafter will be referred as the main model or simply the model.

According to the logistic regression, the chosen model satisfies the following equation:

$$\hat{\pi}(\mathbf{x}) = \frac{e^{3.261\mathrm{l.inst\_reac}-1.705\mathrm{l.l\_his}+1.404\mathrm{l.l\_fwd}+0.181\mathrm{l2.l\_ninc}}}{1+e^{3.261\mathrm{l.inst\_reac}-1.705\mathrm{l.l\_his}+1.404\mathrm{l.l\_fwd}+0.181\mathrm{l2.l\_ninc}}} \tag{8}$$

By executing the logit transformation of the model, the result of the estimated logit is the following:

$$\boxed{\hat{g}(\mathbf{x}) = 3.261\mathrm{l.inst\_reac} - 1.705\mathrm{l.l\_his} + 1.404\mathrm{l.l\_fwd} + 0.181\mathrm{l2.l\_ninc}} \tag{9}$$

Table 4: **Logit Models of Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4
Strategic Decision				-0.930
				(0.730)
L3.Strategic Decision		-1.410*	-2.538**	
		(0.705)	(0.952)	
L1.Log of Historical Disclosure	-1.705**	-1.384**	-1.058	-0.941
	(0.547)	(0.515)	(1.124)	(1.080)
L1.Log of Forward Looking Disclosure	1.404*	1.204*	0.702	0.454
	(0.571)	(0.543)	(0.693)	(0.584)
Log of Revenues			-4.984***	-4.388***
			(1.262)	(1.153)
Log of Net Income			0.359	-0.149
			(0.837)	(0.198)
L2.Log of Net Income	0.181**	0.073		
	(0.066)	(0.117)		
Earnings per Share			1.252	0.859
			(1.005)	(0.918)
Log of Total Assets		0.099	4.913***	4.257***
		(0.226)	(1.328)	(1.217)
ROA			-0.202	-0.097
			(0.139)	(0.117)
Log Debt/Equity Ratio			-1.604	-0.617
			(2.024)	(1.783)
L1.Institutional Reaction	3.261***			
	(0.589)			
Constant				4.219
				(12.151)
AIC	92.1	124.8	100.4	121.4
BIC	102.5	137.5	123.2	147.6
chi2	32.8	12.1	22.0	40.0
p	0.0000	0.0340	0.0089	0.0000

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

If we choose an x, we can compute its *logit* by using the estimated logit of equation (9). Therefore, it is possible to compute point estimates and confidence intervals for linear combinations of coefficients. With this resource, simulations were made in order to evaluate the behavior of the probability of positive reaction, given corporate knowledge disclosure, being historical or forward looking type. For computing the confidence interval for the logistic probability, the estimated variance given by equation (6) and the computation described on expression (7) are needed. By using these expressions and computing the marginal effects, the following graphs were produced:

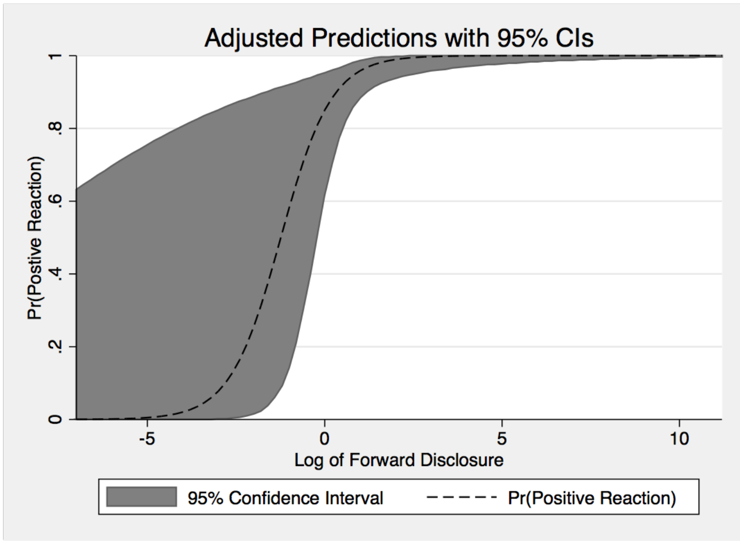

Figure 6: Adjusted Predictions – Forward Looking

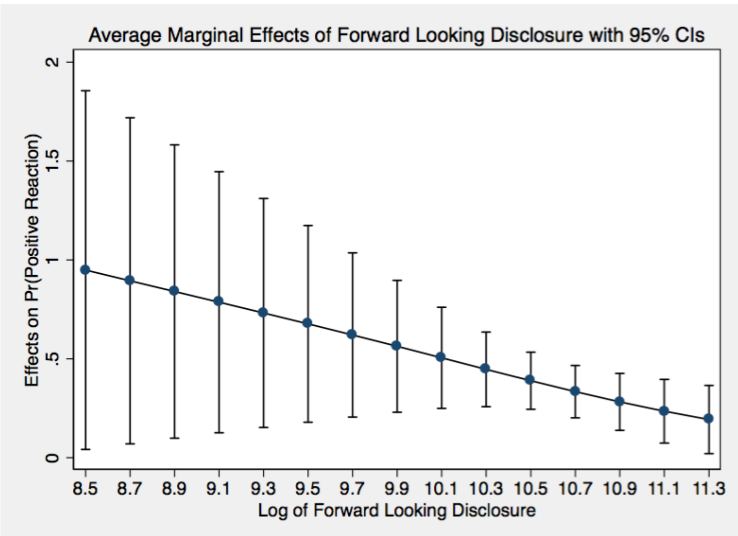

Figure 7: AME of Forward Disclosure with 95% CIs

Figure 6 shows a regular S shaped curve, revealing the ascendent probability of positive reaction, given an increasing amount of forward looking disclosure, keeping all other variables constant. The average marginal effects (AME) of forward looking disclosure is higher than zero within the range seen on figure 7. In contrast, figure 8 shows an inverted S shaped probability curve, revealing the downward probability of positive institutional reaction, given a growing extent of historical corporate disclosure and keeping all other variables constant. The average marginal effects of historical disclosure is below zero as seen on figure 9. The opposite behavior between the effects of forward looking and historical disclosure on the probability of positive institutional reaction could also be assessed by observing the sign of historical disclosure and forward looking disclosure variables in the model. While the latter has a positive sign, the former carries a negative sign.

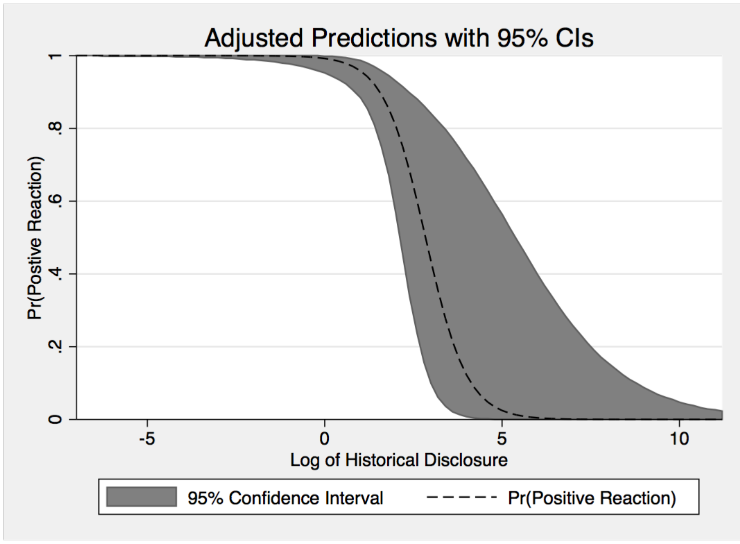

Figure 8: Adjusted Predictions – Historical Disclosure

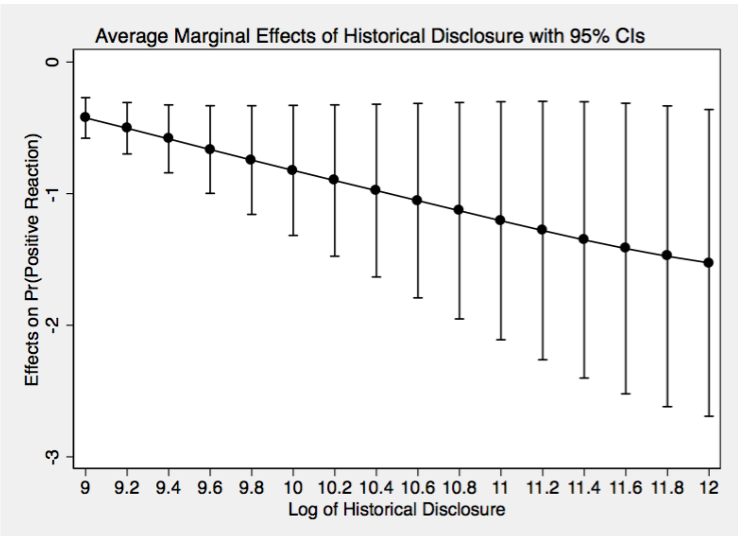

Figure 9: AME of Historical Disclosure with 95% CIs

The results of alternative models are exhibited on the appendix of this work. All the estimates are presented on tables A6 to A13. The marginal effects at the means (MEM) and the AME of some of those models are summarized on table 5. The findings were in general reasonably aligned with the main model.

Table 5: **Marginal Effects**

Model	L.inst_reac	L.l_his	L.l_fwd	L2.l_ninc
Marginal Effects at the Mean (MEM)				
Logistic (4)	0.817	-0.910	0.749	0.097
Probit (4)	0.770	-0.835	0.680	0.092
Panel Logit with PA (4)	0.620	-0.681	0.556	0.076
Panel Probit with PA (4)	0.607	-0.653	0.528	0.074
Average Marginal Effects (AME)				
Logistic (4)	0.299	-0.904	0.744	0.096
Probit (4)	0.315	-0.958	0.780	0.106
Panel Logit with PA (4)	0.279	-0.682	0.558	0.076
Panel Probit with PA (4)	0.295	-0.717	0.580	0.081

4 Discussions and Conclusions

The above preliminary study has limitations. Thousands of documents' pages were coded with the aim of providing an output to the quantitative stage of analysis. It is common that such kind of projects spend less time browsing coded material and thereby not frequently confronting potential inconsistencies. For providing consistency, Richards (2014) offers two recommendations. First, for consistency over time, it is recommended to code a clean version of a document coded earlier. Second, for consistency between members of the research team that worked in the project, each participant should code a duplicate of the same document. Additionally, the following differences should be searched: What categories are used by one but not by the other? What differences are there in the segments selected for coding at each category? Are the styles of coding different? In particular, is one version of the document more richly coded (at more categories) and does one coder select substantially larger passages for coding? Due to restrictions of time and budget, those recommendations were not considered, threatening the validity of the investigation.

In addition, despite the fact that the coding of the four dimensions are independent, according to Beattie et al. (2004), "the frequency of code combinations across dimensions provide a rich understanding of disclosures," a considerable benefit that was not obtained at the current stage of this research. Another downside found in this work is the construct for capturing strategic decisions. Despite the fact that previous qualitative research has shown the main announcements of new products and services during the study period of time, which in turn were transformed to a quantitative measure, the weights of those measures could not be assessed.

Resources allocation for putting those strategies in action would be an option, however difficult to assess and to appropriately calibrate. Finally, only four companies were considered and one of them, namely AT&T, has lived a number of spinning offs, mergers and acquisitions through its history, making difficult the task of analyzing a single entity, the same organization along its existence, including in the period of time here studied.

The results of this work build up strength to some views that have been flourishing in the fields of strategy and finance research. Contrary to the traditional view of strategy, providing the market with information and not withholding it can be beneficial to firms, specially those facing technological change on their business environment and needing access to the capital market.

In the corporate finance literature it is known that investors demand higher returns to hold stocks of greater private than public information. Easley and O'hara (2004) show that the quantity and quality of information affect asset prices. It should be an interesting investigation to test whether the structure and the analysis of non-numerical data and the same phenomenon found here in this study are also a factor of attenuation of competition and cost of capital.

Disclosing knowledge appropriately could be also a remedy to firms with higher equity-dependency. Baker et al. (2003) found that investments of firms of this kind are more sensitive to stock prices than firms that are less equity dependent. Interesting should be testing whether the results of this research apply for firms in need of external equity to finance have their stock prices decrease attenuated when they better disclose information to the market. Likewise, Benner and Ranganathan (2012) identified that firms use financial stratagems such as stock repurchasing in order to offset illegitimacy, in an attempt to signalize alignment with investors and to trigger increases in stock price. Communicating in the right manner, focusing on forward looking disclosure as this study proposes, should be a way of better manage both the strategy and the finance of firms.

As a final conclusion, knowledge disclosure can be used by firms as a weapon in technological changes environments. The size (how much information to disclose) and direction of the artillery bombardment (which other characteristics of the narratives) are a matter of future research. I hope that this study brings a step further toward the search of how a company's use of new knowledge affects its ability not only to compete for recognition of influential outside organizations, but also to avoid divergent reactions, as a means to put their own strategy in place in relative peace.

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Appendices

A Data Supplemental Documentation

In addition to the data collection on the Reuters Datastream database, a couple of data processing were made. Further details about those adjustments and the original variables collected are provided here. First, adjustments were made on some variables that had negative values, which would inhibit log transformations. The general rule for those adjustments was to add to the variable the minimum value of its series plus a negligible 0.001. Table A1 shows the negative minimum values of the log transformed variables *net income* and *debt/equity*. All other log transformed variables have only positive minimum values and have not needed this kind of adjustment. Table A2 exhibits additional information about the dependent variables originally collected.

Table A1: **Negative minimum values of the log transformed variables**

	net income	**debt/equity**
min	-2,118,000	-832

Second, the coding process was made on the documents containing the transcripts of corporate meetings. Transforming the qualitative information of the transcripts into quantitative data were possible through content analysis. All collected documents were read, analyzed and coded by the author and two assistants. Table A3 contains further documentation of the coding instrument, including its category, definition, flags, qualifications, exclusions and some examples. Figure A1 illustrates one of the first outcomes of the content analysis with an example of a document page coded. All the encoded area was computed by the *MAXQDA* software in a measure of size called *pdf units*. Then these data were summarized and exported to the statistical software package *Stata*. A small sample and a summary of the size of the encoded segments by company are showed on tables A4 and A5 respectively.

Table A2: **Dependent Variables Description**

Variable	**Source Code**	**Source Name**	**Source Within Reuters System**	**Source Documentation**
Assets	WC02999A	Total Assets	Worldscope	Total Assets represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.
Revenues	WC01001A	Net Sales or Revenues	Worldscope	Net sales or Revenues represent gross sales and other operating revenue less discounts, returns and allowances.
Net Income	WC01706A	Net Income After Preferred Dividends (Basic EPS)	Worldscope	Net Income After Preferred Dividends represents the net income after preferred dividends that the company uses to calculate its basic earnings per share.
Debt/Equity Ratio	WC08231A	Total Debt % Common Equity	Worldscope	No help found for this datatype.
ROA	WC08326A	Return On Assets	Worldscope	No help found for this datatype.
ROE	WC08301A	Return On Equity Total %	Worldscope	No help found for this datatype.
Earnings Per Share	WC10010A	Earnings Per Share Basic Fiscal	Worldscope	No help found for this datatype.
Stock Price	P	Price (Adjusted - Default)	Datastream	Datatype (P) represents the official closing price. This is the default datatype for all equities and ETFs.

Source: Reuters Datastream Documentation

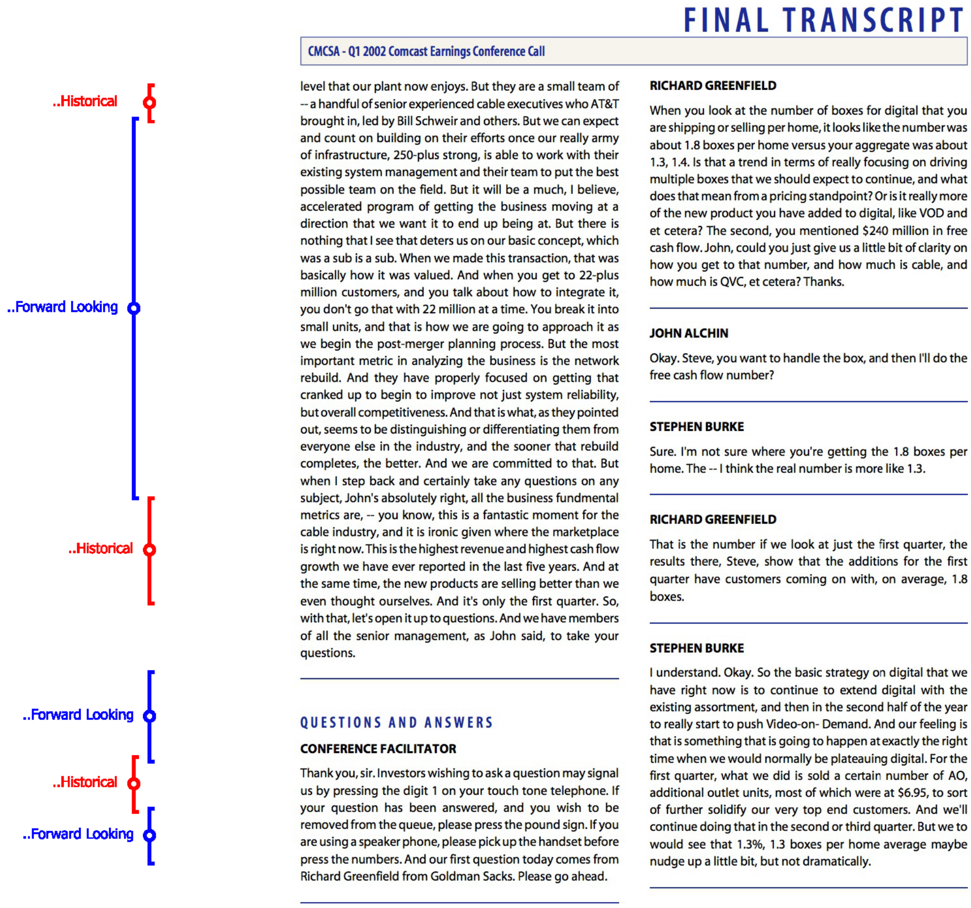
Table A3: **Coding Instrument – Stage 1: Time Orientation**

Code category	**Definition**	**Flags, qualifications & exclusions**	**Examples**
Historical	Narratives related to the present or past of business, industry, etc.	When the narrative is about current feelings, it is needed to evaluate weather those feelings are related to either past business outcomes or re future perspectives. Only the first case should be coded as historical.	“Operating margins increased from about 10 to 15% in the first quarter of last year to about 25% in the first quarter of this year.” “Our last quarter was one of our best, with gains beyond expectations in many areas.”
Forward Looking	Narratives directed to the future of the business, industry, etc.	When the narrative is about current feelings, it is needed to evaluate weather those feelings are related to either past business outcomes or re future perspectives. Only the second case should be coded as forward looking. Setting priorities should be considered as forward-looking.	“We expect the full year to be an improvement from the first quarter. Let me under score what I said earlier. We are confident we have the flexibility to respond on the cost side, and we continue to target 5-7 percent EPS growth for the year.”
Non-time specific	Narratives that are neither forward-looking nor historical. Narratives that are not related to a time dimension for the business.	If an executive mentions that the companys staff have had experience in a determined skill, despite the fact that he wants to provide the audience with a perspective of the future using a fact occurred in the past, this should be coded as non-time specific.	“All of these executives, all six of the division Presidents, plus all of their management team, have done this before. These are the people who have taken us from 4 million subscribers to 8 million subscribers over the last three or four years. They know exactly what to do.” This narrative should be considered non-time specific. However, in the continuation of the paragraph, the following sentence should be considered forward-looking as it contains expectations about the future: “And they have begun the process of planning for life post-merger.”

Table A4: **Sample of Coded Segments**

Document Name	**Code**	**Text Location**		**Segment**	**Area**	**Quarter**	**Company**
		Begin	**End**				
T-Transcript-2006-10-23T14_00	Forward Looking	7:314	7:388	We expect to reach 2.4 million by year end with aggressive scaling in 2007	75	2006q3	ATT
T-Transcript-2002-04-18T14_00	Historical	3:4210	3:4233	Our fixed costs are low.	24	2002q1	ATT
VZ-Transcript-2008-10-27T12_30	Forward Looking	14:668	14:727	I think we've got a good growth opportunity going forward.	59	2008q3	VZN
VZ-Transcript-2005-07-26T12_30	Historical	8:2865	8:3140	Operationally we currently have video trials going on with a few hundred paying customers. In these trials we are testing various aspects of video functionality, including provisioning, maintenance and system flow-through, as well as the aspects of the video product itself	275	2005q2	VZN
CMCSA-Transcript-2002-05-01T14_30	Forward Looking	3:3018	3:3174	This is a product that by the end of this year will be available to 86% of our homes, over 12 million homes will have access to the product at year-end.	156	2002q1	CMC
CMCSA-Transcript-2007-04-26T12_30	Historical	3:2319	3:2434	Net income increased $837 million in the first quarter, up from 466 or $0.15 a share in the first quarter of 2006.	115	2007q1	CMC
CVC-Transcript-2002-11-07T15_00	Forward Looking	6:1748	6:1889	In addition, we plan to launch our satellite in March of next year. Which we are required to do under the terms of our license from the FCC	141	2002q3	CVC
CVC-Transcript-2002-11-07T15_00	Historical	4:4798	4:4878	Advertising revenue for the national entertainment networks totaled $28 million	80	2002q3	CVC

Figure A1: **Example of a Coded Document Page**



FINAL TRANSCRIPT

CMCSA - Q1 2002 Comcast Earnings Conference Call

level that our plant now enjoys. But they are a small team of -- a handful of senior experienced cable executives who AT&T brought in, led by Bill Schweir and others. But we can expect and count on building on their efforts once our really army of infrastructure, 250-plus strong, is able to work with their existing system management and their team to put the best possible team on the field. But it will be a much, I believe, accelerated program of getting the business moving at a direction that we want it to end up being at. But there is nothing that I see that deters us on our basic concept, which was a sub is a sub. When we made this transaction, that was basically how it was valued. And when you get to 22-plus million customers, and you talk about how to integrate it, you don't go that with 22 million at a time. You break it into small units, and that is how we are going to approach it as we begin the post-merger planning process. But the most important metric in analyzing the business is the network rebuild. And they have properly focused on getting that cranked up to begin to improve not just system reliability, but overall competitiveness. And that is what, as they pointed out, seems to be distinguishing or differentiating them from everyone else in the industry, and the sooner that rebuild completes, the better. And we are committed to that. But when I step back and certainly take any questions on any subject, John's absolutely right, all the business fundmental metrics are, -- you know, this is a fantastic moment for the cable industry, and it is ironic given where the marketplace is right now. This is the highest revenue and highest cash flow growth we have ever reported in the last five years. And at the same time, the new products are selling better than we even thought ourselves. And it's only the first quarter. So, with that, let's open it up to questions. And we have members of all the senior management, as John said, to take your questions.

QUESTIONS AND ANSWERS

CONFERENCE FACILITATOR

Thank you, sir. Investors wishing to ask a question may signal us by pressing the digit 1 on your touch tone telephone. If your question has been answered, and you wish to be removed from the queue, please press the pound sign. If you are using a speaker phone, please pick up the handset before press the numbers. And our first question today comes from Richard Greenfield from Goldman Sacks. Please go ahead.

RICHARD GREENFIELD

When you look at the number of boxes for digital that you are shipping or selling per home, it looks like the number was about 1.8 boxes per home versus your aggregate was about 1.3, 1.4. Is that a trend in terms of really focusing on driving multiple boxes that we should expect to continue, and what does that mean from a pricing standpoint? Or is it really more of the new product you have added to digital, like VOD and et cetera? The second, you mentioned $240 million in free cash flow. John, could you just give us a little bit of clarity on how you get to that number, and how much is cable, and how much is QVC, et cetera? Thanks.

JOHN ALCHIN

Okay. Steve, you want to handle the box, and then I'll do the free cash flow number?

STEPHEN BURKE

Sure. I'm not sure where you're getting the 1.8 boxes per home. The -- I think the real number is more like 1.3.

RICHARD GREENFIELD

That is the number if we look at just the first quarter, the results there, Steve, show that the additions for the first quarter have customers coming on with, on average, 1.8 boxes.

STEPHEN BURKE

I understand. Okay. So the basic strategy on digital that we have right now is to continue to extend digital with the existing assortment, and then in the second half of the year to really start to push Video-on- Demand. And our feeling is that is something that is going to happen at exactly the right time when we would normally be plateauing digital. For the first quarter, what we did is sold a certain number of AO, additional outlet units, most of which were at $6.95, to sort of further solidify our very top end customers. And we'll continue doing that in the second or third quarter. But we to would see that 1.3%, 1.3 boxes per home average maybe nudge up a little bit, but not dramatically.

Table A5: **Summary of Coded Segments by Company**

	Coded Area (in pdf units)	
Company	**Historical**	**Forward Looking**
ATT	754,249	267,622
VZN	849,780	466,399
CMC	687,755	389,174
CVC	599,431	195,394

B Testing the Significance of the Logistic Model

The methods for testing the significance of logistic models summarized in this section are simplistic, but provide the essential building blocks for more complex expositions that can be found in the literature. The question that is generally raised when one needs to test the significance of a model is the following: Does the model that includes the variable in question is better to predict the response variable than a model that does not include that variable? The answer to this question is provided by comparing the observed values of the response variable to those predicted by each of two models: the first with the variable in question, the second without. If the predicted values with the variable in the model are better than without it, then the variable in question is “significant”.

B.1 Likelihood Test

In logistic regression, the comparison of observed to predicted values is based on the log-likelihood function defined on equation (5). The comparison of observed to predicted values using the likelihood function is based on the *likelihood test*, that is given by the following expression:

$$D = -2\ln\left[\frac{\text{(likelihood of the fitted model)}}{\text{(likelihood of the saturated model)}}\right] \tag{10}$$

Using equation (5), equation (10) becomes:

$$D = -2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{\hat{\pi}_i}{y_i}\right) + (1-y_i)\ln\left(\frac{1-\hat{\pi}_i}{1-y_i}\right)\right], \tag{11}$$

$$\text{where } \hat{\pi}_i = \hat{\pi}(x_i)$$

The statistic D in equation (11) is called *deviance*. To assess the significance of an independent variable the value of D is compared with or without the independent variable in the equation. The change in D due to the inclusion of the independent variable in the model is G, where:

$$G = -2\ln\left[\frac{\text{(likelihood without the variable)}}{\text{(likelihood with the variable)}}\right] \tag{12}$$

Considering that the model has $p+1$ parameters $\hat{\beta}$, under the hypothesis that the p coefficients for the covariates in the model are equal to zero, the distribution of G is chi-square with p degrees of freedom, which significance can be easily evaluated. This result, along with the associated *p-value* for the chi-square distribution, is commonly reported in statistical software packages.

B.2 Wald Test

The Wald test for a single independent variable is equal to the ratio of the maximum likelihood estimate of the parameter $\hat{\beta}_1$, to an estimate of its standard error. Under the null hypothesis and considering the sample size assumptions, this ratio follows a standard normal distribution. One can easily perform a two tailed test and assess its $p-value$, which also is provided by statistical softwares.

The multivariable analog of the Wald test is obtained from the following vector-matrix calculation:

$$W = \hat{\boldsymbol{\beta}}'[\hat{\boldsymbol{Var}}(\hat{\boldsymbol{\beta}})]^{-1}\hat{\boldsymbol{\beta}} \tag{13}$$

$$= \hat{\boldsymbol{\beta}}'(\boldsymbol{X}\hat{\boldsymbol{V}}\boldsymbol{X})\hat{\boldsymbol{\beta}}, \tag{14}$$

which is distributed as chi-square with $p+1$ degrees of freedom under the hypothesis that each of the $p+1$ coefficients is equal to zero. The multivariable Wald test, equivalent to the likelihood ratio test for the significance of the fitted model, is based on just the slope coefficients and is obtained by eliminating $\hat{\beta}_0$ from $\hat{\boldsymbol{\beta}}$ and the relevant row (first or last) and column (first or last) from $(X'\hat{V}X)$. As the evaluation of this test requires an extra step to perform vector-matrix operations and to obtain $\hat{\boldsymbol{\beta}}$, there is no gain over the likelihood ratio test for determining the significance of the model.

Hosmer et al. (2013) cited the work of researchers that examined the performance of the Wald test and found that it behaved in an aberrant manner, often failing to reject the null hypothesis when the coefficient was significant using the likelihood ratio test. Thus, they recommended that the likelihood ratio test is preferred. They noted that while the assertions are true, they have never seen huge differences in the values of G and the Wald statistic W^2. In practice, the more troubling situation is when the values are close to the established significance level, and in this case, giving the benefit of the doubt, the recommendation is to use the $p-value$ from the likelihood ratio test.

C Alternative Models

A number of alternative models were tested and the results were generally consistent with those presented in this work, as it can be seen below. Table A6 shows the outcomes of the *probit* model. As the logit, the probit is a binary response model where $\pi(x) = \phi(z) = \int_{-\infty}^{x} \phi(v)dv$, where $\phi(z)$ is the standard normal density. As it can be observed, the signs and the significances of logit and probit models are exactly the same. However, Hosmer et al. (2013) suggest the use of probit as an alternative to logit model when the primary focus of analysis is modeling the probability of the outcome and the logit model does not seem to fit the data well, which is not the case of the present study.

Models that deal with correlated binary data are also potential alternatives to the logit. The literature on methods of correlated binary data has grown rapidly. Two approaches, however, are the most common: *random effects* and *population average* models. Both are related to panel data, and they are applied where the independence of responses among the subjects does not hold. In this empirical setting, reactions of institutions to companies performance may not be independent along the period of time studied. With *Stata*, it is possible to run both *logit* and *probit* models, considering *random* or *population average* models. It is also possible to run *logit* models with fixed effects, however, there is no command in *Stata* for a *probit fixed effects* model, as according to the software manual "there does not exist a sufficient statistic allowing the fixed effects to be conditioned out of the likelihood".

Thus, a considerable variety of models were run with different sets of control variables and types of standard errors correction (robust, observed information matrix, bootstrap, etc.). For the sake of comparisons, the results here presented consider whenever workable the same variables with vector correction error robust, unless differently specified. The outcomes of the five model possibilities described above can be seen from tables A7 to A11. Finally, tests were made with *random effects ordered logit* and *random effects ordered probit* models, as can be seen on tables A12 and A13. The results found on those models were fairly analogous. In particular, the marginal effects at the means (MEM) and the average marginal effects (AME) of the models that showed significance on all coefficients are reported on table 5.

Instead of testing and analyzing a further number of alternative models that agree or not with the theory here proposed, it is suggestive that a discussion about all those alternatives can *per se* be the subject of a separate research. Essentially, however, the purpose of this work was met with the model presented in the main body of this document. Additionally to the research limitations already exposed, one can include the test of many other models that have been in quick succession developed in this area. This is both a sign of weakness and strength of this research that brought an interesting and vibrant topic that still needs further research.

Table A6: **Probit Models of Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4
Strategic Decision				-0.569
				(0.427)
L3.Strategic Decision		-0.860*	-1.339**	
		(0.406)	(0.481)	
L1.Log of Historical Disclosure	-0.981**	-0.851**	-0.633	-0.546
	(0.302)	(0.304)	(0.648)	(0.624)
L1.Log of Forward Looking Disclosure	0.799*	0.735*	0.404	0.294
	(0.319)	(0.323)	(0.393)	(0.338)
Log of Revenues			-2.812***	-2.575***
			(0.685)	(0.636)
Log of Net Income			0.216	-0.088
			(0.486)	(0.111)
L2.Log of Net Income	0.108**	0.047		
	(0.037)	(0.073)		
Earnings per Share			0.747	0.497
			(0.609)	(0.554)
Log of Total Assets		0.062	2.709***	2.446***
		(0.138)	(0.679)	(0.644)
ROA			-0.118	-0.062
			(0.084)	(0.071)
Log Debt/Equity Ratio			-0.717	-0.209
			(1.101)	(1.040)
L1.Institutional Reaction	1.926***			
	(0.319)			
Constant				2.109
				(7.205)
AIC	92.1	124.7	101.0	121.0
BIC	102.4	137.4	123.8	147.3
chi2	40.5	13.5	28.6	40.3
p	0.0000	0.0195	0.0007	0.0000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: **Logit Models with Random Effects and Bootstrap for Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4
Strategic Decision				-0.039
				(1.794)
L3.Strategic Decision		-1.559	-1.965	
		(3.905)	(565.905)	
L1.Log of Historical Disclosure	-1.543***	-1.258	-0.627	-0.720
	(0.364)	(4.897)	(2212.576)	(2.794)
L1.Log of Forward Looking Disclosure	1.281*	0.524	1.013	0.789
	(0.511)	(0.945)	(525.830)	(7.660)
Log of Revenues			1.570	0.465
			(1713.814)	(63.213)
Log of Net Income			-1.200	-0.304
			(364.010)	(261.160)
L2.Log of Net Income	0.169	0.067		
	(0.223)	(7.343)		
Earnings per Share			2.569	1.803
			(280.061)	(208.508)
Log of Total Assets		0.427	1.252	1.975
		(8.901)	(240.005)	(8.615)
ROA			-0.156	-0.075
			(225.813)	(3.020)
Log Debt/Equity Ratio			-4.727	-2.150
			(940.152)	(790.041)
L1.Institutional Reaction	2.816			
	(1.609)			
Constant				-23.375
				(8262.762)
lnsig2u				
Constant	-0.636	1.723	2.881	2.872
	(7.659)	(8.421)	(10.510)	(9.570)
AIC	93.6	100.4	96.6	117.1
BIC	106.5	115.7	122.0	146.0
chi2	43.9	4.7	4.5	30.2
p	0.0000	0.4516	0.8752	0.0004

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: **Logit Models with Fixed Effects and Bootstrap for Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4
Strategic Decision				0.204
				(1.655)
L3.Strategic Decision		-2.295	-1.709	
		(13.955)	(36.733)	
L1.Log of Historical Disclosure	-0.077	0.568	0.051	-0.720
	(17.791)	(267.937)	(94.983)	(3.458)
L1.Log of Forward Looking Disclosure	0.993	0.960	1.178	0.818
	(13.541)	(28.666)	(25.361)	(1.142)
Log of Revenues			-1.618	0.765
			(79.843)	(31.877)
Log of Net Income			9.944	-0.304
			(444.878)	(173.178)
L2.Log of Net Income	1.182	1.124		
	(40.522)	(964.210)		
Earnings per Share			-0.449	1.797
			(182.990)	(103.956)
Log of Total Assets		6.066	7.086	2.431
		(168.913)	(153.550)	(10.556)
ROA			0.011	-0.042
			(8.878)	(0.391)
Log Debt/Equity Ratio			1.084	-1.726
			(146.109)	(383.024)
L1.Institutional Reaction	1.935			
	(61.425)			
AIC	69.5	53.7	57.3	84.5
BIC	78.6	64.9	77.6	105.5
chi2	8.0	36.2	28.9	192.8
p	0.0921	0.0000	0.0007	0.0000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: **Panel Logit Models with Population Averaged for Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4 (bootstrap)
Strategic Decision				-0.410
				(0.509)
L3.Strategic Decision		-0.884*	-0.889*	
		(0.424)	(0.415)	
L1.Log of Historical Disclosure	-1.315***	-0.699	-0.568	-0.954
	(0.132)	(0.703)	(0.772)	(0.777)
L1.Log of Forward Looking Disclosure	1.075***	0.334	0.357	0.494
	(0.211)	(0.350)	(0.337)	(0.344)
Log of Revenues			0.125	0.294
			(0.701)	(2.999)
L2.Log of Net Income	0.146***	0.037**	0.038*	0.077
	(0.028)	(0.012)	(0.015)	(3.005)
Log of Total Assets		0.197		
		(0.579)		
L1.Institutional Reaction	2.553**			
	(0.939)			
lnsig2u				
Constant				1.678
				(8.393)
AIC	.	.	.	112.3
BIC	.	.	.	127.8
chi2	1297.6	59.5	11.3	22.2
p	.	.	.	0.0005

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: **Panel Probit with Random Effects and Bootstrap for Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4
Strategic Decision				-0.108
				(1.352)
L3.Strategic Decision		-0.849	-0.989	
		(2.809)	(87.140)	
L1.Log of Historical Disclosure	-0.888***	-0.708	-0.418	-0.616
	(0.186)	(4.110)	(232.759)	(2.431)
L1.Log of Forward Looking Disclosure	0.733**	0.312	0.593	0.479
	(0.253)	(0.768)	(42.661)	(0.484)
Log of Revenues			1.095	0.524
			(165.867)	(4.410)
Log of Net Income			-0.640	-0.196
			(43.518)	(6.291)
L2.Log of Net Income	0.100	0.044		
	(0.116)	(5.197)		
Earnings per Share			1.442	1.157
			(115.683)	(6.442)
Log of Total Assets		0.225	0.581	0.606
		(6.785)	(61.124)	(3.519)
ROA			-0.084	-0.062
			(22.935)	(0.200)
Log Debt/Equity Ratio			-2.839	-2.112
			(182.838)	(11.756)
L1.Institutional Reaction	1.633			
	(0.897)			
lnsig2u				
Constant	-1.522	0.578	1.808	1.403
	(7.947)	(8.096)	(9.677)	(9.953)
AIC	93.3	100.4	96.8	115.5
BIC	106.2	115.6	122.2	141.8
chi2	47.4	5.1	20.8	53.9
p	0.0000	0.4037	0.0135	0.0000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: **Panel Probit Models with Population Averaged for Institutional Reaction**

	Model 1	Model 2	Model 3	Model 4 (bootstrap)
L3.Strategic Decision		-0.555*	-0.555*	-0.597
		(0.252)	(0.246)	(0.329)
L1.Log of Historical Disclosure	-0.782***	-0.444	-0.359	-0.264*
	(0.080)	(0.427)	(0.473)	(0.103)
L1.Log of Forward Looking Disclosure	0.633***	0.206	0.223	0.248
	(0.134)	(0.217)	(0.208)	(0.142)
Log of Revenues			0.080	
			(0.431)	
L2.Log of Net Income	0.089***	0.023**	0.024**	0.028
	(0.016)	(0.007)	(0.009)	(0.081)
Log of Total Assets		0.127		
		(0.355)		
L1.Institutional Reaction	1.548**			
	(0.544)			
AIC	.	.	.	.
BIC	.	.	.	.
chi2	1621.7	39.1	12.0	48.2
p	.	.	.	0.0000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: **Ordered Logit Models with Random Effects for Institutional Reaction**

	Model 1	Model 2	Model 3 (bootstrap)	Model 4 (bootstrap)
Strategic Decision				-0.104
				(6.510)
L3.Strategic Decision		-0.366	0.221	
		(0.734)	(11.671)	
L1.Log of Historical Disclosure	-0.373	1.219	1.279	1.371
	(1.614)	(1.772)	(5.487)	(2.117)
L1.Log of Forward Looking Disclosure	1.907*	1.504	1.536	1.344
	(0.811)	(0.993)	(25.828)	(1.103)
Log of Revenues			2.716	1.810
			(66.534)	(2.643)
L2.Log of Net Income	0.174***	0.116	0.055	0.068
	(0.053)	(0.093)	(13.133)	(6.685)
L1.Institutional Reaction	3.108**			
	(0.964)			
cut1				
Constant	17.089	27.193	69.201	54.477
	(21.841)	(27.379)	(1444.772)	(106.101)
sigma2_u				
Constant	0.332	3.413	25.604	15.139
	(0.763)	(5.362)	(41.596)	(25.517)
AIC	90.6	106.2	108.0	116.0
BIC	98.4	113.8	125.8	134.1
chi2	.	.	1.0	15.8
p	.	.	0.9589	0.0074

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: **Ordered Probit Models with Random Effects for Institutional Reaction**

	Model 1	Model 2	Model 3 (bootstrap)	Model 4
Strategic Decision				-0.079
				(0.507)
L3.Strategic Decision		-0.271	0.070	
		(0.454)	(0.711)	
L1.Log of Historical Disclosure	-0.286	0.551	0.609	0.651
	(0.716)	(0.745)	(0.545)	(0.625)
L1.Log of Forward Looking Disclosure	1.066***	0.797*	0.796	0.684
	(0.315)	(0.399)	(0.744)	(0.394)
Log of Revenues			1.635	1.075
			(1.997)	(1.761)
L2.Log of Net Income	0.106***	0.069	0.035	0.044*
	(0.028)	(0.041)	(7.648)	(0.018)
L1.Institutional Reaction	1.850***			
	(0.493)			
cut1				
Constant	8.950	13.523	38.887	29.731
	(8.941)	(11.288)	(86.317)	(30.912)
sigma2_u				
Constant	0.105	1.135	8.798	4.995
	(0.208)	(1.616)	(4.862)	(11.152)
AIC	90.2	106.3	108.2	108.3
BIC	97.9	113.9	126.0	116.1
chi2	.	.	7.3	.
p	.	.	0.1960	.

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A14: **Logit Models 2 and 3 of Institutional Reaction with Strategic Decision Lags**

	Model 2	Model 2'	Model 3	Model 3'
L3.Strategic Decision	-1.410*	-1.367	-2.538**	-2.783**
	(0.705)	(0.733)	(0.952)	(1.070)
L2.Strategic Decision		-0.237		-0.436
		(0.658)		(0.925)
L1.Strategic Decision		-0.355		-0.418
		(0.663)		(0.824)
Strategic Decision		-0.578		-1.032
		(0.670)		(0.960)
L1.Log of Historical Disclosure	-1.384**	-1.288*	-1.058	-0.588
	(0.515)	(0.523)	(1.124)	(1.156)
L1.Log of Forward Looking Disclosure	1.204*	1.145*	0.702	0.607
	(0.543)	(0.550)	(0.693)	(0.726)
Log of Revenues			-4.984***	-5.012***
			(1.262)	(1.267)
Log of Total Assets	0.099	0.079	4.913***	4.979***
	(0.226)	(0.231)	(1.328)	(1.293)
L2.Log of Net Income	0.073	0.082		
	(0.117)	(0.118)		
Log of Net Income			0.359	0.211
			(0.837)	(0.806)
Log Debt/Equity Ratio			-1.604	-1.933
			(2.024)	(1.998)
ROA			-0.202	-0.158
			(0.139)	(0.147)
Earnings per Share			1.252	0.824
			(1.005)	(1.039)
AIC	124.8	129.2	100.4	103.8
BIC	137.5	149.6	123.2	134.4
chi2	12.1	13.0	22.0	23.3
p	0.0340	0.1121	0.0089	0.0256

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$