HOW DO ANALYSTS DEAL WITH BAD NEWS? GOING-CONCERN OPINIONS AND ANALYST BEHAVIOUR

RÚBEN M. T. PEIXINHO

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To my loving partner, Iduardina

ABSTRACT

Security analysts play a central role in the functioning of financial markets through their privileged position as intermediaries between firms and investors. Analyst activity is important to reduce information uncertainty but it is not unbiased. On the one hand, the literature shows that these sophisticated agents promote market efficiency by facilitating the incorporation of new information into stock prices. On the other hand, there is evidence that analysts underreact to negative information and that they tend to be optimistic about firms they follow.

Recent studies show that the market does not assimilate immediately the disclosure of a first-time going-concern modified (GCM) audit report. This accounting event is part of a wide range of bad news events which investors are particularly inefficient at dealing with. My thesis explores how analysts deal with the GCM audit report and whether they facilitate the correct assimilation of such information into stock prices. In particular, I use a sample of 924 firms for which their auditors disclose a GCM audit report for the first-time between 01.01.1994 and 31.12.2005.

I find that security analysts anticipate the publication of a first-time GCM audit report. My results show that within the one-year period before the GCM disclosure, security analysts downgrade the average recommendation for GCM firms from “buy” to “hold” whereas similar non-GCM firms maintain an average “buy” rating. A number of robustness tests confirm that this finding is not sensitive to the criteria used to select the non-GCM control firm. Moreover, analysts are more likely to cease coverage of GCM firms prior to the GCM event than for matched control firms. In addition, I show that analysts react to the publication of a GCM audit report by ceasing coverage of GCM firms.

My results suggest that investors do not recognize an average “hold” recommendation for a stock of a firm immediately before the announcement of a GCM audit report as an unfavourable message even considering that it represents a downgrade from a previous “buy” rating. In particular, I find that the negative short-term market reaction to the publication of a GCM audit report is significantly higher for firms with pre-event analyst coverage compared to firms with no pre-event analyst coverage. This suggests that analyst activity may be misleading the market in terms of the saliency of pre-GCM unfavourable news by issuing “disconfirming opinions” to the market and thus increasing the “surprise” associated with the publication of a GCM audit report.

In addition, I show that analyst post-GCM coverage does not increase the efficiency with which the market assimilates the GCM audit report into stock prices. In particular, I fail to find significant differences between the post-GCM return performance of covered firms compared to firms with no analyst coverage. However, I show that the percentage of covered firms following the GCM disclosure is significantly higher for those with best post-GCM return performance than for those with worst post-GCM return performance. This suggests that post-GCM return performance explains the decision of analysts to cover GCM firms but analyst coverage does not influence significantly the post-GCM return performance of such firms.

Overall, my thesis contributes to the accounting and finance literature by showing that analyst activity is not providing investors with adequate value-relevant information for their investment decisions in the GCM bad news domain. Firstly, the reluctance of analysts to issue a clear unfavourable message about the stocks of GCM firms seems to explain why the “surprise” associated with the publication of a GCM audit report is greater for covered firms than for non-covered firms. Secondly, the tendency of analysts to cease coverage of GCM firms and the low level of analyst coverage following the GCM announcement may explain why analyst coverage does not reduce the magnitude of the post-GCM negative drift. As such, analyst contribution to the price-discovery process in this case is likely confined to firms with high levels of analyst coverage.

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DECLARATION

I certify that this thesis does not incorporate any material previously submitted for a degree or diploma in any University; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person where due reference is not made in the text. I also certify that the thesis has been composed by myself and that all the work is my own.

Rúben Miguel Torcato Peixinho, August 2008

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CHAPTER 1

INTRODUCTION

Security analysts have long been seen as sophisticated processors of financial information. These market agents play a central role in the functioning of financial markets through their intermediation between firms and investors (Schipper, 1991). The increasing search for value-relevant information in highly competitive markets emphasises the key role of security analysts for this purpose. Nowadays, thousands of analysts are employed by hundreds of brokerage houses to provide investors with information that helps in their investment decisions. Interest in the activity of security analysts is not new. However, security analysts, more than ever, are the focus of much media attention and extensive academic research.

The extant literature suggests that analyst coverage reduces information uncertainty (Zhang, 2006) and that efficient analyst information processing can facilitate the efficiency of security price setting (Beaver, 2002). The evidence that analyst opinions affect the prices of individual stocks is overwhelming. Studies show that, on average, markets react favourably (unfavourably) to positive (negative) information issued by security analysts (e.g., Stickel, 1991; Stickel, 1995; Womack, 1996; Barber et al., 2001; Mokoteli and Taffler, forthcoming). In addition, there is evidence that the market reaction to new information is faster for firms with higher levels of analyst coverage (e.g., Bhattacharya, 2001; Gleason and Lee, 2003; Zhang, 2006).

The above evidence may lead us to believe that, contrary to investors (e.g., Odean, 1999; Barber and Odean, 2000; 2001; 2002), security analysts are efficient processors of information. However, several studies challenge this idea and present conflicting evidence with Easterwood and Nutt's (1999) definition of analyst rationality, which is that they should "*immediately and without bias incorporate information into their forecasts*". For instance, the literature shows that analysts' earnings forecasts are systematically higher than actual earnings (e.g., Brown, 1997) and the number of "*buy*" recommendations is persistently higher than the number of "*sell*" recommendations (e.g., Womack, 1996). Moreover, there is also evidence that analysts tend to report on stocks about which they have favourable views and avoid reporting on stocks about which they have unfavourable views (e.g. McNichols and O'Brien, 1997).

Security analysts have come under fire from investors, politicians and regulators in the last years as a consequence of their biased behaviour. Two important episodes contribute to this hostile environment. The Enron scandal revealed that almost 90% of analysts covering the firm were still recommending the firms' stock as a "buy" or "strong buy" just six weeks before its bankruptcy filing. The Global Analyst Research Settlement culminated in a massive investigation process, which proved that investment banks engaged in practices that created or maintained inappropriate influence over research analysts in seeking lucrative fees. Penalties reached $1.4 million. As a result, the regulatory authorities changed the analyst disclosure environment in an attempt to increase investors' confidence in the integrity of financial markets.

One of the most interesting research agendas in this domain is to explore how analysts deal with bad news events. Two important ideas contribute to the interest of this research question. First, the literature suggests that investors are significantly more inefficient in dealing with bad news in comparison to good news (e.g., Bernard and Thomas, 1989; Womack, 1996; Dichev and Piotroski, 2001; Kausar, Taffler, and Tan, forthcoming). Second, the marginal contribution of security analysts may be greater in the dissemination of bad news to investors given the distinct incentives that managers have to disclose information conditional on its' nature. Using the words of Hong, Lim, and Stein (2000), managers of firms sitting on good news "*will push the news out the door themselves, via increased disclosures, etc*". For the opposite reason, managers will have fewer incentives to bring investors up to date quickly when firms are sitting on bad news. Therefore, the motivation of my thesis is to investigate the role of security analysts in the market's reaction to bad news events and to understand whether they facilitate the correct assimilation of adverse information in stock prices.

Studies suggest that security analysts share similar biases to those of non-sophisticated agents when dealing with negative information. For instance, there is evidence that analysts tend to underreact in the presence of negative information (e.g., Easterwood and Nutt, 1999; Abarbanell and Lehavy, 2003) and that they are predominantly optimistic when forecasting earnings of distressed firms (e.g., Das, 1998; Brown, 2001). The evidence that analysts are particularly inefficient when dealing with bad news is, however, almost exclusively confined to routine events, such as net losses, negative earnings surprises and forecast revisions. In fact, the literature has paid little attention to non-routine bad news events (i.e., those that are not part of the normal reporting cycle) that impact negatively on firms' stock prices.

The few exceptions addressing analyst behaviour in the non-routine bad news domain provide conflicting evidence about security analysts' ability to anticipate such news and about the nature of their reaction (e.g., Griffin, 2003; Clarke et al., 2006). The clarification of these issues is particularly important since analyst activity aims at anticipating changes in company fundamentals as well as reacting to news or corporate reports (Michaely and Womack, 2005). Furthermore, there is little evidence on whether analyst activity promotes the correct assimilation of negative information in stock prices in the non-routine bad news domain. Investigating this issue clarifies whether analysts provide investors with value-relevant information in this particular context. It follows that important questions still await a clear answer before we understand how security analysts behave in the presence of non-routine bad news which is the focus of this thesis. Key questions I address include such issues as: Do sell-side analysts anticipate acute non-routine bad news? How do they react to the announcement of such news? Has there been any behavioural change following the implementation of the new regulatory changes? Do they accelerate the incorporation of negative information in stock prices? Are analysts interested in following such firms?

My overarching research question in this thesis is how do security analysts deal with one of the most acute bad news non-routine accounting events: the going-concern audit report. The going-concern assumption is one of the basic principles underlying the preparation of financial statements. It assumes that accounts are drawn up on the basis that the business will continue to exist in the foreseeable future. This assumption is assessed annually by an independent auditor, who evaluates factors that may impact on the going-concern assumption. Such conditions relate to negative trends (e.g., recurring operating losses, negative cash flows from operating activities, adverse key financial ratios), indicators of possible financial difficulties (e.g., default on loans, denial of usual trade credit from suppliers, restructuring of debt), internal matters (e.g., work stoppages, substantial dependence on the success of a particular project) or external matters (e.g., legal proceedings, loss of a licence or patent). For those cases where the auditor considers that substantial doubt may exist regarding the continuance of the firm in the foreseeable future, he/she includes an explanatory paragraph in their audit report reflecting this uncertainty. As such, the going-concern modified (GCM) audit report offers a unique and original acute bad news context to investigate analyst behaviour.

My thesis contributes to both the academic literature and to investor understanding. From an academic perspective, my thesis links two areas of the accounting and finance literature that have been developing separately so far. By connecting the going-concern disclosure event with analyst behaviour, I provide original evidence about how security analysts deal with a major bad news accounting event. Moreover, I provide original evidence on whether analysts facilitate the assimilation of such adverse accounting events into security prices. From an investor vantage point, my work provides additional evidence of the usefulness and limitations of analysts' activities. In particular, it answers the question of whether security analyst activity in the bad news domain is of value to investors in their investment decisions relating to such financially distressed firms.

The objectives of my thesis may be summarized as follows:

1. To test whether security analysts anticipate the GCM audit report by investigating if they downgrade more aggressively their stock recommendations for GCM firms in comparison to similar non-GCM firms within the pre-GCM period. Additionally, to test if analysts are more likely to cease coverage of GCM firms than similar non-GCM firms.

2. To explore how security analysts react to the publication of a GCM audit report by comparing their stock recommendations for GCM firms between the pre- and post-GCM period. Additionally, to understand if security analyst interest in these firms remains after the announcement of such acute bad news.

3. To investigate if pre-GCM analyst coverage facilitates the incorporation of bad news into the stock prices of GCM firms. In other words, to explore if analyst coverage reduces the market "surprise" associated with the publication of a GCM

audit report in terms of mitigating the short-term market reaction to such an announcement.

4. To explore whether the regulatory changes introduced in the beginning of this decade impact appropriately on pre-GCM analyst expectations and whether these changes lead to investors being provided with better quality information by analysts.

5. To provide evidence about the ability of analysts to facilitate the price-discovery process for GCM firms over the 12 months following publication of a GCM audit report and clarify if their activity promotes market efficiency in this acute scenario of financial distress.

6. To test if security analysts self-select the GCM firms they cover following the publication of a GCM audit report depending on their post-GCM return performance.

These broad research questions are explored in my four empirical chapters where I formally test a number of research hypotheses. My methodology is drawn from previous studies addressing related issues and provides rigorous robustness tests to ensure that my results are not sensitive to potential confounding factors.

The main findings of my thesis can be briefly summarized as follows:

1. I find that security analysts anticipate the GCM audit report announcement. This conclusion is based on the evidence that they become relatively more pessimistic about GCM firms compared with similar non-GCM firms as the event date approaches. In particular, I find that analysts downgrade stock recommendations for GCM firms from “buy” to “hold” within the one year period prior to the publication of a GCM audit report whereas stock recommendations for non-GCM firms maintain an average “buy” recommendation. In addition, I find that analysts are more likely to cease coverage of GCM firms. Overall, my results suggest that analysts recognize the financial deterioration of firms that subsequently receive a GCM audit report.

2. I show that security analysts do not ignore the publication of a GCM audit report. Specifically, my results suggest that analysts are more likely to cease coverage of GCM firms compared with similar non-GCM firms immediately after the disclosure of a GCM audit report. Contrary to my expectations, I fail to find a significant change in their recommendations for GCM firms after the publication of such an adverse event.

3. I find that analyst relative pessimism about the stocks of GCM firms does not provide a clear message to investors. In particular, my results demonstrate that the short-term market reaction to the publication of a GCM audit report is significantly more negative for firms with pre-GCM coverage than for firms with no pre-GCM coverage. This suggests that an average “hold” recommendation for a stock of a firm immediately before the announcement of a GCM audit report is

not perceived as an unfavourable message and may mitigate the impact of other unfavourable economic events in stock prices.

4. My results suggest that the regulatory changes have restrained analysts' pre-GCM recommendations and were effective in providing investors with qualitatively better information for financially distressed firms. In particular, I find that the recommendations for GCM firms become significantly more pessimistic following the implementation of such changes and that the significantly more adverse short-term market reaction for firms with pre-GCM coverage is an exclusive phenomenon of the pre-regulatory changes period.

5. I find that security analysts do not promote the post-GCM price-discovery process. My results suggest that analyst post-GCM coverage does not significantly increase the efficiency with which investors incorporate the GCM audit report in stock prices. I show that the post-event market performance of covered and non-covered GCM firms is not significantly different.

6. I provide evidence that security analysts self-select the GCM firms they cover following the announcement of a GCM audit report. Specifically, I show that the percentage of covered firms with best post-GCM return performance is significantly higher than the percentage of covered firms with worst post-GCM return performance. This suggests that analyst interest in GCM firms following the event announcement is particularly low for firms with the worst return performance.

Overall, my thesis contributes to the accounting and finance literature by showing that analyst activity is not providing investors with value-relevant information in their investment decisions in this bad news domain. Despite analyst recognition of going-concern uncertainties for GCM firms prior to the publication of a GCM audit report, investors do not perceive an average "hold" recommendation immediately before the GCM date as an unfavourable message. In particular, I show that the majority of stock recommendations for GCM firms operate in the wrong direction (i.e., they disconfirm other pre-GCM negative information through a "strong buy", "buy" or "hold" recommendation), obstructing the incorporation of other unfavourable signals (e.g., negative momentum, high distress risk or high GCM probability) in stock prices. I also contribute to the ongoing debate about the efficiency with which the market assimilates the publication of a GCM audit report by showing that analyst disinterest on these firms (especially those with the worst post-GCM return performance) following such an announcement may help explain the post-GCM announcement drift (e.g., Taffler, Lu, and Kausar, 2004; Kausar, Taffler and Tan, forthcoming).

The remainder of my thesis is organized as follows: chapter 2 reviews the relevant literature to understand the scope of my research. Chapter 3 describes the sample selection process and provides the descriptive statistics for my sample. Chapter 4 investigates if security analysts anticipate and react to the publication of a GCM audit report. Chapter 5 re-examines analyst anticipation and reaction to such a bad news event by testing the robustness of my findings. Chapter 6 explores the short-term market reaction to the disclosure of a GCM audit report conditional on analyst coverage. Chapter 7 examines the relationship between post-GCM coverage and post-GCM stock returns performance. Chapter 8 presents my conclusions, discusses the limitations of this study and considers possible extensions for further work.

CHAPTER 2

LITERATURE REVIEW AND RESEACH FRAMEWORK

2.1. Introduction

This chapter reviews the two areas of the literature that I connect in my thesis: analyst behaviour and going-concern opinions. Research on security analyst activity is extensive and continues to grow in quality and quantity. For instance, Ramnath, Rock, and Shane (2008) report that since 1992 no less than 250 such studies have been published in only the nine major research journals. Additionally, I found that more then 200 new working papers were posted in the Social Sciences Research Network with the word "analyst" in their abstract between May 2007 and May 2008. The academic literature related to auditor going-concern opinions is not as vast, nevertheless, there are several dozen studies considering this issue published in research journals.

The objective of this chapter is not to provide an extensive review of all the papers published in these two areas of the literature. Instead, I selectively review and discuss topics that are important to help understand the scope of my research. This chapter benefits from the implementation of a systematic review of the literature based on Tranfield, Denyer, and Smart (2003).[1] This review process was conducted at an initial stage of my research to avoid the weaknesses of the traditional "narrative" review process. The systematic review process is anchored in an explicit method to identify, select and review

[1] This methodology is mainly based in a search strategy that combines keywords in search strings. The search strings are used in citation databases that gather academic papers (ProQuest, EBSCO and Social Science Citation Index) to find studies relevant to my research. Examples of keywords are "going-concern", "analyst behavior", "recommendations", "forecasts", "optimism", "underreaction" or "abnormal reaction".

the relevant studies related to the research topic. These studies were, in a second stage, augmented by traditional methods based on cross-references.

The rest of this chapter is organized as follows. Section 2 reviews the literature related to security analysts that impact on my research. Section 3 focuses on studies that connect analyst behaviour with bad news announcements. Section 4 reviews the going-concern literature, with particular emphasis on the market-based accounting research related to this information uncertainty. Section 5 summarizes the key findings of my literature review and section 6 presents the research framework for my thesis.

2.2. Security analysts

The literature on security analyst behaviour interfaces with several areas of accounting and finance research. This section is divided into five sub-sections and reviews the studies relevant to an understanding of my thesis framework. Firstly, I provide an overview of security analyst activity. Secondly, I review studies that investigate whether such analysts promote market efficiency. Thirdly, I review the literature addressing analyst biased behaviour. Fourthly, I cover studies analysing the impact of the recent regulatory changes on analyst activity. Lastly, I discuss the implications of these findings on my research.

2.2.1. The activity of security analysts

I now briefly describe the activity of security analysts emphasising their importance as intermediaries between firms and investors and whether the market recognizes that security analysts have superior information about the firms they follow.

2.2.1.1. Analysts' reporting environment

Security analysts can be divided into two categories: buy-side and sell-side. Despite their similar fundamental functions, their research differs in a variety of ways. Groysberg et al. (2007) identify and summarize some of these: the scale and scope of their coverage, the sources of information on which their research is based, the private versus public dissemination of reports, their target audiences and the ways that they are compensated. The underlying source of these differences is driven by the differences between the employers of each analyst category. Buy-side analysts tend to be employed by money management firms or institutional investors, whereas sell-side analysts are usually employed at broker/dealer firms that serve individual and institutional investors (Schipper, 1991). As such, sell-side research is widely disseminated to institutional and retail clients, whilst buy-side research is private and only available to the buy-side firm's portfolio managers. For this reason, I focus my research on sell-side analysts.

Security analysts collect, process and disseminate information to current and prospective investors. Ramnath, Rock, and Shane (2008) identify important sources of information used by analysts in their activity: information from the SEC filings, earnings information, industry information, macroeconomic information, management communications and other information. After collecting and processing this information, analysts disseminate it in the form of research reports, which contain four main informational vehicles: earnings forecasts, target price forecasts, investment recommendations and conceptual arguments supporting the forecasts and recommendations.

Analyst activity has increased dramatically over the years. Hong, Lim, and Stein (2000) document that sell-side analyst coverage of U.S. traded firms rose from less than 30% in 1978 to 63% in 1996. This stock coverage is provided by thousands of analysts working for hundreds of sell-side investment firms, who produce regular reports evaluating firms' securities.[2] Given their importance as intermediaries between firms and investors, analysts are usually seen as sophisticated agents, who tend to follow a portfolio of firms in a given industry or economic sector (Schipper, 1991).[3] Their privileged access to information suggests that the stocks they recommend will experience superior performance.[4] In fact, if brokerage houses did not believe that security analysts can generate superior returns, they would not spend large sums of money on security analysis.

2.2.1.2. The importance of analysts

There are several reasons justifying the importance of security analysts. I now present two of the most important. Firstly, there is evidence that analyst monitoring activity reduces the agency costs associated with the separation of ownership and control in the modern corporation (e.g., Jensen and Meckling, 1976; Cote and Goodstein, 1999; Doukas, Kim, and Pantzalis, 2000). In particular, the literature suggests that analyst monitoring and dissemination of managers' decisions contribute to disciplining firm management (Chung and Jo, 1996) since managers are less likely to pursue activities that benefit themselves at the expense of shareholders. This monitoring and information diffusion is also believed to keep stock prices close to their fundamental values. As Doukas, Kim, and Pantzalis (2000) mention, "*firms with weak analyst coverage are more likely to be plagued by information asymmetries and engage in non-value maximizing corporate activities*".

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[2] Jegadeessh et al. (2004) and Doukas et al. (2005) mention over 3.000 analysts working for more than 350 sell-side investment firms in the United States.

[3] Boni and Womack (2006) show that the typical analyst covers 10 firms and that the typical industry has 177 firms.

[4] Beckers et al. (2004) mention that individual and institutional investors use analysts' reports when they make portfolio selections or revision decisions. Additionally, they also state that analysts' earnings forecasts are used in equity valuation models.

Secondly, analyst activity represents a vital source of information to investors and researchers given that analysts are viewed as surrogates for market expectations. This is crucial in the case of less sophisticated agents since they are not able to produce their own predictions (De Bondt and Thaler, 1990). As Beaver (2002) suggests, analyst activity seems to be particularly important for the average investor since he/she may lack the time, skill, or resources to analyse and interpret financial statements. Analysts' forecasts and analysts' recommendations are two key sources of information to the investment community that aim at anticipating changes in company fundamentals as well as reacting to news or company reports (e.g., Michaely and Womack, 2005). In particular, analysts' forecasts are used as proxy for market earnings expectations (e.g., Givoly and Lakonishok, 1984; La Porta, 1996; Brav and Lehavy, 2003) given the evidence that these forecasts often outperform time-series models (e.g., Brown and Rozeff, 1978; Collins and Hopwood, 1980; Fried and Givoly, 1982; Conroy and Harris, 1987)[5] whereas analysts' recommendations provide a clear and unequivocal course of action to investors (Elton, Gruber, and Grossman, 1986).

2.2.1.3. The economic value of analysts' information

Security analysts are seen as sophisticated processors of financial information given their privileged position as intermediaries between firms and investors. Whether or not the market recognizes analysts' superior information about the firms they follow is, in this

[5] Hirshleifer (2001) argues that it is expected that rational agents provide at least positive incremental value in their forecasting activity.

context, particularly important. As such, I now review some of the studies that investigate if analysts' recommendations and earnings forecasts have the ability to move stock prices.[6]

Empirical research finds that, on average, markets react favourably (unfavourably) to recommendation upgrades (downgrades) (e.g., Bjerring, Lakonishok, and Vermaelen, 1983; Elton, Gruber, and Grossman, 1986; Liu, Smith, and Syd, 1990; Beneish, 1991; Stickel, 1995; Womack, 1996; Ryan and Taffler, 2006; Mokoteli and Taffler, forthcoming). In particular, these studies show that positive (negative) changes in analysts' recommendations are associated with positive (negative) abnormal returns. In one of the most frequently cited papers in this area, Womack (1996) finds strong evidence that stock prices are significantly influenced by analysts' recommendation changes. Using U.S. data, he finds that the price impact of a new "buy" recommendation occurs mostly around the announcement date whereas the price impact of a new "sell" recommendation may last for several months.[7] More recently, Mokoteli and Taffler (forthcoming) provide further evidence that the value of new "buy" recommendations is short-lived whereas the market reaction to new "sell" recommendations is slow with the market continuing to underreact for at least 12 months. In a parallel U.K.-based study, Ryan and Taffler (2006) find that the impact of new "sell" recommendations is greater than that of new "buy" recommendations, especially in the case of small firms. In a supplementary study, Barber et al. (2001) documents the potential to earn higher returns by buying the most highly recommended stocks and short selling the least favourably recommended stocks.

[6] Literature also suggests that price targets (e.g., Bradshaw, 2002; Brav and Lehavy, 2003) and the conceptual arguments in the analyst report (Hirst et al., 1995; Asquith et al., 2005) have informative value. For instance, Brav and Lehavy (2003) find a significant market reaction to price targets, both unconditionally and conditionally, on simultaneous recommendations and earnings forecasts revisions. Asquith et al., (2005) find that the stronger the conceptual argument, the more strongly the market reacts to the report.

[7] The post-recommendation drift associated with buy recommendations is significant and short lived (+2.4% for the first post-event month), but the post-recommendation drift associated with sell recommendations is larger and longer (-9.1% for the first six-month post-event period).

The literature also documents that upward (downward) earnings forecasts revisions are associated with positive (negative) abnormal returns. For instance, Abdel-khalik and Ajinkya (1982) find significant firm abnormal performance during the publication week of forecast revisions by Merrill Lynch analysts. Stickel (1991) also finds that earnings revisions affect prices, and that the impact is greater for extreme forecast changes. Moreover, he also documents that prices continue to drift in the direction of the revision for about six months.[8] In a supplementary study, Stickel (1992) claims a positive relationship between analyst's reputation and price impact of an earnings forecast revision announcement. Park and Stice (2000) and Chen, Francis, and Jiang, (2005) suggest a significant positive association between analyst forecast accuracy and the impact of forecast revisions. More recently, Clement and Tse (2003) suggest that investors' responses to forecast revisions are influenced by the number of days elapsed since the last forecast and the forecast timeliness.

In an attempt to understand the relative importance of various sources of analysts' informational advantages, Ivkovic and Jegadeesh (2004) test two hypotheses: 1) analysts might be skilled at analysing the value relevance of public information; 2) analysts might possess the ability to gather a wide variety of information not readily available to investors and to efficiently process this information. Their results suggest that the value of analyst activity stems more from their independent collection of new information than from their interpretation of public information.

[8] Stickel (1991) developed a trading strategy that predicted price reactions based on incomplete incorporation of such publicly available information. He found 6-month average abnormal returns of 8.22% and -5.44% respectively for his predicted best and worst performance portfolios.

2.2.2. Security analysts and market efficiency

In an efficient market, security analyst activity would not able to identify over and undervalued stocks. According to the efficient market hypothesis, security prices fully reflect all available information (Fama, 1970) in the sense that new information is incorporated into securities' prices without delay. Until recently, this paradigm was widely accepted in the academic finance literature. However, since the seminal work of Ball and Brown (1968), who provided the first convincing evidence of an incomplete market reaction to information, the efficient market hypothesis has been challenged by a vast number of empirical studies. Not surprisingly, behavioural finance emerged as an alternative to the traditional finance paradigm, arguing that some financial phenomena can be better understood using models in which some agents are not fully rational (e.g., Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subramanyam, 1998).

2.2.2.1. Conflicting results with the traditional finance paradigm

Generally, the empirical behavioural finance literature finds two pervasive regularities inconsistent with the weak and semi-strong form of market efficiency: overreaction and underreaction (Shleifer, 2000). Overreaction means that security prices facing a long record of good (bad) news tend to become overpriced (underpriced) and have low (high) average returns afterwards. DeBondt and Thaler (1985; 1987) are amongst the first to show the existence of systematic price reversals for stocks experiencing long-term gains and losses.

Underreaction is a widely known phenomenon identified by several empirical and theoretical studies. The theoretical underpinning of this "non-efficient" reaction to new value relevant information is that investors are slow in adjusting their expectations when receiving new information. For instance, Bernard and Thomas (1989) argue in favour of investors' delayed responses, Barberis, Schleifer, and Vishny, (1998) suggest that conservatism leads to the underreaction phenomenon and Hong and Stein (1999) argue that underreaction is due to firm-specific information gradually diffusing across the investing public. In short, when the market underreacts, good (bad) news is associated with an initial positive (negative) reaction that is followed by a subsequent drift in the same direction.

Empirical evidence shows that the market underreacts to a wide range of self-selected and non-self-selected events. In the self-selected domain, examples relate to earning announcements (e.g., Bernard and Thomas, 1989; 1990; Mendenhall, 1991; Chan, Jegadeesh, and Lakonishok, 1996), initial public offerings (e.g., Aggarwal and Rivoli, 1990; Ritter, 1991; Loughran and Ritter, 1995; 2000), seasoned equity offerings (e.g., Spiess and Affleck-Graves, 1995), straight and convertible debt offerings (e.g., Dichev and Piotroski, 1997; Lee and Loughran, 1998; Spiess and Affleck-Graves, 1999), dividend changes (e.g., Michaely, Thaler, and Womack, 1995), capital structure changes (e.g., Agrawal and Jaffe, 2000), stock splits (e.g., Ikenberry, Rankine, and Stice, 1996; Ikenberry and Ramnath, 2002), exchanges listings (e.g., Dharan and Ikenberry, 1995), and spin-off processes (e.g., Cusatis, Miles, and Woolridge, 1993; Desai and Jain, 1999). In the non-self-selected domain, examples relate to bond rating changes (e.g., Dichev and Piotroski, 2001), analysts' forecast and recommendation changes (e.g., Womack, 1996; Ryan and Taffler, 2006) and the going-concern audit report (e.g., Taffler, Kausar, and Tan, 2004; Kausar, Taffler, and Tan, forthcoming).

2.2.2.2. Do security analysts facilitate market efficiency?

The inconsistencies of the traditional paradigm in finance highlight the alleged importance of sophisticated agents that are less likely to misunderstand the implications of new information. As such, security analysts' degree of sophistication may lead us to believe that analysts play a critical role in promoting market efficiency. In this section, I review some studies that investigate the relationship between analyst coverage and the speed with which markets assimilate new information.

Brennan, Jegadeesh, and Swaminathan (1993) investigate the association between the number of analysts following a firm and the speed with which its stock prices react to common information. This study was motivated by evidence of a positive relationship between the number of informed investors and the speed of stock price adjustment to new information (Holden and Subrahmanyam, 1992; Foster and Viswanathan, 1993). Brennan, Jegadeesh, and Swaminathan (1993) find that market reaction to common information is faster for firms followed by a higher number of analysts and that a small number of analysts have little effect on the speed of the adjustment.

Elgers, Lo, and Jr (2001) find that the security prices of firms with lower analyst coverage do not efficiently reflect all of the value-relevant information in their publicly available earnings forecasts. More specifically, these authors find that a simple trading strategy based on the ratio of price to one-year-ahead earnings forecasts yields significant positive abnormal returns. In a supplementary study, Gleason and Lee (2003) provide an explanation for the incomplete market reaction to forecast revisions (e.g., Givoly and Lakonishok, 1980; Stickel, 1991; Chan, Jegadeesh, and Lakonishok, 1996) by showing that analyst coverage affects the speed and efficacy of the price discovery process. In particular, they find that, after controlling for concurrent factors, the total post-revision drift over the subsequent 12 months is much larger for firms with low analyst coverage than for firms with high analyst coverage.

Bhattacharya (2001) suggests that the post-earnings drift (e.g., Bernard and Thomas, 1989, 1990; Barberis, Schleifer, and Vishny, 1998; Hong and Stein, 1999) is attributable to a specific segment of the market, which is characterized by small traders transacting in firms with low-to-moderate analyst coverage. More recently, Zhang (forthcoming) suggests that security analysts play an important role in the efficiency with which the market incorporates earnings announcements in stock prices. This study provides two important results in this domain. First, the author finds that analysts are not responsive to earnings announcements in the sense that an important portion of their earnings forecast revisions do not take place immediately after the earnings announcements.[9] Second, the post-earnings-drift is significantly lower when the percentage of responsive analysts following the firm is higher. Overall, Zhang (forthcoming) suggests that security analysts play an important role in the efficiency with which the market incorporates earnings announcements in stock prices.

In a related study, Hong, Lim, and Stein (2000) show that holding size fixed, momentum strategies work particularly well among stocks that have low analyst coverage, suggesting that momentum reflects the gradual diffusion of firm-specific information across the investing public. Moreover, Hong, Lim, and Stein (2000) find that the market reaction to stocks with low analyst coverage is particularly slow in the presence of bad news.

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[9] Zhang (2005) finds that 50% of analysts do not revise their forecasts within five calendar days after the earnings announcements. Moreover, about 15% (10%) of analysts revise their forecasts during the second (third) month after the earnings announcements.

In two recent studies, Jiang, Lee, and Zhang (2005) and Zhang (2006) explore the relationship between information uncertainty and the cross-section of stock returns. Interestingly, they use analyst coverage as one of the proxies for the level of information uncertainty.[10] Jiang, Lee, and Zhang (2005) find that both price momentum and earnings momentum strategies work particularly well for high information uncertainty companies. For instance, when firms are sorted by recent changes in analyst forecast revisions, a strategy of buying positive revision stocks and shorting negative revision stocks yields average monthly returns that ranges from 0.77% to 1.30% (1.94% to 2.66%) for low (high) information uncertainty firms. Zhang (2006) indicates that the market reaction to new information is relatively complete for low-uncertainty stocks and incomplete for high-uncertainty stocks. Moreover, the author finds that greater information uncertainty produces relatively lower future returns following bad news and relatively higher future returns following good news.

2.2.3. Analyst biased behaviour

Despite the studies pointing to the economic value of analyst information and the evidence that analysts facilitate the efficiency with which the market processes information, several studies suggest that analysts are biased.

Easterwood and Nutt (1999) state that "*a rational analysis of analyst behavior predicts that analysts immediately and without bias incorporate information into their forecasts*". However, there are several studies presenting conflicting evidence with this definition (e.g., Stickel, 1990; DeBondt and Thaler, 1990; Abarbanell, 1991; Brown, 1997; Easterwood and Nutt,

[10] Zhang (2006) clearly defines information uncertainty as the "ambiguity with respect to the implications of new information for a firm's value".

1999). I now review some of these studies and summarize two competitive explanations for such a biased behaviour.

2.2.3.1. Analyst optimism

There are a considerable number of studies claiming that security analysts are optimistic.[11] This optimism is derived from the systematic positive difference between forecast and actual earnings per share (e.g., Stickel, 1990; Abarbaell, 1991; Abarbanell and Bernard, 1992; Kang, O'Brien, and Sivaramakrishnan, 1994; Brown, 1997; Lim, 2001; Brown, 2001) and from the permanent higher number of "buy" recommendations compared to the number of "sell" recommendations (e.g., Womack, 1996; Ho and Harris, 1998; Ryan and Taffler, 2006).

For instance, Brown (1997) finds that predicted quarterly earnings are systematically higher than actual quarterly earnings. In addition, the author suggests that forecast errors are particularly severe for firms with specific characteristics such as non-S&P500 firms, small market capitalization firms and firms followed less by analysts. Using a different approach, Amir and Ganzach (1998) and Easterwood and Nutt (1999) divide analysts' forecasts according to the nature of the information preceding the forecast and conclude that forecast behaviour is consistent with the notion of systematic optimism. In a subsequent study, Lim (2001) argues that positively biased forecasts may be considered a rational strategy to improve forecast accuracy. As the author argues, "*rational analysts who aim to produce accurate forecasts may optimally report optimistically biased forecasts*". In fact, by

[11] There are however, a number of studies arguing that analyst optimism is subject to a variety of caveats (e.g., Keane and Runkle, 1998; Kothari, 2001; Brown, 2001; Richardson et al., 2004; Ramnath et al., 2005): 1) the sample period considered; 2) whether the mean or median forecasts are used as evidence; 3) the forecast horizon; and 4) the use of statistical tests that establish the bias.

trading off bias to improve management access, analysts minimize the expected squared error of their forecasts.

There is also evidence that analysts' recommendations are issued in an optimistic manner. Generally, studies show that the number of "buy" recommendations is systematically higher than the number of "sell" recommendations. For instance, Womack (1996) finds that the "buy"/"sell" ratio is approximately 7/1 in the U.S. whereas Ho and Harris (1998) claim that this ratio varies between 4.1/1 and 5.2/1 depending on the rating system used. In addition, Barber et al. (2006) mention that "buy" recommendations peaked at 74% of the total at the end of the second quarter of 2000 whereas Ryan and Taffler (2006) estimate a ratio of 2.3/1 in the U.K.

However, there is reliable evidence that analyst optimism has declined in recent years (e.g., Brown, 1997; Matsumoto, 1998; Brown, 2001; Barber et al., 2006; Mokoteli and Taffler, forthcoming). For instance, Brown (2001) reports that analyst forecasts turned from optimism to pessimism. In particular, the author finds a significant temporal shift in median earnings surprise from small negative (1984-1990) to small positive (1994-1999). Kothari (2001) highlights three explanations for this evidence: 1) analysts are learning from evidence of past bias; 2) change in analysts' incentives and 3) the improvement in the quality of data used in the research examining analysts' forecast properties. More recently, some studies claim that the regulatory changes in the analysts' reporting environment contributed to the decrease in analyst optimism (e.g., Barber et al., 2006; Madureira et al., 2008).

2.2.3.2. Analyst self-selection bias

In general terms, analyst self-selection bias relates to analysts' tendency to report on stocks about which they have favourable views and to avoid reporting on stocks about which they have unfavourable views. As such, analysts spend less effort in the coverage of underperforming stocks, which can explain, at least partially, why momentum strategies work particularly well for companies with low analyst coverage (e.g., Hong, Lim, and Stein, 2000).

Hayes (1998) developed a mathematical model in which analysts' incentives for gathering information are stronger for stocks that are expected to perform well. In particular, the model predicts that: 1) forecast accuracy should be higher for stocks that perform well than for stocks that perform poorly; 2) analysts seek to follow stocks they expect to perform well; 3) if a stock is not widely held, an analyst will initiate coverage only if the stock's performance is expected to be good.

The theoretical model of Hayes (1998) has empirical support. For instance, McNichols and O'Brien (1997) suggest that analysts tend to start covering firms they view favourably and stop covering firms they view unfavourably. Moreover, the authors find that stocks receiving initial coverage tend to obtain more "buy" recommendations than those already covered whereas stocks they drop tend to have lower ratings than those whose coverage continues. More recently, Das, Guo, and Zhang (2006) document that in the three subsequent years, initial public offerings with high residual coverage have significantly better returns and operating performance than those with low analyst coverage. As such, the authors suggest that the expectation of future firm performance is one latent determinant of selective coverage.

2.2.3.3. Explaining analyst biased behaviour

Kothari (2001) identifies two broad categories of explanations for analyst optimism in analysts' forecasts: incentive-based explanations and cognitive-bias explanations. I now summarize studies providing evidence consistent with these two explanations.

2.2.3.3.1. Economic incentives

Economic incentives are one of the most consistent explanations for analysts' biased behaviour. These incentives are believed to produce conflicts of interest between brokerage firms and their clients, reducing analysts' objectivity and independence.[12]

The literature finds that analysts fear that a negative report may reduce the possibility of their investment banking firm doing business with the target firm in the future. For instance, Dugar and Nathan (1995) find that investment bank analysts produce more optimistic forecasts than non-investment bank analysts. Lin and McNichols (1998) report similar conclusions after exploring analysts' long-term growth forecasts and recommendations. For the particular case of IPO companies, Michaely and Womack (1999) confirm that analysts' recommendations are optimistically biased in the case of underwriter analysts and that their performance is significantly worse than with non-underwriter analysts. In an additional study, O'Brien, McNichols, and Lin (2005) show that affiliated analysts are slower (faster) in downgrading (upgrading) recommendations

[12] According to Michaely and Womack (2005), investment banks traditionally have three income sources that may potentially create conflicts of interest within the bank and with its clients: 1) corporate financing, the issue of securities and merger advisory services; 2) brokerage services and 3) proprietary trading. Some of the main potential conflicts are between the two first sources. The first is responsible primarily for completing transactions for new and current clients, and the second for maximizing commissions and spreads by providing timely, high quality and presumably unbiased information to their clients

compared to unaffiliated analysts. More recently, Barber, Lehavy, and Trueman (2007) find that recommendation upgrades (downgrades) by investment banks underperform (outperform) non-investment bank brokerages and independent research firms.

There is also evidence that analysts working for brokerage firms tend to be significantly more optimistic than analysts working for non-brokerage houses (e.g., Carleton, Glezen, and Benefield, 1998; Hodgkinson, 2001) and that brokerage houses seem to reward analysts for their optimism (Hong and Kubik, 2003).[13] Not surprisingly, commissions generated by followed stocks are one of the most important sources of analyst compensation (Michaely and Womack, 2005). As such, by issuing optimistic forecasts and favourable recommendations, analysts are encouraging investors to buy the company's stock, and thus, generate brokerage commissions. Pessimistic forecasts and unfavourable recommendations generate lower commissions due to restrictions on short sales, limited availability and greater risk for options (Espahbodi, Dugar, and Tehranian, 2001).

Finally, there are also studies arguing that analyst optimistic behaviour is related to their need to maintain good relations with firm management. In fact, analysts depend on corporate management for accurate and timely information about the companies they follow and they fear that companies will use this dependency as a weapon in the case of negative reports (Espahbodi, Dugar, and Tehranian., 2001). This hypothesis is consistent with the findings of Francis and Philbrick (1993) and Das, Guo, and Zhang (1998), who show that analysts' forecasts are more optimistic for companies with greater earnings variability or that had a sell rating.

[13] Hong and Kubik (2003) find that optimistic analysts are 38% less likely to move down the hierarchy and 90% more likely to move up the hierarchy. Moreover, this reward for optimism is more acute when analysts are covering stocks underwritten by their brokerage houses.

Several studies investigate the factors associated with the analyst decision to follow a firm besides the relationship between brokerage firms and their clientsFor instance, Previts et al. (1994) find that analysts prefer to follow firms that smooth earnings whereas Chung and Jo (1996) show that analysts tend to follow stocks of high quality firms. In addition, Lang and Lundholm (1996) find that analysts prefer to follow firms with more forthcoming disclosures, particularly in the context of direct investor relations communications, as opposed to public disclosures in annual and quarterly reports to shareholders. More recently, Botosan and Harris (2000) show that analysts following increases with firms' decisions to include information on segment activity as part of their quarterly (as opposed to only annual) reports whilst Barth, Kasznik, and McNichols (2001) find that relative to industry peers, analyst following increases with R&D and advertising expenditures. Finally, Jegadeesh et al. (2004) show that analysts tend to favour "growth" stocks compared to "value" stocks and that they prefer firms associated with positive momentum.

In a recent study, Liang, Riedl and Venkataraman (2008) augment the exant literature about the relationship between analysts, brokerage houses and firms followed by addressing the specific characteristics of analysts and brokerage houses who follow firms. At the analyst level, this study finds that an analyst is more likely to follow a firm that falls within his or her primary industry expertise and an analyst is more likely to follow a firm when his or her experience is greater relative to the other analysts following that firm. With regard to the employing brokerage house, Liang, Riedl and Venkataraman (2008) find that an analyst is more likely to initiate coverage of a firm if the company was previously followed by another analyst employed at the same brokerage house but who is no longer forecasting for that brokerage house. In addition, they show that an analyst is also more likely to cover a firm when the brokerage house has had a recent investment banking relationship with the firm. Together, these findings suggest that analyst-firm pairings are determined not only by the characteristics of firms but also by a range of factors reflecting characteristics specific to the analyst and the employing brokerage house.

2.2.3.3.2. Cognitive biases

Several psychological errors are perceived to affect both sophisticated and non-sophisticated agents. The tendency to be overoptimistic is one of the best documented examples. Montier (2002) states that such overoptimism results from a number of psychological biases, such as illusion of control and self-attribution.[14] There is also evidence that overconfidence plays an important role in the decision-making process. This bias occurs when one believes the precision of one's information is greater then it actually is and there is evidence that experts tend to be more confident than relatively inexperienced individuals (Griffin and Tversky, 1992). It follows that overconfidence may help to explain why security analysts believe they have superior investment insights. Another important psychological error potentially affecting analyst behaviour is the representativeness bias, first introduced by psychologists Daniel Kahneman and Amos Tversky. In the words of Hirschleifer (2001), representativeness *"involves assessing the probability of a state of the world based on the degree to which the evidence is perceived as similar to or typical of the state of the world"*. Put simply, it means that intuitive judgment is often the

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[14] The illusion of control is related to people feeling that they have influence over the outcome of uncontrollable events, which is described by Hirshleifer (2001) as a type of *"magical thinking"*. The self-attribution bias means that people attribute favourable outcomes to skill while bad outcomes are attributed to bad luck, or else they blame external factors for the failure (e.g., Fischhoff, 1982; Langer and Roth, 1975; Miller and Ross, 1975; Taylor and Brown, 1988).

only practical method for assessing uncertainty, because people do not normally have formal models for computing the probabilities of events.

These cognitive biases help understand analysts' biased behaviour and have been proposed to explain analysts' forecast optimism (e.g., DeBondt and Thaler, 1985; 1987; DeBondt, 1992; Amir and Ganzach, 1998). For instance, De Bondt (1992) finds that long-term earnings forecasts are significantly more optimistic for recent winners compared to recent losers. Amir and Ganzach (1998) argue that representativeness, along with optimism and anchoring, influences analysts' forecasts and that this heuristic leads to extreme predictions or overreaction. In addition, Tamura (2002) suggests that analysts are affected by their personalities in forecasting, since relatively optimistic analysts tend to continue to be optimistic, while pessimistic analysts tend to continue to be pessimistic.

2.2.4. Recent changes in analysts' reporting environment

The previous pages of this chapter highlight that analysts are generally optimistic, especially if they work for investment or brokerage firms. Concerns that investors were being misled by analysts' optimistic research reports and by analyst conflicts of interest were triggered by the stock market downturn of 2000-2002 and by several corporate episodes where analysts were recommending "buy" ratings up until the scandals broke (e.g., Enron, WorldCom, Adelphia, Tyco).

Recently, however, the policy-makers and regulators have introduced changes in the analysts' reporting environment and in their relationship with target firms, investment and brokerage firms and investors. Below, I briefly describe the most important changes and review some studies addressing these issues.

2.2.4.1. Regulation Fair Disclosure

Before October 2000, it was common for firms to communicate value-relevant information to selected market agents before disclosing it to the public. This practice, which disadvantaged the "average" investor, was changed on the 23rd of October 2000 after the implementation of the Regulation Fair Disclosure (Reg FD). In general terms, Reg FD requires the public disclosure of value-relevant information to the entire investment community in an attempt to increase investor confidence in the integrity of capital markets.[15]

Several studies investigate the effectiveness of Reg FD. Heflin, Subramanyam, and Zhang (2003) find that companies significantly increased the quantity and quality of voluntary information disclosures after October 2000, in an apparent compensation for the decrease of private disclosures. This study also finds that abnormal returns following pre-earnings announcements became significantly smaller after that date. This conclusion is consistent with the findings of Bailey et al. (2003) and Eleswarapu, Thompson, and Venkataramen (2003), who suggest that prices became more informative about upcoming earnings after Reg FD.

In an additional study, Gintschel and Markow (2004) observe a significant reduction in the average price impact associated with the dissemination of both earnings forecasts (34%) and stock recommendations (22%), especially for analysts working at prestigious brokerages and for optimistic analysts. There is also evidence that the number of

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[15] However, the introduction of Reg FD was controversial. Security analysts criticised Regulation FD suggesting that it would reduce the flow of information to the market. In broad terms, security analysts argued that managers would fear litigation arising from improperly interpreted public announcements or that the public disclosure of sensitive information that analysts only used to improve earnings forecasts could benefit competitors. For more detail, see Heflin et al. (2003).

companies followed per analyst decreased after Reg FD, reflecting the increase of information costs (Mohanram and Sunder, 2006).

The literature reports mixed evidence about analysts' earnings forecast dispersion following the implementation of Reg FD. For instance, Bailey et al. (2003), Irani and Karamanou (2003) and Mohanram and Sunder (2006) find less consensus among analysts forecasts whereas Heflin, Subramanyam, and Zhang (2003) fail to reach a similar conclusion. In addition, there is also mixed evidence regarding the impact of Reg FD on forecast accuracy. Bailey et al. (2003), Heflin, Subramanyam, and Zhang (2003) and Mohanram and Sunder (2006) find no significant changes whilst Findlay and Mathew (2006) suggest that analysts became less accurate after the implementation of Reg FD.

2.2.4.2. Regulations NASD 2711 and NYSE 472

Following Reg FD implementation, the regulatory authorities also felt the need to provide investors with better information to assess analyst research. This need was triggered by the perception that analysts avoided reporting their true expectations and that analysts' conflicts of interest were conditioning their activity.[16] In 2002, the SEC approved two proposals from the National Association of Security Dealers (NASD) and the New York

[16] One of the most important episodes occurred in June 2001, when a Wall Street Journal article about an alleged misconduct of security analysts encouraged the New York Attorney General (NYAG) to investigate investment banks. This investigation found that investment banks engaged in practices that created or maintained inappropriate influence over research analysts seeking lucrative fees. In fact, in some cases, favourable analyst public recommendations did not match their true expectations expressed in internal e-mails. Following the joint investigation by the regulators, the SEC, the NYSE, the NASD, the NYAG and the ten U.S. investment firms involved reached a settlement commonly known as the "Global Analyst Research Settlement". This settlement was announced on the 28th of April, 2003 and required the sanctioned banks to pay fines and penalties totalling roughly 1.4 billion dollars for their misconduct. In addition, the Settlement reinforces the previous regulatory changes by requiring, for instance, a physical separation between the investment banking and the research departments.

Stock Exchange (NYSE) that aimed at making analysts' research output more meaningful. The NASD proposed the implementation of Rule 2711, "Research Analysts and Research Reports" whilst the NYSE proposed amendments to its Rule 472, "Communications with the Public". These rules were approved on the 8th of May, 2002 with an effective date for implementing the disclosure provision of no later than the 9th of September, 2002 (NASD 2711) and 5th of May 2003 (Rule 472).

Both proposals share the same goals and aim to separate investment banking activity from research departments. Amongst other restrictions, these rules limit the relationships and communications between investment banking and research staff and prohibit analyst compensation based on specific investment banking transactions. In addition, the new regulatory environment requires analyst research reports to reveal the relationships between the security analyst, the investment bank and the subject company. Finally, analyst research reports have to display the proportion of the issuing firm's recommendations that are "buys", "holds" and "sells".

Few studies have investigated the efficacy of NASD Rule 2711 and NYSE Rule 472. However, in one of these few studies, Barber et al. (2006) show that the percentage of "buy" recommendations decreased (from 60% to 45%) and the percentage of "sell" recommendations increased (from 5% to 14%) following the regulatory change implementations.[17] More recently, Mokoteli and Taffler (forthcoming) shows a dramatic change in the distribution of stock recommendations. To be precise, the authors reveal that the ratio of new "buys" to "sells" reaches 49:1 during 2000 but plunges to 0.9:1 in 2002. In

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[17] Barber et al. (2006) also find that before the regulatory changes, the percentage of "buy" recommendations between sanctioned and non-sanctioned brokers in the Global Analyst Research Settlement was economically small. However, after the regulatory changes, the percentage of "buy" recommendations for the sanctioned banks declined more sharply compared to the non-sanctioned banks.

addition, Madureira et al. (2008) show that, following the regulatory changes, optimistic recommendations have become less frequent whereas the neutral and pessimistic recommendations have become more frequent. However, affiliated analysts are still reluctant to issue pessimistic recommendations. Finally, Madureira et al. (2008) show that, contrary to price response to neutral and pessimistic recommendations, the price reaction to optimistic recommendations is significantly higher following the regulatory changes.

2.2.5. Discussion

This section reviews the relevant literature on security analyst activity which feeds into the general framework of my thesis. Two key ideas emerge from the previous pages: 1) security analysts play an important role in the functioning of financial markets, and 2) security analysts do not process information "*immediately and without bias*".

Evidence inconsistent with the efficient market hypothesis makes it hard to believe that investors assimilate new information efficiently (e.g., Bernard and Thomas, 1989; Michaely, Thaler, and Womack, 1995; Dichev and Piotroski, 2001; Taffler, Lu, and Kausar, 2004). As such, security analysts, being sophisticated agents, should not exhibit similar errors and should facilitate the correct assimilation of information in stock prices. However, the literature shows that analyst activity is not unbiased. On the one hand, there is evidence that analyst coverage has a positive impact on the efficiency with which the market processes information (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Bhattacharya, 2001; Gleason and Lee, 2003; Zhang, 2006). On the other hand, the research evidence shows that security analysts are prone to behavioural biases in a similar fashion to non-sophisticated agents (e.g., De Bondt, 1992; Easterwood and Nutt, 1999; Michaely and Womack, 1999).

Despite the evidence that security analysts promote market efficiency, extant studies pay little attention to their role in the bad news domain. This is a puzzling result since the literature suggests that inefficient market reaction is particularly likely to occur in this case. For instance, Bernard and Thomas (1989) find that the post-earnings drift is more severe in the case of negative earnings surprises whereas Womack (1996) shows that the post-recommendation drift is larger and longer in the case of "sell" recommendations. Similarly, Dichev and Piotroski (2001) find that an abnormal reaction to Moody's bond rating changes is concentrated in downgrades as opposed to upgrades whilst Kausar, Taffler, and Tan (forthcoming) suggest similar evidence for the going-concern audit report as opposed to the going-concern audit report withdrawn. It follows that investigating how security analysts deal with bad news may facilitate the understanding of the broader issue of how the market responds to negative information.

In addition, the marginal contribution of security analysts may be greater in the bad news domain. In fact, as Hong, Lim, and Stein (2000) mention, "*if the firm is sitting on bad news, its managers will have much less incentive to bring investors up to date quickly*". Intuitively, it makes sense to consider that managers have less incentive to disclose information that affects the firms' value negatively. This idea is confirmed by Givoly and Palmon (1982) and Chambers and Penman (1984), who suggest that firms tend to delay earnings announcements when they report lower-than-expected earnings. However, it should be noted that there are also reasons to believe that managers have incentives to disclose bad news earlier than good news. Skinner (1994) present two reasons justifying this rationale: litigation and reputation. First, the U.S. legal environment allows stockholders to sue managers when there are large stock price declines on earnings announcement days. Second, the investment community may impose costs on firms whose managers are less than candid about potential earnings problems. Skinner (1994) explores this asymmetric loss function in choosing managers' voluntary disclosure policies and find consistent evidence with these two arguments. More recently, Kothari, Shu, and Wysocki (2008) show that managers withhold bad news up to a certain threshold. As such, do analysts provide investors with value-relevant information in the bad news domain? The next section reviews studies that address analyst behaviour and negative information.

2.3. Security analysts and bad news

Studying how efficiently analysts deal with bad news help us to understand why markets seem particularly slow to incorporate negative information. In this section, I review some studies that investigate: 1) analysts' reaction to negative information; 2) analysts' optimism towards companies in financial distress and 3) analysts behaviour in the presence of non-routine bad news.

2.3.1. Analyst reaction to negative information

The majority of the studies investigating analysts' forecasts in response to new information conclude that analysts do not process fundamental information efficiently. Moreover, there is evidence that analyst reaction depends on the nature of the information.

There are several studies showing that analysts do not revise their forecasts efficiently in response to new information. Despite early evidence that analysts overreact to past earnings (DeBondt and Thaler, 1990), most of the research has concluded that analysts underreact to information, especially when such information is negative. One of the first studies suggesting that analysts underreact to earnings information is that of Abarbanell and Bernard (1992). In particular, these authors fail to find a relationship between extremely high (low) forecasts and firms experiencing recent strong (weak) earnings performance, which is inconsistent with the notion of overreaction. There are other studies suggesting that analysts underreact to information. For instance, Elliott, Philbrick, and Weidman (1995) find that analysts systematically underweigh new information, particularly when revising forecasts downward. Chan, Jegadeesh, and Lakonishok (1996) show that analysts' forecasts of earnings are slow to incorporate past earnings news, especially for firms that have performed poorly in the past. Abarbanell and Bushee (1997) document that analyst forecast revisions fail to consider all of the information in fundamental signals related to future earnings. Finally, Mikhail, Walther, and Willis (2003) also document that analysts underreact to prior earnings information but show their underreaction decreases as their experience following a firm increases.

Two important studies provide clear evidence that analyst reaction to good news is distinct from bad news (Amir and Ganzach, 1998; Easterwood and Nutt, 1999). These studies argue that inefficient earnings forecasts are not characterized by a uniform pattern of overreaction or underreaction to information, but by systematic optimism. For instance, Amir and Ganzach (1998) show that analysts tend to overreact in the case of positive forecast modifications (good news) and to underreact in the presence of negative forecast modifications (bad news).[18] The authors justify their results using a behavioural framework of three heuristics that could influence earnings forecasts: leniency, representativeness, and anchoring and adjustment. Similarly, Easterwood and Nutt (1999) find that analysts' systematic overreaction (underreaction) is exclusively related to positive (negative) earnings information, suggesting that analysts overweigh (underweigh) good

[18] Amir and Ganzach (1998) distinguish between two types of forecast modification. Forecast revisions are defined as the difference between the new earnings forecast and the previous forecast. Forecast changes are defined as the difference between the prediction of future earnings and the previously announced earnings.

(bad) news. As such, the authors conclude that analysts are systematically optimistic in response to information.

2.3.2. Analyst optimism and distressed firms

The literature provides evidence that analyst optimism is not confined to healthy firms and that this bias is particularly manifested for firms in financial distress. For instance, there is evidence that analyst overestimation of earnings is higher for loss-making firms compared to non loss-making firms (e.g., Dowen, 1996; Hwang, Jan, and Basu, 1996; Das, 1998; Degeorge, Patel, and Zeckhauser, 1999; Brown, 2001). In one of these studies, Das (1998) corroborates this conclusion after controlling for forecast horizon, year of forecast and industry affiliation. Using a sample of 480 firms with negative operating performance (loss firms) and 440 control non-loss firms for the period between 1985 and 1993, the author also shows that this bias declines as the earnings announcement date approaches. In a supplementary study, Brown (2001) finds that the percentage of analysts' forecasts above actual earnings is generally higher for loss-making firms (65.8%) compared to profitable firms (53.0%). In addition, he also shows that the percentage of negative earnings surprises (forecast greater than actual) is almost twice as large compared to the percentage of positive surprises near the earnings announcement, suggesting that analysts are particularly inefficient when dealing with adverse information.

Lim (2001) shows that analyst optimism is more severe for firms experiencing prior negative earnings surprise and for firms associated with poor past stock returns. Moreover, Ding, Charoenwong, and Seetoh (2004) demonstrate that analysts exhibit asymmetric behaviour towards positive and negative earnings growth. In particular, they find little evidence of biased earnings forecasts during periods of positive earnings growth whereas for periods of negative earnings growth they show that analysts' earnings forecasts are optimistically biased.

Two studies investigate the relationship between analysts' earnings forecasts and bankrupt firms. Moses (1990) finds that analyst forecasts for bankrupt firms become less accurate and more optimistically biased than for non-bankrupt firms as the bankruptcy date approaches. The author concludes that analyst forecast behaviour for bankrupt firms reflects conditions that are associated with failure. In the same domain, Espahbodi, Dugar, and Tehranian (2001) show that analysts' forecasts are optimistic for both bankrupt and turnaround firms. However, they find that the forecast bias for bankrupt firms declines to insignificant levels one year before the bankruptcy filing whereas the same happens during the year of recovery for turnaround firms. According to Espahbodi, Dugar, and Tehranian (2001), analysts are unable to distinguish between bankrupt and turnaround firms after two or more consecutive years of poor performance.

2.3.3. Analysts dealing with non-routine bad news

Evidence on how security analysts deal with bad news is almost exclusively related to routine events, such as net losses, negative earnings surprises or forecast revisions. In fact, there is little evidence about how analysts deal with negative non-routine events, which can be defined as news that is not part of the normal reporting cycle (Griffin, 2003).

In one of the few studies addressing this issue, Griffin (2003) investigates analyst behaviour for companies with corrective restatements or disclosures that lead to allegation of securities fraud. Two key findings are important for my research. Firstly, analysts seem to have low interest in following these companies. More specifically, Griffin (2003) finds that the number of analysts covering such firms decreases slowly over several months following a corrective disclosure. Secondly, analysts do not anticipate the corrective restatements, but they react to such an event. In effect, there is evidence of strong forecast revision and decrease in forecast errors in the event-month, in contrast to the pre-event period. However, there are two studies showing that analysts are able to detect some types of accounting fraud before its public disclosure (Dechow, Sloan, and Sweeney, 1996; Cotter and Young, 2007). Dechow, Sloan, and Sweeney (1996) find that analysts anticipate the public announcement of an accounting fraud by dropping analyst coverage prior to the disclosure of such an event whereas Cotter and Young (2007) show that analysts use different signals to inform investors about different fraud types. In some cases, analysts cease coverage of firms associated with accounting fraud whilst in other cases analysts downgrade stock recommendations for such firms.

In a recent study, Clarke et al. (2006) compare analysts' recommendations for a sample of 384 bankrupt firms with similar non-bankrupt firms from 1995 to 2001. Their results show that analysts are more aggressive in downgrading their stock recommendations for bankrupt firms than for matched firms as the bankruptcy date approaches, suggesting that analysts do not ignore the financial deterioration of bankrupt firms. As a result, Clarke et al. (2006) reject the notion that analysts issue biased recommendations for bankrupt firms.

Using large price changes to proxy for public information shocks, Conrad et al. (2006) investigate how analysts' recommendations respond to major news. They find that the probability of a change in analysts' recommendations is conditional on the pre 3-day stock price change: analysts are more likely to downgrade a stock following an extreme price decrease than upgrade a stock following an extreme price increase. This suggests that analysts believe they have private information and that recommendation changes are "sticky" in one direction, with analysts reluctant to downgrade. In a parallel study, McNichols, Lin and O'Brien (2005) find that analysts take longer to downgrade a stock compared to the upgrade decision and the reluctance to downgrade is more severe in the case of affiliated analysts.

2.3.4. Discussion

This section provides evidence that security analysts do not assimilate negative public information efficiently. The existing literature finds that analysts tend to underreact in the presence of adverse news and that they are particularly optimistic when forecasting the earnings of distressed firms. In addition, there is conflicting evidence about analysts' ability to anticipate bad news and how they react to such news.

Existing evidence is, however, almost exclusively confined to routine events with adverse market consequences, such as net losses, negative earnings surprises and forecast revisions. In fact, little is known about analyst behaviour in the presence of non-routine events, i.e. those that are not part of the normal reporting cycle. Amongst the few exceptions are the studies by Espahbodi, Dugar, and Tehranian (2001), Griffin (2003), Clarke et al. (2006) and Conrad et al. (2006). Interestingly, these studies provide conflicting results about the role of security analysts in the dissemination of information related to non-routine bad news events. Therefore, my thesis provides further evidence on how analysts deal with firms associated with a bad news event that is not part of the normal reporting cycle. Moreover, I investigate if analysts facilitate the incorporation of negative information in stock prices of such firms.

The selection of my non-routine bad news event to facilitate a comprehensive understanding of the above issues is crucial. I select such an event based on the following criteria: 1) it must not be part of the normal reporting cycle; 2) it must be perceived as a clear case of bad news; 3) it must be preceded by unfavourable economic events allowing its anticipation; 4) it must be evidence of inefficient market reaction; 5) it must provide a reasonable number of cases allowing a comprehensive analysis.

Drawing on the previous literature and the above criteria, I use going-concern modified audit report disclosures as my non-routine bad news event. In fact, the GCM offers unique characteristics that facilitate a comprehensive analysis of the connection between security analysts, bad news and market performance. It is important at this stage to justify why I classify a GCM audit report as a "non-routine" bad news disclosure. SAS No. 59 states that auditors have to explicitly evaluate the going-concern status of a firm as part of the standard audit process. However, auditor decision to issue a GCM audit report is a non-routine event on the actual going-concern audit process given the very low proportion of firms receiving such a severe opinion.[19] The next section reviews research related to the going-concern audit report.

2.4. The going-concern assumption

Financial statements are the privileged information vehicle between firms and their stakeholders. The going-concern assumption is a fundamental principle in the preparation of financial statements. It states that an entity is ordinarily viewed as continuing in business for the foreseeable future.

[19] I only find 924 firm-year observations for which auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005 out of the entire population of non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ.

External auditors contribute to reducing information asymmetry between firms and their potential investors by providing an opinion on financial statements which, among other responsibilities, requires the monitoring of the going-concern assumption. If auditors develop serious doubts about the continuity of the firm in the foreseeable future, the going-concern assumption comes under question. It follows that auditors are required to report these uncertainties in the audit report, which is part of their "client's" annual report. As such, a non-standard audit report about its financial statements is not desirable and, in particular, a going-concern modified audit report is a clear sign of bad news.

2.4.1. Historical background

The Statement on Auditing Practices (SAP) No.15, issued in 1942, represents the American Institute of Certified Public Accountants' (AICPA) first formal effort to consider the effects of uncertainty on the audit report (Bell and Wright, 1995). The Statement suggests that the cumulative effect of uncertainties may be so great as to create a situation in which either an auditor's report might require an exception, or it might not be possible to render an opinion.

Following this, the Securities and Exchange Commission's Accounting Series Release (ASR) No. 90 (1962), and the AICPA's SAP No.33 (1963) required that the phrase *"subject to"* be used to introduce a qualification of opinion when the financial statements were materially affected by uncertainties. The need for a formal going-concern disclosure was first recognized in Statement on Auditing Standards (SAS) No. 2 (AICPA 1974), since the Auditing Standards Executive Committee concluded that uncertainty about the ability of an entity to continue should be reported in the same manner as any other uncertainty. Since then, SAS No. 34 (AICPA 1981) and SAS No. 59 (AICPA 1988) have provided guidelines for the independent auditor's evaluation and for the disclosure of going-concern problems.

SAS No. 34 entitled *"The Auditor's Consideration When a Question Arises about an Entity's Continued Existence"* accepts the premise that audit reports should be modified for going-concern uncertainties and provides operational guidance to auditors on assessing a client's likely continued existence. This statement states that while an audit does not include a search for evidential matter relating to an entity's continued existence, when an auditor becomes aware of information contrary to its continued existence, modification of the audit report might become necessary. Under SAS No. 34, the auditor has a passive responsibility in assessing an entity's continued existence. That is, the auditor is required to assess the firm's going-concern status only when contrary information is discovered during the audit of the financial statements.

Throughout its long history, the obligation to disclose going-concern uncertainties has been controversial (Jones, 1996). For instance, in 1982, the AICPA proposed to eliminate this requirement, but public opposition led this proposal to fail. In fact, there were complaints about situations in which firms had gone bankrupt without any warning about going-concern problems in the independent audit report. Literature addressing the usefulness of the audit opinion in the going-concern domain is also controversial. On the one hand, some studies suggest that independent auditor activity mitigates the information asymmetry between managers and owners given their intimate knowledge of the firm's activities and future plans (e.g., Dopuch, Holthausen, and Leftwich, 1986; Jones, 1996). On the other hand, there are also examples of studies arguing that auditor's evaluation of such uncertainties is not superior to evaluations which statement users can make (e.g., Levitan and Knoblett, 1985; Mutchler, 1985; Dopuch, Holthausen, and Leftwich, 1987).

In response to public concern, AICPA issued expectation gap standards, including SAS No. 59, *"The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern"*. In contrast to SAS No. 34, this statement requires auditors to evaluate whether substantial doubt exists about an audit client's ability to continue as a going-concern for a reasonable period, which does not exceed one year beyond the date of the financial statements being audited. SAS No. 59 increased auditors' responsibilities since it requires an explicit evaluation of a company's continued viability in every audit. The first stage in making this going-concern evaluation requires the consideration of whether the results of the audit procedures identified existing conditions and events that indicate substantial doubt about the client's ability to continue as a going-concern. Those conditions and events are divided into four categories: 1) negative trends, 2) other indications of possible financial difficulties, 3) internal matters, and 4) external matters.

When, after considering conditions and events in the aggregate, the auditor believes that substantial doubt may exist, they should consider management's plans for dealing with the effects of those conditions and events. If, after considering the conditions and events and management's plans, the auditor concludes that substantial doubt remains, the audit report should include an explanatory paragraph to reflect this uncertainty.

2.4.2. Informational content of the GCM audit report

Employing the capital-market paradigm, several studies test whether the market recognizes the importance of a going-concern report by examining the stock price reaction surrounding the GCM announcement date. I now review the studies that find no evidence of market reaction to the GCM audit report, studies that claim there is a significant market reaction to such accounting disclosures and studies that argue that market reaction depends on the ex-ante expectation of a forthcoming GCM audit report.

2.4.2.1. Evidence of no-information value

Some studies suggest that the disclosure of a going-concern audit report does not generate significant stock price reaction.[20] For instance, Elliott (1982) fails to find a significant adverse reaction to such an event during the announcement period as well as for the subsequent 14 weeks. Alternatively, he shows that significant abnormal returns are observed in the 45-week period before the GCM announcement date. However, the author recognizes that his results may be related to his event date definition (i.e., the release date of annual earnings in the Wall Street Journal). In a supplementary study, Dodd et al. (1984) use the earlier of the 10-k or annual report SEC filing dates to define the GCM announcement date. In general, their findings confirm that the publication of a GCM audit report has little impact on stock prices around the event date and that markets anticipate the GCM qualification in the pre-event period.

More recently, Herbohn, Ragunathan, and Garsden (2007) also fail to find evidence of a short-term market reaction to the publication of a first-time GCM audit report in the Australian market. Using a sample of 229 firm-year observations, the authors conclude that significant negative abnormal reaction is concentrated in the year prior to the GCM announcement. However, as the authors argue, there are some limitations in the control of their results that "*might reduce the power of our short event-windows tests*".

[20] There are also some studies claiming that stock price reaction to "subject to" opinions is not significantly different from unqualified opinions (e.g., Davis, 1982; Dodd et al., 1984). In addition, Ball et al. (1979) find that audit qualifications considered as a single group are not associated with a significant reduction in share prices.

2.4.2.2. Evidence of information value

There are several examples of studies which directly (e.g., Firth, 1978; Fleak and Wilson, 1994; Carlson, Glesen, and Benefield, 1998; Citron, Taffler, and Uang, 2008) and indirectly (e.g., Hopwood, McKeown, and Mutchler, 1989; Chen and Church, 1996; Holder-Webb and Wilkins, 2000; Willenborg and McKeown, 2001; Weber and Willenborg, 2003) provide evidence that investors acknowledge the importance of a GCM audit report disclosure.[21]

Firth (1978) finds that the publication of a going-concern report has significant impact on the prices of U.K. companies around the event date. Using a different perspective, Fields and Wilkins (1991) corroborate the notion that going-concern reports have information value by finding significant positive returns associated with the withdrawal of the going-concern report. In a more recent study, Carlson, Glesen, and Benefield (1998) improve on previous research by controlling for concurrent financial statement disclosures in their results and conclude that investors adjust stock prices following the GCM audit report announcement (usually within five days). In a recent study, Citron, Taffler, and Uang (2008) show that going-concern opinions are associated with significant negative price sensitive information in the U.K. market with no significant differences depending on when the going-concern opinion was first reported.

[21] Several studies also support the notion that audit qualifications are associated with declines in stock prices (e.g., Chow and Rice, 1982; Banks and Kinney, 1982; Dopuch et al., 1986; Frost, 1991; Choi and Jeter, 1992). For instance, Chow and Rice (1982) corroborate this conclusion using a market model including an industry factor to calculate firm-specific stock returns. Dopuch et al. (1986) claim that media disclosures of qualified opinions are associated with significant negative stock price effects and the magnitude of the abnormal returns does not depend on whether or not the firm received a similar qualification in the previous year. Frost (1991) shows that the association between qualified opinions and negative returns is robust to changes in the economic climate and to the auditing environment. Finally, Choi and Jeter (1992) conclude that market responsiveness to earnings announcements declines significantly when a qualified opinion is disclosed.

There is also indirect evidence that going-concern opinions have information value. For instance, Hopwood, McKeown, and Mutchler (1989) find that such an opinion increases the likelihood of a forthcoming bankruptcy. In addition, Chen and Church (1996) and Holder-Webb and Wilkins (2000) find that market reaction to the announcement of bankruptcy is significantly lower for firms with previous going-concern opinions compared with non-GCM firms. Chen and Church (1996) demonstrate that results are robust after controlling for the predictability of bankruptcy, whereas Holder-Webb and Wilkins (2000) find similar results after controlling for the macroeconomic environment and firm-specific levels of financial distress.

More recently, Willenborg and McKeown (2001) and Weber and Willenborg (2003) investigate the role of going-concern audit reports in micro-cap IPOs and conclude that the audit opinion is a valuable information to investors. For instance, Willenborg and McKeown (2001) find that a GCM opinion increments the predictive power of delisting IPO stocks, an event that is perceived as negative news by investors. Moreover, this study finds that GCM IPO firms significantly underperform those with no previous GCM.[22] Weber and Willenborg (2003) supplement Willenborg and McKeown's (2001) study by highlighting that larger auditors with national scope (in opposition to local firms) provide more informative opinions.

[22] Willenborg and McKeown (2001) report that the mean (median) two-year raw returns for GCM IPOs is -41% (-65%) compared with +24% (-15%) for non-GCM IPOs.

2.4.2.3. The importance of distinguish between "expected" and "unexpected" reports

One of the factors affecting the market reaction to GCM audit report announcements is the ex-ante likelihood of such an event. The distinction between "expected" and "unexpected" GCM audit reports has in fact enhanced our understanding of whether the market reacts to this bad news event. For instance, studies like Fleak and Wilson (1994) and Jones (1996) show that the market reaction to the GCM audit report critically depends on the extent to which such an event is expected.

These studies were triggered by the findings of Mutchler (1985) and Dopuch, Holthausen, and Leftwich (1987) who suggest that many going-concern qualifications simply confirm a pattern of financial deterioration that can be predicted using publicly available information.[23] For instance, Mutchler (1985) uses discriminant analysis based on the top six ratios ranked by auditors as useful identifiers of going-concern problems and concludes that such a model is able to predict a going-concern opinion with a relatively high level of accuracy. Dopuch, Holthausen, and Leftwich (1987) develop a probit model using publicly available financial and market data to predict whether an auditor will issue a fist-time qualified opinion. They show that such a model works particularly well in the case of the going-concern opinions.

Fleak and Wilson (1994) use Mutchler's (1985) model to distinguish between "unexpected" and "expected" GCM audit qualifications and show that "unexpected" qualifications are in fact associated with negative abnormal returns. However, they do not find a significant

[23] The going-concern prediction can be made using different statistical methods. Koh and Low (2004) compare the performance of different techniques such as neural networks, decision trees and logistic regression for this task. The first two techniques are considered data mining; only logistic regression can be considered a traditional statistical method. The results suggests that all three techniques give adequate results, but highlight that neural networks and decision trees can supplement and complete traditional statistic methods.

market reaction to the disclosure of unqualified opinions when such events are "expected". In a supplementary study, Jones (1996) finds significant negative (positive) abnormal returns surrounding the release of the auditor's report for firms receiving going-concern opinions (unqualified opinions). More interestingly, the author uses a logistic regression containing public information to show that the magnitude of the abnormal returns depends on the extent to which the type of opinion was expected.

Using a different approach, Blay and Geiger (2001) examine whether the magnitude of the abnormal returns surrounding the announcement of a going-concern audit report is related to the firm's subsequent viability. The authors show that the abnormal returns of viable firms are significantly lower than those of firms that subsequently filed for bankruptcy, suggesting that a GCM has a more adverse impact in the case of viable firms.

2.4.3. Medium-term reaction to the publication of a GCM audit report

In three recent papers, Taffler, Lu, and Kausar (2004), Ogneva and Subramanyam (2007) and Kausar, Taffler, and Tan (forthcoming) discuss the medium-term market reaction to disclosure of a GCM audit report. Using a sample of 108 U.K. firms with a first-time GCM audit report published between 1995 and 2000, Taffler et al. (2004) show that markets take time to assimilate the impact of such an announcement. In particular, they find that firms underperform by between 24% and 31%, depending on the adopted benchmark, in the 12-months after the information disclosure. Taffler et al. (2004) additionally show that their findings are not related to a "bad model" problem, with incorrect risk measurement or a post-earnings announcement drift phenomenon. As such, the authors suggest that investors are biased in their ability to process this bad news event "denying" the implications of a GCM audit report in the valuation of firms' stock.

Interestingly, Ogneva and Subramanyam (2007) find no evidence of an anomalous market reaction following the GCM audit report announcement in their sample of 1,159 U.S. cases between 1993 and 2004. Ogneva and Subramanyam (2007) conclude that Taffler's, Lu, and Kausar (2004) results are probably a country-specific phenomenon which may be caused by either specific institutional features or other peculiarities of the U.K. market.

Ogneva and Subramanyam's (2007) results are strongly rejected in a subsequent study by Kausar, Taffler, and Tan (forthcoming). Using a hand-collected sample from EDGAR between 1993 and 2005, this study shows a significant downward drift of -9% to -19%, depending on the benchmark model, over the one-year period subsequent to the GCM announcement date. Importantly, Kausar, Taffler, and Tan (forthcoming) suggest that Ogneva's and Subramanyam (2007) results are contaminated by the use of a highly biased sample and by the approach they take for the notional reinvestment of proceeds of delisted GCM firms.

2.4.4. Discussion

The going-concern principle is one of the most important accounting assumptions that, when questioned by external auditors, is perceived as an acute and unambiguous case of bad news. The role of the auditor's opinion in this context was reinforced over the years and nowadays auditors are required to explicitly evaluate a company's continued viability in every audit they perform.

This section summarizes studies addressing related issues highlighting three key ideas. First, most of the studies that investigate the market value of a GCM audit report conclude that users of financial statements find this disclosure to be value-relevant (e.g., Firth, 1978;

Fleak and Wilson, 1994; Carlson, Glezen, and Benefield, 1998). Second, there is also evidence that the negative reaction to the GCM audit report is significantly more severe for "unexpected" reports than for "expected" reports, emphasizing the importance of ex-ante expectations in the impact with which the market receives such news (e.g., Fleak and Wilson, 1994; Jones, 1996; Blay and Geiger, 2001). Third, there is evidence that investors do not immediately fully incorporate the implications of this bad news event (e.g., Taffler, Lu, and Kausar, 2004; Kausar, Taffler, and Tan, forthcoming).

In this context, exploring how analysts behave in the presence of going-concern problems provides original evidence about the role of security analysts in the bad news domain more generally. More specifically, I investigate if analysts, as sophisticated agents, are able to detect going-concern problems before the public disclosure of a GCM audit report and tailor their stock recommendations and coverage decisions accordingly. At a different level, my thesis explores if analysts provide investors with value-relevant information in this scenario of high distress risk by facilitating the incorporation of negative information in stock prices. Firstly, I test if pre-GCM analyst coverage contributes to reducing the "surprise" associated with the publication of a GCM audit report. Secondly, I test if post-GCM analyst coverage reduces the post-GCM announcement drift.

2.5. Key Findings

The preceding literature review highlights some important stylised facts relating to the scope and nature of my research. I now summarize the most important findings:

1. Analysts' recommendations and earnings forecasts have market impact. In general terms, the market reacts favourably (unfavourably) to recommendation upgrades

(downgrades) and reacts in the same way to upward (downward) earnings forecasts revisions.

2. Analyst activity seems to facilitate market efficiency. There is evidence that analyst coverage reduces information uncertainty and has a positive impact on the speed with which the market assimilates new information in stock prices.

3. There is also evidence that analysts are optimistic in their outputs, although the potential decrease in this bias more recently. Generally, analysts' earnings forecasts are systematically higher than actual earnings outcomes and the number of "buy" recommendations is persistently higher than the number of "sell" recommendations.

4. Research suggests that analyst optimism is not confined to healthy firms. Studies show that analysts underreact to negative information in a similar fashion to investors. Moreover, there is evidence that analysts are particularly optimistic when forecasting the earnings of distressed firms.

5. The literature identifies two broad categories of explanation to help understand analyst optimism. First, economic incentives are believed to produce conflicts of interest between brokerage firms and their clients, reducing analysts' objectivity and independence. Second, cognitive biases proposed by behavioural studies are believed to affect both sophisticated and non-sophisticated agents.

6. Some studies argue that analysts are self-selective. In particular, there is evidence that analysts tend to report on companies for which their true expectations are favourable while avoiding reporting on those for which their true expectations are unfavourable.

7. Regulatory changes introduced in the beginning of this decade in an attempt to increase investors' confidence in the integrity of financial markets and to provide them with better information to access analysts' research have impacted on analyst behaviour and market reaction to their outputs.

8. There are conflicting findings about the ability of analysts to anticipate non-routine bad news events, and how they react to the announcement of such news. Specifically, analysts use two signals to communicate negative information: downgrade of stock recommendations and coverage cessation.

9. Investors perceive the going-concern audit report as a clear signal of bad news. In particular, most studies show that the market responds negatively to this event, especially when the audit report is "unexpected".

10. There is clear evidence that the market does not immediately fully assimilate the information conveyed by the going-concern audit report, i.e., prices continue to drift down for an extended period of time following the event announcement.

2.6. Research Framework

My literature review has identified a number of important research gaps that I explore in my thesis. In broad terms, the main contribution of my research relates to the connection between two areas of the literature that have developed separately until now: the going-concern audit report and security analyst behaviour. In fact, no study to date has addressed this issue.

There are different reasons that justify the importance of investigating how analysts deal with the GCM audit report. Firstly, Schipper (1991) highlights the importance of investigating how analysts behave in extreme situations since there is evidence that optimism is more pronounced in forecasts preceded by share price declines or earnings declines. Secondly, investors seem particularly slow in assimilating negative information (e.g., Bernard and Thomas, 1989; Michaely, Thaler, and Womack, 1995; Womack, 1996; Dichev and Piotroski, 2001), a phenomenon that also occurs with the disclosure of a GCM audit report (Taffler, Lu, and Kausar, 2004; Kausar, Taffler, and Tan, forthcoming). Thirdly, little is known about how analysts deal with non-routine bad news events.

My thesis provides clear evidence on the role of security analysts in the market reaction to the publication of a GCM audit report and contributes to the accounting and finance literature in several ways. I now explicitly state the motivations and the research gaps that I cover in my thesis:

1. Prior research finds conflicting evidence about the ability of analysts to anticipate non-routine bad news events. For instance, Griffin (2003) argues that analysts are not able to anticipate firms' corrective restatements whereas Clarke et al. (2006) show that analysts respond to the financial deterioration of bankrupt firms before the event announcement. The comparison between stock recommendations for GCM and similar non-GCM firms before the publication of a GCM audit report provides a clean test to investigate the ability of analysts to anticipate non-routine bad news events. In fact, the GCM audit report provides a unique scenario to clarify this issue since it is perceived as a clear case of bad news that tends to follow a series of unfavourable economic events.

2. Existing studies suggest that analysts are reluctant to issue unfavourable recommendations (e.g., McNichols and O'Brien, 1997; Conrad et al., 2006). In addition, there is evidence that analysts are less interested in following firms associated with bad news (e.g., Griffin, 2003). As such, I provide original evidence on the nature of analyst reaction to the publication of a GCM audit report by investigating how they behave in the period surrounding the publication of a GCM audit report. In particular, I test if analysts downgrade stock recommendations for GCM firms and if they cease coverage of such stocks following the GCM announcement.

3. Previous research finds that the short-term market reaction to the publication of a GCM audit report is significantly more adverse when the report is "unexpected". In my thesis, I test whether analysts are providing investors with value-relevant information in this scenario of highly distressed firms allowing investors' recognition of going-concern problems. Considering that analysts are seen as surrogates for market expectations, I investigate if the short-term market reaction to the GCM announcement critically depends on pre-GCM analyst coverage.

4. The regulatory changes implemented at the beginning of this decade attempt to provide investors with better information to assess the quality of analyst research. Despite some evidence that these changes could represent an overreaction by regulatory authorities (e.g., Clarke et al., 2006), there is also indication of analyst optimism decrease following the implementation of such rules (e.g., Barber et al., 2006; Madureira et al., 2008). My thesis contributes to the understanding of how these regulatory changes affected analyst optimism in the specific case of financially distressed firms and whether investors were being provided with more useful and material information to make their investment decisions as a result.

5. Studies show that security analysts reduce information uncertainty and facilitate the price-discovery process (e.g., Gleason and Lee, 2003; Zhang, 2006). However, evidence that analysts do not process information efficiently, particularly when dealing with negative news, suggests the need to investigate this hypothesis in the bad news domain. By studying post-GCM price formation, I contribute to the ongoing debate of how the market assimilates bad news. In particular, I provide clear evidence about the role of analysts in the price-discovery process of highly distressed firms.

6. Prior studies show that security analysts are self-selective (e.g., McNichols and O'Brien, 1997; Das, Guo, and Zhang, 2006). In other words, analysts tend to cease (start) the coverage of companies about which they have unfavourable (favourable) views. In my thesis, I provide original evidence about analyst self-selection of GCM firms following the GCM announcement depending on firms' post-GCM return performance.

In short, my original connection between analyst behaviour, GCM audit reports and market performance contributes to the accounting and finance literature in several ways. In the next chapter, I define my sample of first-time GCM firms.

CHAPTER 3

SAMPLE SELECTION

3.1. Introduction

This chapter is divided into two parts. First, I describe my methodology to identify first-time GCM firms. Second, I provide some descriptive statistics about my sampled firms.

3.2. The first-time GCM sample

In my thesis, I work exclusively with first-time GCM firms since the information value of a continuing going-concern report is less clear than that of a first-time report (Mutchler, Hopwood, and McKeown, 1997). In fact, the literature shows that a company with a going-concern qualification in a given year is more likely to receive a qualification the next year (Mutchler, 1985). Moreover, the use of first-time GCM firms is consistent with more recent literature addressing going-concern issues (e.g., Blay and Geiger, 2001; Taffler, Lu, and Kausar, 2004; Ogneva and Subramanyam 2007; Kausar, Taffler, and Tan, forthcoming).

The sample selection process is important for two reasons. Firstly, identifying a first-time GCM company is not a straightforward process. For instance, Butler, Leone, and Willenborg (2004) find that from 1994 to 1999, 16% of cases classified as "unqualified opinion with explanatory language" in the COMPUSTAT database are clean but coded incorrectly whereas only 36% of these cases have the "going-concern" mentioned in the audit report.[24] Using Butler's, Leone, and Willenborg (2004) words, "*it seems that COMPUSTAT simply flags all audit opinions as 'modified' if they deviate in any way from a standard 'boiler plate' clean opinion*".

Secondly, the literature shows that contradictory results in some of the going-concern literature are due to the use of biased samples. For instance, Asare (1990) suggests that conflicting results about the value-relevance of audit qualifications are partially explained by the research methodologies employed to investigate the going-concern case. More recently, Kausar, Taffler and Tan (forthcoming) find that Ogneva's and Subramanyam (2007) first-time GCM sample is highly biased due to inconsistencies in the Compact Disclose-SEC database, which partially explains their problematic results.

Overall, the use of a clean sample is crucial to produce meaningful and robust results in the going-concern domain.

3.2.1. Sample selection process

Table 3.1. summarizes the sample construction process, which draws heavily on Kausar, Taffler, and Tan (forthcoming). I start by using 10k Wizard's free text search tool to explore the information on the EDGAR database and identify firms with going-concern modified audit reports from 1994 to 2005. The combination of keywords used as search strings are "raise substantial doubt" and "ability to continue as a going concern". This search identifies 29,102 audit reports and constitutes the starting point for the selection of a clean sample of first-time GCM firms between 01.01.1994 and 31.12.2005.

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[24] Cases containing no qualifying or explanatory language or containing trivial explanatory language fundamentally different from that contained in other collected opinions.

Investigating my research questions requires both accounting and market information about my sample firms. I exclude 16,866 cases where firms are not found in the CRSP/COMPUSTAT merged file. Following recent studies addressing GCM companies (e.g., Ogneva and Subramanyam, 2007; Kausar, Taffler, and Tan, forthcoming), I work exclusively with first-time GCM cases. In particular, I define a GCM audit report as first-time if a firm has not received a GCM opinion in the previous fiscal year. Through the reading of the firms' audit reports, I exclude a further 9,940 cases that were not first-time GCMs.

Next, from my 2,296 remaining cases I delete firms with insufficient accounting or market data for my purpose in the COMPUSTAT and CRSP databases, respectively. This includes: 1) companies not listed on the NYSE, AMEX and NASDAQ during the 12-months previous to the GCM date; 2) companies not trading ordinary common stocks; 3) companies with unavailable accounting information for the 2-year period before the GCM year on COMPUSTAT. After considering all these restrictions, I delete a total of 1,017 cases.

In step 4 and following Kausar, Taffler, and Tan (forthcoming), I delete cases that could potentially bias my results due to their specific characteristics. In particular, I remove companies classified as "utilities" or "financials" according to the 49 industry portfolios defined by Kenneth French. Academic studies usually exclude "utility" companies because their financial decisions are affected by specific regulations and "financial" firms since their accounting information is not comparable to that of the remaining firms. Companies classified as foreign are also deleted to ensure a consistent legal framework. Moreover, I exclude companies classified as in a "development stage" since these companies have unique characteristics and have a considerable chance of failure.[25] Lastly, I delete companies that file Chapter 11 before the audit report publication date since this filing cancels the impact of a first-time GCM audit report on market prices.

It is possible that the reporting lag between financial year end and the GCM publication date influences analyst knowledge about the going-concern status of a firm. However, for the large majority of my sample cases (95%), the GCM audit report is disclosed through the 10-K annual report, which ensures that the auditor report is released together with firm's financial statements. The only exception is when the audit opinion was amended with a going-concern modification and reported in the subsequent 10-K/A filing. For those cases, I use the 10-K/A report date as my event date. Therefore, the potential problem arising from the lag between financial year end and the GCM publication date is confined to only 5% of my sample firms. This procedure is consistent with prior research defining the GCM announcement date as the first date of publication of the audit report taken from the SEC-EDGAR database (10-K or 10-K/A filing date). Moreover, since going-concern evaluations are partly forward-looking, I use the probability of a forthcoming GCM audit report (PREDGC) computed as Mutchler (1985) as a proxy for market expectation about the going-concern status of a firm.

In the end, I identify 924 non-finance, non-utility, industry firms with first-time going-concern modified audit reports published between 01.01.1994 and 31.12.2005 with stocks listed on the NYSE, AMEX or NASDAQ and with sufficient data on COMPUSTAT.[26]

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[25] The Statements of Financial Accounting Standards (SFAS) define a development stage enterprise as a company that: 1) devotes substantially all its efforts to establishing a new business and has not begun planned operations or 2) has begun operations, but has not generated significant revenue.

[26] These 924 cases represent 871 companies.

Table 3.1.
Sample Selection Process for the First-Time GCM Audit Report

This table shows how my population of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which the auditors disclosed a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005 is derived.
The sample is obtained by using the 10k Wizard free search tool facility. The combination of keywords used for identifying my GCM cases is "raise substantial doubt" and "ability to continue as a going-concern". Conditional on a firm having data in the CRSP/COMPUSTAT merged database, I manually verify if the company has a GCM audit report in that fiscal year and if the previous fiscal year is clean in order to identify the first-time GCM companies. I then exclude all cases that filed Chapter 11 before the audit report publication date, all cases classified as development stage enterprise, foreign, utilities or financials, and cases with insufficient CRSP/COMPUSTAT data.

	N
Firm-year observations identified through 10k wizard	29.102
Firm-year observations not found in CRSP/Compustat merged	-16.866
Firm-year observations that do not constitute First-time GCM	-9.940
Firm-year observations with insufficient CRSP/COMPUSTAT data	-1.017
Firm-year observations classified as utilities or financials	-142
Firm-year observations classified as foreign	-56
Firm-year observations classified as development stage enterprise	-112
Firm-year observations filing Chapter 11 before audit report publication date	-45
First-time GCM sample cases (1994-2005)	924

3.2.2. Sample Description

I now present some descriptive statistics for my sample. I find that, from my 924 first-time GCM cases, 84 traded on the NYSE, 149 on the AMEX and 691 on the NASDAQ at the time the GCM audit report was disclosed. Table 3.2. presents the annual distribution of the GCM cases. As can be seen, there are some differences in the number of first-time GCM cases per year in my sample. However, the annual number of first-time GCM audit reports disclosed is, for most of the years, between 60 and 100 cases. The exceptions are the years of 1994, 1995, 2004 and 2005, for which the number of cases is below 60 and the years of 2001 and 2002 for which the number of cases is above 100.

Table 3.2.
Annual Distribution of the GCM cases

This table presents the distribution of going-concern modified audit reports disclosed for the first-time between 01.01.1994 and 31.12.2005 for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ.

Year	Number of cases
1994	21
1995	44
1996	62
1997	85
1998	96
1999	92
2000	69
2001	136
2002	145
2003	90
2004	38
2005	46
	924

Table 3.3. presents other characteristics of my 924 GCM firms. Panel A shows that my sample is typically composed of small companies. For instance, firms have low market capitalization (mean size = \$89.6m; median size = \$33.6m), low net sales (mean sales = \$103.7m; median sales = \$21.55m) and low total assets (mean total assets = \$120.7m; median total assets = \$25.34m). Not surprisingly, I find that my sample firms are highly financially distressed. In particular, the firms are highly loss making (mean return on assets = -63%; median return on assets = -37%), have low ability to meet short-term debt obligations (mean current ratio = 1.72; median current ratio = 1.16), and are highly leveraged, with leverage defined as total debt/total assets (mean leverage ratio = 38%; median leverage ratio = 32%). Additionally, the mean (median) Altman (1968) z-score is 1.15 (0.93), well below the reference cut-off score of 1.81, indicating a high probability of failure in the near future. The mean (median) score of the discriminant model that predicts

a forthcoming GCM audit report (PREDGC) is 0.20 (0.01), suggesting that my GCM firms are close to the cut off score of 0.01 that I use to distinguish "expected" from "unexpected" events.[27] The mean (median) book-to-market ratio (BM) is 0.77 (0.40), showing that book value per share is low relative to the stock price. Finally, momentum indicates that mean (median) monthly past returns is -4% (-4%).

Panel B of table 3.3. indicates that almost 85% of my GCM firms have positive book value of equity. In addition, I find that only 7.8% of them report positive earnings in the year preceding the publication of a GCM audit report and that only 2.5% pay dividends. Importantly, 45.7% of my companies are delisted within the one-year period subsequent to the GCM announcement date. From these 422 cases, I find that 43 cases (10.2% of the total delisted firms) enter into bankruptcy/liquidation (delisting codes: 400, 572, 574) within the same period.[28] The data analysis also reveals that 67.5% of firms are audited by the one of the five audit companies that dominate the supply of audit services worldwide (BIG5). Finally, I find 171 firms that do not receive a GCM audit report in the following fiscal year.

Overall, consistent with prior studies (e.g., Ogneva and Subramanyan, 2007; Kausar, Taffler, and Tan, forthcoming) my 924 sample firms are characterized mainly by small market capitalization and by high levels of distress risk. The next chapter initiates the empirical analysis to investigate how analysts deal with the GCM event.

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[27] The probability of a GCM audit report (PREDGC) is based on the multiple discriminant model used by Mutchler (1985), Fleak and Wilson (1994) and Blay and Geiger (2001). The discriminant model typically minimizes the classification error based on an auditor's decision of issuing/not issuing a GCM audit report. However, since I work exclusively with GCM firms, I follow Blay and Geiger (2001) and use Fleak's and Wilson (1994) minimum cut off score of 0.01 to distinguish "expected" from "unexpected" reports.

[28] Besides bankruptcy/liquidation, firms delisted within the one year-period subsequent to the GCM date are associated with 1) mergers (13.7% of the total delisted firms); 2) price below acceptable level to maintain listing (18.5% of the total delisted firms); 3) insufficient capital/equity (7.3% of the total delisted firms); 4) insufficient float or assets (16.6% of the total delisted firms); 5) violation of stock exchange financial guidelines for continued listing (18.0% of the total delisted firms). The remaining cases relate to other performance reasons.

Table 3.3.
Descriptive Statistics – Sample Firms

This table presents the descriptive statistics of my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which the auditors disclosed a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Panel A reports continuous financial variables and Panel B other firms characteristics.

Panel A: Continuous variables

Variable	Mean	Median	St. Deviation
SIZE	89.57	33.66	167.08
SALES	103.68	21.55	227.20
TA	120.68	25.34	283.01
ROA	-0.63	-0.37	0.76
CR	1.72	1.16	1.71
LEV	0.38	0.32	0.31
ZSCORE	1.15	0.93	1.10
PREDGC	0.20	0.01	2.84
BM	0.77	0.40	1.23
MOM	-0.04	-0.04	0.07

SIZE = market value of equity measured by market capitalization in $ million; SALES = sales in $ million; TA = total assets in $ million; ROA=return on assets (net income/total assets); CR = current ratio (current assets/current liabilities); LEV=total debt/total assets; ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985). All variables are computed with data taken from the last annual financial accounts reported before the GCM date. BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM = momentum, defined as the monthly average of prior 11 months (t-12 to t-2) raw returns.

Panel B: Other characteristics

Variable	Number of positive cases	% of sample
EQUITY	781	84.5
EPS	72	7.8
DIVID	23	2.5
DEAD	43	4.7
DELIST	422	45.7
AUDITOR	624	67.5
GCMW	171	18.5

EQUITY = book value of equity dummy (1 if positive, 0 othewise); EPS = earnings per share dummy (1 if positive EPS, 0 othewise); DIVID = dividend paid (1 if dividend paid, 0 othewise). All variables are computed with data taken from the last annual financial accounts reported before the GCM date. DEAD = bankruptcy dummy (1 if the firm enters into Chapter 7, Chapter 11, voluntary liquidation or is wound up within one year of the audit report date, 0 otherwise); DELIST = delist dummy (1 if the firm is delisted due to any reason within one year of the audit report date, 0 otherwise); AUDITOR = audit quality proxy dummy (1 if BIG5, 0 otherwise); GCMW = going-concern withdrawn dummy (1 if the firm receives a non-GCM opinion within one year, 0 otherwise).

CHAPTER 4

ANALYSTS' ANTICIPATION AND REACTION TO THE PUBLICATION OF A GCM AUDIT REPORT

4.1. Introduction

Security analysts have long been seen as sophisticated processors of financial information who are less likely to misunderstand the implications of such information when compared to naïve investors (Ramnath, Rock, and Shane, 2008). Analyst activity aims primarily at anticipating changes in companies' fundamentals and reacting to news or/and companies' reports (Michaely and Womack, 2005). As such, analyst activity is vital for the average investor given his/her limited time, skill and resources to analyse and interpret financial information (Beaver, 2002).

Despite the importance of security analysts to the functioning of financial markets, there is evidence that they do not process information efficiently, a phenomenon that is particularly evident in the bad news domain. For instance, analysts seem to underreact to negative information (e.g., Amir and Ganzach, 1992; Easterwood and Nutt, 1999) and are likely to be optimistic when forecasting earnings of distressed firms (e.g., Moses, 1990; Brown, 1997; Das, Guo, and Zhang, 1998; Lim, 2001; Espahbodi, Dugar, and Tehranian, 2001; Ding, Charoenwong, and Seethoh, 2004). This chapter investigates whether security analysts are efficient processors of information related to going-concern problems. More specifically, I test if security analysts anticipate the publication of a GCM audit report and whether or not they react to such an event.

This is important because the evidence about the ability of analysts to anticipate bad news is mixed. On the one hand, studies suggest that analysts fail to anticipate earnings declines associated with high accruals, and that they do not revise their forecasts in anticipation of predictable accrual reversals (Bradshaw, Richardson, and Sloan, 2001; Teoh and Wong, 2002; Barth and Hutton, 2004). In addition, Griffin (2003) fails to find a significant downward revision in analyst forecasts before a corrective restatement. On the other hand, studies suggest that analysts are able to anticipate some types of accounting fraud before they become publicly known (e.g., Dechow, Sloan, and Sweeney, 1996; Cotter and Young, 2007). In a recent study, Clarke et al. (2006) show that analysts downgrade more aggressively the stock recommendations for bankrupt firms than similar non-bankrupt firms, prior to the bankruptcy announcement date.

Investigating the ability of analysts to anticipate the publication of a GCM audit report offers a powerful context in which to explore the bad news issue since: 1) going-concern qualifications tend to follow a series of unfavourable economic events, such as sales declines, failures to make payments on debt, dividend reductions, production problems, lost contracts and quarterly losses (Elliot, 1982); 2) there is evidence that the GCM audit opinion can be predicted, to some extent, using accounting information (e.g., Mutchler, 1985; Dopuch, Holthause, and Leftwich, 1987); 3) there is evidence that the impact of the GCM announcement depends on the extent to which the GCM audit report was expected (e.g., Fleak and Wilson, 1994; Jones, 1996). Investigating whether or not analysts react to the publication of a GCM audit report provides a comprehensive overview of analyst behaviour about GCM firms.

The remainder of this chapter is organized as follows: section 2 describes the data and the methodology of the chapter. Section 3 provides the results and section 4 summarizes and discusses the results of the chapter.

4.2. Data and methodology

4.2.1. Data

I study analyst anticipation and reaction to the announcement of a GCM audit report using one of their most important information transmission vehicles: analysts' recommendations. In fact, analysts' recommendations have unique characteristics since: 1) they represent a clear and unequivocal course of action to investors (Elton, Gruber, and Grossman, 1986); 2) they are viewed as the bottom line of the research report (e.g., Shipper, 1991); 3) they are reported on a simple and finite scale common to all stocks, avoiding ambiguous interpretations of information (McNichols and O'Brien, 1997). In the words of Jegadeesh et al. (2004), *"recommendations offer a unique opportunity to study analyst judgment and preferences across large samples of stocks"*.

I collect analyst recommendations from the Institutional Broker Estimates System (I/B/E/S) database and accounting and market data from COMPUSTAT and CRSP, respectively. The I/B/E/S Recommendations database starts in October 1993 and contains, among other information, recommendations from a wide range of brokerage firms.[29] I follow the I/B/E/S recommendations ranking scheme, which codes recommendations on a five-point scale: (1) "strong buy"; (2) "buy"; (3) "hold"; (4) "underperform"; (5) "sell".[30] It should be noted that the I/B/E/S codification maps each broker's recommendation into one of their standard ratings using an assigned numerical value, mitigating the problem of different ratings provided by different brokers.

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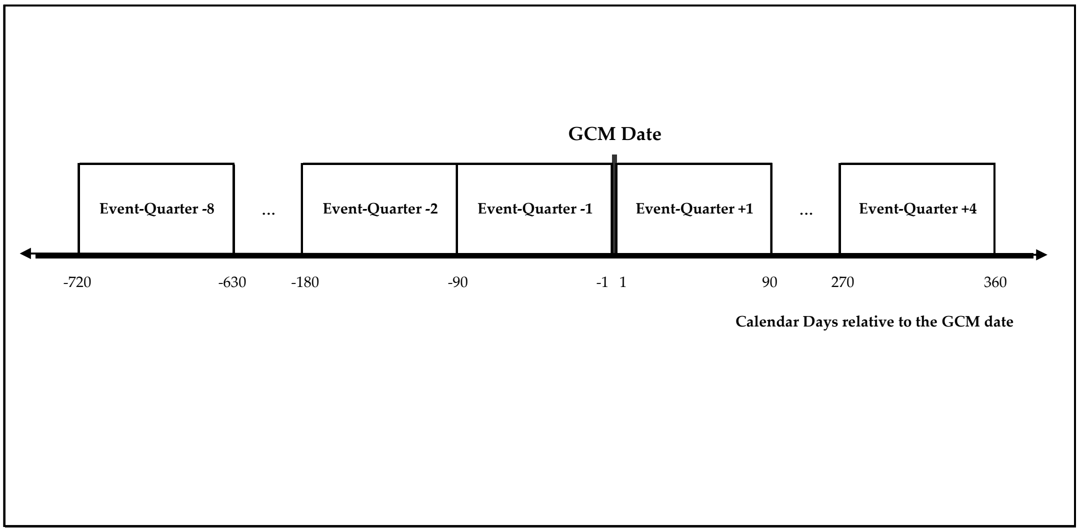
[29] I/B/E/S provides consensus and detail forecasts from security analysts, including earnings per share, revenue, cash flow, long-term growth projections and stock recommendations.

[30] Because I/B/E/S codes "strong buy" recommendations as 1 and "sell" as 5, more optimistic recommendations have lower numerical values.

Stock recommendations for my sample firms are obtained through the intersection of my 924 first-time GCM companies with those firms included on the I/B/E/S database. I obtain the following information for each analyst stock recommendation: recommendation date; broker identification; analyst identification and I/B/E/S recommendation code. Following Zhang (forthcoming), I delete observations with zero analyst-specific identification code.[31] My final data consists of 3,395 recommendations issued by 1,289 different security analysts for 463 sample firms from event-quarter -8 to event quarter +4. Event-quarters are defined as periods of 90 calendar days relative to the GCM announcement date as illustrated in figure 4.1. For example, event-quarter -1 is the period between the calendar day -1 and calendar day -90 relative to the GCM date and event-quarter -2 is the period between the calendar day -91 and calendar day -180 relative to the GCM date.

Figure 4.1.
Event-Quarter Definition

This figure graphs the definition of event-quarters relative to the GCM announcement date taken from the SEC-EDGAR database. Event-quarters are defined as a period of 90 calendar days relative to the GCM announcement date (day 0).



[31] I/B/E/S assigns a zero identification code if the broker did not provide an analyst name to be associated with the recommendation.

4.2.2. Methodology

In this section, I describe how the three different recommendation categories used in my analysis are defined. In addition, I describe the tests used to investigate whether analysts anticipate and react to the publication of a GCM audit report.

4.2.2.1. Recommendation categories

Following Clarke et al. (2006), I use different categories of recommendations to test the robustness of my results. In fact, working exclusively with recommendations readily obtained from the I/B/E/S database ignores analyst opinions when no recommendations are available for a specific time period. There are two reasons for a missing recommendation: 1) the analyst did not issue a recommendation or 2) the analyst decided to cease coverage of the company. These reasons are fundamentally different and have distinct interpretations. Accordingly, I use three recommendation categories to mitigate this problem: a) reported recommendations; b) current recommendations; c) inferred recommendations.

Next, I describe how I compute each recommendation category on an event-quarterly basis.

a) Reported recommendations

Reported recommendations are those made and issued by the analyst and are readily available on the I/B/E/S Recommendations – Detail File. I define analyst *i* reported recommendation for firm *j* at event-quarter *q* ($REPREC_{i,j,q}$) as: 1) the last recommendation issued by analyst *i* within event-quarter *q*, if he/she does not drop the coverage of firm *j* after the last recommendation date; 2) no recommendation, if analyst *i* does not issue a new recommendation within event-quarter *q* or if analyst *i* decides to drop the coverage of firm *j* after the last recommendation date within event-quarter *q*.

The reported recommendation for firm *j* at event-quarter *q* ($REPREC_{j,q}$) is then calculated as the simple average of analyst reported recommendations for firm *j* at event-quarter *q*, mathematically:

$$REPREC_{j,q} = \frac{1}{N} \sum_{i=1}^{N} REPREC_{i,j,q} \tag{4.1}$$

where *N* is the number of analysts with available reported recommendations at event-quarter *q* for firm *j*.

Finally, I define firms' average reported recommendations at quarter *q* as follows:

$$REPREC_{q} = \frac{1}{M} \sum_{j=1}^{M} REPREC_{j,q} \tag{4.2}$$

where *M* is the number of firms with available reported recommendations in event-quarter *q*.

b) Current recommendations

Current recommendations are similar to reported recommendations but with a major difference. In particular, for those cases where a missing recommendation for a given event-quarter is not due to the analyst decision to drop coverage,[32] I assume that the last reported recommendation still applies to the current event-quarter. Specifically, I define analyst *i's* current recommendation for firm *j* at event-quarter *q* ($CURREC_{i,j,q}$) as: 1) the last reported recommendation issued by analyst *i* if he/she does not decide to drop the coverage of firm *j* after the last recommendation date; 2) no recommendation, if analyst *i* decides to drop the coverage of firm *j* after the last recommendation date.

The current recommendation for firm *j* at event-quarter *q* ($CURREC_{j,q}$) is then calculated as the average of analyst current recommendations for firm *j* at event-quarter *q*, mathematically:

$$CURREC_{j,q} = \frac{1}{N}\sum_{i=1}^{N} CURREC_{i,j,q} \tag{4.3}$$

where *N* is the number of analysts with available current recommendations at event-quarter *q* for firm *j*.

Finally, I define firms' average current recommendations in event-quarter *q* as follows:

[32] The date on which a particular analyst stopped coverage for a particular firm is taken from the I/B/E/S Recommendations – Stopped Estimates File.

$$CURREC_q = \frac{1}{M}\sum_{j=1}^{M} CURREC_{j,q} \tag{4.4}$$

where M is the number of firms with available current recommendations at event-quarter q.

c) Inferred recommendations

Analysts generally remain at the same brokerage company after deciding to stop covering a given firm (Clarke et al., 2006). Additionally, we know that they are reluctant to issue unfavourable investment advice (McNichols and O'Brien, 1997). As such, the decision to cease coverage of a firm is likely to be associated with unfavourable information available to the analyst about the firm's future prospects. Inferred recommendations are estimated in my study with the objective of capturing this phenomenon. In particular, inferred recommendations are similar to current recommendations with one difference. When an analyst ceases coverage of a firm, I infer an unfavourable recommendation for that event-quarter and for the subsequent two event-quarters.[33]

Drawing on Clarke et al. (2006), I define analyst i's inferred recommendation for firm j at event-quarter q ($INFREC_{i,j,q}$) as: 1) the last current recommendation issued by analyst i if he/she does not decide to drop the coverage of firm j after the last recommendation date; 2) an "underperform" recommendation if analyst i decides to drop the coverage of firm j within event-quarter q or the last two event-quarters and if the last recommendation issued by the analyst prior to coverage cessation is a "strong buy" or a "buy"; 3) a "sell"

[33] I limit the inferring of the unfavourable recommendation to the two event-quarters following coverage cease given the evidence that the impact of a recommendation change may last 6-month (Womack, 1996).

recommendation if analyst i decides to drop the coverage of firm j within event-quarter q or the last two event-quarters and if the last recommendation issued by the analyst prior to the coverage cessation is a "hold", "underperform" or "sell"; 4) no recommendation, if analyst i decided to drop the coverage of firm j for more than two event-quarters.

The inferred recommendation for firm j at event-quarter q ($INFREC_{j,q}$) is then calculated as the average of analyst inferred recommendations for firm j at event-quarter q, mathematically:

$$INFREC_{j,q} = \frac{1}{N}\sum_{i=1}^{N} INFREC_{i,j,q} \tag{4.5}$$

where N is the number of analysts with available inferred recommendations at event-quarter q for firm j.

Finally, I define firms' average inferred recommendations at event-quarter q as follows:

$$INFREC_{q} = \frac{1}{M}\sum_{j=1}^{M} INFREC_{j,q} \tag{4.6}$$

where M is the number of firms with available inferred recommendations at event-quarter q.

4.2.2.2. Testing analyst anticipation and reaction to the GCM audit report

I investigate analyst anticipation of the GCM audit report by comparing analyst recommendations for GCM and similar non-GCM firms over the 8 event-quarters preceding the GCM date in a similar fashion to Clarke et al. (2006). In particular, I test the significance of the differences in analyst mean and median recommendations and percentage of "buy" recommendations between sample and control firms using the two-tailed t-test, the Wilcoxon-Mann-Whitney test and the binomial test, respectively.

Analyst reaction to the publication of a GCM audit report is investigated through the comparison of analyst recommendations for my sample firms before and after the GCM date. Specifically, I compare analyst stock recommendations for GCM firms between event-quarter -1 and event-quarter +1. I focus my attention on a shorter period surrounding the GCM announcement date since analyst reaction (if any) should occur shortly after the event becomes publicly known. Similarly as above, I test the significance of the differences in analyst mean and median recommendations and percentage of "buy" recommendations for GCM firms in event-quarter -1 and event-quarter +1 using the two-tailed t-test, the Wilcoxon-Mann-Whitney test and the binomial test, respectively.

4.3. Results

4.3.1. Initial evidence

Table 4.1. presents the quarterly trend for stock recommendations of GCM firms from event-quarter -8 to event-quarter +4. Panel A summarizes analyst coverage over this period, where firms are classified as covered in event-quarter *q* if there is at least one recommendation available within that period. To provide robust results, I use the three recommendation categories mentioned above. Broadly, reported recommendations assume the last recommendation issued by the analyst within each event-quarter. Current recommendations assume the last recommendation issued by the analyst if he/she does not decide to cease coverage of the company whereas inferred recommendations also assume an unfavourable recommendation when the analyst decides to cease coverage of the company.

My results show that the number of GCM firms with analyst coverage remains stable until the event-quarter preceding the GCM announcement date. In this particular event-quarter, there is a sharp decrease in the number of firms with analyst coverage and in the number of recommendations available. For instance, the number of reported (current) recommendations decreases from 349 (1,147) in the event-quarter -2 to 208 (966) in the event-quarter -1 whereas the number of firms with available reported (current) recommendations decreases from 159 (371) to 118 (353) in the same period. Moreover, the comparison between firms with available current recommendations in event-quarter -4 and event-quarter -1 reveals that 52 companies stopped being covered. Not surprisingly, panel A also shows that coverage cessation is more frequent after the GCM announcement date, a result that is partially explained by the number of firms delisted in that period.

Panel B of table 4.1. reports event-quarter mean and median recommendations for GCM firms and the percentage of firms with "buy" and "sell" recommendations around the GCM date. As can be seen, analysts downgrade the stock recommendations for GCM firms as the GCM date approaches. For instance, the mean (median) reported recommendation for GCM firms increases from 1.99 (2.00) to 2.70 (3.00) from event-quarter -8 to event-quarter -1. Moreover, the percentage of firms for which their average reported recommendation is classified as "buy" ("sell") decreases (increases) from 69% (3%) to 33% (17%) over the same period. The analysis of current and inferred recommendations shows that this pattern is robust.

Taken together, the results in table 4.1. suggest that security analysts do not ignore the going-concern problems of GCM firms and adjust their recommendations and their decision to cover such firms accordingly.

TABLE 4.1.
Quarterly Trend in Analyst stock Recommendations – Sample Firms

This table presents the event-quarter trend in analyst recommendations from event-quarter -8 to event-quarter +4 for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
Average reported recommendation for firm j at event-quarter q ($REPREC_{j,q}$) is the average of the last recommendation issued by each analyst within that period. Firms' reported recommendation at event-quarter q ($REPREC_{q}$) is then calculated as the average of ($REPREC_{j,q}$). Average current recommendation for firm j at event-quarter q ($CURREC_{j,q}$) is the average of the last recommendation issued by each analyst when he/she does not cease coverage of the firm before the end of that period. Firms' current recommendation at event-quarter q ($CURREC_{q}$) is then calculated as the average of ($CURREC_{j,q}$). Average inferred recommendation for firm j at event-quarter q ($INFREC_{j,q}$) is similar to the average current recommendation with one difference. When an analyst ceases coverage of a company within event-quarter q after the last recommendation date, I infer an unfavourable recommendation for event-quarter q and for the subsequent two event-quarters. Firms' inferred recommendation at event-quarter q ($INFREC_{q}$) is then calculated as the average of ($INFREC_{j,q}$). Section 4.2.2.1. provides detailed explanation about the estimation of the recommendation categories. Event-quarters are defined as periods of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).
Panel A summarizes analyst coverage. Number of recommendations provides the total number of estimated recommendations available over the event-quarters. Number of firms provides the number of GCM companies with available recommendations over the event-quarters. The number of recommendations per firm is computed as the number of recommendations to the number of firms. Panel B summarizes analyst recommendations for GCM firms. The percentage of "buy" ("sell") recommendations is computed as the number of firms whose average recommendation is classified as a "buy" ("sell") divided by the total number of firms with available recommendations. Specifically, firms are classified as "buy" ("sell") if the average numerical recommendation is below (above) 2.5 (3.5).

Panel A: Analyst coverage summary

Event-Quarter	Number of Recommendations (A)			Number of Firms (B)			Number of Rec. per Firm (A)/(B)		
	Reported	Current	Inferred	Reported	Current	Inferred	Reported	Current	Inferred
-8	380	1,025	1,025	180	347	347	2.11	2.95	2.95
-7	453	1,199	1,287	211	385	397	2.15	3.11	3.24
-6	427	1,298	1,520	204	404	434	2.09	3.21	3.50
-5	418	1,343	1,709	194	407	458	2.15	3.30	3.73
-4	377	1,350	1,785	189	405	462	1.99	3.33	3.86
-3	359	1,277	1,794	158	391	464	2.27	3.27	3.87
-2	349	1,147	1,754	159	371	460	2.19	3.09	3.81
-1	208	966	1,666	118	353	446	1.76	2.74	3.74
1	140	780	1,538	85	310	429	1.65	2.52	3.59
2	108	665	1,341	67	277	398	1.61	2.40	3.37
3	87	593	1,145	56	256	379	1.55	2.32	3.02
4	89	526	952	55	227	337	1.62	2.32	2.82

Panel B: Analyst recommendations summary

Event-Quarter	GCM firm recommendation rating						% BUY and % SELL recommendations					
	Reported ($REPREC_q$)		Current ($CURREC_q$)		Inferred ($INFREC_q$)		Reported ($REPREC_q$)		Current ($CURREC_q$)		Inferred ($INFREC_q$)	
	Mean	Median	Mean	Median	Mean	Median	% Buy	% Sell	% Buy	% Sell	% Buy	% Sell
-8	1.99	2.00	2.05	2.00	2.05	2.00	0.69	0.03	0.69	0.05	0.69	0.05
-7	2.16	2.00	2.09	2.00	2.22	2.00	0.64	0.03	0.68	0.04	0.62	0.09
-6	2.09	2.00	2.10	2.00	2.39	2.33	0.67	0.03	0.67	0.04	0.54	0.13
-5	2.20	2.00	2.15	2.00	2.57	2.50	0.61	0.06	0.65	0.04	0.46	0.19
-4	2.32	2.00	2.20	2.00	2.66	2.67	0.55	0.06	0.62	0.04	0.41	0.21
-3	2.63	2.79	2.31	2.25	2.81	3.00	0.39	0.15	0.57	0.06	0.34	0.28
-2	2.68	3.00	2.37	2.40	2.95	3.00	0.32	0.15	0.51	0.07	0.28	0.35
-1	2.70	3.00	2.44	2.50	3.09	3.21	0.33	0.17	0.44	0.09	0.22	0.41
1	2.68	3.00	2.44	2.50	3.18	3.43	0.39	0.17	0.45	0.10	0.21	0.49
2	2.52	2.00	2.44	2.50	3.21	3.50	0.54	0.19	0.49	0.11	0.22	0.52
3	2.45	2.27	2.46	2.33	3.21	3.40	0.52	0.12	0.51	0.11	0.23	0.50
4	2.21	2.00	2.38	2.25	3.14	3.33	0.62	0.15	0.53	0.09	0.27	0.47

4.3.2. Analyst anticipation of the GCM audit report

Table 4.1. shows the analysts become more pessimistic about GCM firms as the GCM event date approaches. However, investigating the ability of these market participants to anticipate the GCM audit report by solely studying stock recommendations for GCM firms might introduce a selection bias since security analysts cannot know ex-ante which firms will receive a GCM audit report. Drawing on Clarke et al. (2006), I mitigate this problem by comparing analyst stock recommendations across GCM and similar non-GCM firms. As Clarke et al. (2006) argue, "*This comparison of recommendations for sample firms against their matched firm counterparts allows us to control any possible selection bias and permits useful conclusions regarding the nature of analyst recommendations for financially distressed firms*".

In my main results, I identify my control firms by matching each of my sample firms with the firm with most similar size and book-to-market (BM) ratio at one year period before the GCM announcement. This procedure is commonly used in the literature (e.g., Fama and French, 1992) and aims at matching each sample firm with a "similar" control firm in terms of risk/return at a specific date. It is arguable that in my case, the introduction of an additional matching distress factor would be also appropriate given my focus on an unusually bad news situation. However, most of the studies addressing similar issues in the financial distress domain use size and BM as their main control firm selection criteria (Dichev and Piotroski, 2001; Taffler, Lu, and Kausar, 2004; Ogneva and Subramanyam, 2007; Kausar, Taffler, and Tan, forthcoming). As such, although I use size and BM ratios as my main benchmark firm matching criteria, I also provide extensive robustness tests re-running my analysis using variables that account specifically for distress risk as control measures.

Moreover, there are other reasons justifying the importance matching my sample firms with similar firms in terms of size and BM ratio. For instance, size is one of the most important variables associated with stock returns (e.g., Banz, 1981; Keim, 1983, Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). Generally, research suggests that small firm stocks experience different returns from large firm stocks, a phenomenon that is particularly important in my setting since my sample firms usually have a small market value. In addition, the literature suggests that analyst coverage is strongly correlated with firm size (e.g., Bhushan, 1989; Hong, Lim, and Stein, 2000), highlighting that size proxies for level of analyst coverage. BM ratio has also demonstrated ability to predict stock returns. For instance, Fama and French (1992) find a significant positive correlation between the expected return of a firm and its BM ratio. These findings are further supported by Rosenberg, Reid, and Lanstein (1985) and Lakonishok, Shleifer, and Vishny (1994). In addition, Jegadeesh et al. (2004) show that analysts tend to favour "growth" stocks compared to "value" stocks, which again highlights the importance of benchmarking my GCM firms with non-GCM firms sharing a similar BM ratio.

I identify my 924 non-GCM control firms by matching each of my sample firms with the company with most similar size and BM ratio. This process is as follows. First, for each sample firm, I identify all non-financial, non-utility and non-GCM firms listed on the NYSE, AMEX and NASDAQ at the GCM announcement date. Sample and match candidate size is defined as market capitalization (shares outstanding times price) at one year before the GCM announcement.[34] Subsequently, among the match candidates for each sample firm, I identify those with a market value between 70% and 130% of the sample firm. Finally, from this list of candidates, I choose as a control firm the firm which has the

[34] I also measure the market value o for sample and control firms six and one month before the GCM announcement date to ensure the robustness of my results. Results are materially the same.

closest BM ratio to that of my GCM firm. Fama and French (1992, 1993) argue that it is important to ensure that accounting variables are known before the market variables they are paired to. As such, the book-value of equity is that taken from the last annual accounts reported before the date used to calculate the market value of equity.

Table 4.2. compares the descriptive statistics between my 924 GCM firms and their control firms. As expected, there are no significant differences between the mean and median size and BM ratio, which are the criteria used to match each of my GCM firms. However, there are significant differences in the other variables presented in table 4.2. For instance, GCM firms have a significant more negative return on assets (mean ROA_{GCM}=-0.63; mean $ROA_{CONTROL}$=-0.17, $p<0.0001$ and median ROA_{GCM}=-0.37; median $ROA_{CONTROL}$=-0.01, $p<0.0001$). Not surprisingly, GCM firms are associated with greater bankruptcy risk (mean $ZSCORE_{GCM}$=1.15; mean $ZSCORE_{CONTROL}$=1.52, $p<0.0001$ and median $ZSCORE_{GCM}$=0.93; median $ZSCORE_{CONTROL}$=1.22, $p<0.0001$) and greater ex-ante GCM probability (mean $PREDGC_{GCM}$=0.20; mean $PREDGC_{CONTROL}$=2.08, $p<0.0001$ and median $PREDGC_{GCM}$=0.01; median $PREDGC_{CONTROL}$=0.57, $p<0.0001$). Importantly, my GCM firms have significantly more negative past raw returns than control firms (mean MOM_{GCM}=-0.04; mean $MOM_{CONTROL}$=0.02, $p<0.0001$ and median MOM_{GCM}=-0.04; median $MOM_{CONTROL}$=0.01, $p<0.0001$). These results show that my GCM firms are associated with higher levels of financial distress and have worst past return performance, highlighting the need to control my results for these variables.[35]

I now empirically test if there are significant differences between my GCM firms and non-GCM firms sharing similar size and BT ratio. The formal null hypothesis to test is as follows:

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[35] Chapter 5 addresses these issues.

H1: In the pre-event period, there is no difference in analyst mean and median recommendations and percentage of "buy" recommendations between firms that receive a GCM audit report and similar firms that do not receive a GCM audit report.

Table 4.3. summarizes my results. I find no significant differences between mean and median stock recommendations for GCM and non-GCM firms from event-quarter -8 to event-quarter -5. Moreover, the difference between the percentage of sample and control firms for which the average recommendation is classified as "buy" is not significant at conventional levels. Importantly, these findings are consistent across all three different recommendation categories I consider. These results suggest that analysts are advising investors to buy both GCM and non-GCM firm stocks in the most distant event-quarters, a fact emphasised by the high percentage of firms for which their average recommendation is "buy" (above 60% for the large majority of quarters). As such, I conclude that approximately two years before the event, analysts do not distinguish GCM from control firms, sharing similar expectations for both types of firms.

The analysis of the most recent event-quarters reveals a different pattern. Table 4.2. shows that starting from event-quarter -4, the average stock recommendation for GCM firms becomes significantly more unfavourable than that of non-GCM firms. Broadly, analysts downgrade their stock recommendations for GCM firms from "buy" to "hold" while maintaining their recommendations for the control firms. More importantly, the differences in the mean and median stock recommendations between groups are now statistically significant at the 0.1% level in most cases. Once again, the results are materially the same for all the three different recommendation categories I consider. As an example, consider the reported recommendations for quarter -1. The mean (median) recommendation for GCM firms is 2.70 (3.00) whereas the mean (median) recommendation for non-GCM firms is 1.90 (2.00), with these differences both significant at the 0.1% level. In addition, only 33% of GCM firms have their average recommendation classified as “buy” in contrast with the 75% for the control firms (difference significant at the 0.1% level). These results suggest that analysts recognize the going-concern problems as the GCM date approaches and downgrade their recommendations for GCM firms more aggressively than the recommendations of control firms.

Overall, my results show that the growing pessimism of analysts as the event date approaches is an exclusive phenomenon of my sample firms. As such, I conclude that analysts anticipate the publication of a GCM audit report and reject null hypothesis H1.

TABLE 4.2.
Descriptive Statistics – Sample Firms vs. Control Firms

This table presents descriptive statistics for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005 and for control firms. Control firms are selected employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm. Results are reported separately. The last four columns report the mean and median differences between the variables of each portfolio. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets on the right of the mean (median) differences.

Variable	GCM FIRMS (n = 924)			CONTROL FIRMS (n = 924)			Mean Diference	p-value	Median Diference	p-value
	Mean	Median	St. Deviation	Mean	Median	St. Deviation				
SIZE	89.57	33.66	167.08	90.88	33.62	184.36	-1.31	(0.8727)	0.04	(0.6924)
SALES	103.68	21.55	227.20	144.14	30.58	330.11	-40.46	(0.0022)	-9.03	(<0.0001)
TA	120.68	25.34	283.01	119.74	30.65	255.18	0.94	(0.9404)	-5.31	(0.0095)
ROA	-0.63	-0.37	0.76	-0.17	-0.01	0.43	-0.46	(<0.0001)	-0.36	(<0.0001)
CR	1.72	1.16	1.71	3.07	2.07	3.33	-1.35	(<0.0001)	-0.91	(<0.0001)
LEV	0.38	0.32	0.31	0.28	0.22	0.25	0.10	(<0.0001)	0.10	(<0.0001)
ZSCORE	1.15	0.93	1.10	1.52	1.22	1.46	-0.37	(<0.0001)	-0.29	(<0.0001)
PREDGC	0.20	0.01	2.84	2.08	0.57	6.76	-1.88	(<0.0001)	-0.56	(<0.0001)
BM	0.77	0.40	1.23	0.77	0.40	1.14	0.00	(0.9825)	0.00	(0.8670)
MOM	-0.04	-0.04	0.07	0.02	0.01	0.07	-0.06	(<0.0001)	-0.05	(<0.0001)

SIZE = market value of equity measured by market capitalization in $ million; SALES = sales in $ million; TA = total assets in $ million; ROA=return on assets (net income/total assets); CR = current ratio (current assets/current liabilities); LEV=total debt/total assets; ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985). All variables are computed with data taken from the last annual financial accounts reported before the GCM date. BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM = momentum, defined as the monthly average of prior 11 months (t-12 to t-2) raw returns.

TABLE 4.3.
Quarterly Trend in Analyst stock Recommendations – Sample Firms vs. Control Firms

This table presents the event-quarter trend in analyst stock recommendations from event-quarter -8 to event-quarter -1 for my population of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005 and for control firms. Control firms are selected employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.

Average reported recommendation for firm j at event-quarter q ($REPREC_{j,q}$) is the average of the last recommendation issued by each analyst within that period. Firms' reported recommendation at event-quarter q ($REPREC_{q}$) is then calculated as the average of ($REPREC_{j,q}$). Average current recommendation for firm j at event-quarter q ($CURREC_{j,q}$) is the average of the last recommendation issued by each analyst when he/she does not cease coverage of the firm before the end of that period. Firms' current recommendation at event-quarter q ($CURREC_{q}$) is then calculated as the average of ($CURREC_{j,q}$). Average inferred recommendation for firm j at event-quarter q ($INFREC_{j,q}$) is similar to the average current recommendation with one difference. When an analyst ceases coverage of a company within event-quarter q after the last recommendation date, I infer an unfavourable recommendation for event-quarter q and for the subsequent two event-quarters. Firms' inferred recommendation at event-quarter q ($INFREC_{q}$) is then calculated as the average of ($INFREC_{j,q}$). Section 4.2.2.1. provides detailed explanation about the estimation of the recommendation categories. Event-quarters are defined as a period of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).

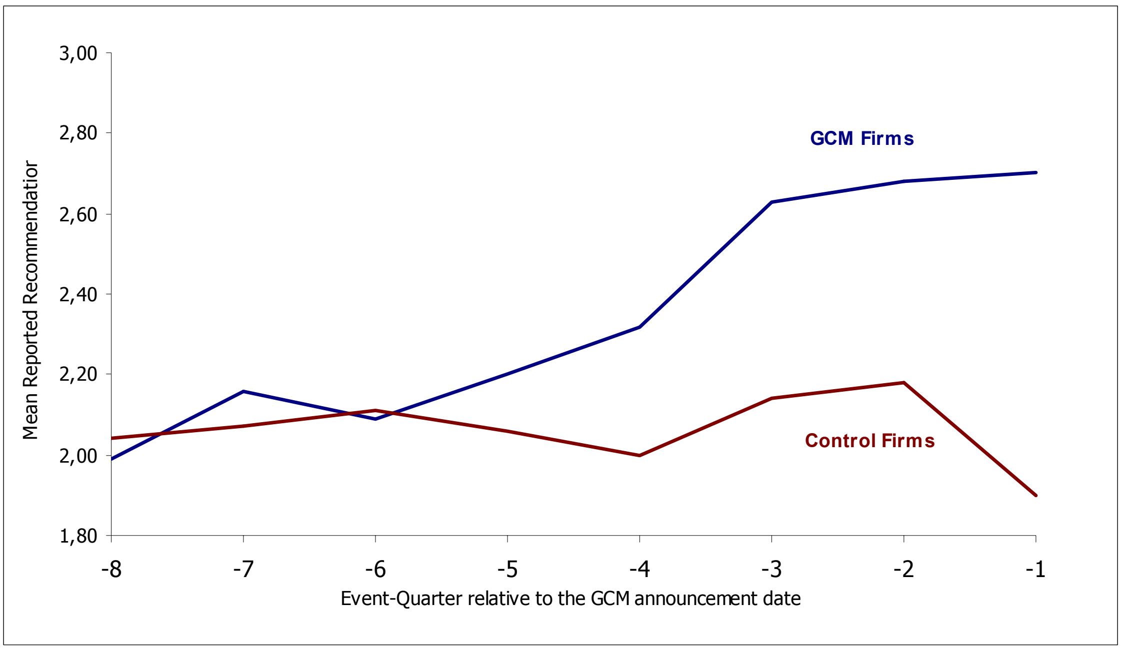
The percentage of "buy" recommendations is computed as the number of firms whose average recommendation is classified as a "buy" divided by the total number of firms with available recommendations. Specifically, firms are classified as "buy" if the average numerical recommendation is below 2.5. For each event-quarter, the "N" column indicates the number of firms with available recommendations. The last two columns in each recommendation category indicate the difference between the mean and median recommendation and percentage of "buy" recommendations as well as its significance. In particular, the two-tailed significance of the t-test (Wilcoxon-Mann-Whitney test) is reported in parentheses for the mean (median) recommendation difference, whereas the significance of the binomial test is used for the difference between the percentages of "buy" recommendations.

Event-Quarter	Recommendation	Reported ($REPREC_q$)						Current ($CURREC_q$)						Inferred ($INFREC_q$)					
		GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value
	Mean	1.99		2.04		-0.05	(0.5510)	2.05		2.04		0.01	(0.7554)	2.05		2.04		0.01	(0.7554)
-8	Median	2.00	180	2.00	170	0.00	(0.5222)	2.00	347	2.00	336	0.00	(0.6466)	2.00	347	2.00	336	0.00	(0.6466)
	% Buy	0.69		0.71		-0.02	(0.6164)	0.69		0.69		0.00	(0.9633)	0.69		0.69		0.00	(0.9633)
	Mean	2.16		2.07		0.09	(0.2554)	2.09		2.05		0.04	(0.4546)	2.22		2.23		-0.01	(0.8804)
-7	Median	2.00	211	2.00	151	0.00	(0.5365)	2.00	385	2.00	341	0.00	(0.9667)	2.00	397	2.00	357	0.00	(0.5562)
	% Buy	0.64		0.65		-0.01	(0.8923)	0.68		0.68		0.00	(0.8309)	0.62		0.60		0.02	(0.2991)
	Mean	2.09		2.11		-0.02	(0.7462)	2.10		2.07		0.03	(0.5822)	2.39		2.39		0.00	(0.9612)
-6	Median	2.00	204	2.00	174	0.00	(0.7610)	2.00	404	2.00	356	0.00	(0.9499)	2.33	434	2.33	387	0.00	(0.7751)
	% Buy	0.67		0.61		0.06	(0.1287)	0.67		0.67		0.00	(0.8387)	0.54		0.53		0.01	(0.7649)
	Mean	2.20		2.06		0.14	(0.7852)	2.15		2.07		0.08	(0.1551)	2.57		2.52		0.05	(0.4059)
-5	Median	2.00	194	2.00	153	0.00	(0.0801)	2.00	407	2.00	357	0.00	(0.2096)	2.50	458	2.50	402	0.00	(0.4327)
	% Buy	0.61		0.69		-0.08	(0.0165)	0.64		0.68		-0.04	(0.1056)	0.46		0.46		0.00	(0.9423)
	Mean	2.32		2.00		0.32	(0.0001)	2.20		2.05		0.15	(0.0061)	2.66		2.49		0.17	(0.0065)
-4	Median	2.00	189	2.00	168	0.00	(0.0004)	2.00	405	2.00	369	0.00	(0.0123)	2.67	462	2.50	409	0.17	(0.0063)
	% Buy	0.55		0.70		-0.15	(<0.0001)	0.62		0.68		-0.06	(0.0166)	0.41		0.47		-0.06	(0.0037)
	Mean	2.63		2.14		0.49	(<0.0001)	2.31		2.06		0.25	(0.0588)	2.81		2.52		0.29	(<0.0001)
-3	Median	2.79	158	2.00	165	0.79	(<0.0001)	2.25	391	2.00	369	0.25	(<0.0001)	3.00	464	2.50	414	0.50	(<0.0001)
	% Buy	0.39		0.68		-0.29	(<0.0001)	0.57		0.67		-0.10	(<0.0001)	0.34		0.45		-0.11	(<0.0001)
	Mean	2.68		2.18		0.50	(<0.0001)	2.37		2.12		0.25	(<0.0001)	2.95		2.56		0.39	(<0.0001)
-2	Median	3.00	159	2.00	173	1.00	(<0.0001)	2.40	371	2.00	377	0.40	(<0.0001)	3.00	460	2.50	417	0.50	(<0.0001)
	% Buy	0.32		0.63		-0.31	(<0.0001)	0.51		0.63		-0.12	(<0.0001)	0.28		0.42		-0.14	(<0.0001)
	Mean	2.70		1.90		0.80	(<0.0001)	2.44		2.03		0.41	(<0.0001)	3.09		2.56		0.53	(<0.0001)
-1	Median	3.00	118	2.00	173	1.00	(<0.0001)	2.50	353	2.00	380	0.50	(<0.0001)	3.21	446	2.50	431	0.71	(<0.0001)
	% Buy	0.33		0.75		-0.42	(<0.0001)	0.44		0.69		-0.25	(<0.0001)	0.22		0.45		-0.23	(<0.0001)

Figure 4.2. graphs the quarterly trend of firms' average reported recommendation from event-quarter -8 to event-quarter -1 for both GCM and control firms. This figure illustrates my main conclusion so far. Analyst recommendations for sample and control firms are very similar from event-quarter -8 to event-quarter -5. As the event date approaches, stock recommendations for GCM firms become significantly more unfavourable than matched firms, confirming that analysts are responsive to the financial deterioration of the sample firms.

Figure 4.2.
Quarterly Trend in Mean Reported Recommendation – Sample Firms vs. Control Firms

This figure graphs the quarterly trend in mean inferred recommendation from event-quarter -8 to event-quarter -1 for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005 and for control firms. Control firms are selected employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.
Average reported recommendation for firm j at event-quarter q ($REPREC_{j,q}$) is the average of the last recommendation issued by each analyst within that period. Firms' reported recommendation at event-quarter q ($REPREC_q$) is then calculated as the average of ($REPREC_{j,q}$). Section 4.2.2.1. provides detailed explanation about the estimation of the recommendation categories. Event-quarters are defined as a period of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).



4.3.3. Analyst reaction to the GCM audit report

In this subsection, I investigate whether or not analysts react to the publication of a GCM audit report by adjusting their recommendations following the disclosure of such an event. More specifically, I compare the mean and median recommendations and the percentage of "buy" recommendations for GCM firms between event-quarter -1 and event-quarter +1. As discussed previously, I assume that analyst reaction (if any) to the publication of a GCM audit report should occur shortly after the event becomes publicly known.

The formal null hypothesis is as follows:

> *H2.: There is no difference in analyst mean and median recommendation and percentage of "buy" recommendations for firms that receive a GCM audit report between event-quarter -1 and event-quarter +1.*

Table 4.4. summarizes my results. In panel A (panel B), I present the results for reported (current) recommendations, whereas panel C shows the results for inferred recommendations. As can be seen, there is no apparent difference in analyst recommendations following the publication of a GCM audit report. For instance, the mean (median) reported recommendation in event-quarter -1 is 2.70 (3.00) and 2.68 (3.00) in event-quarter +1, with no significant differences between them. Moreover, I find that, generally, the differences between current and inferred recommendations from event-quarter -1 to event-quarter +1 are not significant at conventional levels.

Overall, I conclude that analysts do not react to the publication of a GCM audit report by changing their stock recommendations of firms for which their auditors disclose a going-concern modified audit report for the first-time following the disclosure date. Hence, I do not reject null hypothesis H2.

TABLE 4.4.
Analyst Recommendation around the GCM Audit Report - Sample Firms

This table presents a comparison between quarter -1 and quarter +1 analyst stock recommendations for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
Average reported recommendation for firm j at event-quarter q (REPRECj,q) is the average of the last recommendation issued by each analyst within that period. Firms' reported recommendation at event-quarter q (REPRECq) is then calculated as the average of (REPRECj,q). Average current recommendation for firm j at event-quarter q (CURRECj,q) is the average of the last recommendation issued by each analyst when he/she does not cease coverage of the firm before the end of that period. Firms' current recommendation at event-quarter q (CURRECq) is then calculated as the average of (CURRECj,q). Average inferred recommendation for firm j at event-quarter q (INFRECj,q) is similar to the average current recommendation with one difference. When an analyst ceases coverage of a company within event-quarter q after the last recommendation date, I infer an unfavourable recommendation for event-quarter q and for the subsequent two event-quarters. Firms' inferred recommendation at event-quarter q (INFRECq) is then calculated as the average of (INFRECj,q). Section 4.2.2.1. provides detailed explanation about the estimation of the recommendation categories. Event-quarters are defined as a period of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).
The percentage of "buy" recommendations is computed as the number of firms with "buy" recommendations divided by the total number of firms with available recommendations. Specifically, "buy" recommendations are those with ratings below 2.5. For each quarter, the "N" column indicates the number of companies with available recommendations. The last two columns in each recommendation category indicate the difference between the mean and median recommendation and percentage of "buy" recommendations as well as their significance. In particular, the two-tailed significance of the t-test (Wilcoxon-Mann-Whitney test) is reported in parentheses for the mean (median) recommendation difference, whereas the binomial test is used to test for the significance in the differences between the percentages of "buy" recommendations.

Panel A: Reported recommendation comparison

Recommendation	Reported ($REPREC_q$)					
	Q-1	N	Q+1	N	Difference	p-value
Mean	2.70		2.68		0.02	(0.8712)
Median	3.00	118	3.00	85	0.00	(0.7929)
% Buy	0.33		0.39		-0.06	(0.1985)

Panel B: Current recommendations comparison

Recommendation	Current ($CURREC_q$)					
	Q-1	N	Q+1	N	Difference	p-value
Mean	2.44		2.44		0.00	(0.9325)
Median	2.50	353	2.50	310	0.00	(0.8950)
% Buy	0.44		0.45		-0.01	(0.7048)

Panel C: Inferred recommendations comparison

Recommendation	Inferred ($INFREC_q$)					
	Q-1	N	Q+1	N	Difference	p-value
Mean	3.09		3.18		-0.09	(0.1766)
Median	3.21	446	3.43	429	-0.22	(0.0499)
% Buy	0.22		0.21		0.01	(0.7006)

4.4. Summary and discussion

This chapter examines whether or not security analysts anticipate and react to the publication of a GCM audit report by changing their recommendations. My results provide original evidence that security analysts are able to anticipate one of the most acute accounting bad news events: the going-concern audit report. I find that they anticipate the publication of a GCM audit report by downgrading more aggressively stock recommendations of GCM firms than stock recommendations of control firms. In particular, analysts downgrade their recommendations for GCM firms from "buy" to "hold" from event-quarter -4 to event-quarter -1 whereas their recommendations for non-GCM firms maintain an average "buy" rating. Conversely, I fail to find significant changes in stock recommendations for GCM firms following the GCM date. To be precise, there are no statistical differences in stock recommendations for my sample firms in event-quarter -1 and event-quarter +1, suggesting that analysts do not react to the announcement of a GCM audit report by reporting negatively on firms following the disclosure date.

Overall, I provide further evidence that analysts anticipate extreme negative non-routine bad news events (e.g., Dechow, Sloan, and Sweeney, 1996; Clarke at al. 2006; Cotter and Young, 2007) by downgrading their stock recommendations but fail to find similar behaviour following the event announcement. However, despite analyst recommendations becoming relatively more pessimistic for GCM firms than control firms as the GCM event approaches, it is hard to believe that common investors recognize an average "hold" recommendation as an unfavourable message for firms immediately before the announcement of such an extreme bad news event, even considering that it represents a downgrade from a previous "buy". This is particularly important in the GCM context since we know that retail investors hold 74% of these stocks right before the GCM date (Kausar, Taffler, and Tan, forthcoming). In fact, there is evidence that small investors follow analyst stock recommendations literally. For instance, Malmendier and Shanthikumar (2007) show that large investors react negatively to a "hold" recommendation whereas small investors display no significant trade reaction. As Shefrin (2002) mentions, "*investors are slow to learn that security analysts do not always mean what they say. (…) They frequently say 'hold' but mean 'sell', or say 'buy' when they mean 'hold'*."

The conclusions of this chapter are mainly based on the comparison between stock recommendations for my GCM firms and control sharing similar size and BT ratio. However, as reported in table 4.2., control firms share higher distress risk and have worst past return performance, which might be driving analyst decision to downgrade my sample firms. As such, in chapter 5, I conduct additional tests to ensure the robustness of my conclusions and explore whether analyst decision to cease coverage of firms is related to the publication of a GCM audit report.

CHAPTER 5
RE-EXAMINING ANALYSTS' ANTICIPATION AND REACTION TO THE PUBLICATION OF A GCM AUDIT REPORT

5.1. Introduction

My previous chapter shows that analysts anticipate the publication of a GCM audit report by downgrading more aggressively stock recommendations of GCM firms than control firms of similar size and BM ratio. However, I acknowledge that control firms have other characteristics that are significantly different from those of sample firms, which might drive analyst recommendations, thus contaminating my conclusions.

This chapter aims primarily at ensuring that my prior results are not due to analysts' preferences for certain stocks nor are they a mere statistical artefact. In effect, analyst stock recommendations for GCM firms might be related to other firm characteristics than size and BM ratio, which seem to have the ability to predict returns (e.g., Fama and French, 1992; Jegadeesh and Titman, 1993; Dichev, 1998). As Jegadeesh et al. (2004) state, "*Analysts may be explicitly or intuitively aware of the ability of these variables to predict future returns. If so, we would expect the variables to be correlated with analyst recommendations in the same way they are correlated with future returns*". As such, I test the robustness of my results by using alternative control firm sets that account for different firms' characteristics.

In addition, I supplement my previous analysis by focusing on another key signal used by analysts to communicate negative information: coverage cessation. Investigating analysts' decision to cease coverage of GCM firms before and after the GCM date provides further evidence on the ability of security analysts to anticipate and react to the publication of such bad news.

The remainder of this chapter is organized as follows: section 2 revisits analyst anticipation of a GCM audit report, section 3 revisits analyst reaction to the publication of a GCM audit report and section 4 summarizes and discusses the results of the chapter.

5.2. Revisiting analyst anticipation of the GCM audit report

In this subsection, I test the robustness of my prior results relating to the ability of security analysts to anticipate a GCM audit report. In particular, I employ alternative sets of control firms using different matching procedures for GCM firm characteristics. I also examine to what extent the regulatory changes introduced in 2002 impact on my results. Finally, I provide a multivariate analysis that investigates if analysts are more likely to cease coverage of GCM firms than control firms prior to the GCM date.

5.2.1. Controlling for alternative benchmarks

I now re-run my previous research framework testing analyst anticipation of the GCM audit report using three different control-firm benchmarks based on alternative firm characteristics. As discussed in section 4.3.2., size is related to both future stock returns and level of analyst coverage. For this reason, all benchmarks use size as a variable to identify my control firms.

5.2.1.1. Matching on size and momentum

Prior stock performance is described as an important predictor of future returns. For instance, De Bondt and Thaler (1985; 1987) find that portfolios of past losers outperform past winners over the subsequent 3- to 5-years. In addition, Jegadeesh and Titman (1993; 2001) find that firms with higher (lower) short-term price momentum earn higher (lower) returns over the subsequent 12 months. Importantly, Jegadeesh et al. (2004) find a positive association between analysts' recommendations and stock momentum, suggesting that analysts are aware of this relationship.

To investigate if the more aggressive downgrade of stock recommendations for GCM firms is related to firm momentum, I identify a new set of control firms by matching each of my sample firms with the firm with most similar size and momentum. Control firms are identified as follows. First, for each sample firm, I identify all non-financial, non-utility and non-GCM firms listed on the NYSE, AMEX and NASDAQ at the GCM announcement date. Sample and match candidate size is defined as market capitalization (shares outstanding times price) at one year before the GCM announcement.[36] Subsequently, among the match candidates for each sample firm, I identify those with a market value between 70% and 130% of the sample firm. Finally, from this list of candidates, I choose a control firm with the closest momentum to that of my GCM firm. Momentum is defined as the average monthly raw returns for the prior 11-month period (t-12 to t-2) relative to the GCM announcement month.

Panel A of Table 5.1. summarizes my results. As can be seen, results confirm my previous findings that analysts anticipate the disclosure of a GCM audit report by downgrading

[36] I also measure the market value for sample and control firms six and one month before the GCM announcement date to ensure the robustness of my results. Results are materially the same.

more aggressively the stock recommendations for GCM firms. However, it should be noted that the size and momentum-based results are weaker than those obtained matching on size and BM. In particular, the differences in analyst stock recommendation between GCM and control firms become significant only after event-quarter -3. In addition, the significance of the results is now lower. These weaker results are consistent with those of Jegadeesh et al. (2004) who uncover an analyst predisposition to rate more unfavourably companies with negative momentum. However, my results still show that for the event-quarter immediately before the GCM date, stock recommendations for GCM firms are significantly more unfavourable than for control firms across all the recommendation categories I consider.

To sum up, I conclude that, although analysts downgrade also stock recommendations for firms with lower momentum, their downgrade is more aggressive for GCM firms than for non-GCM firms with similar size and momentum.

5.2.1.2. Matching on industry, size and BM

Industry affiliation is also perceived as a characteristic that might explain returns (e.g., Lyon, Barber, and Tsai, 1999). To mitigate the potential problem arising from the association between industry affiliation and analyst recommendations, I identify a new set of control firms by matching each of my sample firms with firms of the same industry. More specifically, for each sample firm, I identify all non-financial, non-utility and non-GCM firms listed in on the NYSE, AMEX and NASDAQ at the GCM announcement date with the same two-digit SIC code. Next, among these companies, I identify those with a market value between 70% and 130% of the market value of the sample firm. Once again, sample and match candidate size is defined as market capitalization (shares outstanding times price) one year before the GCM announcement date.[37] Finally, from this list of candidates, I choose as a control firm the firm which has the closest BM ratio to that of my GCM firm. The BM ratio is defined as in section 4.3.2.

Panel B of table 5.1. shows that my results are very similar to those reported when I use size and BM as matching criteria. In particular, I find that stock recommendations for GCM firms become significantly more unfavourable than non-GCM firms after event-quarter -5 and that my results are consistent over the three different recommendation categories I consider. Hence, I conclude that analyst ability to anticipate the publication of a GCM audit report is not driven by an industry bias.

5.2.1.3. Matching on size and distress risk

Existing research suggests that highly distressed firms tend to underperform less distressed firms (e.g., Dichev, 1998; Griffin and Lemmon, 2002). As such, analysts may be more prone to downgrade their recommendation for firms with high distress risk, a fact that is particularly important for my research since table 3.3. shows that my sample firms are highly financially distressed.[38]

To investigate if the more aggressive downgrade of stock recommendations for GCM firms is related to their distress risk, I identify control firms by matching each of my sample firms with the firm with most similar size and z-score. Control firms are identified as follows. First, for each sample firm, I identify all non-financial, non-utility and non-GCM

[37] I also measure the market value for sample and control firms six and one month before the GCM announcement date to ensure the robustness of my results. Results are materially the same.

[38] In particular, it shows that mean (median) Altman z-score is 1.15 (0.93). Moreover, Altman (1968) suggests that firm for which z-score is inferior to 1.8 clearly fall into the bankruptcy category.

firms listed on the NYSE, AMEX and NASDAQ at the GCM announcement date. Sample and match candidate size is defined as market capitalization (shares outstanding times price) one year before the GCM announcement.[39] Subsequently, among the match candidates for each sample firm, I identify those with a market value between 70% and 130% of the sample firm. Finally, from this list of candidates, I choose a control firm with the closest z-score to that of each GCM sample firm. The z-score is used as a proxy for distress risk and is computed following Altman's (1968) model. The accounting information from the fiscal year ending one year before the GCM announcement date is employed to compute each firm's z-score.

Panel C of table 5.1. summarizes my results. Consistent with my previous findings, I show that stock recommendations for GCM firms become significantly more unfavourable than for non-GCM firms with similar levels of financial distress after event-quarter -5. As such, I conclude that my previous conclusion about the ability of analysts to anticipate the GCM audit report is not driven by firms' distress risk.

[39] I also measure the market value for sample and control firms six and one month before the GCM announcement date to ensure the robustness of my results. Results are materially the same.

TABLE 5.1.
Quarterly Trend in Analyst Stock Recommendations – Sample Firms vs. Control Firms (Alternative Benchmarks)

This table presents the event-quarter trend in analyst stock recommendations from event-quarter -8 to event-quarter -1 for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which the auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005 and for control firms. Control firms are selected employing the control firm approach based on three different criteria. In panel A, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with the closest momentum to that of the sample firm. In panel B, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with the same two-digit SIC code at the GCM announcement date of the sample firm. I then identify those firms with market value of equity between 70% and 130% of the market value of equity of the sample firm and choose that firm from this set with the closest BM ratio to that of the GCM firm. In panel C, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with the closest z-score to that of the sample firm.

Average reported recommendation for firm j at event-quarter q (REPRECj,q) is the average of the last recommendation issued by each analyst within that period. Firms' reported recommendation at event-quarter q (REPRECq) is then calculated as the average of (REPRECj,q). Average current recommendation for firm j at event-quarter q (CURRECj,q) is the average of the last recommendation issued by each analyst when he/she does not cease coverage of the firm before the end of that period. Firms' current recommendation at event-quarter q (CURRECq) is then calculated as the average of (CURRECj,q). Average inferred recommendation for firm j at event-quarter q (INFRECj,q) is similar to the average current recommendation with one difference. When an analyst ceases coverage of a company within event-quarter q after the last recommendation date, I infer an unfavourable recommendation for event-quarter q and for the subsequent two event-quarters. Firms' inferred recommendation at event-quarter q (INFRECq) is then calculated as the average of (INFRECj,q). Section 4.2.2.1. provides detailed explanation about the estimation of the recommendation categories. Event-quarters are defined as a period of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).

The percentage of "buy" recommendations is computed as the number of firms whose average recommendation is classified as a "buy" divided by the total number of firms with available recommendations. Specifically, firms are classified as "buy" if the average numerical recommendation is below 2.5. For each event-quarter, the "N" column indicates the number of firms with available recommendations. The last two columns in each recommendation category indicate the difference between the mean and median recommendation and percentage of "buy" recommendations as well as its significance. In particular, the two-tailed significance of the t-test (Wilcoxon-Mann-Whitney test) is reported in parentheses for the mean (median) recommendation difference, whereas the significance of the binomial test is used for the differences between the percentages of "buy" recommendations.

Panel A: Matching on size and momentum

Event-Quarter	Recommendation	Reported ($REPREC_q$)						Current ($CURREC_q$)						Inferred ($INFREC_q$)					
		GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value
	Mean	1.99		2.07		-0.08	(0.3766)	2.05		2.01		0.04	(0.4975)	2.05		2.01		0.04	(0.4975)
-8	Median	2.00	180	2.00	174	0.00	(0.3858)	2.00	347	2.00	351	0.00	(0.9495)	2.00	347	2.00	351	0.00	(0.9495)
	% Buy	0.69		0.66		0.03	(0.4277)	0.69		0.72		-0.03	(0.2771)	0.69		0.72		-0.03	(0.2771)
	Mean	2.16		1.92		0.24	(0.0028)	2.09		1.99		0.10	(0.0674)	2.22		2.17		0.05	(0.4058)
-7	Median	2.00	211	2.00	195	0.00	(0.0020)	2.00	385	2.00	373	0.00	(0.1553)	2.00	397	2.00	387	0.00	(0.5441)
	% Buy	0.64		0.74		-0.10	0.0010)	0.68		0.74		-0.06	(0.0039)	0.62		0.65		-0.03	(0.1867)
	Mean	2.09		2.05		0.04	(0.6142)	2.10		2.00		0.10	(0.0435)	2.39		2.29		0.10	(0.1196)
-6	Median	2.00	204	2.00	195	0.00	(0.6871)	2.00	404	2.00	395	0.00	(0.1323)	2.33	434	2.06	423	0.27	(0.1873)
	% Buy	0.67		0.66		0.01	(0.8761)	0.67		0.73		-0.06	(0.0056)	0.54		0.57		-0.03	(0.1128)
	Mean	2.20		1.98		0.22	(0.0075)	2.15		2.03		0.12	(0.0351)	2.57		2.45		0.12	(0.0624)
-5	Median	2.00	194	2.00	211	0.00	(0.0153)	2.00	407	2.00	408	0.00	(0.0914)	2.50	458	2.50	453	0.00	(0.1016)
	% Buy	0.61		0.68		-0.07	(0.0387)	0.64		0.70		-0.06	(0.0157)	0.46		0.50		-0.04	(0.0839)
	Mean	2.32		2.20		0.12	(0.1774)	2.20		2.11		0.09	(0.0817)	2.66		2.56		0.10	(0.1239)
-4	Median	2.00	189	2.00	174	0.00	(0.1709)	2.00	405	2.00	394	0.00	(0.1130)	2.67	462	2.50	453	0.17	(0.1450)
	% Buy	0.55		0.59		-0.04	(0.2430)	0.62		0.64		-0.02	(0.4002)	0.41		0.44		-0.03	(0.1116)
	Mean	2.63		2.38		0.25	(0.0059)	2.31		2.21		0.10	(0.0898)	2.81		2.71		0.10	(0.1165)
-3	Median	2.79	158	2.33	185	0.46	(0.0143)	2.25	391	2.11	381	0.14	(0.1253)	3.00	464	2.75	455	0.25	(0.0887)
	% Buy	0.39		0.51		-0.12	0.0023)	0.57		0.61		-0.04	(0.0949)	0.34		0.39		-0.05	(0.0510)
	Mean	2.68		2.53		0.15	(0.1318)	2.37		2.29		0.08	(0.1511)	2.95		2.79		0.16	(0.0113)
-2	Median	3.00	159	2.73	161	0.27	(0.0496)	2.40	371	2.31	386	0.09	(0.1547)	3.00	460	3.00	456	0.00	(0.0045)
	% Buy	0.32		0.43		-0.11	(0.0060)	0.51		0.54		-0.03	(0.3009)	0.28		0.34		-0.06	(0.0212)
	Mean	2.70		2.47		0.23	(0.0389)	2.44		2.34		0.10	(0.0952)	3.09		2.86		0.23	(0.0003)
-1	Median	3.00	118	2.50	147	0.50	(0.0220)	2.50	353	2.44	373	0.06	(0.0874)	3.21	446	3.00	445	0.21	(<0.0001)
	% Buy	0.33		0.46		-0.13	(0.0040)	0.44		0.50		-0.06	(0.0336)	0.22		0.30		-0.08	(0.0003)

Panel B: Matching on industry, size and BM

Event-Quarter	Recommendation	Reported ($REPREC_q$)						Current ($CURREC_q$)						Inferred ($INFREC_q$)					
		GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value
	Mean	1.99		1.99		0.00	(0.9804)	2.05		1.96		0.09	(0.0919)	2.05		1.96		0.09	(0.0919)
-8	Median	2.00	180	2.00	188	0.00	(0.9615)	2.00	347	2.00	343	0.00	(0.2772)	2.00	347	2.00	343	0.00	(0.2772)
	% Buy	0.69		0.70		-0.01	(0.8174)	0.69		0.75		-0.06	(0.0090)	0.69		0.75		-0.06	(0.0090)
	Mean	2.16		2.18		-0.02	(0.8563)	2.09		2.05		0.04	(0.4809)	2.22		2.23		-0.01	(0.8198)
-7	Median	2.00	211	2.00	176	0.00	(0.8502)	2.00	385	2.00	347	0.00	(0.7368)	2.00	397	2.00	365	0.00	(0.6809)
	% Buy	0.64		0.59		0.05	(0.0802)	0.68		0.68		0.00	(0.9373)	0.62		0.60		0.02	(0.3124)
	Mean	2.09		2.12		-0.03	(0.6467)	2.10		2.06		0.04	(0.4412)	2.39		2.35		0.04	(0.4865)
-6	Median	2.00	204	2.00	178	0.00	(0.4450)	2.00	404	2.00	368	0.00	(0.8744)	2.33	434	2.29	393	0.04	(0.7640)
	% Buy	0.67		0.65		0.02	(0.6537)	0.67		0.68		-0.01	(0.7950)	0.54		0.54		0.00	(0.7495)
	Mean	2.20		2.09		0.11	(0.1867)	2.15		2.06		0.09	(0.1286)	2.57		2.44		0.13	(0.0402)
-5	Median	2.00	194	2.00	165	0.00	(0.1891)	2.00	407	2.00	380	0.00	(0.3076)	2.50	458	2.47	411	0.03	(0.0703)
	% Buy	0.61		0.67		-0.06	(0.0784)	0.64		0.68		-0.04	(0.0990)	0.46		0.50		-0.04	(0.0677)
	Mean	2.32		2.08		0.24	(0.0055)	2.20		2.08		0.12	(0.0239)	2.66		2.52		0.14	(0.0255)
-4	Median	2.00	189	2.00	183	0.00	(0.0096)	2.00	405	2.00	371	0.00	(0.0631)	2.67	462	2.50	414	0.17	(0.0289)
	% Buy	0.55		0.64		-0.09	(0.0066)	0.62		0.68		-0.06	(0.0095)	0.41		0.47		-0.06	(0.0058)
	Mean	2.63		2.13		0.50	(<0.0001)	2.31		2.13		0.18	(0.0024)	2.81		2.55		0.26	(<0.0001)
-3	Median	2.79	158	2.00	207	0.79	(<0.0001)	2.25	391	2.00	390	0.25	(0.0038)	3.00	464	2.50	431	0.50	(<0.0001)
	% Buy	0.39		0.66		-0.27	(<0.0001)	0.57		0.65		-0.08	(0.0008)	0.34		0.46		-0.12	(<0.0001)
	Mean	2.68		2.04		0.64	(<0.0001)	2.37		2.12		0.25	(<0.0001)	2.95		2.61		0.34	(<0.0001)
-2	Median	3.00	159	2.00	181	1.00	(<0.0001)	2.40	371	2.00	392	0.40	(<0.0001)	3.00	460	2.65	444	0.35	(<0.0001)
	% Buy	0.32		0.70		-0.38	(<0.0001)	0.51		0.66		-0.15	(<0.0001)	0.28		0.45		-0.17	(<0.0001)
	Mean	2.70		2.09		0.61	(<0.0001)	2.44		2.05		0.39	(<0.0001)	3.09		2.60		0.49	(<0.0001)
-1	Median	3.00	118	2.00	185	1.00	(<0.0001)	2.50	353	2.00	383	0.50	(<0.0001)	3.21	446	2.50	447	0.71	(<0.0001)
	% Buy	0.33		0.68		-0.35	(<0.0001)	0.44		0.70		-0.26	(<0.0001)	0.22		0.46		-0.24	(<0.0001)

Panel C: Matching on size and z-score

Event-Quarter	Recommendation	Reported ($REPREC_q$)						Current ($CURREC_q$)						Inferred ($INFREC_q$)					
		GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value	GCM Firms	N	Control Firms	N	Difference	p-value
	Mean	1.99		1.94		0.05	(0.5257)	2.05		2.01		0.04	(0.5149)	2.05		2.01		0.04	(0.5149)
-8	Median	2.00	180	2.00	186	0.00	(0.5603)	2.00	347	2.00	351	0.00	(0.6353)	2.00	347	2.00	351	0.00	(0.6353)
	% Buy	0.69		0.70		-0.01	(0.6505)	0.69		0.70		-0.01	(0.8855)	0.69		0.70		-0.01	(0.8855)
	Mean	2.16		2.12		0.04	(0.6534)	2.09		2.02		0.07	(0.2113)	2.22		2.15		0.07	(0.2663)
-7	Median	2.00	211	2.00	179	0.00	(0.7452)	2.00	385	2.00	372	0.00	(0.2399)	2.00	397	2.00	380	0.00	(0.3367)
	% Buy	0.64		0.66		-0.02	(0.6534)	0.68		0.69		-0.01	(0.5855)	0.62		0.64		-0.02	(0.4074)
	Mean	2.09		2.18		-0.09	(0.2774)	2.10		2.05		0.05	(0.3713)	2.39		2.32		0.07	(0.3062)
-6	Median	2.00	204	2.00	177	0.00	(0.3827)	2.00	404	2.00	386	0.00	(0.3814)	2.33	434	2.23	412	0.10	(0.2769)
	% Buy	0.67		0.59		0.08	(0.0327)	0.67		0.69		-0.02	(0.4917)	0.54		0.57		-0.03	(0.2288)
	Mean	2.20		2.09		0.11	(0.2129)	2.15		2.02		0.13	(0.0228)	2.57		2.44		0.13	(0.0358)
-5	Median	2.00	194	2.00	187	0.00	(0.2033)	2.00	407	2.00	396	0.00	(0.0496)	2.50	458	2.44	435	0.06	(0.0415)
	% Buy	0.61		0.65		-0.04	(0.2540)	0.64		0.70		-0.06	(0.0257)	0.46		0.50		-0.04	(0.0547)
	Mean	2.32		2.07		0.25	(0.0068)	2.20		2.06		0.14	(0.0090)	2.66		2.52		0.14	(0.0382)
-4	Median	2.00	189	2.00	172	0.00	(0.0025)	2.00	405	2.00	399	0.00	(0.0087)	2.67	462	2.50	445	0.17	(0.0302)
	% Buy	0.55		0.67		-0.12	(0.0003)	0.62		0.68		-0.06	(0.0138)	0.41		0.48		-0.07	(0.0011)
	Mean	2.63		2.19		0.44	(<0.0001)	2.31		2.12		0.19	(0.0011)	2.81		2.59		0.22	(0.0005)
-3	Median	2.79	158	2.00	154	0.79	(<0.0001)	2.25	391	2.00	394	0.25	(0.0005)	3.00	464	2.58	437	0.42	(0.0002)
	% Buy	0.39		0.64		-0.25	(<0.0001)	0.57		0.69		-0.12	(<0.0001)	0.34		0.45		-0.11	(<0.0001)
	Mean	2.68		2.03		0.65	(<0.0001)	2.37		2.08		0.29	(<0.0001)	2.95		2.56		0.39	(<0.0001)
-2	Median	3.00	159	2.00	164	1.00	(<0.0001)	2.40	371	2.00	399	0.40	(<0.0001)	3.00	460	2.50	448	0.50	(<0.0001)
	% Buy	0.32		0.70		-0.38	(<0.0001)	0.51		0.70		-0.19	(<0.0001)	0.28		0.46		-0.18	(<0.0001)
	Mean	2.70		2.07		0.63	(<0.0001)	2.44		2.06		0.38	(<0.0001)	3.09		2.55		0.54	(<0.0001)
-1	Median	3.00	118	2.00	186	1.00	(<0.0001)	2.50	353	2.00	399	0.50	(<0.0001)	3.21	446	2.48	452	0.73	(<0.0001)
	% Buy	0.33		0.71		-0.38	(<0.0001)	0.44		0.72		-0.28	(<0.0001)	0.22		0.50		-0.28	(<0.0001)

5.2.2. Controlling for GCM firm characteristics

My previous results indicate that the ability of analysts to anticipate the publication of a GCM audit report is a robust conclusion. In this subsection, I revisit this result in more detail by investigating if such a phenomenon is particularly clear for specific groups of sample firms. Specifically, I investigate whether the growing pessimism on analysts' inferred recommendations[40] varies systematically with the following characteristics related to future returns: size, BM ratio, momentum and distress risk. Size and BM ratio are defined as in section 4.3.2., momentum is defined as in section 5.2.1.1. and distress risk (z-score) is computed as in section 5.2.1.3.

Table 5.2. summarizes my results. Panel A of table 5.2. compares pre-GCM stock recommendations between small and large GCM firms. Firms are allocated to the "small size" ("large size") portfolio if their market value of equity is below (above) the total sample's median value ($33.7 million). I find that stock recommendations for small GCM firms are significantly more unfavourable than stock recommendations for larger GCM firms for the more distant event-quarters. However, these differences become statistically insignificant as the GCM date approaches. These results suggest that analyst recognition of going-concern problems occurs later for larger firms than for small firms.

In panel B of table 5.2., the analysis controls for the impact of the BM ratio. Firms with a BM ratio lower (higher) than that of the total sample's median BM ratio (0.40) are allocated to the low (high) BM portfolio. I find that stock recommendations for GCM firms with low BM ratio are significantly more favourable than those for GCM firms with high BM ratio. As an example, consider the results in event-quarter -1. Mean (median) stock recommendations for firms with high BM ratio is 3.21 (3.30) whereas for firms with low

[40] Conclusions are very similar when I use reported and current recommendations.

BM ratio is 2.97 (3.00). In addition, the percentage of GCM firms with high BM ratio for which their average recommendation is classified as "buy" is 18% whilst for GCM firms with low BM ratio is 26%. Importantly, all differences between groups are significant at the 1% level. Overall, I conclude that analysts are relatively more pessimistic about GCM firms with high BM ratio than GCM firms with low BM ratio, consistent with the notion that analysts tend to favour "growth" stocks (Jegadeesh et al., 2004).

Panel C of table 5.2. compares pre-GCM stock recommendations for my sample firms conditional on their pre-event momentum. Firms with negative (positive) prior 11-month period (t-12 to t-2) raw returns are assigned to the "negative momentum" ("positive momentum") portfolio. I find that stock recommendations for firms with negative momentum become significantly more unfavourable than for firms with positive momentum immediately before the GCM announcement date. In fact, for event-quarter -1, the mean (median) recommendation for firms with positive momentum is 2.87 (3.00) and 3.14 (3.30) for firms with negative momentum. Moreover, the percentage of GCM firms with positive momentum for which their average recommendation is classified as "buy" is 30% whilst for GCM firms with negative momentum it is 20%. All differences are highly significant, suggesting that negative momentum is related to the decision of downgrade, consistent with the notion that analysts prefer positive momentum companies (Jegadeesh et al., 2004).

In Panel D of table 5.2., I present stock recommendations for GCM firms conditional on their pre-event distress risk. Companies with z-score <= 1.81 (> 1.81) are allocated to the "High Distress Risk" ("Low Distress Risk") portfolio. I find that, generally, there are no significant differences in stock recommendations for GCM firms with high distress risk and GCM firms with low distress risk. As such, I conclude that distress risk does not impact significantly on the analyst opinion about GCM firms or the z-score model does not discriminate effectively between high and low distress risk firms.

TABLE 5.2.
Quarterly Trend in Analyst Stock Recommendations – Controlling for Firm Characteristics

This table presents the event-quarter trend in analysts' recommendations from event-quarter -8 to event-quarter -1 for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
Average inferred recommendation for firm j at event-quarter q ($INFREC_q$) is the average of the last recommendation issued by each analyst when he/she does not cease coverage of the firm before the end of that period. When an analyst ceases coverage of a company within event-quarter q after the last recommendation date, I infer an unfavourable recommendation for event-quarter q and for the subsequent two event-quarters. Firms' inferred recommendation at event-quarter q ($INFREC_q$) is then calculated as the average of ($INFREC_{j,q}$). Section 4.2.2.1 provides detailed explanation about the estimation of this recommendation category. Event-quarters are defined as periods of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).
The percentage of "buy" recommendations is computed as the number of firms whose average recommendation is classified as a "buy" divided by the total number of firms with available recommendations. Specifically, firms are classified as "buy" if the average numerical recommendation is below 2.5. For each event-quarter, the "N" column indicates the number of firms with available recommendations. The last two columns indicate the difference between the mean and median recommendation and percentage of "buy" recommendations as well as its significance. In particular, the two-tailed significance of the t-test (Wilcoxon-Mann-Whitney test) is reported in parentheses for the mean (median) recommendation difference, whereas the significance of the binomial test is used for the difference between the percentages of "buy" recommendations.
Panel A provides separate results for the portfolio of 462 (462) GCM companies with market capitalization below (above) the sample median ($33.7m). Market capitalization is calculated one year before the GCM date. Panel B reports separate results for the portfolio of 462 (462) GCM companies with a BM ratio lower (higher) than that of the total sample's median BM ratio (0.40). BM ratio is defined as the ratio of book value to market value of equity, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date. Panel C reports separate results for the portfolio of 235 (689) GCM companies with positive (negative) pre-event momentum. Momentum is defined as the average monthly raw returns for the prior 11-month period (t-12 to t-2) relative to the GCM announcement month. Panel D provides separate results for the portfolio of 775 (149) GCM companies with z-score <=1.81 (>1.81). Z-score is computed following Altman's (1968) model using the accounting information from the fiscal year ending one year before the GCM announcement date.

Panel A: Inferred recommendations conditional on firm size

Event-Quarter	**Recommendation**	*Inferred ($INFREC_q$)*					
		Small Size	N	Large Size	N	Difference	p-value
	Mean	2.37		2.15		0.22	(0.0162)
-7	Median	2.25	121	2.00	276	0.25	(0.0101)
	% Buy	0.54		0.65		-0.11	(0.0106)
	Mean	2.86		2.45		0.41	(<0.0001)
-5	Median	3.00	135	2.44	323	0.56	(<0.0001)
	% Buy	0.36		0.50		-0.14	(0.0007)
	Mean	2.92		2.77		0.15	(0.1695)
-3	Median	3.00	129	3.00	335	0.00	(0.1463)
	% Buy	0.32		0.36		-0.04	(0.3751)
	Mean	3.09		3.09		0.00	(0.9666)
-1	Median	3.33	119	3.17	327	0.16	(0.5618)
	% Buy	0.27		0.20		0.07	(0.0836)

Panel B: Inferred recommendations conditional on firm BM ratio

Event-Quarter	Recommendation	Inferred ($INFREC_q$)					
		High BM ratio	N	Low BM ratio	N	Difference	p-value
	Mean	2.33		2.09		0.24	(0.0048)
-7	Median	2.25	215	2.00	182	0.25	(0.0029)
	% Buy	0.54		0.71		-0.17	(<0.0001)
	Mean	2.77		2.37		0.40	(<0.0001)
-5	Median	3.00	236	2.20	222	0.80	(<0.0001)
	% Buy	0.34		0.59		-0.25	(<0.0001)
	Mean	2.95		2.67		0.28	(0.0020)
-3	Median	3.00	228	2.70	236	0.30	(0.0034)
	% Buy	0.27		0.42		-0.15	(<0.0001)
	Mean	3.21		2.97		0.24	(0.0071)
-1	Median	3.33	218	3.00	228	0.33	(0.0041)
	% Buy	0.18		0.26		-0.08	(0.0033)

Panel C: Inferred recommendations conditional on firm momentum

Event-Quarter	Recommendation	Inferred ($INFREC_q$)					
		Negative Momentum	N	Positive Momentum	N	Difference	p-value
	Mean	2.18		2.34		-0.16	(0.1889)
-7	Median	2.00	311	2.00	86	0.00	(0.3403)
	% Buy	0.64		0.57		0.07	(0.0172)
	Mean	2.52		2.77		-0.25	(0.0348)
-5	Median	2.50	363	2.86	95	-0.36	(0.0475)
	% Buy	0.47		0.42		0.05	(0.0684)
	Mean	2.79		2.87		-0.08	(0.5117)
-3	Median	3.00	372	3.00	92	0.00	(0.5402)
	% Buy	0.35		0.34		0.01	(0.6900)
	Mean	3.14		2.87		0.27	(0.0161)
-1	Median	3.30	359	3.00	87	0.30	(0.0122)
	% Buy	0.20		0.30		-0.10	(<0.0001)

Panel D: Inferred recommendations conditional on firm distress risk

Event-Quarter	Recommendation	Inferred ($INFREC_q$)					
		High Distress Risk	N	Low Distress Risk	N	Difference	p-value
	Mean	2.21		2.26		-0.05	(0.7037)
-7	Median	2.00	345	2.15	52	-0.15	(0.5711)
	% Buy	0.63		0.56		0.07	(0.0055)
	Mean	2.55		2.71		-0.16	(0.2581)
-5	Median	2.50	401	3.00	57	-0.50	(0.2200)
	% Buy	0.47		0.39		0.08	(0.0007)
	Mean	2.79		2.91		-0.12	(0.3733)
-3	Median	3.00	401	3.00	63	0.00	(0.3641)
	% Buy	0.34		0.35		-0.01	(0.8317)
	Mean	3.07		3.19		-0.12	(0.4094)
-1	Median	3.20	389	3.33	57	-0.13	(0.2788)
	% Buy	0.22		0.21		0.01	(0.5246)

5.2.3. Controlling for regulatory regime

NASD Rule 2711 and the NYSE Rule 472 were introduced in 2002 with the objective of increasing investor confidence in the integrity of financial markets and providing investors with better information to assess their research. Barber et al. (2006) and Madureira et al. (2008) show that following the implementation of these regulatory changes, "buy" recommendations become less frequent whereas "sell" recommendations become more frequent. This suggests that the reporting environment explains, at least partially, the recent decrease in analyst optimism.

In this context, it is important to investigate the impact of these regulatory changes on analyst recommendations for GCM firms to understand if the documented decrease in analyst optimism holds for a specific group of financially distressed firms. If analysts become more pessimistic for GCM firms due to the implementation such regulatory changes, I expect their stock recommendations for my sample firms to be significantly more unfavourable after that period. I test the following hypothesis:

> *H3: In the pre-event period, there is no difference in analyst mean and median recommendation and percentage of "buy" recommendations between firms that receive a GCM audit report before and after the implementation of the regulatory changes.*

I formally test this null hypothesis by separating my sample firms conditional on the regulatory regime existing at their GCM announcement date. Considering that the NASD

Rule 2711 was implemented on the 9th of September 2002,[41] I allocate a company to the "Pre-NASD 2711" portfolio whenever the GCM audit report is published before that date. All remaining companies are allocated to the "Post-NASD 2711" portfolio. I then compare pre-GCM stock recommendations between "Pre-NASD 2711" and "Post-NASD 2711" portfolios using the two-tailed t-test, the Wilcoxon-Mann-Whitney test and the binomial test to investigate the differences in analyst mean and median recommendations and percentage of "buy" recommendations, respectively.

Table 5.3. summarizes my results. I find that the implementation of NASD Rule 2711 appears to have been effective in adjusting analyst pre-GCM recommendations. In effect, stock recommendations for my sample firms became significantly more unfavourable following the implementation of NASD Rule 2711. For instance, the mean (median) inferred recommendation for the "Pre-NASD 2711" portfolio immediately before the GCM announcement date is 3.05 (3.11) whereas for the "Post-NASD 2711" portfolio it is 3.23 (3.50). Moreover, the percentage of GCM firms for which their average recommendation is classified as "buy" decreases from 23% to 19% following NASD Rule 2711. Importantly, all these differences across groups are highly significant in most of the event-quarters I consider.

These results suggest that analysts are relatively more pessimistic about the future prospects of GCM firms following the implementation of NASD Rule 2711 than before that period. This relative pessimism might also be explained by the softening in economic conditions and the market crash that occurred at this point in time. However, Barber et al. (2006) claim that the new regulatory regime is, at least, a partial explanation for the

[41] I concentrate my discussion on NASD Rule 2711 since it was implemented before the NYSE Rule 472. However, my conclusions apply for both rules since the regulatory changes share the same goals.

adjustment on analyst expectations and consequently, their recommendations. In fact, they show that the reduction in percentage of "buy" recommendations is more pronounced in the period that coincides with the implementation of the regulatory changes. As such, I conclude that constraints on analyst optimism following NASD Rule 2711 are also manifested for firms experiencing high levels of financial distress. This evidence leads me to reject null hypothesis H3.

TABLE 5.3.
Quarterly Trend in Analysts Recommendations – Controlling for GCM Announcement Date

This table presents the event-quarter trend in analysts' recommendations from event-quarter -8 to event-quarter -1 for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
Average inferred recommendation for firm j at event-quarter q ($INFREC_q$) is the average of the last recommendation issued by each analyst when he/she does not cease coverage of the firm before the end of that period. When an analyst ceases coverage of a company within event-quarter q after the last recommendation date, I infer an unfavourable recommendation for event-quarter q and for the subsequent two event-quarters. Firms' inferred recommendation at event-quarter q ($INFREC_q$) is then calculated as the average of ($INFREC_{j,q}$). Section 4.2.2.1 provides detailed explanation about the estimation of this recommendation category. Event-quarters are defined as a period of 90 calendar days relative to the GCM announcement date. Recommendations are coded as 1 (strong buy), 2 (buy), 3 (hold), 4 (underperform) and 5 (sell).
The percentage of "buy" recommendations is computed as the number of firms whose average recommendation is classified as a "buy" divided by the total number of firms with available recommendations. Specifically, firms are classified as "buy" if the average numerical recommendation is below 2.5. For each event-quarter, the "N" column indicates the number of firms with available recommendations. The last two columns indicate the difference between the mean and median recommendation and percentage of "buy" recommendations as well as its significance. In particular, the two-tailed significance of the t-test (Wilcoxon-Mann-Whitney test) is reported in parentheses for the mean (median) recommendation difference, whereas the significance of the binomial test is used for the difference between the percentages of "buy" recommendations.
Results are presented separately conditional on the existing regulatory regime at the GCM announcement date. Companies are allocated to the "Pre-NASD 2711" portfolio if the GCM announcement date is before the 9th of September 2002. All the remaining cases are allocated in the "Post- NASD 2711" portfolio.

Event-Quarter	**Recommendation**	*Inferred ($INFREC_q$)*					
		Pre-NASD 2711	N	Post-NASD 2711	N	Difference	p-value
	Mean	2.59		2.90		-0.31	(0.0034)
-4	Median	2.58	357	2.82	105	-0.24	(0.0047)
	% Buy	0.45		0.25		0.20	(<0.0001)
	Mean	2.69		3.20		-0.51	(<0.0001)
-3	Median	2.78	358	3.27	106	-0.49	(<0.0001)
	% Buy	0.40		0.17		0.23	(<0.0001)
	Mean	2.87		3.23		-0.36	(0.0021)
-2	Median	3.00	357	3.50	103	-0.50	(0.0003)
	% Buy	0.31		0.20		0.09	(<0.0001)
	Mean	3.05		3.23		-0.18	(0.1196)
-1	Median	3.11	348	3.50	98	-0.39	(0.0236)
	% Buy	0.23		0.19		0.04	(0.0895)

5.2.4. Analyst coverage cessation before the GCM announcement

Up until now, my results demonstrate that the more aggressive downgrade on stock recommendations for GCM firms than control firms is a robust phenomenon and that analysts became more pessimistic about GCM firms following the implementation of the new regulatory regime. I now focus my attention on an alternative signal that is associated with negative information: coverage cessation.

I investigate to what extent, in the pre-event period, analysts are more likely to cease coverage of a GCM firm than a similar non-GCM firm using a binary logistic regression model fitted to sample and control firms.[42] The model is defined as follows:

$$Pr(CEASE_i = 1 \mid X_i) = \frac{e^z}{1+e^z} \qquad (5.1)$$

where $Pr(CEASE_i = 1)$ is the probability of analyst i ceasing coverage of firm j from event-quarter -4 to event-quarter -1 and z represents a vector of explanatory variables, defined as follows:

$$z_i = \alpha_0 + \sum_{n=1}^{9} \beta_n X_{ni} + u_i \qquad (5.2)$$

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[42] Non-GCM firms share similar size and BM ratio and are selected as in section 4.3.2. Test results are materially the same when I match my GCM firms on size and momentum (as in section 5.2.1.1.), industry, size and BM (as in section 5.2.1.2.) and size and financial distress (as in section 5.2.1.3.)

I employ 9 independent variables to estimate equation 5.1., all of which are expected to be related to the probability of analyst coverage cessation. The variables are as follows:

1. Going-concern modified group (GCMG): This is the key independent variable and is defined as a binary variable that equals 1 when the company receives a first-time GCM audit report, 0 otherwise. As such, observations for my sample firms assume 1 whereas observations for control firms sharing similar size and BM ratio assume 0. A positive (negative) and significant coefficient suggests that analysts are more (less) likely to cease coverage of a GCM firm than a control firm;

2. Market capitalization (LOGSIZE): This explanatory variable proxies for the information environment and is defined as the natural log of the firms' market value computed as in section 4.3.2. Given that analysts tend to follow larger firms (e.g., Bhushan, 1989; Hong, Lim, and Stein, 2000), I assume that they are more likely to cease coverage of small firms than large firms;

3. Number of analysts following the firm (ANALY): This variable, directly related to the analyst information environment, is used as proxy for the level of information available about a firm (e.g., Hong, Lim, and Stein, 2000; Jiang, Lee, and Zhang, 2005; Zhang, 2006). Specifically, I define ANALY as the number of analysts following the firm at the end of event-quarter -4. Similarly to LOGSIZE, I expect analysts to be more likely to cease coverage of firms associated with higher levels of information uncertainty (lower number of analysts following) than firms associated with lower levels of information uncertainty (higher number of analysts following);

4. Book-to-market ratio (BM): This explanatory variable is used as proxy for the market's expectations about the firm's future prospects and it is defined as in section 4.3.2. The inclusion of this variable is justified by the relationship between BM ratio, stock returns and analyst preferences (e.g., Fama and French, 1992; Jegadeesh et al., 2004). Considering that analysts prefer growth stocks, I expect that they are more likely to cease coverage of GCM stocks with high BM ratios (value stocks) than stocks with low BM ratios (growth stocks);

5. Momentum (MOM): this independent variable proxies for pre-event stock performance and is defined as in section 5.2.1.1. The inclusion of this variable is justified by evidence that momentum is able to predict future returns (e.g., De Bondt and Thaler, 1985; 1987; Jegadeesh and Titman, 1993; 2001) and that analysts prefer firms associated with positive momentum (Jegadeesh et al., 2004). As such, I expect analysts to be more likely to cease coverage of stocks with negative momentum than stocks with positive momentum;

6. Return on assets ratio (ROA): this variable is used as a proxy for firm economic performance and is computed as the ratio of net income to the value of total assets using data from the last annual financial accounts reported before the GCM date. Given the evidence that analysts are self-selective (e.g., McNichols and O'Brien, 1997; Das, Guo, and Zhang, 2006), I assume that they are more likely to cease coverage of firm stocks with lower profitability than firm stocks with higher profitability;

7. Altman's (1968) z-score (ZSCORE): This independent variable proxies for bankruptcy risk and is computed as in Altman (1968) using data from the last annual financial accounts reported before the GCM date. Considering that firms

with high distress risk tend to underperform firms with low distress risk (e.g., Dichev, 1998; Griffin and Lemmon, 2002), I expect that analysts are more likely to cease coverage of stocks with low z-scores (more distressed firms) than stocks with higher z-scores (less distressed stocks);

8. Probability of a GCM audit report (PREDGC): This variable proxies for the ex-ante probability of a GCM disclosure using accounting information from the last annual financial accounts reported before the GCM date as in Mutchler (1985). I expect that analysts are more likely to cease coverage of stocks with low PREDGC scores (more likely to receive a GCM audit report) than stocks with higher PREDGC scores (less likely to receive a GCM audit report);

9. Leverage (LEV): This proxy controls for default risk and is defined as total debt to total assets using data from the last annual financial accounts reported before the GCM date. Once again, I expect that analysts will be more likely to cease coverage of stocks with higher LEV ratios (higher distress risk) than stocks with low LEV ratios (lower distress risk);

Table 5.4. provides the correlation between all variables. As can be seen, correlation between my dependent variable (CEASE) and independent variables is significant in all cases and consistent with my predictions. The independent variables for which the correlation is strongest with CEASE are GCMG (Pearson correlation= 0.155; Spearman rank correlation = -0.155, p-value<0.0001), BM (Pearson correlation= 0.092; Spearman rank correlation = 0.103, p-value<0.0001) and MOM (Pearson correlation= -0.117; Spearman rank correlation = -0.125, p-value<0.0001). This suggests that the analyst decision to cease

coverage of firms is associated with firms receiving a GCM audit report, value firms and firms with negative momentum.

Moreover, for the majority of cases, the correlation between my independent variables is lower than 20% suggesting that the variables are not strongly correlated. There are some exceptions like LOGSIZE and ANALY (Pearson correlation= 0.563; Spearman rank correlation = 0.606, p-value<0.0001), which is consistent with the previous findings of Bhushan (1989), Hong, Lim, and Stein (2000), etc. Moreover, there is also a considerable degree of association between ZSCORE, PREDGC and LEV and between GCMG and some other firm characteristics. In order to ensure that my results are not contaminated by correlation between my independent variables, I re-run my logistic regression using alternative sets of data. Specifically, I use alternative sets of control firms matched on different characteristics, I exclude the variables that are highly correlated with the significant ones and I use a stepwise technique to estimate the regression.

The null hypothesis to test is as follows:

> *H4: In the pre-event period, analysts do not cease coverage of a firm that receives a GCM audit report more often than a firm that does not receive a GCM audit report.*

Table 5.5. summarizes the results for my logistic regression model, which are highly significant (Wald x^2 = 107.11, p-value<0.0001). As can be seen, the GCMG variable coefficient is positive and highly significant, suggesting that, *ceteris paribus*, analysts are more prone to cease coverage of GCM firms than control firms. Importantly, this conclusion does not change when I use different sets of control firms matched based on momentum, industry or z-score as in section 5.2.1. Hence, I reject null hypothesis H4.

Besides GCMG, I also find three significant independent variables, for which coefficients are consistent with my predictions. For instance, *LOGSIZE* is negatively related to the analyst decision to cease coverage of firms, suggesting that analysts are more prone to cease coverage of small firms. This finding is consistent with previous research showing that analyst coverage is strongly related to firms' size (e.g., Bhushan, 1989; Hong, Lim, and Stein, 2000). Similar to that earlier literature (e.g., Jegadeesh et al., 2004), which shows analyst preference for growth stocks and stocks associated with positive momentum, the coefficients of BM and MOM suggest that the analyst's decision to cease coverage of firms is facilitated in the case of value firms and firms with negative momentum. Importantly, I find that these conclusions are robust when I re-run the model excluding the independent variables that are highly correlated with the significant ones. In addition, the sign and significance of these coefficients does not change when I use a stepwise technique to estimate the logistic regression model.

Overall, I show that analysts also anticipate the publication of a GCM audit report by ceasing coverage of sample firms more aggressively than match firms over the one-year period before the GCM date. As such, investors should be particularly aware that analyst decision to cease coverage of a firm is likely to be associated with unfavourable information about the future prospects of such firm.

TABLE 5.4.
Pearson and Spearman correlations: Equation 5.1. Variables

This table provides the Pearson (Spearman rank) correlation above (below) the diagonal between all variables used to estimate equation 5.1. for both GCM and control firms receiving stock recommendations before the GCM date. The two-tailed p-value is provided in parenthesis below the correlation. GCM companies are my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Control firms are selected employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.
Dummy variable CEASE=1 if analyst *i* decides to drop the coverage of firm *j* between event-quarter -4 and event-quarter -1; Dummy variable GCMG=1 if the company receives a GCM audit report, and 0 otherwise; LOGSIZE=natural log of market capitalization measured one year before the GCM announcement date; ANALY=number of analysts following the firm in quarter -4; BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM=monthly average of prior 11 month (t-12 to t-2) raw returns; ROA=return on assets (net income/total assets); CR=current ratio (current assets/current liabilities); ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985); LEV=total debt/total assets. All variables are computed with data taken from the last annual financial accounts reported before the GCM date.

	CEASE	GCMG	LOGSIZE	ANALY	BM	MOM	ROA	ZSCORE	PREDGC	LEV
CEASE		0.155 (<0.0001)	-0.071 (0.0004)	-0.036 (0.0735)	0.092 (<0.0001)	-0.117 (<0.0001)	-0.088 (<0.0001)	-0.062 (0.0017)	-0.052 (0.0090)	0.046 (0.0206)
GCMG	0.155 (<0.0001)		0.015 (0.4387)	0.062 (0.0019)	0.079 (<0.0001)	-0.547 (<0.0001)	-0.253 (<0.0001)	-0.192 (<0.0001)	-0.067 (0.0007)	0.168 (<0.0001)
LOGSIZE	-0.070 (0.0005)	0.020 (0.3213)		0.563 (<0.0001)	-0.251 (<0.0001)	-0.229 (<0.0001)	0.092 (<0.0001)	0.038 (0.0536)	0.054 (0.0064)	0.143 (<0.0001)
ANALY	-0.053 (0.0082)	0.063 (0.0015)	0.606 (<0.0001)		-0.030 (0.1313)	-0.118 (<0.0001)	-0.074 (0.0002)	-0.047 (0.0194)	0.066 (0.0010)	0.168 (<0.0001)
BM	0.103 (<0.0001)	0.099 (<0.0001)	-0.334 (<0.0001)	-0.016 (0.4334)		0.037 (0.064)	-0.161 (<0.0001)	-0.046 (0.0221)	-0.000 (0.9995)	-0.151 (<0.0001)
MOM	-0.125 (<0.0001)	-0.588 (<0.0001)	-0.162 (<0.0001)	-0.098 (<0.0001)	-0.055 (0.0062)		0.179 (<0.0001)	0.207 (<0.0001)	0.037 (0.0160)	-0.147 (<0.0001)
ROA	-0.118 (<0.0001)	-0.509 (<0.0001)	0.190 (<0.0001)	0.063 (0.0015)	-0.077 (0.0001)	0.392 (<0.0001)		0.040 (0.0472)	-0.054 (0.0070)	0.080 (<0.0001)
ZSCORE	-0.089 (<0.0001)	-0.305 (<0.0001)	-0.036 (0.0731)	-0.059 (0.0320)	-0.009 (0.6620)	0.323 (<0.0001)	0.365 (<0.0001)		0.521 (<0.0001)	-0.186 (<0.0001)
PREDGC	-0.061 (0.0021)	-0.374 (<0.0001)	-0.025 (0.2027)	-0.041 (0.0403)	0.121 (<0.0001)	0.237 (<0.0001)	0.361 (<0.0001)	0.470 (<0.0001)		-0.153 (<0.0001)
LEV	0.050 (0.0123)	0.196 (<0.0001)	0.109 (<0.0001)	0.105 (<0.0001)	-0.080 (<0.0001)	-0.161 (<0.0001)	0.031 (0.1168)	-0.383 (<0.0001)	-0.746 (<0.0001)	

TABLE 5.5.
Logistic Regression Model Estimating the Probability of Cessation of Analyst Coverage before the GCM announcement

This table presents the results of a binary logistic regression model estimating the probability of cessation of analyst coverage of a firm from event-quarter -4 to event-quarter -1 using both GCM and control firms. GCM companies are my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Control firms are selected employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.
The binary logistic regression model is defined in equation 5.1. The binary dependent variable (CEASE) assumes 1 if analyst *i* decides to drop the coverage of firm *j* between event-quarter -4 and event-quarter -1. Nine independent variables are employed to estimate equation 5.1: Dummy variable GCMG=1 if the company receives a GCM audit report, and 0 otherwise; LOGSIZE=natural log of market capitalization measured one year before the GCM announcement date; ANALY=number of analysts following the firm in quarter -4; BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM=monthly average of prior 11 month (t-12 to t-2) raw returns; ROA=return on assets (net income/total assets); CR=current ratio (current assets/current liabilities); ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985); LEV=total debt/total assets. All variables are computed with data taken from the last annual financial accounts reported before the GCM date.

Independent variable	Expected sign	Coefficient	Wald	p-value
Intercept	N.A.	-0.59	9.42	0.0021
GCMG	+	0.41	14.94	0.0001
LOGSIZE	-	-0.08	4.42	0.0354
ANALY	-	-0.01	0.85	0.3554
BM	+	0.09	9.91	0.0016
MOM	-	-1.81	7.79	0.0052
ROA	-	-0.09	3.73	0.0536
ZSCORE	-	-0.00	0.05	0.8154
PREDGC	-	-0.00	2.25	0.1340
LEV	+	0.24	3.12	0.0685

Likelihood ratio x^2 (d.f.=9) = 107.11 with p<0.0001

5.3. Revisiting analyst reaction to the GCM audit report

5.3.1. Analyst coverage cessation after the GCM announcement

Similarly to the previous subsection, I employ a multivariate analysis to investigate if analysts are more prone to cease coverage of GCM firms immediately after the GCM announcement. This is particularly important since my previous chapter indicates that analysts do not change their recommendations from event-quarter -1 to event-quarter +1 relative to the GCM announcement. As such, I now investigate if analysts simply ignore such a bad news announcement or if their reaction is related to their decision to cease coverage of firms receiving a GCM audit report.

To be precise, I run a similar binary logistic regression model as in equation 5.1. to investigate to what extent, following the disclosure of a GCM audit report, analysts are more likely to cease coverage of a GCM firm than a similar non-GCM.[43] To avoid the potential problem arising from the relationship between delisting firms and analyst decision to drop the coverage of such firms, I exclude all recommendations of firms delisted within event-quarter +1.

The model is as follows:

$$Pr(CEASE_i = 1 | X_i) = \frac{e^w}{1+e^w} \qquad (5.3)$$

[43] Once again, non-GCM firms share similar size and BM ratio and are selected as in section 4.3.2. Test results are materially the same when I match my GCM firms on size and momentum (as in section 5.2.1.1.), industry, size and BM (as in section 5.2.1.2.) and size and financial distress (as in section 5.2.1.3.)

where *Pr(CEASE$_i$ =1)* is the probability of analyst *i* ceasing coverage of firm *j's* from event-quarter -1 to event-quarter +1 and *w* represents a vector of independent variables defined as follows:

$$w_i = \alpha_0 + \sum_{n=1}^{9} \beta_n X_{ni} + u_i \tag{5.4}$$

Equation 5.4. uses 8 of the same 9 explanatory variables defined in equation 5.2.: *GCMG*, LOG*SIZE*, *BM*, *MOM*, *ROA*, *ZSCORE*, *PREDGC* and *LEV* together with *ANALY* defined slightly differently. In particular, *ANALY* is now defined as the number of analysts following the company at the end of the event-quarter -1.

The null hypothesis to test is as follows:

> *H5: : Analysts do not cease coverage of a firm that receives a GCM audit report more often than a firm that does not receive a GCM audit report immediately after the GCM date.*

Table 5.6. shows the results of my logistic regression model, which are highly significant (Wald x^2 = 97.87, p-value<0.0001). The key finding relates to the positive and highly significant coefficient associated with the *GCMG* variable (p<0.0001). This suggests that analysts are more prone to cease coverage of GCM firms than control firms within the first event-quarter following the disclosure of a GCM audit report. One again, I find similar conclusions when using the alternative sets of control firms as in section 5.2.1. As such, I

conclude that analyst react to the publication of a GCM audit report by ceasing coverage of my sample firms and reject null hypothesis H5.

I also find an additional significant independent variable in my model. Interpreting the negative and significant coefficient associated with *MOM* suggests that, *ceteris paribus*, the analyst's decision to cease coverage of a firm is facilitated when firms have negative momentum. Importantly, I find that my conclusions are robust when I re-run the model excluding the independent variables that are highly correlated with GCMG and MOM. Moreover, the signal and significance of GCMG and MOM coefficients do not change when I use a stepwise technique to estimate the regression model.

Overall, I show that analysts do not ignore the publication of a GCM audit report. Together with the results of the previous chapter, I find that analyst reaction to the GCM event is not related to their decision to downgrade such firms. Instead, I demonstrate that analysts prefer to cease coverage of GCM firms avoiding the need to report negatively on them. Once again, this suggests that investors should be particularly aware that analysts avoid to issue unfavourable recommendations following the GCM announcement and that a coverage cessation is likely to be associated with unfavourable information about the future prospects of firms.

TABLE 5.6.
Logistic Regression Model Estimating the Probability of Cessation of Analyst Coverage after the GCM Announcement

This table presents the results of a binary logistic regression model estimating the probability of cessation of analyst coverage of a firm from event-quarter -1 to event-quarter +1 using both GCM and control firms. The GCM companies are my population of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994. Control firms are selected employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.
The binary regression model is defined in equation 5.3. The binary dependent variable (CEASE) assumes 1 if analyst *i* decides to drop the coverage of firm *j* from event-quarter -1 to event-quarter +1. Nine independent variables are employed to estimate equation 5.1: Dummy variable GCMG=1 if the company receives a GCM audit report, and 0 otherwise; LOGSIZE=natural log of market capitalization measured one year before the GCM announcement date; ANALY=number of analysts following the firm in quarter -1; BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM=monthly average of prior 11 month (t-12 to t-2) raw returns; ROA=return on assets (net income/total assets); CR=current ratio (current assets/current liabilities); ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985); LEV=total debt/total assets. All variables are computed with data taken from the last annual financial accounts reported before the GCM date.

Independent variable	Expected sign	Coefficient	Wald	p-value
Intercept	N.A.	-2.37	55.52	<0.0001
GCMG	+	0.91	29.65	<0.0001
LOGSIZE	-	-0.00	0.00	0.9488
ANALY	-	-0.02	0.70	0.4016
BM	+	0.03	0.32	0.5687
MOM	-	-1.94	3.74	0.0531
ROA	-	-0.06	0.47	0.4945
ZSCORE	-	-0.03	0.67	0.4127
PREDGC	-	0.00	0.02	0.8853
LEV	+	0.21	1.17	0.2786

Likelihood ratio x^2 (d.f.=9) = 88.15 with p<0.0001

5.4. Summary and discussion

This chapter provides further evidence about whether security analysts anticipate and react to the publication of a GCM audit report. I find the previous conclusion that analysts anticipate the publication of a GCM audit report by downgrading more aggressively their recommendations for GCM firms than control firms is robust after controlling for confounding factors like size, BM ratio, momentum, industry and distress risk. In addition, I show that stock recommendations for GCM firms with high BM ratio and lower momentum are significantly more pessimistic than for GCM firms with low BM ratio and higher momentum. This suggests that analyst recognition of going-concern problems is facilitated for value firms and firms with negative momentum, consistent with the findings of Jegadeesh et al. (2004). Importantly, I find that pre-GCM stock recommendations become significantly more unfavourable after the implementation of regulatory changes in 2002, suggesting that the decrease in analyst optimism (e.g., Barber et al., 2006, Madureira et al., 2008) is also manifested for firms experiencing high levels of financial distress.

This chapter shows that analysts also anticipate the publication of a GCM audit report by ceasing coverage of such firms within the one-year period before the GCM date. In addition, since we know that analysts do not downgrade stock recommendations when they cease coverage (e.g., McNichols and O'Brien, 1997), leading the lower tail of the recommendation distribution to be censored, the average observed recommendation will be more favourable than the true unobservable average recommendation. This can explain, at least partially, why the average analyst recommendation for GCM firms immediately before the event is a "hold" and not an "underperform" or "sell" rating. This is particularly important in this context since, as discussed in the previous chapter, there is evidence that small investors do not perceive a "hold" recommendation as an unfavourable message (Malmendier and Shanthikumar, 2007).

Finally, I find that analysts react to the GCM audit report by ceasing coverage of GCM firms following the disclosure of such an event. Together with the results of chapter 4, in which I show that analysts do not change their recommendations after the disclosure of the GCM audit report, this provides further evidence that analysts are less interested in following companies associated with bad news (e.g., Griffin, 2003) and that they are reluctant to issue unfavourable recommendations (e.g., McNichols and O'Brien, 1997; Conrad et al., 2006). This is also consistent with the notion that analysts have finite resources and tend to replace coverage of firms associated with bad news with firms associated with good news (e.g., McNichols and O'Brien, 1997; Kecskés and Womack, 2007). This has important implications for investors' understanding of analyst value-relevance in bad news scenarios. In fact, despite a prior expectation that the marginal contribution of the security analysts to investors may be greater in the case of dissemination of bad news to investors (e.g., Hong, Lim, and Stein, 2000), investors should not rely on analysts as messengers of bad news and should be particularly aware that the analyst decision to cease coverage is associated with negative information in this context.

The evidence in this chapter supplements my previous findings that analysts anticipate the publication of a GCM audit report. More specifically, I show that analysts use two different signs to communicate negative information about GCM firms. First, they downgrade the stock recommendations for GCM firms more aggressively than for similar non-GCM firms as the event approaches. Second, they tend to cease coverage of such firms within the one-year period before the GCM announcement. Whether or not analyst message is clearly understood by investors as negative information remains an open question. The next chapter answers this question.

CHAPTER 6

ANALYST COVERAGE AND SHORT-TERM MARKET REACTION TO THE GCM ANNOUNCEMENT

6.1. Introduction

Extant literature provides conflicting results about the short-term market reaction to the publication of a GCM audit report. On the one hand, studies find no evidence of an abnormal reaction surrounding the GCM announcement date (e.g., Elliott, 1982, Dodd et al., 1984; Herbohn, Ragunathan, and Gardsen, 2007). On the other hand, other studies show a significant adverse market reaction to such an event (e.g., Firth, 1978; Fleak and Wilson, 1994; Jones, 1996; Carlson, Glezen, and Benefield, 1998; Citron, Taffler, and Uang, 2008). These conflicting results are explained by a number of factors, such as inconsistencies in the definition of the GCM announcement date, sample selection biases, inadequate control for prior and concurrent disclosures or the inability to distinguish “unexpected” from “expected” audit reports (e.g., Craswell, 1985; Asare, 1990).

This chapter revisits the short-term market reaction to the publication of a GCM audit report and introduces a new variable in the discussion: security analyst activity. Investigating the role of security analysts in the short-term market reaction to such a negative event provides further evidence on the usefulness of analyst opinions in this particular scenario of highly distressed firms. There are reasons to believe that analyst activity impacts positively on the efficiency with which the market assimilates going concern problems.

First, the literature provides evidence that the GCM audit report can be predicted with a high level of accuracy using publicly available information (e.g., Mutchler, 1985; Dopuch, Holthause, and Leftwich, 1987) and that the market reaction to such a negative event depends on market expectations of a forthcoming audit opinion (e.g., Fleak and Wilson, 1994; Jones, 1996). Because security analysts are sophisticated users of financial statements who use fundamental analysis of accounting numbers (Block, 1999) as well as a variety of information not readily available to investors (Ivkovic and Jegadeesh, 2004), I expect their activities to enhance the market's awareness of a potential forthcoming GCM announcement. As such, analyst coverage should reduce the "surprise" associated with the publication of a GCM audit report.

Second, there is evidence that investors are particularly inefficient in dealing with negative information (e.g., Bernard and Thomas, 1989; Womack, 1996; Dichev and Piotroski, 2001; Taffler, Lu, and Kausar, 2004) and that the marginal contribution of security analysts may be greater in the bad news domain (e.g., Hong, Lim, and Stein, 2000). As such, analyst opinions may help investors to incorporate negative information related to going-concern problems in stock prices of firms. Investigating this particular issue adds to the evidence of chapter 4 where I show that analysts downgrade and cease the coverage of GCM firms more aggressively than similar non-GCM firms over the year preceding the GCM announcement date. However, it is hard to believe that an average "hold" recommendation is a fair assessment for these firms, even considering that it represents a downgrade from a previous "buy" rating. Whether or not investors recognize analyst relative pessimism about GCM firms remains an open question.

To sum up, if security analysts are providing investors with value-relevant information before the disclosure of a GCM audit report, I expect them to facilitate the incorporation of other pre-GCM negative signals in stock prices thus reducing the "surprise" associated with the publication of such an event. It follows that the short-term market reaction to the GCM announcement should be less negative for companies with analyst coverage.

The remainder of this chapter is organised as follows: section 2 describes the data and methodology. Section 3 presents the results. Section 4 summarizes and discusses the results of the chapter.

6.2. Data and Methodology

The main purpose of this chapter is to evaluate the role of security analysts in the short-term market reaction to the publication of a GCM audit report. My research design is based on the comparison between the short-term market reaction of firms with pre-GCM analyst coverage and firms with no pre-GCM analyst coverage. As such, the definition of analyst coverage and the computation of abnormal returns assume particular relevance. The data used in this chapter is collected from three different sources: security analyst data is from I/B/E/S/ Recommendations – Detailed File whereas market and accounting data are provided by CRSP and COMPUSTAT respectively.

6.2.1. Defining analyst coverage

The definition of analyst coverage is one of the key issues in this chapter. Unless otherwise stated, firms are allocated to the "analyst coverage" portfolio if there is at least one new recommendation or one new EPS forecast available within the 6-month window prior to their GCM announcement date. The 6-month window used to define analyst coverage is consistent with Das, Guo, and Zhang (2006), who estimate the level of analyst coverage based on a similar period. In order to provide robust results, I use the three recommendation categories defined in section 4.2.2.1.: reported recommendations, current recommendations and inferred recommendations.

As discussed in section 4.2.2.1., reported recommendations are those made and issued by analysts in each event-quarter. Current recommendations are similar to reported recommendations with one difference: they assume that the last available recommendation still applies for the current event-quarter in those cases where a missing recommendation is not related to analyst coverage cessation. Finally, inferred recommendations are used to deal with those cases where the analyst ceases the coverage of firms by inferring an unfavourable recommendation in such cases. I assume that coverage cessation is likely to be associated with analyst negative expectations about the prospects of a firm given that analysts are reluctant to issue unfavourable investment advice (McNichols and O'Brien, 1997) and because they generally remain at the same brokerage company following the coverage cessation decision (Clarke et al., 2006). Therefore, and drawing on Clarke et al. (2006), all inferred recommendations of firms associated with coverage cessation are classified as "underperform" or "sell" depending on the previous recommendation.

6.2.2. Computing short-term abnormal returns

As Kothari and Warner (2007) state, short-horizon methods are "*relatively straightforward and trouble-free*". I investigate the short-term market reaction to the publication of a first-time GCM audit report using the cumulative abnormal return (CAR) methodology.[44] In particular, I study three different trading windows centred on the GCM announcement date: (-1, +1), (-2, +2) and (-3, +3). Identifying the exact going-concern disclosure date is a crucial issue. In efficient capital markets, price adjustments to new information are expected to occur as soon as the new value-relevant information becomes available to

[44] Results using buy-and-hold abnormal returns are very similar to those reported here.

investors.[45] Drawing on Kausar, Taffler, and Tan (forthcoming), I define trading day 0 as the GCM announcement date taken from the SEC-EDGAR database.[46] The market-adjusted model is employed to measure the abnormal returns (AR) for each sample firm and is computed as follows:

$$AR_{it} = R_{it} - R_{mt} \tag{6.1}$$

where R_{it} is the return of firm i on day t and R_{mt} is the return of the smallest decile of the NASDAQ index on day t. I use this index since my sample firms usually have small size and the majority of them trade in the NASDAQ at the GCM announcement date.[47] The cumulative abnormal return (CAR) for security i from trading day a to trading day b is given by:

$$CAR_{it} = \sum_{t=a}^{b} AR_{it} \tag{6.2}$$

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[45] Dodd et al. (1984) show that a qualified opinion can occur at any one of the following moments: i) when the annual earnings are first publicly announced; ii) when the annual report is made publicly available; iii) when the 10-k report is made publicly available, or iv) when the firm announces the qualification in a press release. As such, prior conflicting results about the value of the GCM may be explained, at least partially, by the use of different announcement dates. For instance, Firth (1978) defines the publication date of the annual report as the event date, Elliott (1982) uses the release date of earnings in the Wall Street Journal whereas Dodd et al. (1984) and Carlson, Glezen, and Benefield (1998) use the earlier of the receipt date of the 10-k or the annual report.

[46] Kausar, Taffler, and Tan (forthcoming) reveal that textual search of press articles using Factiva uncovers less than 1% of cases associated with prior publication of news of the forthcoming GCM opinion in their sample.

[47] From my 924 first-time GCM cases, 691 trade on the NASDAQ at their GCM announcement date. I also use the other deciles to compute the abnormal returns as well as the NASDAQ index. However, my results are not sensitive to the index used to compute the abnormal returns.

where AR_{it} is defined as above. The cumulative abnormal returns are then averaged across the number of firms in the sample (n) to provide an average abnormal return for each period t. I consider:

$$\overline{CAR_t} = \frac{1}{n}\sum_{i=1}^{n} CAR_{it} \tag{6.3}$$

where CAR_{it} is defined as above. In order to properly deal with the problems resulting from extreme outliers that affect CARs, I winzorize the extreme values at the first (99th) percentile of both tails of the distribution as in Kausar, Taffler, and Tan (forthcoming).[48] The parametric t-test is employed to examine the significance of the mean CARs whereas the non-parametric Wilcoxon signed rank-test is used to examine the significance of the median abnormal returns. The Fisher sign-test is also presented below. When I split my sample in two portfolios, I use the two-tailed t-test and the Wilcoxon-Mann-Whitney test to investigate mean and median differences between groups, respectively.

[48] The non-winsorized results are not significantly different from the winsorized results.

6.3. Results

6.3.1. Short-term market reaction to the first-time GCM audit report

In this subsection, I investigate the short-term market reaction to the announcement of a first-time GCM audit report and control my results for different GCM firm characteristics. This analysis aims at clarifying if investors find this accounting event value-relevant in terms of the prospects of my GCM firms.

6.3.1.1. Initial evidence

The short-term abnormal returns are presented in table 6.1. I find a highly negative and significant market reaction to the publication of a GCM audit report on a risk-adjusted basis. For instance, the 3-day, 5-day and 7-day mean (median) CARs are -4.2%, -5.4% and -4.9% (-3.2%, -4.2% and -4.7%) respectively, all significant at the 0.01% level. Moreover, the number of negative abnormal returns is significantly greater than the number of positive abnormal returns for all the event windows considered. As such, my results indicate that investors find the publication of a GCM audit report as value-relevant.

Table 6.1.
Short-term Market Reaction to the First-Time GCM Audit Report

This table presents the cumulative abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as benchmark index. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) CAR. The percentage of positive (negative) CARs is shown in the positive (negative) column, whereas the significance of the sign test is reported in parentheses.

Period	**CAR**				**Sign test**
(trading days)	**Mean**	**Median**	**Positive**	**Negative**	
(-1, +1)	-0.042 (<0.0001)	-0.032 (<0.0001)	39%	61%	(<0.0001)
(-2, +2)	-0.054 (<0.0001)	-0.042 (<0.0001)	37%	63%	(<0.0001)
(-3, +3)	-0.049 (<0.0001)	-0.047 (<0.0001)	37%	63%	(<0.0001)

6.3.1.2. Controlling for GCM firm characteristics

I now explore the short-term market reaction to the GCM audit report conditional on firm characteristics. This procedure helps us understand if the adverse market reaction is more severe for specific groups of GCM firms. I focus my attention on three variables that the literature has shown to have ability to predict cross-sectional returns: size (e.g., Banz, 1981; Keim, 1983; Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994), momentum (e.g., DeBondt and Thaler, 1985; 1987; Jegadeesh and Titman, 1993; 2001) and earnings surprise (e.g., Ball and Brown, 1968; Bernard and Thomas, 1989; 1990). In addition, I control my results for two variables that are proxy for distress risk (z-score, Altman, 1968) and GCM probability (PREDGC, Mutchler, 1985), which are important dimensions to consider given the nature of my sample firms.

Table 6.2. reports the results. Panel A provides the abnormal returns for my GCM companies conditional on size. Companies for which the market value of equity is below

the sample median ($33.7m) are classified as “small size” (n=462) whereas companies for which the market value of equity is above the median are classified as “large size” (n=462).[49] I find that the reaction to the publication of a GCM audit report is generally significantly more negative for large GCM firms than small GCM firms. For instance, for the (-1,+1) trading period, mean (median) abnormal reaction for the “small size” portfolio is -2.9% (-2.7%) and for the “large size” portfolio it is -5.7% (-3.8%), all significant at the 0.1% level. More importantly, both parametric and nonparametric tests show that, generally, the differences in the abnormal returns are significant at conventional levels. As such, I conclude that the market is more surprised by the publication of a GCM audit report in the case of larger firms.

CARs for GCM companies conditional on pre-event momentum are presented in panel B of table 6.2, with momentum defined as in section 5.2.1.1. Companies with negative momentum are assigned to the “negative momentum” portfolio (n=689) whilst companies with positive momentum are assigned to the “positive momentum” portfolio (n=235). Generally, my results show a significant negative market reaction to the GCM announcement for both “negative momentum” and “positive momentum” portfolios, with no significant differences in mean and median CARs. As such, I conclude that the short-term market reaction to the publication of a GCM audit report does not depend on pre-event stock performance.

Panel C of table 6.2. reports the short-term market reaction to the announcement of a GCM audit report depending on firm z-score (Altman, 1968), computed as in section 5.2.1.3. Companies with z-score <= 1.81 are allocated to the “high distress risk” portfolio (n=775) whilst all others are allocated to the “low distress risk” portfolio (n=149). My results show

[49] Market value of equity is defined as in section 4.3.2.1.

a negative and significant reaction to the publication of a GCM audit report for both "high distress risk" and "low distress risk" portfolios for the majority of the trading periods under scrutiny. More importantly, I find no significant differences in mean and median CARs between groups, suggesting that the market reaction to the publication of a GCM audit report does not depend on risk of bankruptcy.

In Panel D of table 6.2., I report the short-term market reaction to the publication of a GCM audit report conditional on the firm's likelihood of a forthcoming GCM audit report. The probability of a forthcoming GCM audit report (PREDGC) is estimated following Mutchler's (1985) model using data taken from the last annual financial accounts reported before the GCM date. Given that my sample contains only firms that receive a GCM audit report, I use the Fleak and Wilson (1994) cut off score of 0.01 to distinguish firms depending on their PREDGC as in Blay and Greiger (2001). Companies with PREDGC <= 0.01 are classified as "high GCM likelihood" whilst companies with PREDGC > 0.01 are classified as "low GCM likelihood". Once again, I find a negative market reaction to both "high GCM probability" and "low GCM probability", with no significant differences in mean and median CARs. As such, I conclude that the market reaction to the publication of a GCM audit report does not depend on the ex-ante probability of a forthcoming GCM audit report.

Panel E provides separate results for the two portfolios of GCM firms conditional on the signal of standardized unexpected earnings (SUE). SUE is defined as follows. I start by calculating quarterly earnings change (ΔNI_q) as the difference between the quarterly income before extraordinary items (NI_q) and the quarterly income before extraordinary items in the previous year (NI_{q-4}). Following Dichev and Piotroski (2001), I define quarter q as the most recent quarter preceding the GCM announcement date. Following Foster, Olsen, and Shevlin (1984), I then compute SUE=(ΔNI_q / $|NI_q|$). Companies with negative

SUE are allocated to the “Negative earnings surprise” portfolio (n=528) and companies with positive SUE are allocated to the “Positive earnings surprise” portfolio (n=396). I find a significant and negative market reaction to the GCM event both for firms with negative and positive earnings surprises. However, importantly, my results show that the negative reaction to the GCM event is significantly more pronounced for firms with negative earnings surprises. For instance, for the (-1,+1) trading period, mean (median) abnormal reaction for the “Negative earnings surprise” is –5.9% (-3.6%) and for the “Positive earnings surprise” portfolio it is -2.1% (-2.5%), all significant at the 5% level. Importantly, both parametric and nonparametric tests mean and median differences between portfolios are significant at conventional levels. Hence, I conclude that the adverse impact of a GCM audit report decreases when companies are associated with positive earnings surprises.

Overall, I conclude that the negative reaction to the publication of a GCM audit report is a consistent phenomenon, affecting all groups of firms under analysis. Nevertheless, there is evidence that the adverse impact of such bad news is more severe for large firms and for firms with negative earnings surprise.

Table 6.2.
Short-term Market Reaction to the First-Time GCM Audit Report – Controlling for Firm Characteristics

This table presents the cumulative abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as benchmark index. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) CAR. The last two columns report the mean and median differences between the CARs of the portfolios under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.
Panel A provides separate results for the portfolio of 462 (462) GCM companies with market capitalization below (above) the sample median ($33.7m). Market capitalization is calculated one year before the GCM date. Panel B reports separate results for the portfolio of 235 (689) GCM companies with positive (negative) pre-event momentum. Momentum is defined as the average monthly raw returns for the prior 11-month period (t-12 to t-2) relative to the GCM announcement month. Panel C provides separate results for the portfolio of 775 (149) GCM companies with z-score <=1.81 (>1.81). Z-score is computed following Altman's (1968) model using the accounting information from the fiscal year ending one year before the GCM announcement date. Panel D reports separate results for the portfolio of 454 (470) GCM companies where PREDGC is <=0.01 (>0.01), defined as minimum cut-off score by Fleak and Wilson (1994). Panel E provides separate results for the portfolio of 528 (396) GCM companies where SUE is negative (positive). SUE=(ΔNI_q / $|NI_q|$), where ΔNI_q is the quarterly earnings change computed as the difference between the quarterly income before extraordinary items (NI_q) and the quarterly income before extraordinary items in the previous year (NI_{q-4}).

Panel A: CARs conditional on firm size

	Small Size (A) (n = 462)		**Large Size (B)** (n = 462)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1, +1)	-0.029	-0.027	-0.057	-0.038	0.028	0.011
	(0.0002)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0125)	(0.0421)
(-2, +2)	-0.041	-0.037	-0.067	-0.049	0.026	0.012
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0733)	(0.1247)
(-3, +3)	-0.027	-0.036	-0.073	-0.057	0.046	0.021
	(0.0241)	(0.0003)	(<0.0001)	(<0.0001)	(0.0048)	(0.0109)

Panel B: CARs conditional on firm momentum

	Negative Mom. (A) (n = 689)		**Positive Mom. (B)** (n = 235)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1, +1)	-0.043	-0.031	-0.040	-0.032	-0.003	0.001
	(<0.0001)	(<0.0001)	(0.0002)	(<0.0001)	(0.8158)	(0.9329)
(-2, +2)	-0.057	-0.055	-0.043	-0.027	-0.014	-0.028
	(<0.0001)	(<0.0001)	(0.0006)	(0.0007)	(0.3383)	(0.1251)
(-3, +3)	-0.054	-0.049	-0.037	-0.036	-0.017	-0.013
	(<0.0001)	(<0.0001)	(0.0084)	(0.0025)	(0.3257)	(0.1264)

Panel C: CARs conditional on firm distress risk

	High Distress Risk (A) (n = 775)		Low Distress Risk (B) (n = 149)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1, +1)	-0.042	-0.032	-0.050	-0.029	0.008	-0.003
	(<0.0001)	(<0.0001)	(0.0012)	(0.0038)	(0.6179)	(0.9556)
(-2, +2)	-0.056	-0.047	-0.037	-0.031	-0.019	-0.016
	(<0.0001)	(<0.0001)	(0.0955)	(0.0205)	(0.4363)	(0.4036)
(-3, +3)	-0.054	-0.048	-0.014	-0.038	-0.040	-0.010
	(<0.0001)	(<0.0001)	(0.662)	(0.0224)	(0.2287)	(0.6361)

Panel D: CARs conditional on firm GCM probability

	High GCM Probability (A) (n = 454)		Low GCM Probability (B) (n = 470)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1, +1)	-0.040	-0.025	-0.045	-0.036	0.005	0.011
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.7041)	(0.5538)
(-2, +2)	-0.049	-0.036	-0.059	-0.049	0.010	0.013
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.4743)	(0.3212)
(-3, +3)	-0.046	-0.048	-0.050	-0.046	0.004	-0.002
	(0.0003)	(<0.0001)	(<0.0001)	(<0.0001)	(0.8324)	(0.9274)

Panel E: CARs conditional on firm SUE

	Neg. Earnings Surp. (A) (n = 528)		Pos. Earnings Surp. (B) (n = 396)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1, +1)	-0.059	-0.036	-0.021	-0.025	-0.038	-0.011
	(<0.0001)	(<0.0001)	(0.0142)	(0.0005)	(0.0007)	(0.0118)
(-2, +2)	-0.070	-0.056	-0.031	-0.028	-0.039	-0.028
	(<0.0001)	(<0.0001)	(0.0029)	(0.0006)	(0.0052)	(0.0064)
(-3, +3)	-0.066	-0.058	-0.027	-0.029	-0.039	-0.029
	(<0.0001)	(<0.0001)	(0.0435)	(0.0012)	(0.0239)	(0.0264)

6.3.2. Short-term market reaction to the GCM announcement and analyst coverage

This section investigates the relationship between the short-tem market reaction to the GCM announcement and analyst coverage. Considering the role of these sophisticated agents in the functioning of financial markets, I expect the announcement of a GCM audit report to be more "expected" for firms with analyst coverage than for firms with no analyst coverage. It follows that, in this context, the short-term market reaction to the GCM announcement should be less negative in the case of firms with analyst coverage. In addition, below I control my results for different firm characteristics, previous stock recommendations and reporting environment period.

6.3.2.1. Descriptive statistics

Table 6.3. presents descriptive statistics for my sample firms conditional on pre-event analyst coverage. I allocate firms to the "analyst coverage" portfolio if analysts report at least one new recommendation or issue one new annual EPS forecast within the 6-month period before the GCM announcement date. All the remaining firms are allocated to the "no analyst coverage" portfolio.

I find that firms with analyst coverage are significantly larger than firms with no analyst coverage, which is consistent with Hong's, Lim, and Stein (2000) finding that size is the most important variable to explain analyst coverage. This holds for three size proxies: market capitalization, sales and total assets. For instance, the mean (median) size measured as market capitalization one year before the GCM date is \$219.8 million (\$82.3 million) for companies with analyst coverage and \$37.6 million (\$22.1 million) for companies with no analyst coverage (difference significant at the 0.1% level). I also observe that covered companies have significantly higher distress risk (mean $ZSCORE_{COVERED}$=0.99; mean $ZSCORE_{NON\text{-}COVERED}$=1.23, p=0.0009) and exhibit significantly stronger negative momentum (mean $MOM_{COVERED}$=-0.06; mean $MOM_{NON\text{-}COVERED}$=-0.03, p<0.0001) relative to non-covered companies. There is also some evidence that the average BM ratio of covered firms is significantly lower than the average BM ratio of non-covered firms. Finally, I find no significant differences for return on assets, current ratio, leverage, and the likelihood of a forthcoming GCM audit report.

Table 6.3.
Descriptive Statistics – Non-covered vs. Covered Firms

This table presents descriptive statistics for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Each of my 924 companies is allocated to one of two portfolios conditional on the definition of "analyst coverage". Companies are allocated to the "analyst coverage" portfolio if analysts report at least one new recommendation or issue one new annual EPS forecast within the 6-month period before the GCM announcement date. All the remaining firms are allocated to the "no analyst coverage" portfolio. Results are reported separately. The last four columns report the mean and median differences between the variables of each portfolio. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets on the right of the mean (median) differences.

Variable	NO ANALYST COVERAGE (n = 607)			ANALYST COVERAGE (n = 317)			Mean Diference	p-value	Median Diference	p-value
	Mean	Median	St. Deviation	Mean	Median	St. Deviation				
SIZE	37.63	22.06	50.68	219.78	82.30	407.38	-182.15	(<0.0001)	-60.24	(<0.0001)
SALES	55.95	14.48	102.47	211.86	50.29	416.17	-155.91	(<0.0001)	-35.81	(<0.0001)
TA	50.97	16.07	98.17	270.12	60.61	540.48	-219.15	(<0.0001)	-44.54	(<0.0001)
ROA	-0.62	-0.35	0.76	-0.66	-0.41	0.78	0.04	(0.5434)	0.06	(0.5715)
CR	1.73	1.15	1.80	1.69	1.23	1.49	0.04	(0.7258)	-0.08	(0.5800)
LEV	0.37	0.33	0.31	0.37	0.31	0.32	0.00	(0.9709)	0.02	(0.5238)
ZSCORE	1.23	0.98	1.14	0.99	0.76	1.02	0.24	(0.0009)	0.22	(0.0003)
PREDGC	0.03	0.01	2.04	0.16	-0.01	5.88	-0.13	(0.7103)	0.02	(0.9097)
BM	0.87	0.42	1.57	0.63	0.35	0.89	0.24	(0.0039)	0.07	(0.1664)
MOM	-0.03	-0.03	0.07	-0.06	-0.06	0.07	0.03	(<0.0001)	0.03	(<0.0001)

SIZE = market value of equity measured by market capitalization in $ million; SALES = sales in $ million; TA = total assets in $ million; ROA=return on assets (net income/total assets); CR = current ratio (current assets/current liabilities); LEV=total debt/total assets; ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985). All variables are computed with data taken from the last annual financial accounts reported before the GCM date. BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM = momentum, defined as the monthly average of prior 11 months (t-12 to t-2) raw returns.

6.3.2.2. Initial evidence

I now empirically test if the short-term market reaction to the publication of a GCM audit report depends on pre-event analyst coverage. To ensure the robustness of my results, I use the three categories of recommendations as in section 4.2.2.1. As such, when using reported (current) recommendations to define analyst coverage, I allocate firms to the "analyst coverage" portfolio if there is at least one reported (current) recommendation or a new annual EPS forecast available within the 6-month period prior to the GCM date. In the case of inferred recommendations, firms are allocated to the "analyst coverage" portfolio if there is at least one inferred recommendation or a new EPS forecast available within the coverage definition window. All the remaining firms are allocated to the "no analyst coverage" portfolio.[50] As previously discussed, I expect short-term market reaction to be less negative for covered companies as a result of prior price adjustments to analyst opinions. I formally test the following null hypothesis:

> *H6.: There is no difference in the short-term market reaction to the GCM audit report for companies with pre-event analyst coverage and companies with no pre-event analyst coverage.*

Table 6.4. summarizes my results. In panel A (B), I present the short-term market reaction to the announcement of a GCM audit report using reported (current) recommendations to define analyst coverage. In panel C, I use inferred recommendations with the same purpose.

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[50] As can be seen in table 6.3., when I use reported recommendations to define analyst coverage, I allocate 317 firms to the "analyst coverage" portfolio and the remaining 607 to the "no analyst coverage" portfolio. When I define a company as covered using current (inferred) recommendations, I classify 408 (474) firms to the "analyst coverage" portfolio. The remaining 516 (450) are allocated to the "no analyst coverage" portfolio. The characteristics of both "analyst coverage" and "no analyst coverage" firms do not differ very much from those shown in table 6.3. for alternative definitions of analyst coverage.

I find that the short-term market reaction to the publication of a GCM audit report depends on pre-event analyst coverage. However, contrary to my initial expectations, the short-term market reaction is significantly more negative for firms with analyst coverage than for firms with no analyst coverage. As an example consider the results in panel A. I find that the mean (median) $CARs_{(-1,+1)}$ are -2.9% (-2.7%) for non-covered firms and -6.9% (-4-6%) for covered firms, all significant at the 0.1% level. More importantly, both parametric and nonparametric tests show that the return performance between the portfolios is significantly different.

Results in panel B and panel C are consistent with my previous findings. In particular, I show that there is an adverse short-term market reaction to the GCM announcement for both covered and non-covered firms using alternative definitions of analyst coverage. Similarly to above, the market reaction to the GCM event is significantly more negative for firms with analyst coverage, suggesting that the differential short-term market reaction to the GCM announcement is robust to alternative definitions of analyst coverage. Hence, I reject null hypothesis H6.

Overall, I show that the short-term market reaction to the publication of a GCM audit report is significantly more negative when firms are being followed by at least one analyst. The results in chapter 4, where I show that analysts slightly downgrade the recommendations for GCM stocks from “buy” to “hold” as the event date approaches, provide an appealing explanation for this result. In fact, it is possible that an average “hold” recommendation for firms immediately before the announcement of a GCM audit report does not provide a clear message to the investment community. Put differently, it is likely that investors do not perceive pre-GCM analyst opinions as “unfavourable”. As previously discussed, retail investors hold 74% of the GCM stocks right before the GCM date (Kausar, Taffler, and Tan, forthcoming). In addition, there is evidence that small investors follow analyst recommendations literally and that, contrary to large investors, which react negatively to a "hold" recommendation, small investors do not display significant trade reaction to such a recommendation (Malmendier and Shanthikumar, 2007). It follows that the average "hold" recommendation may contribute, in this context, to reduce the impact of other negative economic events in stock prices and fuelling an inaccurate expectation regarding GCM stocks in the pre-event period. This is consistent with the notion that analyst recommendations may temporarily delay the incorporation of negative information in stock prices (Jegadeesh et al., 2004). As such, this may explain why the market seems more "surprised" by the publication of a GCM audit report in the case of firms followed by analysts.

Alternatively, it is possible that firms with analyst coverage are associated with more rapid assimilation of the information conveyed by a GCM audit report. The next subsections provide further evidence on these issues.

Table 6.4.
Short-term Market Reaction to the First-Time GCM Audit Report Conditional on Analyst Coverage

This table presents the cumulative abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as the benchmark index. Two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) CAR. The last two columns report the mean and median differences between the CARs of the portfolios under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.
In panel A (panel B), firms are allocated to the "analyst coverage" portfolio if there is at least one reported (current) recommendations available or one annual EPS forecast within the 6-month period prior to the GCM announcement date. In panel C, firms are allocated to the "analyst coverage" portfolio if there is at least one inferred recommendation available or one annual EPS forecast within the 6-month period prior to the GCM announcement date. All remaining firms are allocated to the "no analyst coverage" portfolio. Section 4.2.2.1 provides detailed explanation about the estimation of the recommendation categories.

Panel A: Reported Recommendations

	NO ANALYST COVERAGE (A) (n = 607)		**ANALYST COVERAGE (B)** (n = 317)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1, +1)	-0.029	-0.027	-0.069	-0.046	0.040	0.019
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0011)	(0.0263)
(-2, +2)	-0.037	-0.034	-0.086	-0.065	0.049	0.031
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0009)	(0.0085)
(-3, +3)	-0.029	-0.038	-0.090	-0.067	0.061	0.029
	(0.0060)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0003)	(00037)

Panel B: Current Recommendations

	NO ANALYST COVERAGE (A) (n = 516)		**ANALYST COVERAGE (B)** (n = 408)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1, +1)	-0.028	-0.027	-0.060	-0.042	0.032	0.015
	(0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0057)	(0.0542)
(-2, +2)	-0.040	-0.036	-0.072	-0.057	0.032	0.021
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0231)	(0.0643)
(-3, +3)	-0.031	-0.036	-0.074	-0.058	0.043	0.022
	(0.0052)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0095)	(0.0225)

Panel C: Inferred Recommendations

	NO ANALYST COVERAGE (A) (n = 450)		**ANALYST COVERAGE (B)** (n = 474)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1, +1)	-0.024	-0.023	-0.061	-0.041	0.037	0.018
	(0.0024)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0010)	(0.0109)
(-2, +2)	-0.034	-0.033	-0.073	-0.057	0.039	0.024
	(0.0008)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0056)	(0.0245)
(-3, +3)	-0.028	-0.039	-0.068	-0.050	0.040	0.011
	(0.0208)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0171)	(0.0738)

6.3.2.2.1. Controlling for GCM firm characteristics

Similarly to section 6.3.1.2., I now test the differential short-term market reaction to the GCM announcement between covered and non-covered firms conditional on firm characteristics. This analysis assumes particular relevance in the case of some firm characteristics that are correlated with analyst coverage. For instance, I have previously shown that the adverse short-term market reaction to the publication of a GCM audit report is more severe for large firms. As such, one can conjecture that pre-event analyst coverage is a mere proxy for size with no incremental explanation power. To properly deal with this issue, I control my results for the same characteristics as in section 6.3.1.2.

Table 6.5. summarizes my results. Panel A presents the short-term market reaction conditional on firm size. From my 462 (462) companies allocated to the "small size" ("large size") portfolio, I observe 98 (310) with analyst coverage and 364 (152) with no analyst coverage. I find a significant negative market reaction to the GCM announcement for all portfolios of firms based on firm size and analyst coverage. However, the differences in the mean and median CARs are only significant for small firms, suggesting that differential market reaction to the GCM announcement conditional on analyst coverage is concentrated in small firms. As such, I conclude that analyst opinion is particularly salient for firms with higher levels of information uncertainty.

Panel B reports separate results conditional on firm pre-event momentum. From my 689 (235) companies with negative (positive) momentum, I allocate 264 (53) to the "analyst coverage" portfolio and 425 (182) to the "no analyst coverage" portfolio. My results suggest that differences in the short-term market reaction to the publication of a GCM audit report conditional on analyst coverage are statistically significant only for the "negative momentum" portfolio. This suggests that the differential short-term market reaction depending on analyst coverage is concentrated on firms where prior negative signals are particularly clear. As such, it seems that analyst opinions are disconfirming negative stock momentum and temporarily delaying the incorporation of this adverse information in stock prices in the pre-GCM period leading to a stronger reaction when the GCM audit report is announced.

In Panel C of table 6.5., I distinguish GCM firms conditional on firm distress risk. Specifically, the high distress group allocates firms with z-score is <= 1.81 and the low distress group allocates firms with z-score > 1.81, where z-score is computed as in section 5.2.1.3. I assign the 285 (32) high (low) distress firms to the "analyst coverage" portfolio and the remaining 490 (117) to the "no analyst coverage" portfolio. Similar to above, I find that differences in the short-term market reaction to the GCM announcement conditional on analyst coverage concentrated on firms where prior negative signals are particularly clear. In fact, both parametric and nonparametric tests show that mean and median differences in CARs are consistently significantly for firms with high distress risk.

Panel D presents the results conditional on the probability of a forthcoming GCM audit report, where PREDGC is computed as in section 6.3.1.2. Specifically, the high GCM probability group allocates firms where PREDGC score is <= 0.01 and the low GCM probability group allocates firms where PREDGC score is > 0.01, where PREDGC is computed as in section 6.3.1.2. From the initial 464 (460) companies with high (low) GCM probability, I allocate 163 (154) to the "analyst coverage" portfolio and 301 (306) to the "no analyst coverage" portfolio. I find that the differences in the short-term market reaction between covered and non-covered firms are particularly evident for the group of firms with higher GCM probability. Once again, this indicates that differential market reaction conditional on analyst coverage is clearer for the group of firms where the pre-event negative signals are more acute.

Finally, in panel E, I report separate results conditional on the earnings surprise signal. For the 396 (528) companies with positive (negative) SUE, I assign 115 (202) to the "analyst coverage" portfolio and 281 (326) to the "no analyst coverage" portfolio, where SUE is defined as in section 6.3.1.2. In this particular case, I find that differences in the short-term market reaction between covered and non-covered firms are generally significant for both negative and positive earnings surprise portfolios, suggesting that differential market reaction to the GCM announcement depending on analyst coverage is not driven by earnings surprise.

Overall, my results show that the differential market reaction to the GCM audit report conditional on analyst coverage is particularly evident for small firms and firms associated with other pre-GCM negative signals (negative momentum, high distress risk and high GCM probability). This is consistent with the idea that an average "hold" recommendation for GCM firms may delay the assimilation of other negative signals in stock prices and fuelling an inaccurate expectation regarding GCM stocks, leading to a stronger adjustment in the stocks of covered firms when the bad news is publicly disclosed. The next subsection provides clear evidence on the importance of the message conveyed by analyst recommendations.

Table 6.5.
Short-term Market Reaction to the First-Time GCM Audit Report Conditional on Analyst Coverage – Controlling for Firm Characteristics

This table presents the cumulative abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as the benchmark index. Day t=0 is the GCM announcement day. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) CAR. The last two columns report the mean and median differences between the CARs of the portfolios under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is shown in brackets below the mean (median) differences.
Companies are allocated to the "analyst coverage" portfolio if analysts report at least one new recommendation or issue one new annual EPS forecast within the 6-month period before the GCM announcement date. All the remaining firms are allocated to the "no analyst coverage" portfolio.
Panel A provides separate results for the portfolio of 462 (462) GCM companies with market capitalization below (above) the sample median ($33.7m). Market capitalization is calculated one year before the GCM date. Panel B reports separate results for the portfolio of 235 (689) GCM companies with positive (negative) pre-event momentum. Momentum is defined as the average monthly raw returns for the prior 11-month period (t-12 to t-2) relative to the GCM announcement month. Panel C provides separate results for the portfolio of 775 (149) GCM companies with z-score <=1.81 (>1.81). Z-score is computed following Altman's (1968) model using the accounting information from the fiscal year ending one year before the GCM announcement date. Panel D reports separate results for the portfolio of 454 (470) GCM companies where PREDGC is <=0.01 (>0.01), defined as minimum cut-off score by Fleak and Wilson (1994). Panel E provides separate results for the portfolio of 528 (396) GCM companies where SUE is negative (positive). SUE=(ΔNI_q / $|NI_q|$), where ΔNI_q is the quarterly earnings change computed as the difference between the quarterly income before extraordinary items (NI_q) and the quarterly income before extraordinary items in the previous year (NI_{q-4}).

Panel A: CARs conditional on firm size and analyst coverage

			NO ANALYST COVERAGE (A)		ANALYST COVERAGE (B)		DIFERENCE (A - B)	
		Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
Small Size	[n = 364 (A)] [n = 98 (B)]	(-1,+1)	-0.017	-0.018	-0.074	-0.063	0.057	0.045
			(0.0491)	(0.0071)	(<0.0001)	(<0.0001)	(0.0040)	(0.0070)
		(-2,+2)	-0.030	-0.032	-0.087	-0.062	0.057	0.030
			(0.0085)	(0.0008)	(0.0003)	(<0.0001)	(0.0261)	(0.0491)
		(-3,+3)	-0.012	-0.032	-0.075	-0.048	0.063	0.016
			(0.3820)	(0.0102)	(0.0006)	(0.0024)	(0.0143)	(0.1679)
Large Size	[n = 152 (A)] [n = 310 (B)]	(-1,+1)	-0.060	-0.040	-0.057	-0.033	-0.003	-0.007
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.8773)	(0.3909)
		(-2,+2)	-0.064	-0.045	-0.068	-0.054	0.004	0.009
			(0.0002)	(<0.0001)	(<0.0001)	(<0.0001)	(0.8605)	(0.9707)
		(-3,+3)	-0.076	-0.044	-0.072	-0.065	-0.004	0.021
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.8721)	(0.6192)

Panel B: CARs conditional on firm momentum and analyst coverage

			NO ANALYST COVERAGE (A)		ANALYST COVERAGE (B)		DIFERENCE (A - B)	
		Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
Positive Mom.	[n = 182 (A)] [n = 53 (B)]	(-1,+1)	-0.032	-0.027	-0.071	-0.063	0.039	0.036
			(0.0078)	(0.0010)	(0.0065)	(0.0036)	(0.1627)	(0.1086)
		(-2,+2)	-0.033	-0.026	-0.077	-0.033	0.044	0.007
			(0.0209)	(0.0109)	(0.0093)	(0.0148)	(0.1646)	(0.2253)
		(+3,+3)	-0.022	-0.032	-0.081	-0.049	0.059	0.017
			(0.1908)	(0.0289)	(0.0138)	(0.0222)	(0.1019)	(0.2801)
Negative Mom.	[n = 425 (A)] [n = 264 (B)]	(-1,+1)	-0.028	-0.027	-0.069	-0.042	0.041	0.015
			(0.0010)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0037)	(0.0757)
		(-2,+2)	-0.038	-0.043	-0.087	-0.065	0.049	0.022
			(0.0008)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0046)	(0.0434)
		(-3,+3)	-0.031	-0.040	-0.092	-0.069	0.061	0.029
			(0.0189)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0023)	(0.0148)

Panel C: CARs conditional on firm distress risk and analyst coverage

			NO ANALYST COVERAGE (A)		ANALYST COVERAGE (B)		DIFERENCE (A - B)	
		Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
Low Distr. Risk	[n = 117 (A)] [n = 32 (B)]	(-1,+1)	-0.041	-0.032	-0.086	0.005	0.045	-0.037
			(0.0135)	(0.0119)	(0.0373)	(0.1642)	(0.2992)	(0.8917)
		(-2,+2)	-0.019	-0.022	-0.103	-0.044	0.084	0.022
			(0.4546)	(0.1092)	(0.0171)	(0.0501)	(0.0901)	(0.3750)
		(+3,+3)	0.009	-0.035	-0.098	-0.083	0.107	0.048
			(0.8137)	(0.1506)	(0.0180)	(0.0178)	(0.0548)	(0.2115)
High Distr. Risk	[n = 490 (A)] [n = 285 (B)]	(-1,+1)	-0.027	-0.026	-0.067	-0.047	0.040	0.021
			(0.0004)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0022)	(0.0155)
		(-2,+2)	-0.039	-0.040	-0.084	-0.065	0.045	0.025
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0046)	(0.0159)
		(-3,+3)	-0.032	-0.040	-0.089	-0.067	0.057	0.027
			(0.0035)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0015)	(0.0096)

Panel D: CARs conditional on firm GCM probability and analyst coverage

			NO ANALYST COVERAGE (A)		ANALYST COVERAGE (B)		DIFERENCE (A - B)	
		Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
Low GCM Prob.	[n = 306 (A)] [n = 154 (B)]	(-1,+1)	-0.040	-0.034	-0.061	-0.043	0.021	0.009
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.2172)	(0.7906)
		(-2,+2)	-0.050	-0.045	-0.083	-0.059	0.033	0.014
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0885)	(0.4441)
		(+3,+3)	-0.032	-0.039	-0.093	-0.053	0.061	0.014
			(0.0212)	(0.0004)	(<0.0001)	(<0.0001)	(0.0081)	(0.0281)
High GCM Prob.	[n = 301(A)] [n = 163 (B)]	(-1,+1)	-0.019	-0.015	-0.075	-0.049	0.056	0.034
			(0.0354)	(0.0088)	(<0.0001)	(<0.0001)	(0.0022)	(0.0047)
		(-2,+2)	-0.025	-0.022	-0.088	-0.066	0.063	0.044
			(0.0424)	(0.0180)	(<0.0001)	(<0.0001)	(0.0041)	(0.0046)
		(-3,+3)	-0.022	-0.036	-0.086	-0.068	0.064	0.032
			(0.1670)	(0.0026)	(<0.0001)	(<0.0001)	(0.0134)	(0.0535)

Panel D: CARs conditional on firm SUE and analyst coverage

		Period (trading days)	NO ANALYST COVERAGE (A) Mean CAR	NO ANALYST COVERAGE (A) Median CAR	ANALYST COVERAGE (B) Mean CAR	ANALYST COVERAGE (B) Median CAR	DIFERENCE (A - B) Mean CAR	DIFERENCE (A - B) Median CAR
Pos. Earnings Surpr.	[n = 281 (A)] [n = 115 (B)]	(-1,+1)	-0.012 (0.2451)	-0.020 (0.0329)	-0.048 (0.0047)	-0.039 (0.0015)	0.036 (0.0620)	0.019 (0.1165)
		(-2,+2)	-0.012 (0.3759)	-0.021 (0.0812)	-0.070 (<0.0001)	-0.048 (0.0002)	0.058 (0.0074)	0.027 (0.0375)
		(-3,+3)	0.001 (0.9463)	-0.021 (0.0837)	-0.075 (0.0008)	-0.048 (0.0009)	0.076 (0.0085)	0.027 (0.0530)
Neg. Earnings Surp.	[n = 326 (A)] [n = 202 (B)]	(-1,+1)	-0.044 (<0.0001)	-0.032 (<0.0001)	-0.080 (<0.0001)	-0.051 (<0.0001)	0.036 (0.0278)	0.019 (0.1764)
		(-2,+2)	-0.056 (<0.0001)	-0.043 (<0.0001)	-0.094 (<0.0001)	-0.070 (<0.0001)	0.038 (0.0599)	0.027 (0.1698)
		(-3,+3)	-0.047 (0.0006)	-0.050 (<0.0001)	-0.097 (<0.0001)	-0.071 (<0.0001)	0.050 (0.0193)	0.021 (0.0538)

6.3.2.2.2. Controlling for recommendations rating

My previous results suggest that the market reacts negatively in the short-term to the publication of a GCM audit report, a phenomenon particularly severe in the case of companies followed by analysts. This result may be explained by analysts delaying the incorporation of pre-event negative information in stock prices through the issue of an average "hold" recommendation that is not perceived by investors as an unfavourable message. Alternatively, coverage may be associated with more rapid assimilation of the information conveyed by a GCM audit report. To investigate which of the hypothesis explain the phenomenon, I now provide a more detailed analysis based on analysts' recommendation ratings.

Analyst recommendations have a qualitative interpretation that offers a unique opportunity to test the importance of their message on the short-term market reaction to the announcement of a GCM audit report. Generally, brokerage firms (e.g., Credit Suisse, UBS Warburg, Salomon Smith Barney, Morgan Stanley, Merrill Lynch) issue a "buy" recommendation when a stock is perceived to be undervalued by at least 10% whereas a "sell" recommendation is issued when a stock is believed to be overvalued by at least 10%.

Companies rated with a "hold" recommendation are believed to be fairly priced. As such, it is reasonable to expect that a firm receiving a "buy" recommendation will perform differently from a firm receiving a "sell" rating.

In this subsection, I separate firms receiving "conforming" average recommendations from those receiving "nonconforming" average recommendations before the GCM announcement date.[51] Considering the above definition of recommendation ratings and the fact that, in the medium run, the GCM firms underperform by around -14% following the publication of a GCM audit report (Kausar, Taffler, and Tan, forthcoming), I assume that a "conforming" recommendation for a GCM firm immediately before receiving a GCM audit report is made through an "underperform" or "sell" rating. All the remaining stock recommendations for GCM firms are classified as "nonconforming".

More specifically, I argue that analysts are encouraging investors to sell the stock when their recommendation before the GCM announcement is classified as "conforming", which should mitigate the impact of a GCM announcement. Conversely, I argue that analysts are encouraging investors to keep or add GCM firms to their portfolios when their average recommendation before the GCM announcement is "hold", "buy" or "strong buy", which should amplify the impact of a GCM audit report disclosure. In particular, I classify a case as "conforming" if the firm average numeric recommendation is above 3.5. All the remaining cases are classified as "nonconforming".

[51] In this particular case, I only consider analyst recommendations to distinguish "conforming" from "nonconforming" cases since, contrary to analyst forecasts, recommendations are disclosed on a simple and finite scale common to all stocks avoiding ambiguous interpretation of analyst message. For this reason, the number of GCM firms classified as covered is lower than that in my previous analyses.

I explore this issue allocating my 924 first-time GCM companies to three portfolios. The first portfolio includes firms with no recommendations available within the 6-month period prior to the GCM announcement date. The second (third) portfolio allocates firms with recommendations available within the same period for which their average recommendation is classified as "conforming" ("nonconforming"). If the differential short-term market reaction to the GCM announcement conditional on analyst coverage is in fact due to more rapid assimilation of the information conveyed by a GCM audit report in the case of covered firms, there should be no differences in the conclusions after splitting covered firms between "conforming" and "nonconforming" cases. The hypotheses I test are as follows:

> *H7: There is no difference in the short-term market reaction to the GCM announcement for companies with pre-event conforming recommendations compared to companies with no analyst coverage.*
>
> *H8: There is no difference in the short-term market reaction to the GCM announcement for companies with pre-event nonconforming recommendations compared to companies with no analyst coverage.*

Table 6.6. summarizes my results. Panel A (panel B) compares the short-term market reaction between non-covered firms and firms for which their average reported (current) recommendation prior to the GCM announcement is classified as "conforming"/"nonconforming". Panel C uses inferred recommendations with the same purpose. I find that security analysts are reluctant to issue "conforming" recommendations for GCM firms. For instance, from the 196 (384) firms with reported (current) recommendations available within the 6-month period prior to the GCM announcement date, I find that only 24 (26) have an average "conforming" recommendation, representing

only 13% (7%) of the total firms. After inferring an unfavourable recommendation when analysts cease coverage of firms (panel C for inferred recommendations), the percentage of firms for which their average recommendation is classified as "conforming" increases to 40% (187 in 466).

I find that the short-term market reaction to the publication of a GCM audit report depends critically on the message conveyed by analysts. When firms' average reported (current) recommendations are classified as "conforming", there is no abnormal reaction to the announcement of a GCM audit report. Conversely, for all the remaining cases, there is a negative and significant short-term market reaction to the publication of a GCM audit report. In addition, the short-term market reaction to the event is significantly more negative for firms with analyst coverage only when their average recommendation is classified as "nonconforming".

As an example, consider panel A of table 6.6. Firms allocated to the "no analyst coverage" and "nonconforming stocks" portfolios face a significant negative short-term market reaction to the GCM announcement. Mean (median) CARs for the (-1, +1) period are -3.6% (-3.0%) for the "no analyst coverage" portfolio and -8.8% (-5.3%) for the "nonconforming stocks" portfolio, all significant at the 0.1% level. Importantly, both parametric and nonparametric tests show that mean and median differences are significant at conventional levels, suggesting that the short-term market reaction is more negative for firms receiving "nonconforming" recommendations than for firms with no analyst coverage. Interestingly, there are no significant differences in the short-term market reaction to the GCM announcement between firms receiving "conforming" recommendations and firms with no analyst coverage.

Panels B and C of table 6.6. show that my previous results do not change significantly when I use current and inferred recommendations to classify the average recommendation of a company as “conforming”, “nonconforming” or with no analyst coverage. Similar to panel A, I find that the abnormal reaction for firms with analyst coverage is significantly more negative than for firms with no analyst coverage only when their average recommendation is classified as “nonconforming”. Hence, I reject null hypothesis H7 and do not reject null hypothesis H8.

However, panel C shows that, contrary to reported and current “conforming” portfolios, there is a significant adverse short-term market reaction for firms receiving average inferred “conforming” recommendations for most of the trading periods under scrutiny. This suggests that “conforming” recommendations are particularly useful to investors when disclosed through reported recommendations and less useful when investors have to infer that a drop in analyst coverage should be perceived as an unfavourable message.

Overall, my results suggest that the possible association between coverage and more rapid assimilation of the information conveyed by a GCM audit report seems not a convincing explanation for the differential short-term market reaction to the GCM audit report conditional on analyst coverage. In fact, if this was the case, this phenomenon should not be sensitive to the distinction between “conforming” and “nonconforming” recommendations. As such, I conclude that analysts play an important role in the assimilation of pre-GCM negative information in stock prices. However, the usefulness of their recommendations to investors depends critically on the direction of such information. When analyst recommendations are consistent with the forthcoming GCM audit report (i.e., issuing “underperform” or “sell” recommendations), they facilitate the incorporation of other negative information in stock prices in the pre-GCM period, thus reduce the “surprise” associated with the publication of a GCM audit report. When analyst recommendations are inconsistent with the forthcoming GCM audit report (i.e., by issuing "strong buy", "buy" or "hold" recommendations), they obstruct the incorporation of other negative information, thus increase the "surprise" associated with the publication of a GCM audit report. Importantly, the percentage of firms where analyst average recommendation is classified as "conforming" is reduced explaining why the overall short-term market reaction to the GCM announcement is significantly more negative for firms with analyst coverage than firms with no analyst coverage.

Table 6.6.
Short-term Market Reaction to the First-Time GCM Audit Report Conditional on Analyst Coverage – Controlling for Recommendation Rating

This table presents the cumulative abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as the benchmark index. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) CAR. The last two columns report the mean and median differences between the CARs of the portfolios under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.
In panel A (panel B), firms are allocated to the "conforming" portfolio if their average reported (current) recommendation is classified as "conforming", i.e., if their average recommendation is numerically lower than 3.5. Firms are allocated to the "nonconforming" portfolio if their average reported (current) recommendation is classified as "nonconforming", i.e., if their average recommendation is numerically higher than 3.5. All remaining firms for which there are no reported (current) recommendations available within that period are allocated to the "no coverage" portfolio. In panel C, I use exactly the same classification criterion based on inferred recommendations. Section 4.2.2.1 provides detailed explanation about the estimation of the recommendation categories.

Panel A: Reported recommendations

	NO ANALYST COVERAGE (A) (n = 728)		CONFORM. STOCKS (B) (n = 24)		DIFERENCE (A - B)	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.036	-0.030	0.044	0.013	-0.080	-0.043
	(<0.0001)	(<0.0001)	(0.2713)	(0.1573)	(0.0538)	(0.0123)
(-2,+2)	-0.045	-0.039	-0.000	0.005	-0.045	-0.044
	(<0.0001)	(<0.0001)	(0.9973)	(0.9559)	(0.3341)	(0.2087)
(+3,+3)	-0.041	-0.043	0.024	0.041	-0.065	-0.084
	(<0.0001)	(<0.0001)	(0.6360)	(0.6175)	(0.2078)	(0.0957)

	NO ANALYST COVERAGE (A) (n = 728)		NONCONFORM. STOCKS (B) (n = 172)		DIFERENCE (A - B)	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.036	-0.030	-0.088	-0.053	0.052	0.023
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0019)	(0.0134)
(-2,+2)	-0.045	-0.039	-0.099	-0.066	0.054	0.027
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0046)	(0.0133)
(+3,+3)	-0.041	-0.043	-0.093	-0.066	0.052	0.023
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0180)	(0.0367)

Panel B: Current recommendations

	NO ANALYST COVERAGE (A) (n = 540)		CONFORM. STOCKS (B) (n = 26)		DIFERENCE (A - B)	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.031	-0.028	-0.007	-0.023	-0.024	-0.005
	(<0.0001)	(<0.0001)	(0.8373)	(0.3509)	(0.4642)	(0.8386)
(-2,+2)	-0.042	-0.037	-0.042	-0.029	0.000	-0.008
	(<0.0001)	(<0.0001)	(0.2880)	(0.2665)	(0.9919)	(0.9379)
(+3,+3)	-0.035	-0.036	-0.013	0.041	-0.022	-0.077
	(0.0017)	(<0.0001)	(<0.0001)	(<0.0001)	(0.6404)	(0.2157)

	NO ANALYST COVERAGE (A) (n = 540)		NONCONFORM. STOCKS (B) (n = 358)		DIFERENCE (A - B)	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.031	-0.028	-0.064	-0.042	0.033	0.014
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0068)	(0.0758)
(-2,+2)	-0.042	-0.037	-0.073	-0.059	0.031	0.022
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0382)	(0.0627)
(+3,+3)	-0.035	-0.036	-0.075	-0.068	0.040	0.032
	(0.0017)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0175)	(0.0113)

Panel C: Inferred recommendations

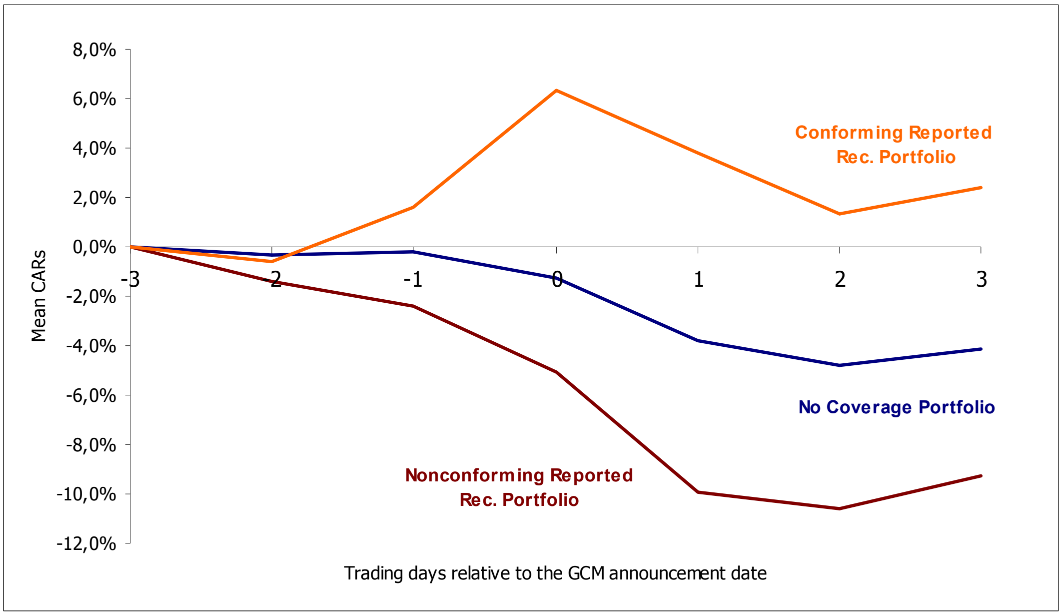
	NO ANALYST COVERAGE (A) (n = 458)		CONFORM. STOCKS (B) (n = 187)		DIFERENCE (A - B)	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.025	-0.024	-0.050	-0.038	0.025	0.014
	(0.0011)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0803)	(0.0920)
(-2,+2)	-0.036	-0.035	-0.039	-0.047	0.003	0.012
	(0.0003)	(<0.0001)	(0.0828)	(<0.0001)	(0.9010)	(0.3395)
(+3,+3)	-0.032	-0.039	-0.031	-0.030	-0.001	-0.009
	(0.0092)	(<0.0001)	(0.1812)	(0.0060)	(0.9597)	(0.9412)

	NO ANALYST COVERAGE (A) (n = 458)		NONCONFORM. STOCKS (B) (n = 279)		DIFERENCE (A - B)	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.025	-0.024	-0.068	-0.043	0.043	0.019
	(0.0011)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0024)	(0.0495)
(-2,+2)	-0.036	-0.035	-0.081	-0.059	0.045	0.024
	(0.0003)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0065)	(0.0433)
(+3,+3)	-0.032	-0.039	-0.082	-0.068	0.050	0.029
	(0.0092)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0094)	(0.0341)

Figure 6.1. graphs mean daily CARs computed from trading day -3 to trading day +3 relative to the GCM announcement date for the three portfolios of stocks: firms with no reported recommendations, firms for which their average reported recommendation is classified as "conforming" and firms for which their average reported recommendation is classified as "nonconforming". This graph clearly illustrates the main conclusion of this subsection: when analyst recommendations operate in the right direction consistent with other negative signals, they decrease the "surprise" associated with the publication of a GCM audit report. As a result, the short-term market reaction to the GCM announcement for "conforming" stock firms is less negative in comparison with non-covered firms. Conversely, when analyst recommendations are in the opposite direction to other negative signals, they increase the "surprise" associated with the publication of a GCM audit report. As such, the short-term market reaction to the GCM announcement for "nonconforming" stock firms is more negative than firms with no analyst coverage.

Figure 6.1.
Short-term Market Reaction to the GCM Announcement – Controlling for Recommendation Rating

This figure graphs the mean cumulative abnormal returns from event-trading-day -3 to event-trading-day +3 for my population of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as the benchmark index. Results are reported separately for "conforming" cases (n=24), "nonconforming" cases (172) and non-covered cases (n=728).
Firms are allocated to the "conforming" portfolio if their average reported recommendation is classified as "conforming", i.e., if their average recommendation is numerically lower than 3.5. Firms are allocated to the "nonconforming" portfolio if their average reported recommendation is classified as "nonconforming", i.e., if their average recommendation is numerically higher than 3.5. All remaining firms for which there are no reported recommendations available within that period are allocated to the "no coverage" portfolio.



6.3.2.2.3. Controlling for regulatory regime

Section 5.2.3. suggests that analyst pre-event recommendations for GCM firms became significantly more pessimistic after the implementation of the regulatory changes of 2002. In this subsection, I investigate to what extent the new reporting environment impact the short-term market reaction to this event. I conjecture that more pessimistic pre-GCM recommendations and the additional information that analysts are required to disclose following the implementation of the regulatory changes might have provided investors with better information to interpret analyst message in the GCM audit report context. If this is the case, I expect the differential short-term market reaction to the GCM announcement conditional on analyst coverage significantly reduces following the post-regulatory change period.

I test this hypothesis by allocating each of my sample firms to the pre (post)-NASD 2711 period if the GCM audit report was announced before (following) the 9th of September 2002 (when the rule was implemented). The hypotheses to test are as follows:

> *H9.: In the pre-regulatory changes period, there is no difference in the short-term market reaction to the GCM announcement for companies with pre-event analyst coverage compared to companies with no pre-event analyst coverage.*
>
> *H10: In the post-regulatory changes period, there is no difference in the short-term market reaction to the GCM announcement for companies with pre-event analyst coverage compared to companies with no pre-event analyst coverage.*

Table 6.7. summarizes my results. There are 723 (201) sample firms for which the GCM disclosure date occurred prior to (following) the implementation of NASD 2711. In panel A (B) of table 6.7., I compare the short-term market reaction to the GCM announcement

depending on analyst coverage before and after the implementation of NASD 2711. Firms are allocated to the "analyst coverage" portfolio if they have at least one reported (current) recommendation or one annual EPS forecast available within the 6-months prior to the GCM announcement date. In panel C, I allocate firms to the "analyst coverage" portfolio if they have at least one inferred recommendation or one annual EPS forecast available over the same period.

I find that the differential short-term market reaction to the publication of a GCM audit report conditional on analyst coverage is an exclusive phenomenon of the pre-NASD 2711 period. My results for the pre-NASD 2711 period show that the short-term market reaction to the GCM announcement is significantly more negative for firms with analyst coverage. For instance, panel A of table 6.7. reports that mean (median) $CAR_{(-1,+1)}$ for the "analyst coverage" portfolio is -7.3% (-4.9%) and -1.9% (-1.9%) for the "no analyst coverage" portfolio, all highly significant. Importantly, both parametric and nonparametric tests show that the abnormal reaction for the "analyst coverage" portfolio is significantly more negative than for the "no analyst coverage" portfolio. Moreover, panel B and C shows that results are robust when I use current and inferred recommendations to define analyst coverage.

The same analysis for the post-NASD 2711 period reveals a different pattern. Interestingly, my results suggest that the differential short-term market reaction to the GCM announcement conditional on analyst coverage is no longer present after the implementation of the NASD 2711 Rule. Considering the reduced number of cases subsequent to the implementation of NASD 2711 Rule, the analysis of median values assumes particular importance. However, my results consistently suggest that differences in mean and median CARs between firms with analyst coverage and firms with no analyst coverage are not statistically significant. As an example, consider the results in panel A of table 6.7. The mean (median) $CAR_{(-1,+1)}$ for the "analyst coverage" portfolio is -5.5% (-3.3%) and -7.0% (-5.4%) for the "no analyst coverage" portfolio, all significant at the 1% level. However, both parametric and nonparametric tests fail to find differences in performance of these two portfolios.

Overall, my results suggest that following the implementation of the regulatory changes, the market is no longer more surprised by the publication of a GCM audit report by firms with analyst coverage. As such, I conclude that investors became more aware that relying solely on analyst's recommendations for distressed firms might be unwise and that regulatory changes were effective in providing investors with better information to access analysts' research in the GCM audit report context. Hence, I reject null hypothesis H9 but do not reject null hypothesis H10.

Table 6.7.
Short-term Market Reaction to the First-Time GCM Audit Report Conditional on Analyst Coverage – Controlling for Regulatory Regime

This table presents the cumulative abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. Abnormal returns are market-adjusted returns, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. The smallest decile of the NASDAQ index is used as the benchmark index. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) CAR. The last two columns report the mean and median differences between the CARs of the portfolios under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.
Firms are allocated to the "Pre-NASD 2711" portfolio if the GCM audit report was announced before the 9th of September 2002. All the remaining cases are allocated to the "Post-NASD 2711" portfolio. For each portfolio, firms are then reallocated conditional on analyst coverage.
In panel A (panel B), firms are allocated to the "analyst coverage" portfolio if there is at least one reported (current) recommendations available or one annual EPS forecast within the 6-month period prior to the GCM announcement date. In panel C, firms are allocated to the "analyst coverage" portfolio if there is at least one inferred recommendation available or one annual EPS forecast within the 6-month period prior to the GCM announcement date. All remaining firms are allocated to the "no analyst coverage" portfolio. Section 4.2.2.1 provides detailed explanation about the estimation of the recommendation categories.

Panel A: Reported Recommendations

	NO ANALYST COVERAGE (A) (Pre-NASD 2711) (n = 472)		**ANALYST COVERAGE (B)** (Pre-NASD 2711) (n = 251)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.019	-0.019	-0.073	-0.049	0.054	0.030
	(0.0182)	(0.0003)	(<0.0001)	(<0.0001)	(0.0002)	(0.0047)
(-2,+2)	-0.033	-0.035	-0.092	-0.065	0.059	0.030
	(0.0017)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0005)	(0.0052)
(+3,+3)	-0.024	-0.035	-0.095	-0.067	0.071	0.032
	(0.0396)	(0.0005)	(<0.0001)	(<0.0001)	(0.0003)	(00026)

	NO ANALYST COVERAGE (A) (Post-NASD 2711) (n = 135)		**ANALYST COVERAGE (B)** (Post-NASD 2711) (n = 66)		**DIFERENCE (A - B)**	
Period (trading days)	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**	**Mean CAR**	**Median CAR**
(-1,+1)	-0.070	-0.054	-0.055	-0.033	-0.015	-0.021
	(<0.0001)	(<0.0001)	(0.0100)	(0.0017)	(0.5570)	(0.3916)
(-2,+2)	-0.050	-0.029	-0.037	-0.053	-0.013	0.024
	(0.0049)	(0.0024)	(0.3722)	(0.0074)	(0.7837)	(0.7777)
(+3,+3)	-0.033	-0.057	-0.049	-0.055	0.016	-0.002
	(0.1980)	(0.0014)	(0.2105)	(0.0020)	(0.7235)	(0.6752)

Panel B: Current Recommendations

	NO ANALYST COVERAGE (A) (Pre-NASD 2711) (n = 401)		ANALYST COVERAGE (B) (Pre-NASD 2711) (n = 322)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1,+1)	-0.018	-0.020	-0.061	-0.042	0.043	0.022
	(0.0324)	(0.0013)	(<0.0001)	(<0.0001)	(0.0011)	(0.0143)
(-2,+2)	-0.038	-0.038	-0.075	-0.059	0.037	0.021
	(0.0005)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0249)	(0.0569)
(+3,+3)	-0.028	-0.034	-0.077	-0.058	0.049	0.024
	(0.0268)	(0.0006)	(<0.0001)	(<0.0001)	(0.0103)	(0.0238)

	NO ANALYST COVERAGE (A) (Post-NASD 2711) (n = 115)		ANALYST COVERAGE (B) (Post-NASD 2711) (n = 86)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1,+1)	-0.070	-0.052	-0.058	-0.039	-0.012	-0.013
	(<0.0001)	(<0.0001)	(0.0019)	(0.0005)	(0.6206)	(0.4910)
(-2,+2)	-0.046	-0.029	-0.044	-0.045	-0.002	0.016
	(0.0080)	(0.0043)	(0.2069)	(0.0052)	(0.9597)	(0.7218)
(+3,+3)	-0.030	-0.045	-0.050	-0.063	0.020	0.018
	(0.2947)	(0.0035)	(0.1294)	(0.0011)	(0.6487)	(0.5946)

Panel C: Inferred Recommendations

	NO ANALYST COVERAGE (A) (Pre-NASD 2711) (n = 353)		ANALYST COVERAGE (B) Pre-NASD 2711) (n = 370)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1,+1)	-0.011	-0.016	-0.061	-0.041	0.050	0.025
	(0.1821)	(0.0182)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0024)
(-2,+2)	-0.031	-0.033	-0.077	-0.059	0.046	0.026
	(0.0074)	(0.0005)	(<0.0001)	(<0.0001)	(0.0049)	(0.0166)
(+3,+3)	-0.024	-0.035	-0.073	-0.051	0.049	0.016
	(0.0717)	(0.0016)	(<0.0001)	(<0.0001)	(0.0104)	(0.0362)

	NO ANALYST COVERAGE (A) (Post-NASD 2711) (n = 97)		ANALYST COVERAGE (B) (Post-NASD 2711) (n = 104)		DIFERENCE (A - B)	
Period (trading days)	Mean CAR	Median CAR	Mean CAR	Median CAR	Mean CAR	Median CAR
(-1,+1)	-0.064	-0.052	-0.058	-0.048	-0.006	-0.004
	(0.0008)	(<0.0001)	(0.0001)	(<0.0001)	(0.7729)	(0.6016)
(-2,+2)	-0.044	-0.029	-0.060	-0.041	0.016	0.012
	(0.0471)	(0.0122)	(0.0028)	(0.0016)	(0.5698)	(0.8321)
(+3,+3)	-0.012	-0.058	-0.051	-0.047	0.039	-0.011
	(0.8164)	(0.0020)	(0.0132)	(0.0022)	(0.4780)	(0.8170)

6.3.2.2.4. Multivariate analysis

My previous results suggest that the short-term market reaction to the publication of a GCM audit report is significantly more negative for firms with analyst coverage than firms with no analyst coverage. I now test the robustness of this result using a multivariate test, which evaluates the combined effect of analyst coverage controlling for firms' characteristics on the short-term market reaction to the publication of a GCM audit report. In particular, I use a binary logistic regression model to investigate if firms with pre-GCM analyst coverage are more likely to experience a strong negative short-term market reaction to the GCM announcement.[52] The null hypothesis is defined as follows:

> *H11.: Firms experiencing a strong negative abnormal reaction to the publication of a GCM audit report do not tend to be covered by analysts.*

The model to test this hypothesis is as follows:

$$Pr(SNCAR_i = 1 | X_i) = \frac{e^v}{1+e^v} \tag{6.4}$$

where Pr(SNCAR$_i$=1) is the probability of firm i experiencing a strong negative abnormal return from trading day -1 to trading day +1 relative to the GCM date (defined as day zero) and v represents the vector of independent variables, defined as follows:

---

[52] There are alternative econometric techniques that could be used to perform this test. The most obvious approach would be to estimate a regression using an OLS procedure. However, the use of a continuous dependent variable would be problematic in the context I address. In fact, my data is not a simple cross-section nor a simple time series since I have: 1) observations that are spread over time and 2) firms that appear more than once in my sample. As a consequence, simply pooling the data together to run an OLS regression would result in biased estimates of the relevant parameters (for details see Wooldridge, 2001). I will explore these issues in more detail in further work.

$$v_i = \alpha_0 + \sum_{n=1}^{11} \beta_n X_{ni} + u_i \tag{6.5}$$

The dependent variable (SNCAR) is a binary variable defined as follows. First, I compute the 3-day abnormal return ($CAR_{(-1,+1)}$) centred on the GCM disclosure date. Firms are then ranked accordingly to their 3-day abnormal returns and divided into two groups. Specifically, the bottom 33.3% performers are allocated to the "strong negative abnormal reaction" group and are classified as 1. All other firms are classified as 0.

I employ eleven independent variables in equation 6.5., which are expected to be related to the probability of a firm experiencing a strong negative short-term market reaction to the publication of a GCM audit report. The explanatory variables are defined as follows:

1. Conforming recommendation (CONFORM): This is a binary variable that equals 1 when the firm's average reported recommendation within the 6-month period before the GCM date is classified as "conforming", i.e., an "underperform" or "sell" recommendation. Considering my prior univariate analysis, I expect firms receiving "conforming" recommendations to be less likely to experience a strong negative short-term market reaction to the GCM announcement.

2. Nonconforming recommendation (NONCONFORM): This is the second binary variable that equals 1 when the firm's average reported recommendation within the 6-month period before the GCM date is classified as "nonconforming", i.e., "hold", "buy" or "strong buy" recommendation. I expect firms receiving

"nonconforming" recommendations to be more likely to experience a strong negative short-term market reaction to the publication of a GCM audit report.

3. Market capitalization (LOGSIZE): I control my results for size, which proxies for the information environment. I have previously shown that the short-term market reaction to the publication of a GCM audit report is significantly more adverse for large firms, suggesting that the "surprise" associated with the publication of a GCM audit report is higher for these firms. As such, I expect larger firms to be more likely to experience a strong negative short-term market reaction to the GCM announcement. LOGSIZE is computed as in section 5.2.4.

4. Number of analysts following the firm (ANALY): This is the second proxy for the level of information and is directly related to the analyst coverage environment. For the same reason as for LOGSIZE, I expect firms with a greater analyst following to be more likely to experience a strong negative short-term market reaction to the GCM announcement. ANALY is defined as section 5.2.4.

5. Book-to-market ratio (BM): The BM ratio may potentially explain cross-sectional short-term abnormal returns given the relationship between BM ratio and firms' expected returns (e.g., Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). If high BM firms (value stocks) are expected to experience lower returns, I expect firms with higher BM ratios to be more likely to experience a strong negative short-term market reaction to the publication of a GCM audit report. The BM ratio is defined as in section 4.3.2.

6. Momentum (MOM): This is the other variable related to firms' returns (e.g., DeBondt and Thaler, 1985, 1987; Jegadeesh and Titman, 1993; 2001). Momentum

controls for pre-GCM stock returns and is defined as in section 5.2.1.1. Given that market expectations of a GCM audit report are likely to be lower for firms with positive prior returns, I expect firms with positive momentum to be more likely to experience a strong negative short-term market reaction to the GCM announcement.

7. Return on assets ratio (ROA): This variable proxies for firm economic performance and is computed as in section 5.2.4. Considering that market expectations of a GCM are likely to be higher for firms with negative profitability, I expect profitable firms to be more likely to experience a strong negative short-term market reaction to the GCM announcement.

8. Altman's (1968) z-score (ZSCORE): This variable proxies for bankruptcy risk and is computed as section 5.2.1.3. Considering that higher z-scores are associated with lower distress risk, the market expectations of a GCM audit report are likely to be higher for firms with lower z-scores. As such, I expect firms with higher z-scores (lower distress risk) to be more likely to experience a strong negative short-term market reaction to the GCM announcement.

9. Probability of a GCM audit report (PREDGC): This variable proxies for market expectations of a forthcoming GCM audit report and is computed as in section 6.3.1.2. The importance of this variable is related to the finding that the short-term market reaction to the publication of a GCM announcement depends on the likelihood of such an announcement (e.g., Fleak and Wilson, 1994, Jones, 1996). I expect firms with higher PREDGC scores (lower distress risk) to be more likely to experience a strong negative short-term market reaction to the GCM announcement.

10. Leverage (LEV): This variable proxies for default risk and is defined as in section 5.2.4. Given that higher distress risk is associated with higher LEV ratios, the market expectations of a GCM audit report are likely to be higher for firms with low distress risk. Consequently, I expect firms with higher LEV ratios (high default risk) to be less likely to experience a strong negative short-term market reaction to the GCM announcement.

11. Standardized unexpected earnings (SUE): This variable controls for earnings surprises and is defined as in section 6.3.1.2. Positive earnings surprises are expected to mitigate the impact of a GCM announcement, as I have previously shown in my univariate analysis. As such, I expect firms with positive earnings surprises to be less likely to experience a strong negative short-term market reaction to the publication of a GCM audit report.

Table 6.8. provides the correlation between all variables mentioned above. As can be seen, there is a negative and significant correlation between SNCAR and CONFORM (Pearson correlation= -0.072, p-value=0.0283; Spearman rank correlation = -0.072, p-value=0.0283) and a positive and significant correlation between SNCAR and NONCONFORM (Pearson correlation= 0.098, p-value=0.0028; Spearman rank correlation = 0.098, p-value=0.0028). This suggests that firms for which their average reported recommendation is classified as "conforming" are inversely associated with strong negative abnormal returns surrounding the GCM date whereas firms for which their average reported recommendation is classified as "nonconforming" are associated with strong negative abnormal returns surrounding the GCM date. Although the correlation between my independent variables are in many cases lower than 20%, suggesting that variables are not strongly correlated, as

expected, LOGSIZE is highly correlated with ANALY (Pearson correlation= 0.609; Spearman rank correlation = 0.578, p-value<0.0001), also NONCONFORM and LOGSIZE and NONCONFORM and ANALY are similarly highly correlated, reflecting larger firms being better covered by analysts. To ensure the robustness of my results, I re-run the regression model defined in equation 6.4. excluding the independent variables that are highly correlated with the significant ones and use a stepwise technique to estimate the regression.

TABLE 6.8.
Pearson and Spearman correlations: Equation 6.4. Variables

This table provides the Pearson (Spearman rank) correlation above (below) the diagonal between all variables used to estimate equation 6.4. for GCM firms. The two-tailed p-value is provided in parenthesis below the correlation. GCM companies are my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
Dummy variable SNCAR=1 if the firm's abnormal returns for the (-1,+1) trading period are in the bottom 33.3% performers within my sample firms; Dummy variable CONFORM=1 if the firm's average reported recommendations within the 6-month period before the GCM date is classified as "conforming", i.e., "underperform" or "sell" recommendation, and 0 otherwise; Dummy variable NONCONFORM= 1 if the firm's average reported recommendations within the 6-month period before the GCM date is classified as "nonconforming", i.e., "hold", "buy" or "strong buy" recommendation, and 0 otherwise; LOGSIZE=natural log of market capitalization measured one year before the GCM announcement date; ANALY=number of analysts following the firm in quarter -4; BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM=monthly average of prior 11 month (t-12 to t-2) raw returns; ROA=return on assets (net income/total assets); CR=current ratio (current assets/current liabilities); ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985); LEV=total debt/total assets. SUE=(ΔNI_q / $|NI_q|$), where ΔNI_q is the quarterly earnings change computed as the difference between the quarterly income before extraordinary items (NI_q) and the quarterly income before extraordinary items in the previous year (NI_{q-4}). All variables are computed with data taken from the last annual financial accounts reported before the GCM date.

	SNCAR	CONFORM	NONCONF	LOGSIZE	ANALY	BM	MOM	ROA	ZSCORE	PREDGC	LEV	SUE
SNCAR		-0.072	0.098	0.123	0.097	-0.044	-0.069	-0.006	0.071	0.038	-0.018	-0.025
		(0.0283)	(0.0028)	(0.0002)	(0.0033)	(0.1846)	(0.0348)	(0.8631)	(0.0302)	(0.2525)	(0.5851)	(0.4485)
CONFORM	-0.072		-0.078	0.109	0.118	0.015	-0.091	-0.006	-0.010	0.003	-0.008	0.193
	(0.0283)		(0.0176)	(0.0009)	(0.0003)	(0.6546)	(0.0058)	(0.8511)	(0.7567)	(0.9160)	(0.8036)	(<0.0001)
NONCONF.	0.098	-0.078		0.448	0.530	-0.054	-0.133	-0.022	-0.045	-0.003	0.013	-0.021
	(0.0028)	(0.0176)		(<0.0001)	(<0.0001)	(0.1041)	(<0.0001)	(0.4958)	(0.1720)	(0.9272)	(0.6959)	(0.5102)
LOGSIZE	0.114	0.126	0.411		0.609	-0.190	-0.337	-0.095	-0.096	-0.006	0.006	0.032
	(0.0005)	(0.0001)	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)	(0.0038)	(0.0036)	(0.8570)	(0.8645)	(0.3332)
ANALY	0.090	0.183	0.532	0.578		0.009	-0.175	-0.062	-0.070	0.051	0.016	0.061
	(0.0061)	(<0.0001)	(<0.0001)	(<0.0001)		(0.7749)	(<0.0001)	(0.0608)	(0.0323)	(0.1219)	(0.6217)	(0.0627)
BM	-0.028	0.039	-0.094	-0.312	0.040		0.036	0.004	0.033	0.022	-0.023	0.008
	(0.3992)	(0.2387)	(0.0044)	(<0.0001)	(0.2223)		(0.2734)	(0.8958)	(0.3193)	(0.5101)	(0.4799)	(0.8180)
MOM	-0.056	-0.111	-0.106	-0.331	-0.174	0.107		0.123	-0.004	0.007	-0.019	0.027
	(0.0863)	(0.0007)	(0.0013)	(<0.0001)	(<0.0001)	(0.0011)		(0.0002)	(0.9122)	(0.8328)	(0.5734)	(0.4079)
ROA	-0.043	0.003	-0.006	-0.130	-0.049	0.246	0.171		-0.010	0.105	-0.052	0.008
	(0.1906)	(0.9253)	(0.8554)	(<0.0001)	(0.1373)	(<0.0001)	(<0.0001)		(0.7570)	(0.0014)	(0.1170)	(0.8106)
ZSCORE	0.001	-0.016	-0.105	-0.183	-0.104	0.136	0.028	0.223		0.248	-0.011	-0.025
	(0.9627)	(0.6328)	(0.0014)	(<0.0001)	(0.0016)	(<0.0001)	(0.3981)	(<0.0001)		(<0.0001)	(0.7388)	(0.4487)
PREDGC	0.002	-0.012	0.032	-0.102	0.032	0.254	0.101	0.416	0.374		-0.053	0.001
	(0.9490)	(0.7176)	(0.3332)	(0.0018)	(0.3265)	(<0.0001)	(0.0021)	(<0.0001)	(<0.0001)		(0.1057)	(0.9769)
LEV	-0.032	-0.001	-0.027	-0.062	-0.072	-0.025	-0.007	0.180	-0.081	-0.545		0.015
	(0.3230)	(0.9759)	(0.4176)	(0.0590)	(0.0288)	(0.4513)	(0.8206)	(<0.0001)	(0.0136)	(<0.0001)		(0.6551)
SUE	-0.043	-0.011	-0.042	-0.086	-0.052	-0.019	-0.010	-0.310	-0.111	-0.122	-0.111	
	(0.1875)	(0.7468)	(0.2063)	(0.0089)	(0.1141)	(0.5590)	(0.7536)	(<0.0001)	(0.0007)	(0.0002)	(0.0007)	

I use only two dummy variables (CONFORM and NONCONFORM) to distinguish between three cases: 1) a firm with no analyst coverage; 2) a covered firm receiving a “conforming” recommendation; 3) a covered firm receiving a “nonconforming” recommendation. This procedure avoids the case of perfect collinearity by defining a category for which no dummy variable is assigned, known as the “base” category (Gujarati, 2003). In my regression, the “base” category is that for which firms have no analyst following (i.e., when CONFORM=0 and NONCONFORM=0). Importantly, because I have two dummies to discriminate between three complementary cases, the intercept has a particular meaning. To be precise, positive (negative) and statistically significant estimates of the intercept indicate that no analyst coverage increases (decreases) the likelihood of a firm experiencing a strong negative abnormal return with the publication of a GCM audit report.

Table 6.9. summarizes my results, which are highly significant (Wald x^2 = 32.60, p-value=0.0006). I find that the model’s intercept is negative and highly significant, suggesting that, *ceteris paribus*, firms with no analyst coverage are less likely to experience a strong negative short-term market reaction to the GCM announcement controlling for all other factors. Moreover, the CONFORM variable is also negative and significant at the 5% level, suggesting that firms receiving “conforming” recommendations, i.e., “sell” and “underperform” ratings have a reduced likelihood of experiencing a strong negative short-term abnormal reaction to the GCM event. I find two additional independent variables significant at the 10% level. The negative (positive) coefficient associated with the MOM (ZSCORE) variable suggests that firms with lower past performance (higher ZSCORE, i.e., lower distress risk) are more likely to experience a strong negative short-term market reaction to the GCM announcement. None of the remaining variables are statistically significant at conventional levels. Importantly, I find that my results are robust after re-

running the model excluding the independent variables more correlated with the significant ones and using the stepwise technique to estimate the regression.

In order to ensure the robustness of my results, I re-estimate equation 6.4. using different thresholds to define the worse performing firms. Specifically, in sequential rounds, firms in the bottom 10%, 20%, 30%, 40% and 50% by 3-day CAR, are classified in the "strong negative abnormal reaction" portfolio. I then run distinct regressions only to find that the intercept is highly significant for all them and that the signals associated with the coefficients are robust as well as their significance.

Overall, multivariate results confirm my previous conclusion that analyst coverage, in general terms, amplifies the "surprise" associated with the publication of a GCM audit report. However, when the average analyst recommendation operates in the right direction ("conforming" recommendation), analysts reduce the likelihood of a firm experiencing a strong negative short-term market reaction to the publication of a GCM audit report. Hence, I reject null hypothesis H11.

Table 6.9.
Logistic Regression Model Estimating the Probability of a Firm Experiencing a Strong Negative Short-term Market Reaction to the Publication of a GCM Audit Report

This table presents the results of a binary logistic regression model estimating the probability of a GCM firm experiencing a strong negative abnormal reaction for the (-1,+1) trading period centred on the GCM event date. The GCM companies are my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994.

The binary logistic regression model is defined in equation 6.4. The binary dependent variable (SNCAR) is computed as follows. First, I compute the 3-day abnormal returns ($CAR_{(-1,+1)}$) centred on the GCM event date. Firms are ranked accordingly to their 3-day abnormal returns and divided into two groups. The worst 33.3% returns are classified as 1, and 0 otherwise. Eleven independent variables are employed to estimate equation 6.4.: Dummy variable CONFORM=1 if the firm's average reported recommendations within the 6-month period before the GCM date is classified as "conforming", i.e., "underperform" or "sell" recommendation, and 0 otherwise; Dummy variable NONCONFORM= 1 if the firm's average reported recommendations within the 6-month period before the GCM date is classified as "nonconforming", i.e., "hold", "buy" or "strong buy" recommendation, and 0 otherwise; LOGSIZE=natural log of market capitalization measured one year before the GCM announcement date; ANALY=number of analysts following the firm in quarter -4; BM= book value of equity divided by market capitalization, where book value of equity is taken from the last annual accounts reported prior to the date used to calculate the market capitalization at one year before the GCM announcement date; MOM=monthly average of prior 11 month (t-12 to t-2) raw returns; ROA=return on assets (net income/total assets); CR = current ratio (current assets/current liabilities); ZSCORE=financial distress measure computed as Altman (1968); PREDGC=probability of a forthcoming GCM audit report disclosure computed as Mutchler (1985); LEV=total debt/total assets. SUE=(ΔNI_q / $|NI_q|$), where ΔNI_q is the quarterly earnings change computed as the difference between the quarterly income before extraordinary items (NI_q) and the quarterly income before extraordinary items in the previous year (NI_{q-4}). All variables are computed with data taken from the last annual financial accounts reported before the GCM date.

Predictor	Expected sign	Coefficient	Wald	p-value
Intercept	-	-1.27	20.96	<0.0001
CONFORM	-	-1.51	5.65	0.0175
NONCONFORM	+	0.08	0.13	0.7175
LOGSIZE	+	0.12	2.60	0.1071
ANALY	+	0.03	1.97	0.1600
BM	+	-0.02	0.22	0.6427
MOM	+	-1.84	3.27	0.0708
ROA	+	-0.00	0.00	0.9827
ZSCORE	+	0.10	3.79	0.0517
PREDGC	+	-0.00	0.58	0.4449
LEV	-	-0.31	2.44	0.1186
SUE	-	-0.00	0.15	0.6983

Model x^2 (d.f.=11) =32.60 with p=0.0006

6.4. Summary and discussion

This chapter investigates the role of security analysts in providing investors with value-relevant information before the publication of a first-time GCM audit report. I use an event-time approach to test whether pre-GCM analyst coverage is related to the short-term market reaction of such a major accounting event. I additionally control my results for a number of firm characteristics (size, momentum, financial distress, GCM probability and earnings surprises), previous recommendation ratings and reporting environment.

My results suggest that pre-GCM analyst coverage does not facilitate investors' recognition of going-concern problems. In particular, I show that the short-term market reaction to the publication of a GCM audit report is significantly more adverse for firms with analyst coverage, suggesting that analyst activity increases the "surprise" associated with the publication of a GCM audit report. These results suggest that, despite analyst recommendations become relatively more pessimistic for GCM firms than for similar non-GCM firms as the GCM date approaches, investors do not recognize an average "hold" recommendation as an unfavourable message even considering that it represents a downgrade from a previous "buy" rating.

Consistent with the notion that security analysts may temporarily delay the incorporation of negative information in stock prices (Jegadeesh et al., 2004), I find that the differences in the short-term market reaction to the GCM announcement between covered and non-covered firms are particularly evident for firms where other negative signals are clearer (negative momentum, high distress risk, high GCM probability). A more detailed analysis shows that the usefulness of analyst recommendations to investors depends on the direction of such information. When analyst recommendations are consistent with the forthcoming GCM (i.e., when they issue "underperform" or "sell" recommendations), they facilitate the incorporation of other unfavourable signals, thus reduce the "surprise" associated with the publication of a GCM audit report. When analyst recommendations are inconsistent with the forthcoming GCM (i.e., when they issue "strong buy", "buy" or "hold" recommendations), they delay the incorporation of other unfavourable signals, thus increase the "surprise" associated with the publication of a GCM audit report. Importantly, the percentage of firms where analyst average recommendation is classified as "conforming" is reduced explaining why the overall short-term market reaction is significantly more negative for firms with analyst coverage than firms with no analyst coverage.

My results help to understand the SEC concerns about investors relying solely on analyst recommendations when buying or selling a stock. In one of their online publications aiming at protecting investors, the SEC is particularly clear when discussing analyst stock recommendations:[53] "*We advise all investors to do their homework before investing. If you purchase a security solely because analyst said the company was one of his or her 'stock picks', you may be doing yourself a disservice. Especially if the company is one you've never heard of (…) Above all, remember that even the soundest recommendation from the most trust-worthy analyst may not be a good choice for you. That's one reason we caution investors never to rely solely on analyst's recommendations when buying or selling a stock.*"

This chapter also shows that the significantly more negative short-term market reaction for firms with analyst coverage is an exclusive phenomenon of the pre-NASD 2711 period. In fact, after the implementation of this new regulatory regime, the significant differences in the short-term between covered and non-covered firms become statistically insignificant. This suggests that more pessimistic pre-GCM recommendations and the additional

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[53] See http://www.sec.gov/investor/pubs/analysts.htm for details.

information that analysts are required to disclose following the implementation of the regulatory changes provide investors with better information to access analysts' research in the GCM audit report context.

The next chapter provides additional evidence on the value-relevance of analyst activity in the GCM audit report domain. In particular, I investigate the relationship between post-GCM analyst coverage and stock return performance following the publication of a GCM audit report.

CHAPTER 7
ANALYST COVERAGE AND POST-GCM STOCK RETURN PERFORMANCE

7.1. Introduction

In three recent studies, Taffler, Lu, and Kausar (2004), Ogneva and Subramanyam (2007) and Kausar, Taffler, and Tan (forthcoming) discuss the market reaction to the publication of a GCM audit report. Taffler, Lu, and Kausar (2004) demonstrate that the U.K. market takes time to assimilate the publication of such a bad news event whereas Ogneva and Subramanyam (2007) find no abnormal reaction following the GCM announcement for the U.S. and Australian markets. However, using a hand collected sample from the EDGAR database, appropriate adjustment for outliers and a correct treatment of post-delisting returns, Kausar, Taffler, and Tan (forthcoming) show that the market underreaction to the first-time GCM audit report is a robust phenomenon in the U.S., suggesting that Ogneva's and Subramanyam (2007) conclusions are due to the use of a biased sample and methodological problems.

Previous studies have also discussed the reasons for the incomplete market reaction to new information. In broad terms, these studies share a common idea: investors are slow in adjusting their expectations when receiving new information (Bernard and Thomas, 1989; Barberis, Schleifer, and Vishny, 1998; Hong and Stein, 1999). For instance, Bernard and Thomas (1989) argue in favour of investors' delayed responses, Barberis, Schleifer, and Vishny (1998), in their model of investor sentiment, suggest that conservatism plays an important role in the underreaction phenomenon whilst Hong and Stein (1999) claim that underreaction is due to firm-specific information diffusing gradually across the investing public.

The role of security analysts in the incomplete market reaction to new information has also been explored in the literature. In fact, there are reasons to believe that security analysts may play an important role in mitigating the phenomenon of incomplete market reaction to new information. In particular, there is evidence that analysts' opinions have the ability to move stock prices (e.g., Stickel, 1991; Stickel, 1995; Womack, 1996; Park and Stice, 2000; Ryan and Taffler, 2006). Moreover, the research shows that analyst coverage reduces information uncertainty and has a positive impact on the speed with which the market assimilates new information (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Walther, 1997; Bhattacharya, 2001; Elgers, Lo, and Jr, 2001; Gleason and Lee, 2003, Zhang, forthcoming).

The literature highlights the importance of security analysts in the functioning of financial markets. For instance, Brennan, Jegadeesh, and Swaminathan (1993) find that the market's reaction to common information is faster for firms with higher levels of analyst coverage. Bhattacharya (2001) suggests that the post-earnings drift is stronger for firms with low-to-moderate analyst coverage and Zhang (forthcoming) shows that the post-earnings drift decreases as the percentage of responsive analysts following the firm increases. Gleason and Lee (2003) find that the post-analyst forecast revision drift is lower for companies with higher levels of analyst coverage. These results are consistent with the recent findings of Jiang, Lee, and Zhang (2005) and Zhang (2006), who find that the incomplete market reaction is particularly strong for companies with greater information uncertainty.

In this chapter, I evaluate the role of security analysts in the medium-term market reaction to the publication of a GCM audit report. In fact, despite the evidence that the market takes time to incorporate the publication of a GCM audit report (e.g., Taffler, Lu, and Kausar, 2004; Kausar, Taffler, and Tan, forthcoming) and that analysts promote market efficiency, no study to date explores directly how security analysts affect the efficiency with which the market processes this accounting disclosure.

This chapter also explores if analysts engage in self-selecting activities in the going-concern domain. The self-selection bias is the tendency of analysts to report on stocks about which they have favourable views and to avoid reporting on stocks about which they have unfavourable views (e.g., McNichols and O'Brien, 1997; Das, Guo, and Zhang, 2006). Investigating whether the analyst's decision to cover a firm following the publication of a GCM audit report depends on its post-GCM return performance provides original evidence about analyst self-selection bias in the bad news domain.

The chapter is organised as follows: section 2 describes the data and methodology. Section 3 presents the results and section 4 summarizes and discusses the results of the chapter.

7.2. Data and methodology

The main purpose of this chapter is to evaluate the role of security analysts in the medium-term market reaction to the publication of a GCM audit report. Similarly to the previous chapter, I compare the post-GCM stock price performance conditional on post-event analyst coverage. Once again, the definition of analyst coverage and the computation of abnormal returns are key issues. The data used in this chapter is from three sources: security analyst data is taken from the I/B/E/S/ Recommendations – Detailed File, whereas the market and accounting data are collected from CRSP and COMPUSTAT, respectively.

7.2.1. Defining analyst coverage

There are two common methods to define analyst coverage. The first uses the number of analysts following a firm in a given period. For instance, Elgers, Lo, and Jr (2001) and Gleason and Lee (2003) allocate firms to the high (low) coverage category if the number of analysts following is above (below) the sample's median. The second method uses a measure of residual analyst coverage as an alternative to the raw number of analysts following the firm (Hong, Lim, and Stein, 2000; Das, Guo, and Zhang, 2006). This method aims at controlling the influence of firms' specific characteristics such as size, BM, market index or industry in the number of analysts following a firm.

However, in my thesis, I use the raw number of analysts following a firm since my sample firms have either no analyst coverage or very limited coverage, a fact that is especially clear after the GCM announcement date. This makes it almost impossible to distinguish between levels of analyst coverage. As such, the use of residual analyst coverage would not be meaningful given little the variation in analyst coverage that occurs with my sample firms.[54]

Analyst coverage is defined as follows. I allocate each of my 924 first-time GCM firms to the "analyst coverage" portfolio if there is at least one new recommendation or a new annual EPS forecast following the GCM announcement date. All the remaining companies are allocated to the "no analyst coverage" portfolio. The post-GCM window used to define a company as covered depends on the empirical test. Importantly, in this chapter, I work exclusively with reported recommendations to ensure that firms classified as covered are confined to those for which analysts issue new opinions *following* the GCM audit report, i.e., when it is already publicly known.

7.2.2. Computing medium-term abnormal returns

I investigate the medium-term stock market reaction to the publication of a first-time GCM audit report using the buy-and-hold abnormal return (BHAR) methodology. I use this approach as an alternative to cumulative abnormal returns (CARs) since the literature advocates BHARs as the best method to measure medium and long-term performance. For instance, Barber and Lyon (1997) show that BHARs accurately represent investors' long term experience. These authors also advocate the use of BHARs over CARs since this second method is a biased predictor of BHARs. In addition, recent event studies exploring a similar context also use BHARs to measure stock price medium-term performance (e.g., Ogneva and Subramanyam, 2007; Kausar, Taffler, and Tan, forthcoming).

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[54] Hong et al. (2000) ignore the bottom quintile of firms by size in their residual analyst coverage regressions given that only 18% of these companies are followed by analysts.

I use a single control firm approach to compute my medium-term abnormal returns.[55] Barber and Lyon (1997) argue that, contrary to reference portfolios, the control firm approach eliminates the new listing bias, the rebalancing bias and the skewness problem. In fact, this procedure ensures that both sample and control firm are listed in the event month, that both sample and control firm returns are calculated without rebalancing and that both firms are equally likely to experience large positive or negative returns. Additionally, Ang and Zhang (2004) suggest that reference portfolios may not provide a good estimate of expected firm return since the event firm may not be near the centroid of the respective control portfolio, a problem that I overcome with the single firm method.

Buy-and-hold abnormal returns are computed as follows:

$$BHAR_{it} = \prod_{t=a}^{b}[1+R_{it}] - \prod_{t=a}^{b}[1+E(R_{it})] \qquad (7.1)$$

As explained above, the expected return $E(R_{it})$ is given by the return of a similar non-GCM firm. Following Barber and Lyon (1997), sample firms are matched to a control firm on the basis of specific firm characteristics. As recommended by these authors, I use size and BM ratio in my main results. The matching procedure is described in section 4.3.2. Considering

[55] Long-horizons studies require extreme caution since existing methods still have serious limitations (Kothari and Warner, 2007). There are several critical issues in evaluating long-term stock return performance, which include risk adjustment, the aggregation of security-specific abnormal returns and the calibration of the statistical significance of abnormal returns (Kothari and Warner, 2007). Long-run abnormal return measurement problems using BHARs usually occur in a 3-5 year time horizon (e.g., Kothari and Warner, 1997; Barber and Lyon 1997). Nevertheless, in my thesis, I restrict my BHAR calculation to a one-year period in a similar approach to Taffler et al. (2004), Ogneva and Subramanyam (2007) and Kausar, Taffler, and Tan (forthcoming). This is due to two fundamental reasons: 1) there is a significant percentage of firms delisted in the year following the GCM date; 2) some of the GCM firms have their GCM audit report withdrawn in the subsequent fiscal year.

that controlling for size and BM ratio alone does not guarantee well-specified test statistics (Lyon, Barber, and Tsai, 1999), I also use different matched samples based on alternative characteristics (pre-event momentum, industry or distress risk). Alternative control samples are defined as in section 5.2.1.

The individual abnormal returns for each of my sample firms are then averaged using an equally weighted strategy. I use equally weighted returns in preference to value-weighted returns to avoid problems related to the small average size of my sample. According to Loughran and Ritter (2000), value-weighted returns result in low power to detect abnormal performance due to large standard errors and low t-statistics. Therefore, mean abnormal returns are given by the average of the buy-and-hold abnormal returns, wherein the number of firms considered in the period t is as follows:

$$\overline{BHAR_t} = \frac{1}{n}\sum_{i=1}^{n} BHAR_{it} \tag{7.2}$$

where $BHAR_{it}$ is defined as above.

I also estimate buy-and-hold raw returns (BHRR) to corroborate the results obtained with the BHAR methodology. According to Kausar, Taffler, and Tan (forthcoming), this method is viewed as a more stringent test of market mispricing that may help to highlight mis-measurement problems associated with my various expected return proxies. BHRRs are calculated as follows:

$$\mathrm{BHRR}_{it} = \prod_{t=a}^{b} [1 + \mathrm{R}_{it}] - 1 \tag{7.3}$$

For the same reasons discussed with BHARs, I also average individual BHRRs using an equally weighted strategy as follows:

$$\overline{BHRR_t} = \frac{1}{n} \sum_{i=1}^{n} BHRR_{it} \tag{7.4}$$

I compute both BHARs and BHRRs using daily returns since they allow a more precise measurement of abnormal returns (Kothari and Warner, 2007). BHARs and BHRRs are computed over different periods starting from trading day a to trading day b relative to the event date. The event date is defined as the GCM announcement date taken from the SEC-EDGAR database.

As table 3.3. shows, 45.7% of my companies are delisted in the one year period following the GCM announcement date. Drawing on Shumway (1997) and Shumway and Warther (1999), I include the delisting return in the calculation of compounded returns each time a firm is delisted. Moreover, I assume zero abnormal returns in the post-delisting period as in Kausar, Taffler, and Tan (forthcoming). As these authors argue, this method minimizes the reinvestment bias, allowing better estimates of abnormal returns for their sample of GCM firms.

I also winzorize the extreme values at the first (99th) percentile of both tails of the BHAR distribution.[56] I use the parametric t-test to verify the significance of the mean BHARs and the non-parametric Wilcoxon signed rank-test and sign-test to examine the significance of the median abnormal returns and if the number of negative BHARs differs to the number of positive BHARs, respectively.

7.3. Results

7.3.1. Revisiting medium-term market reaction to the first-time GCM audit report

In this section, I visit the medium-term market reaction to the GCM announcement employing a control firm approach based on size and BM ratio to compute abnormal returns. In addition, I explore the medium-term market reaction conditional on firms' characteristics to evaluate the existence of possible "correlated omitted variables" (Dichev and Piotroski, 2001).

7.3.1.1. Initial evidence

Table 7.1. reports mean and median post-GCM BHARs from trading day +2 over the following 252 trading days subsequent to the GCM date. As can be seen, first-time GCM audit report disclosures are followed by substantial negative abnormal returns. For instance, the mean (median) $BHARs_{(+2,+126)}$ are -13.2% (-21.1%) whereas for the (+2, +252) window, results are -17.4% (-30.2%) consistent with Kausar, Taffler, and Tan (forthcoming). More importantly, both parametric and nonparametric tests show that the

[56] The non-winsorized results are not significantly different from the winsorized results.

BHARs are highly significant at the 1% level or better for all the post-event windows. The results of the sign test indicate that the number of negative BHARs is significantly greater than the number of positive BHARs. Interestingly, the corresponding median BHARs are systematically more negative than the mean BHARs, suggesting that extreme observations are more concentrated in the positive side. Overall, my results are in line with those of Taffler, Lu, and Kausar (2004) and Kausar, Taffler, and Tan (forthcoming), who conclude that the market underreacts to the publication of a GCM audit report.

Table 7.1.
Medium-term Market Reaction to the First-Time GCM Audit Report

This table presents the buy-and-hold abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. The abnormal returns are computed in trading days, from trading day +2 over the following 250 trading days, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. Returns earned by delisted firms are assumed to have zero abnormal returns in the post-delisting period. The BHARs are computed employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) BHAR. The number of positive (negative) BHARs is shown in the positive (negative) column, whereas the significance of the sign test is reported in parentheses.

Period	BHAR				Sign test	Listed Firms
	Mean	Median	Positive	Negative		
(+2,+63)	-0.082 (0.0003)	-0.126 (<0.0001)	40%	60%	(<0.0001)	852
(+2,+126)	-0.132 (<0.0001)	-0.211 (<0.0001)	36%	64%	(<0.0001)	712
(+2,+189)	-0.160 (<0.0001)	-0.247 (<0.0001)	36%	64%	(<0.0001)	580
(+2,+252)	-0.174 (<0.0001)	-0.302 (<0.0001)	35%	65%	(<0.0001)	551

7.3.1.2. Controlling for GCM firm characteristics

I now investigate if the underreaction phenomenon is a result of some other variable that is correlated with future returns. I address this issue as in section 6.3.1.2., controlling my results for size, momentum, distress risk, GCM probability and earnings surprise.

Table 7.2. summarizes my results. Panel A reports the results of the portfolios of small and large GCM firms. Generally, I find that the market does not immediately incorporate the information conveyed by the GCM audit report for both small and large firms. In fact, with the exception of the 12-month mean BHAR for the portfolio of large firms, mean and median abnormal returns are negative and highly significant. Moreover, both parametric and nonparametric tests suggest that the differences in the mean and median BHARs between “small firms” and “large firms” are not significant at conventional levels. As such, I find that market mispricing is not more concentrated amongst small firms.

Panel B of table 7.2. reports separate results for the post-GCM return performance of firms conditional on pre-event momentum. Generally, I find that, overall, the negative market reaction to the publication of a GCM audit report does not depend on firms’ prior raw returns since mean and median BHARs are significant at the conventional levels for both portfolios for all post-event periods. Moreover, the differences between BHARs are not significantly different with the exception of the shorter post-GCM window. In fact, 3-month BHARs for the “positive momentum” portfolio are significantly more negative than for the “negative momentum” portfolio. In particular, mean (median) BHARs are -16.0% (-16.4%) for “positive momentum” portfolio and -5.5% (-12.1%) for “negative momentum” portfolio, with the mean (median) differences significant at the 5% (10%) level. These results can be explained by the higher surprise with which the market receives a GCM audit report for firms with positive pre-event raw returns. To ensure that market abnormal reaction to the GCM announcement is not due to the omission of this risk factor (momentum), I compute BHARs using the control firm approach based on size and momentum as in section 5.2.2.1. Results are materially the same.

In Panel C (Panel D) of table 7.2., I present the abnormal returns for the GCM companies conditional on firm distress risk (GCM probability). Companies with z-scores <=1.81 (>1.81) are allocated to the high (low) distress risk portfolio. Similarly, companies with PREDGC <=0.01 (>0.01) are classified as high (low) GCM probability cases. Generally, both Panel C and D show that the incomplete market reaction to the GCM announcement is not sensitive to either of these characteristics. Importantly, both parametric and nonparametric tests show that differences in the mean and median BHARs are not significant between portfolios of firms conditional on their z-score and PREDGC. Using a similar approach to ensure that my results are not due to the omission of this risk factor (z-score), I compute BHARs using the control firm approach based on size and financial distress as in section 5.2.1.3. Once again, results are materially the same.

Panel E of table 7.2. shows separate results for the portfolios of firms with positive and negative earnings surprises as in section 6.3.1.2. I find a negative and highly significant abnormal reaction to the publication of a GCM audit report for the "negative earnings surprise" portfolio for all post-GCM windows considered. However, for the portfolio of "positive earnings surprise", results are mixed. As can be seen, mean BHARs are not significant whereas median BHARs are significant at the 10% level. More important, I show that the abnormal returns for the "negative earnings surprise" portfolio are significantly more negative than the "positive earnings surprise" portfolio. For instance, the 12- month mean (median) BHARs are -39.1% (-38.9%) for firms with negative earnings surprise and 11.3% (-12.5%) for firms with positive earnings surprise, with mean and median differences between the portfolios significant at the 1% level. As such, this indicates that earnings surprises are important in explaining post-GCM returns and that negative abnormal reaction to the GCM event is concentrated in the negative earnings surprise firms.

In short, I find that the incomplete market reaction to the GCM announcement is a robust phenomenon. In addition, I show that negative abnormal market reaction to the GCM event is concentrated in firms associated with negative earnings surprise. Hence, I conclude that the market does not immediately incorporate the information conveyed by the GCM announcement, supporting Taffler, Lu, and Kausar (2004) and Kausar, Taffler, and Tan (forthcoming) studies.

Table 7.2.
Medium-term Market Reaction to the First-Time GCM Audit Report - Controlling for Firm Characteristics

This table presents the buy-and-hold abnormal returns for my population of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005. The abnormal returns are computed in trading days, from trading day +2 over the following 250 trading days, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. Returns earned by delisted firms are assumed to have zero abnormal returns in the post-delisting period. The BHARs are computed employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm. The two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) BHAR. The last two columns of each panel report the mean and median differences between the BHARs of each portfolio under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.
Panel A provides separate results for the portfolio of 462 (462) GCM companies with market capitalization below (above) the sample median ($33.7m). Market capitalization is calculated one year before the GCM date. Panel B reports separate results for the portfolio of 235 (689) GCM companies with positive (negative) pre-event momentum. Momentum is defined as the average monthly raw returns for the prior 11-month period (t-12 to t-2) relative to the GCM announcement month. Panel C provides separate results for the portfolio of 775 (149) GCM companies with z-score <=1.81 (>1.81). Z-score is computed following Altman's (1968) model using the accounting information from the fiscal year ending one year before the GCM announcement date. Panel D reports separate results for the portfolio of 454 (470) GCM companies where PREDGC is <=0.01 (>0.01), defined as minimum cut-off score by Fleak and Wilson (1994). Panel E provides separate results for the portfolio of 528 (396) GCM companies where SUE is negative (positive). SUE=(ΔNIq / |NIq|), where ΔNIq is the quarterly earnings change computed as the difference between the quarterly income before extraordinary items (NIq) and the quarterly income before extraordinary items in the previous year (NIq-4).

Panel A: Post-GCM announcement BHARs conditional on firm size

	Small Firms (A) (n=462)			Large Firms (B) (n=462)			DIFERENCE (A - B)	
Period (trading days)	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR
(+2,+63)	-0.095 (0.0033)	-0.160 (<0.0001)	450	-0.069 (0.0269)	-0.115 (<0.0001)	455	-0.026 (0.5686)	-0.045 (0.5087)
(+2,+126)	-0.157 (0.0008)	-0.216 (<0.0001)	374	-0.099 (0.0345)	-0.205 (<0.0001)	374	-0.058 (0.3766)	-0.011 (0.3327)
(+2,+189)	-0.217 (0.0001)	-0.263 (<0.0001)	295	-0.104 (0.0556)	-0.216 (<0.0001)	311	-0.113 (0.1494)	-0.047 (0.2626)
(+2,+252)	-0.247 (0.0004)	-0.306 (<0.0001)	254	-0.108 (0.1612)	-0.293 (<0.0001)	268	-0.139 (0.1800)	-0.013 (0.3550)

Panel B: Post-GCM announcement BHARs conditional on firm momentum

	Negative Momentum (n=689)			Positive Momentum (n=235)			DIFERENCE (A - B)	
Period (trading days)	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR
(+2,+63)	-0.055 (0.0357)	-0.121 (<0.0001)	671	-0.160 (0.0002)	-0.164 (<0.0001)	234	0.105 (0.0356)	0.043 (0.0653)
(+2,+126)	-0.089 (0.0304)	-0.220 (<0.0001)	541	-0.233 (<0.0001)	-0.176 (<0.0001)	207	0.144 (0.0279)	-0.044 (0.7157)
(+2,+189)	-0.136 (0.0043)	-0.263 (<0.0001)	430	-0.255 (<0.0001)	-0.203 (<0.0001)	176	0.119 (0.1355)	-0.060 (0.9549)
(+2,+252)	-0.155 (0.0139)	-0.311 (<0.0001)	367	-0.221 (0.0122)	-0.282 (<0.0001)	155	0.066 (0.5413)	-0.029 (0.9168)

Panel C: Post-GCM announcement BHARs conditional on firm distress risk

	High Distress Risk (A) (n=775)			Low Distress Risk (B) (n=149)			DIFERENCE (A - B)	
Period (trading days)	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR
(+2,+63)	-0.088 (0.0002)	-0.123 (<0.0001)	761	-0.053 (0.3808)	-0.164 (0.0167)	144	-0.035 (0.5781)	0.041 (0.9979)
(+2,+126)	-0.131 (0.0002)	-0.200 (<0.0001)	640	-0.137 (0.1188)	-0.289 (<0.0001)	108	0.006 (0.9442)	0.089 (0.4645)
(+2,+189)	-0.157 (0.0003)	-0.209 (<0.0001)	520	-0.187 (0.0650)	-0.310 (<0.0001)	86	0.030 (0.7814)	0.101 (0.3757)
(+2,+252)	-0.197 (0.0004)	-0.297 (<0.0001)	452	-0.090 (0.5086)	-0.336 (0.0002)	70	-0.107 (0.4663)	0.039 (0.6005)

Panel D: Post-GCM announcement BHARs conditional on firm GCM probability

	High GCM Probability (A) (n=454)			Low GCM Probability (B) (n=470)			DIFERENCE (A - B)	
Period (trading days)	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR
(+2,+63)	-0.064 (0.0632)	-0.144 (<0.0001)	445	-0.099 (0.0006)	-0.116 (<0.0001)	445	0.035 (0.4387)	-0.028 (0.4713)
(+2,+126)	-0.076 (0.1499)	-0.233 (<0.0001)	356	-0.184 (<0.0001)	-0.204 (<0.0001)	356	0.108 (0.1079)	-0.029 (0.8222)
(+2,+189)	-0.104 (0.0850)	-0.212 (<0.0001)	280	-0.226 (<0.0001)	-0.279 (<0.0001)	280	0.122 (0.1182)	0.067 (0.6033)
(+2,+252)	-0.094 (0.2608)	-0.280 (<0.0001)	252	-0.254 (<0.0001)	-0.337 (<0.0001)	252	0.160 (0.1271)	0.057 (0.6124)

Panel E: Post-GCM announcement BHARs conditional on firm earnings surprise

	Negative Earnings Surprise (A) (n = 528)			Positive Earnings Surprise (B) (n = 396)			DIFERENCE (A - B)	
Period (trading days)	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR	Listed Firms	Mean BHAR	Median BHAR
(+2,+63)	-0.138 (<0.0001)	-0.186 (<0.0001)	516	-0.007 (0.8527)	-0.079 (0.0558)	389	-0.131 (0.0041)	-0.107 (0.0033)
(+2,+126)	-0.239 (<0.0001)	-0.298 (<0.0001)	428	-0.005 (0.9202)	-0.090 (0.0065)	320	-0.234 (0.0005)	-0.208 (0.0004)
(+2,+189)	-0.318 (<0.0001)	-0.366 (<0.0001)	342	0.043 (0.5010)	-0.126 (0.0922)	264	-0.361 (<0.0001)	-0.240 (<0.0001)
(+2,+252)	-0.391 (<0.0001)	-0.389 (<0.0001)	286	0.113 (0.2139)	-0.125 (0.0733)	236	-0.504 (<0.0001)	-0.264 (<0.0001)

7.3.2. Medium-term market reaction to the GCM audit report and analyst coverage

Chapter 6 suggests that pre-event analyst coverage does not reduce the market impact of a GCM audit report disclosure. However, the role of security analysts in the post-GCM period remains an open question. In this section, I investigate the relationship between post-GCM coverage and post-GCM stock return performance. In particular, I test analyst contribution to the price-discovery process following the announcement of this bad news event and if analysts engage in self-selecting activities in my sample firms.

7.3.2.1. Analyst coverage and subsequent price performance

After the publication of a GCM audit report, investors are likely to require additional guidance in order to understand the implications of this accounting disclosure for firms' future prospects. This is particularly important since research suggests that investors are slow in adjusting their expectations (Bernard and Thomas, 1989; Barberis, Schleifer, andVishny, 1998; Hong and Stein, 1999), especially for companies with higher information uncertainty (Jiang, Lee, and Zhang, 2005; Zhang, 2006).

In this subsection, I investigate whether analysts reduce the magnitude of the post-GCM drift by comparing the return performance of firms following an initial post-GCM window to define analyst coverage.[57] I allocate my GCM firms to two portfolios conditional on analyst coverage over different post-GCM windows. Drawing on Das, Guo, and Zhang (2006) and Zhang (forthcoming), I minimize the potential problem arising from the use of

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[57] Zhang (2005) investigates the impact of analyst responsiveness and market underreaction to earnings announcements. She finds that analyst responsiveness mitigates the extent of the post-earnings announcement drift.

overlapping windows to define analyst coverage and to compute the abnormal returns. Specifically, I define an initial post-GCM window to classify firms as covered or not and compute the returns after this initial window. To ensure robust results, I choose different post-GCM windows to classify a firm as covered (varying between 1- and 6-months post-GCM).

In particular, companies are allocated to the “analyst coverage” portfolio over the different post-GCM windows if they receive at least one new recommendation or a new annual EPS forecast within that period. All the remaining companies are allocated to the “no analyst coverage” portfolio. I then compute separate BHARs for each portfolio, starting one trading day after the end of the period used to define the coverage status of the firms. As an example, consider the (+1, +62) window used to define analyst coverage. First, I separate my 924 first-time GCM firms into the “analyst coverage” and “no analyst coverage” portfolios conditional on the existence of new recommendations or new annual EPS forecasts within the (+1, +62) window relative to the GCM date. BHARs are then computed separately for each portfolio for the (+63, +252) trading period. Finally, I test the significance of the mean and median BHAR differences between the two portfolios using the t-test and the Wilcoxon-Mann-Whitney test respectively. If analysts are contributing to the price-discovery process, I expect firms with analyst coverage to experience subsequent abnormal returns closer to zero than firms with no analyst coverage.

The associated null hypothesis is defined as follows:

> *H12: There is no difference in the subsequent abnormal returns of firms with analyst coverage within an initial window relative to those with no analyst coverage.*

Table 7.3. summarizes my results. As can be seen, there are no significant differences in the mean and median BHARs between the "analyst coverage" and "no analyst coverage" portfolios over the different windows under scrutiny. In particular, I find negative and significant abnormal return performance of firms with no analyst coverage over the different post-GCM windows. For the "analyst coverage" portfolio, mean BHARs are not significant whereas median BHARs are significant at conventional levels. More importantly, both parametric and nonparametric tests show no significant differences in the mean and median BHARs of both portfolios. As an example, consider the (+1, +62) window to define analyst coverage. I find that mean (median) $BHARs_{(+63, +252)}$ are -12.2% (-6.4%) for the "no analyst coverage" portfolio and -10.7% (-11.6%) for the "analyst coverage" portfolio, with no significant differences in mean and median BHARs. As such, I conclude that analyst coverage is not reducing the magnitude of the post-GCM abnormal returns.

In order to ensure the robustness of my results, I re-run my test using the alternative control samples based on size and momentum (as in section 5.2.1.1.), industry, size and BM (as in section 5.2.1.2.) and size and distress risk (as in section 5.2.1.3.) to compute the abnormal returns. However, I find that my conclusions do not change when I use these different benchmark samples to compute the abnormal returns. In addition, I also control my results from the potential bias arising from the relationship between delisted firms and analyst coverage since analysts are less likely to cover a firm that is subsequently delisted.[58] Nevertheless, in line with my previous results, there are no significant differences in mean and median BHARs between the two portfolios. Hence, this suggests that delisted firms are not contaminating my previous conclusions.

[58] Only 27% of my companies with analyst coverage following the GCM date are delisted during the year following the GCM announcement whereas this percentage increases to almost 50% when considering companies with no analyst coverage.

Table 7.3.
Subsequent Return Performance Conditional on post-GCM Analyst Coverage

This table presents the buy-and-hold abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
For each coverage definition window, I allocate each of my 924 companies to one of two portfolios conditional on analyst coverage. Companies are allocated to the "analyst coverage" portfolio if analysts report at least one new recommendation or issue one new annual EPS forecast within the coverage definition window. All the remaining firms are allocated to the "no analyst coverage" portfolio. Abnormal returns are then computed in trading days, starting one trading day after the period used to define the coverage status of the firm until trading day +252, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. Returns earned by delisted firms are assumed to have zero abnormal returns in the post-delisting period. The BHARs are computed employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.
Two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) BHAR, whereas the significance of the sign test is shown in parentheses below the "Sign test" column of each portfolio. The last two columns of each panel report the mean and median differences between the BHARs of each portfolio under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.

Coverage Definition Window	Return Period	NO ANALYST COVERAGE (A)			ANALYST COVERAGE (B)			DIFERENCE (A - B)	
		Mean BHAR	Median BHAR	n	Mean BHAR	Median BHAR	n	Mean BHAR	Median BHAR
(+1,+20)	(+21,+252)	-0.181	-0.251	816	-0.094	-0.362	108	-0.087	0.111
		(0.0003)	(<0.0001)		(0.4881)	(0.0057)		(0.5494)	(0.8607)
(+1,+41)	(+42,+252)	-0.153	-0.138	752	-0.189	-0.248	172	0.036	0.110
		(0.0007)	(<0.0001)		(0.0717)	(0.0018)		(0.7510)	(0.3812)
(+1,+62)	(+63,+252)	-0.122	-0.064	739	-0.107	-0.116	185	-0.015	0.052
		(0.0011)	(<0.0001)		(0.2103)	(0.0031)		(0.8696)	(0.4384)
(+1,+83)	(+84,+252)	-0.105	0.000	727	-0.097	-0.182	197	-0.008	0.182
		(0.0032)	(<0.0001)		(0.2623)	(0.0014)		(0.9362)	(0.2052)
(+1,+104)	(+105,+252)	-0.066	0.000	721	-0.054	0.000	203	-0.012	0.000
		(0.0472)	(<0.0001)		(0.4164)	(0.0613)		(0.8756)	(0.8800)
(+1,+125)	(+126,+252)	-0.042	0.000	715	-0.019	0.000	209	-0.023	0.000
		(0.1714)	(0.0014)		(0.7529)	(0.0658)		(0.7262)	(0.6385)

In an addition robustness test, I run a similar test based on a shorter window to define both analyst coverage and to compute the abnormal returns. This is a more powerful test to investigate if analyst opinions contribute to the adjustment of prices after the GCM disclosure date since it is more restrictive on the definition of analyst coverage. In particular, companies are now allocated to the "analyst coverage" portfolio if they receive at least one new recommendation or a new annual EPS forecast for each of the six months following the GCM date. All the remaining companies are allocated to the "no analyst coverage" portfolio. I then calculate and compare the subsequent 3-month BHARs for each portfolio in a similar fashion to the previous test.[59]

Table 7.4. summarizes my results. I find that my conclusions do not change significantly when I use shorter windows to define analyst coverage and to compute the abnormal returns. In fact, I find that the differences between mean and median 3-month BHARs following a specific month to define analyst coverage are not significant at conventional levels. As an example, consider the (+1, +20) window to define analyst coverage. I find that mean (median) abnormal returns for the (+21, +84) trading period are -6.8% (-12.9%) for the "no analyst coverage" portfolio and -7.4% (-10.5%) for the "analyst coverage" portfolio, with no significant differences in mean and median BHARs. Once again, I find similar results when I use the alternative benchmark samples mentioned above to compute the abnormal returns and when I restrict my analysis to firms listed over the different post-GCM windows used to define analyst coverage.

Overall, I conclude that analyst coverage does not reduce the magnitude of the abnormal returns following the GCM announcement. In fact, the subsequent return performance of

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[59] I also compute abnormal returns for the subsequent 1, 2, 4, 5 and 6-month following the coverage definition month. Results are materially the same.

my sample firms with analyst coverage is not different from the return performance of GCM firms with no analyst coverage, which leads me not to reject null hypothesis H12. As such, it seems that, in the specific case of the GCM audit report, analysts are not contributing to the price-discovery process.

Table 7.4.
Subsequent Return Performance Conditional on post-GCM Analyst Coverage – A more restrictive test

This table presents the buy-and-hold abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclose a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
For each coverage definition window, I allocate each of my 924 companies to one of two portfolios conditional on analyst coverage. Companies are allocated to the "analyst coverage" portfolio if analysts report at least one new recommendation or issue one new annual EPS forecast within the coverage definition window. All the remaining firms are allocated to the "no analyst coverage". Abnormal returns are then computed in trading days, starting one trading day after the period used to define the coverage status of the firm over the subsequent 63 trading days, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. Returns earned by delisted firms are assumed to have zero abnormal returns in the post-delisting period. The BHARs are computed employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm.
Two-tailed significance of the t-test (Wilcoxon signed rank-test) is reported in parentheses below the mean (median) BHAR, whereas the significance of the sign test is shown in parentheses below the "Sign test" column of each portfolio. The last two columns of each panel report the mean and median differences between the BHARs of each portfolio under analysis. The significance of the t-test (Wilcoxon-Mann-Whitney test) is showed in brackets below the mean (median) differences.

Panel A: All first-time GCM firms

Coverage Definition Window	Return Period	NO ANALYST COVERAGE (A)			ANALYST COVERAGE (B)			DIFERENCE (A - B)	
		Mean BHAR	Median BHAR	n	Mean BHAR	Median BHAR	n	Mean BHAR	Median BHAR
(+1,+20)	(+21,+84)	-0.068 (0.0072)	-0.129 (<0.0001)	816	-0.074 (0.1819)	-0.105 (0.0472)	108	0.006 (0.9212)	-0.024 (0.4848)
(+21,+41)	(+42,+105)	-0.083 (0.0002)	-0.075 (<0.0001)	804	-0.099 (0.0876)	-0.034 (0.0673)	120	0.016 (0.7886)	-0.041 (0.8450)
(+42,+62)	(+63,+126)	-0.089 (<0.0001)	-0.043 (<0.0001)	855	0.000 (0.9945)	-0.089 (0.3720)	69	-0.089 (0.2363)	0.046 (0.3002)
(+63,+83)	(+84,+147)	-0.111 (<0.0001)	-0.021 (<0.0001)	849	0.003 (0.9647)	-0.141 (0.2501)	75	-0.114 (0.1577)	0.120 (0.9809)
(+84,+104)	(+105,+168)	-0.089 (<0.0001)	0.000 (<0.0001)	846	-0.023 (0.7633)	-0.035 (0.5614)	78	-0.066 (0.4043)	0.035 (0.5595)
(+105,+125)	(+126,+189)	-0.017 (0.4064)	0.000 (0.0022)	876	-0.026 (0.7743)	-0.084 (0.5656)	48	0.009 (0.9298)	0.084 (0.8046)

7.3.2.2. Price performance and subsequent analyst coverage

In this subsection, I test the self-selection hypothesis in the going-concern domain by investigating if analysts are more likely to cover firms with better return performance after the GCM disclosure date. The literature on analyst self-selection bias is limited. The basic idea is that analysts tend to report on stocks about which their true expectations are favourable and avoid reporting on stocks about which their true expectations are unfavourable. For instance, McNichols and O'Brien (1997) show that the distribution of recommendations for newly added stocks is shifted significantly towards more favourable ratings whereas the distribution of recommendations for dropped firms is shifted towards less favourable ratings. In a more recent study, Das, Guo, and Zhang (2006) find that long-term returns and operating performance of IPO firms with high residual coverage is significantly better than IPO firms with low residual analyst coverage.

I test if analysts self-select GCM firms they cover after the GCM disclosure date by allocating my sample firms to different portfolios depending on their post-GCM return performance. I now start by defining initial post-GCM windows to compute firm stock returns, which are used to allocate firms into three different portfolios conditional on their post-GCM return performance. In a second step, for each of these portfolios, I classify firms as covered or not if they receive new recommendations or new EPS forecasts following the post-GCM window used to compute the abnormal returns. Once again, I use different post-GCM windows to ensure the robustness of my results.

The three portfolios of firms conditional on firms' post-GCM return performance are defined as follows. First, I compute post-GCM price performance (BHARs) for each of my 924 first-time GCM firms over different post-GCM windows. For each window, firms are ranked according to their BHARs and divided into three portfolios: the lowest 33.3%

BHARs of the total sample firms (*low subsequent performance*), between 33.3% and 66.7% BHARs of the total sample firms (*medium subsequent performance*), and the highest 33.3% BHARs of the total sample firms (*high subsequent performance*). The percentage of firms followed by analysts after the initial window is then calculated separately for the "low performance" and "high performance" portfolios. Finally, the binomial test is used to investigate the significance of the differences between the percentages of covered firms in these two portfolios. If analysts are self-selective, I expect the percentage of firms with analyst coverage to be significantly higher for the "high performance" portfolio than for the "low performance" portfolio.

The hypothesis to test is as follows:

> *H13: There is no difference in the proportion of firms covered between the portfolio of firms with best stock return performance relative to those with worst stock return performance following the GCM announcement.*

Table 7.5. summarizes my findings. My results show that the percentage of firms with analyst coverage following the post-GCM windows used to define the coverage status of my sample firms is, generally, significantly higher for the "high performance" portfolio. As an example, consider the (+2, +63) window to compute the abnormal returns. I find that only 15.6% of firms allocated to the "low performance" portfolio are covered over the (+63, +252) window whereas the percentage increases to 27.6% in the case of "high performance" firms. Moreover, the binomial test shows that the proportion of firms covered in the "high performance" portfolio is significantly greater than the proportion of firms covered in the "low performance" portfolio at the 0.1% level.

Similar to the pervious subsection, I re-run my analysis using the alternative control samples as in section 5.2.1. to compute the abnormal returns. In addition, I exclude all the GCM firms that are delisted over the different windows used to compute the abnormal returns. Nevertheless, for both tests, the differences in the proportion of firms with analyst coverage between "low subsequent performance" and "high subsequent performance" portfolios are generally significant at the 0.1% level. These robustness tests suggests that my conclusions are not sensitive to the benchmark used to calculate the abnormal returns and are not influenced by the potential bias arising from firms being delisted in the year following the GCM announcement.

To sum up, it seems that the analyst's decision to cover a GCM firm critically depends on its post-GCM price performance. This is consistent with the notion that analysts selectively cover the GCM firms for which their true expectations are favourable and censor the firms for which their true expectations are unfavourable. This evidence leads me to reject null hypothesis H13. As such, I conclude that there is a relationship between analyst coverage and the post-GCM return performance. However, it is the post-GCM return performance of my sample firms that is driving the analyst decision to report on firms following the GCM date and not the analyst coverage that is driving the post-GCM return performance of my sample firms.

Table 7.5. Subsequent Analyst Coverage Conditional on post-GCM Return Performance

This table presents the buy-and-hold abnormal returns for my sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ, for which their auditors disclosed a going-concern modified audit report for the first-time between 01.01.1994 and 31.12.2005.
For each return period, I allocate each of my 924 companies to one of two portfolios conditional on their post-GCM return performance. Firms are ranked accordingly to their post-GCM BHARs and allocated into two portfolios as follows: firms with the lowest 33.3% BHARs of the total sample firms are allocated to the "low subsequent performance" portfolio whereas firms with the highest 33.3% BHARs of the total sample firms are allocated to the "high subsequent performance" portfolio.
Abnormal returns are computed in trading days, over different return periods, where trading day t=0 is the GCM announcement day taken from the SEC-EDGAR database. Returns earned by delisted firms are assumed to have zero abnormal returns in the post-delisting period. The BHARs are computed employing the control firm approach based on size and BM. Specifically, each of my 924 first-time GCM companies is matched with that non-finance, non-utility, non-GCM firm listed on the NYSE, AMEX or NASDAQ with market value of equity between 70% and 130% of that of the sample firm. The control firm is then selected as that firm with BM ratio closest to that of the sample firm. Percentage of covered firms is then calculated from the first trading day after the period used to define the subsequent performance of a firm until trading day +252. In particular, percentage of covered firms is computed by dividing the number of firms receiving a new recommendation or a new annual EPS forecast by the total number of firms in each portfolio. The binomial test is used to test the significance in the differences between the percentage of covered firms between the low performance and high performance portfolios.

Panel A: All first-time GCM firms

Return Period	Coverage Definition Window	LOW SUBSEQUENT PERFORMANCE (A)					HIGH SUBSEQUENT PERFORMANCE (B)					DIFERENCE % Covered Firms (A - B)
		N	Mean BHAR	Median BHAR	Covered Firms	% Covered Firms	N	Mean BHAR	Median BHAR	Covered Firms	% Covered Firms	
(+2,+21)	(+21,+252)	308	-0.396	-0.336	69	0.224	308	0.410	0.276	79	0.257	-0.052 (0.1714)
(+2,+42)	(+42,+252)	308	-0.596	-0.498	50	0.162	308	0.591	0.379	78	0.253	-0.091 (<0.0001)
(+2,+63)	(+63,+252)	308	-0.737	-0.640	48	0.156	308	0.619	0.416	85	0.276	-0.120 (<0.0001)
(+2, +84)	(+84,+252)	308	-0.844	-0.712	39	0.127	308	0.748	0.490	71	0.231	-0.104 (<0.0001)
(+2,+105)	(+105,+252)	308	-0.950	-0.764	35	0.114	308	0.758	0.4556	65	0.211	-0.097 (<0.0001)
(+2,+126)	(+126,+252)	308	-1.012	-0.831	29	0.092	308	0.838	0.479	64	0.208	-0.116 (<0.0001)

7.4. Summary and discussion

This chapter explores the relationship between post-GCM analyst coverage and post-GCM stock returns. Similar to the previous chapter, I use an event-time approach to test if post-GCM analyst coverage reduces the incomplete market reaction to such an announcement and if analyst self-selection bias is also manifested in the going-concern domain.

I find that firms receiving new recommendations or new annual EPS forecasts do not experience a different return performance from those with no analyst coverage in the post-GCM period. These results are robust to different post-GCM windows to define analyst coverage and to compute abnormal returns, suggesting that analyst activity in the GCM domain does not accelerate the post-event price adjustment of my sample firms.

These results contribute to a better understanding of the analyst role in the bad news domain. In fact, despite the evidence that analysts help improve the market efficiency with their forecast revisions (Gleason and Lee, 2003), or that analyst responsiveness contributes to mitigate the extent of the post-earnings drift (Zhang, forthcoming), I fail to find a similar pattern in my particular domain. There are some reasons that might explain why my results differ from previous studies. First, my sample firms are all highly financially distressed and associated with one of the most acute and unambiguous cases of bad news in the wide financial reporting domain. As such, despite the theoretical argument that the marginal contribution of security analysts may be greater in the dissemination of bad news to investors (e.g., Hong, Lim, and Stein, 2000), I confirm chapter 6's results that analyst activity is not helping investors in this bad news domain. Second, the reduced number of firms with analyst coverage following the GCM announcement may increase the degree of information uncertainty associated with these firms, thus facilitate investors' psychological biases such as overconfidence, which are related to the incomplete market reaction to new information (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998; 2001; Hirshleifer, 2001). Therefore, low analyst interest in following GCM companies is an appealing contribution to understand the post-GCM announcement drift.

This chapter also provides original evidence that analysts self-select the GCM companies they cover following the disclosure of this bad news. In particular, I find that the proportion of covered firms with best post-GCM return performance is significantly higher than the proportion of covered firms with worst post-GCM return performance. The fact that analysts avoid reporting on GCM firms associated with worst post-GCM return performance provides further evidence about the low interest of analysts in disseminating this particular type of bad news. This provides original evidence that analysts leave investors with no guidance for firms suffering from GCMs, a phenomenon that is particularly evident when they have unfavourable views on such firms (e.g., McNichols and O'Brien, 1997; Das, Guo, and Zhang, 2006). Hence, investors should not expect analysts to disseminate the GCM audit report and should be aware that analysts' silence is likely to be associated with negative information.

CHAPTER 8

CONCLUSIONS, LIMITATIONS AND FURTHER WORK

8.1. Introduction

My thesis provides the first study addressing how security analysts behave in the going-concern domain. In particular, my findings enhance our knowledge regarding how appropriately these sophisticated market agents deal with one of the most acute bad news accounting events and whether investors benefit from analyst coverage in such an acute environment, both on the short and medium-term.

In particular, my thesis is designed to provide a comprehensive analysis on the extent to which analyst activity reflects the negative information associated with the disclosure of a going concern audit report and how the market's reaction to this event is affected by the nature of analyst coverage. My first chapter offers a brief introduction to my work, highlighting the objectives and motivations of the present study. In the second chapter, I conduct a critical review of the key literature that contextualizes my research, which helps to define my research framework. Chapter 3 describes the methodology used to identify my 924 first-time GCM firms and provides some descriptive statistics about these firms. Chapters 4, 5, 6 and 7 are the empirical chapters of my thesis, in which I test my null hypotheses. In particular, chapter 4 investigates if analysts are able to anticipate the publication of a GCM audit report and whether or not they react to such a disclosure. Chapter 5 explores the robustness of my results using different tests and controlling for confounding factors. Chapter 6 investigates if the short-term market reaction to the publication of a GCM announcement critically depends on pre-event analyst coverage. Finally, chapter 7 examines if post-event analyst coverage reduces the magnitude of the post-GCM announcement drift and if analysts engage in self-selective activities in the going-concern domain.

In this chapter I summarize and discuss my main empirical findings, highlighting my key contributions to the accounting and finance literature. I also discuss the limitations of my research and outline possible future developments of my work.

8.2. Summary and contributions

The role of security analysts in the functioning of financial markets has been addressed in several studies. On the one hand, research suggests that analysts anticipate changes in firms' fundamentals and that investors benefit from the information they produce. Moreover, there is evidence that analysts reduce information uncertainty and promote market efficiency (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Elgers Lo, and Jr, 2001; Bhattacharya, 2001; Gleason and Lee, 2003; Zhang, 2005; Zhang, 2006). On the other hand, the literature suggests that analysts are often biased, overestimating firms' future performance and self-selecting firms with specific characteristics (e.g., Brown, 1997; McNichols and O'Brien, 1997; Easterwood and Nutt, 1999). My thesis explores related issues in the going-concern domain using a sample of 924 non-finance, non-utility industry firms listed on the NYSE, AMEX or NASDAQ for which their auditors disclosed a GCM audit report for the first-time between 01.01.1994 and 31.12.2005.

I contribute to the ongoing discussion about analyst behaviour by exploring how security analysts deal with one of the most extreme bad news events: the going-concern modified audit report. The connection between analyst behaviour and the going-concern disclosure is particularly important since no study to date has addressed this issue and because little is known about analyst behaviour in extreme situations. Moreover, there are reasons to believe that analyst role in this acute bad news domain may be vital to investors given the evidence that markets take time to assimilate negative information (e.g., Bernard and Thomas, 1989; Michaely, Thaler, and Womack, 1995; Womack, 1996; Dichev and Piotroski, 2001; Kausar, Taffler, and Tan, forthcoming). My thesis contributes directly to the accounting and finance literature by supplementing existent knowledge at different levels: security analyst behaviour, market pricing and going-concern disclosures.

My results contribute to the analyst behaviour literature in several ways. First, I find that security analysts anticipate the publication of a GCM audit report using two different signs to communicate unfavourable information about a firm before the bad news disclosure: 1) they downgrade more aggressively their stock recommendations for GCM firms compared to control firms as the event date approaches; 2) analysts are more likely to cease coverage of GCM firms than similar non-GCM firms within the one-year period before the event date. These results provide original evidence that analysts acknowledge firms' going-concern problems and provide further evidence that analysts are able to anticipate bad news information disclosures (e.g., Dechow, Sloan, and Sweeney, 1996; Clarke et al., 2006; Cotter and Young, 2007). Importantly, my results are robust to the use of alternative control firms based on size, BM ratio, momentum, industry and distress risk.

Second, I show that analysts react to the publication of a GCM audit report by ceasing coverage of such firms. Analyst propensity to cease coverage of my sample firms provides original evidence that analysts are less interested in following companies associated with going-concern problems and provides additional evidence that these sophisticated agents tend to replace firms associated with bad news with firms associated with good news (e.g., McNichols and O'Brien, 1997; Kecskés and Womack, 2007). Moreover, I also show that analyst decision to cease coverage of a GCM firm is accentuated in the case of value firms and firms with negative momentum, providing additional evidence on analyst preference for growth stocks and stocks associated with positive momentum (Jegadeesh et al., 2004).

Third, I conclude that analysts are reluctant to issue unfavourable recommendations for GCM stocks. This result augments the extant literature on analyst reluctance to disclose negative information (e.g., McNichols and O'Brien, 1997; Conrad et al., 2006) by focusing on an acute an unambiguous case of bad news. In particular, I find that the percentage of firms for which analysts issue "underperform" or "sell" recommendation is very low given the negative short- and medium-term market reaction to the publication of a GCM audit report (e.g., Citron, Taffler, and Uang, 2008; Kausar, Taffler, and Tan, forthcoming). In fact, it is hard to believe that an average "hold" recommendation represents a fair assessment for a firm immediately before the announcement of such a bad news. Analyst coverage cessation explains, at least partially, this phenomenon. As McNichols and O'Brien (1997) show, analysts do not downgrade stock recommendations when they cease coverage of firms. As such, the lower tail of the recommendation distribution for GCM firms is censored leading the average observed recommendation to be more favourable than the true unobservable average recommendation. This rationale sheds light on the words of Shefrin (2002), who state that analysts "*do not always mean what they say. (…) They frequently say 'hold' but mean 'sell', or say 'buy' when they mean 'hold*'" and indicates that coverage cessation is contributing to disguising of the analyst's true opinion about GCM firms.

Fourth, I find that the analyst's decision to cover GCM firms following the publication of a GCM audit report critically depends on their post-GCM return performance. To be precise, I show that analyst coverage of the GCM firms with best post-event return performance is significantly higher than that of the GCM firms with worst post-event return performance. These results supplement previous literature claiming that security analysts are self-selective (e.g., McNichols and O'Brien, 1997; Das, Guo, and Zhang, 2006) by showing that the analyst coverage decision is associated with their expectations of the firm's prospects even in the bad news domain.

My research also allows me to contribute to the market pricing literature. In particular, I show that security analysts do not provide investors with value-relevant information in the GCM domain. Two results support this conclusion. 1) analyst pre-GCM activity does not reduce the "surprise" associated with the publication of a GCM audit report; 2) analyst post-GCM activity does not accelerate the post-event price adjustment of my sample firms.

The short-term market reaction to the publication of a GCM audit report conditional on analyst coverage reveals that analyst activity influences negatively the price of GCM stocks over the pre-event period. In particular, I find that the short-term market reaction to the publication of a GCM audit report is, on average, significantly more negative for firms with pre-GCM coverage then for firms with no analyst coverage. This suggests that investors do not recognize an average "hold" recommendation and coverage cessation as an unfavourable message. A more detailed analysis reveals that the differential market reaction to the GCM announcement conditional on analyst coverage depends on the message being conveyed by analysts. To be precise, when analyst recommendations are inconsistent with the forthcoming GCM audit report (i.e., "strong buy", "buy" or "hold" recommendations), they seem to obstruct the recognition of negative information in stock prices in the pre-GCM period, thus increasing the impact of a GCM audit report disclosure. In sharp contrast, when analyst recommendations are consistent with the forthcoming GCM audit report (i.e., "underperform" or "sell" recommendations), they seem to facilitate the recognition of negative information in stock prices in the pre-GCM period, thus reducing the impact of a GCM audit report announcement. Interestingly, my results indicate that the percentage of firms with a "conforming" average recommendation is very reduced, which explains why the overall short-term market reaction is significantly more negative for firms with analyst coverage.

It is important to highlight that the differences in the short-term market reaction between covered and non-covered firms are not significant following the implementation of the regulatory changes in 2002. This result can be explained, at least partially, by the increase in analyst pessimism regarding GCM firms and the new information disclosed in analyst reports (e.g., the distribution of stock ratings across the brokerage house coverage universe) as a consequence of such regulatory changes. As such, I conclude that investors are now provided with more useful and material information to make their investment decisions in the GCM domain and challenge Clarke et al's. (2006) view that the implementation of the new regulatory regime was an overreaction by the regulatory authorities.

The medium-term market reaction to the publication of a GCM audit report conditional on analyst coverage shows that analyst activity does not contribute to the price-discovery process of GCM stocks in the post-event period. In particular, I find no significant differences between the return performance of GCM firms with analyst coverage and GCM firms with no analyst coverage following an initial period to define the coverage status of a firm. This result contributes to a better understanding of the analyst's role in the stock market in the specific case of firms with low levels of analyst coverage. Contrary to previous research suggesting that analyst coverage promote market efficiency (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Elgers, Lo, and Jr, 2001; Bhattacharya, 2001; Zhang, 2005) and that analysts contribute to the price-discovery process of stocks (e.g., Givoly and Lakonishok, 1980; Gleason and Lee, 2003), my results show that analyst coverage per se does not reduce the magnitude of the post-GCM announcement drift. These results are consistent with Das, Guo, and Zhang (2006), who find that the abnormal returns of IPO firms with no coverage are not significantly different from those experienced by firms with low analyst coverage.

My thesis also allows me to add to the GCM disclosure literature. For instance, I supplement extant literature on the short-term market reaction to the publication of a GCM audit report (e.g., Elliott, 1982; Fleak and Wilson, 1994; Herbohn, Ragunathan, and Gardsen, 2007; Citron, Taffler, and Uang, 2008) by providing original evidence that: 1) the short-term market reaction to such an event critically depends on analyst pre-event coverage; 2) analysts may temporarily delay the incorporation of other negative information in stock prices. These results show that, as indicated above, analyst activity may potentially serve to mislead of investor expectations about firms with going-concern problems. Moreover, it suggests that the magnitude of the downgrade (from "buy" to "hold") and their associated decision to cease coverage of GCM firms does not provide investors with adequate value-relevant information to generate appropriate expectations about these firms' future prospects.

One way to understand why the market appears to find difficulty in interpreting analyst unfavourable messages before the GCM disclosure event could be related to the holding pattern of GCM stocks. Kausar, Taffler, and Tan (forthcoming) show that retail investors (unsophisticated agents) increase their holdings of these stocks as the GCM date approaches. In particular, retail investors hold, on average, around 74% of GCM stocks right before the GCM date. This is important since Malmendier and Shanthikumar (2007) show that small investors follow analyst recommendations literally and do not react negatively to a "hold" recommendation. As such, apparent market inability to understand analyst unfavourable messages about GCM firms may well be associated with the low sophistication of investors who hold the stocks of such firms. My results clearly support Malmendier and Shanthikumar's (2007) findings, by suggesting that retail investors follow literally analyst recommendations even in such extreme situations.

My results also supplement the extant literature addressing the medium-term market reaction to the publication of a GCM audit report. In fact, I conjecture that analyst lower interest in firms associated with bad news provides an appealing explanation regarding why investors are particularly inefficient in dealing with negative information (e.g., Bernard and Thomas, 1989, Womack, 1996; Dichev and Piotroski, 2001, Kausar, Taffler, and Tan, forthcoming). For instance, Zhang (2005) argues that analyst "responsiveness", i.e., prompt analyst reaction to new information, mitigates the magnitude of the post-earnings announcement drift. In my case, it seems that analyst "no response", i.e., analyst coverage cessation after the GCM disclosure, is a partial explanation for the post-GCM drift documented by Taffler, Lu, and Kausar (2004) and Kausar, Taffler, and Tan (forthcoming).

From an investor perspective, my thesis suggests that investors should not rely on security analysts as messengers of bad news in the going-concern domain. In fact, despite analyst anticipation of the GCM audit report, investors should be particularly aware that analysts do not communicate their unfavourable views about GCM firms in a way retail investors understand, i.e., through the issue of "underperform" or "sell" recommendations. Alternatively, analysts communicate negative information in the GCM domain by downgrading their stock recommendations from "buy" to "sell" and by ceasing the coverage of such stocks. Therefore, investors should be conscious that relying solely on analyst recommendation for firms associated with bad news may not be a good guide to understanding analysts' true beliefs about firms' prospects. As the SEC highlight[60], "*We advise all investors to do their homework before investing. (…) remember that even the soundest recommendation from the most trust-worthy analyst may not be a good choice for you. That's one reason we caution investors never to rely solely on analyst's recommendations when buying or selling a stock*."

8.3. Limitations

My thesis is subject to some limitations that must be acknowledged to avoid biased interpretations of my results. Here, I highlight the most important aspects that readers should take into consideration.

In my thesis, I work exclusively with U.S. firms for which their auditors disclose a GCM audit report for the first-time between 01.01.1994 and 31.12.2005. As such, all my conclusions should be confined to the specific case of the GCM audit report in the U.S. environment for the time window addressed.

My sample of 924 first-time GCM firms is larger than the majority of the studies addressing going-concern issues. However, in some empirical tests requiring the sample to be divided into sub-groups, there is some concern about the statistical robustness of my results. Moreover, the fact that my sample firms have either no analyst coverage or limited coverage makes it almost impossible to investigate whether different levels of analyst

[60] See http://www.sec.gov/investor/pubs/analysts.htm for details.

coverage impact my results. This restriction is particularly important for the post-GCM period for which analyst coverage is very limited. Consequently, the conclusion that analysts do not provide value-relevant information in the bad news domain may be related to the particular characteristics of my GCM firms and it should not be generalized to other bad news events, especially for environments characterized by higher levels of analyst coverage.

Another limitation of my thesis is that it relies solely on archival data. In fact, archival studies may fail to determine the full extent of analyst behaviour. Experimental research could enhance our knowledge about analyst behaviour in the bad news domain by exploring the importance of analysts' private information in this context. As such, it is possible that my empirical framework does not capture fully the phenomenon I address.

I work exclusively with analyst recommendations and annual EPS forecasts, ignoring other informational vehicles that analysts use like price targets and conceptual narrative arguments supporting the forecasts and recommendations. As such, it is possible that the use of these sources of information could provide a clearer perspective on analyst behaviour in the going-concern domain.

My thesis does not offer an unambiguous explanation of why analysts avoid providing a clear negative message about GCM firms. Despite the theoretical rationale that economic incentives are minimized in contexts of highly financial distressed firms (e.g., the potential to generate brokerage commissions is likely to be small compared with healthy low risk firms), it is possible to argue that economic incentives may still play an important role in my context. As such, whether analyst behaviour for GCM firms relates to their economic incentives or to cognitive bias remains an open question.

A final limitation should be noted in respect of the methodology used to compute abnormal returns. A crucial issue here is how to control for the risk characteristics of the firm experiencing the event. Put differently, it is essential that, when using the single-matched firm approach, researchers identify a "similar" firm in terms of risk/return. However, given the peculiarities associated with my GCM firms, readers must be aware that my control firms are not "equal" to my sample firms.

8.4. Further work

My thesis provides original evidence on how security analysts deal with the going-concern event. There are several research opportunities that I aim to explore further to enhance the overall understanding of this phenomenon.

I find that analyst recommendations become relatively more pessimistic for GCM firms compared to similar non-GCM firms as the GCM date approaches. However, there are other information vehicles that analysts use to disseminate information (e.g., EPS forecasts, price targets, conceptual arguments supporting their forecasts and recommendations) that I intend to explore in the future. These analysts' outputs provide additional pieces of information that could be important to a comprehensive analysis of analyst behaviour.

Investigating whether analysts issue optimistic EPS forecasts for GCM firms seems to be particularly interesting. First, analysts EPS forecasts offer a different research scenario since, contrary to recommendations, their outcomes are well defined and observable. If analyst recommendations are the best way to evaluate analysts' preferences across stocks (Jegadeesh et al., 2004), analyst EPS forecasts seem to be the best way to explore analyst optimism. Second, there is evidence that analysts strategically choose to display optimistic messages through their recommendations (which are key to small investors) whilst abstain from doing so through their earnings forecasts (which are key to large investors) (Malmendier and Shanthikumar, 2007). Exploring EPS forecasts in the GCM context supplements my results and provides evidence on whether analysts "speak in two tongues".

The conceptual arguments supporting forecasts and recommendations may provide a unique piece of information to investigate if analyst speech provides relevant information to detect going-concern problems and to explore their reaction to such an announcement. The use of a content analysis approach may supplement my empirical tests based on archival data and enhance our knowledge in this domain.

Another important issue in this domain is to explore whether the economic incentives that analysts face impact my results. There is evidence that analysts are more optimistic when there is a corporate relationship between brokerage firms and their clients, reducing analyst objectivity and independence. Exploring to what extent these conflicts of interest explain why analysts avoid reporting negatively on GCM firms may provide further evidence in helping us understand if economic incentives play an important role in this domain. In addition, investigating the characteristics of analysts who continue to follow these firms after the GCM date may offer a compelling insight about their post-GCM behaviour: are they simply "loser analysts" or are they anticipating a reversal?

Exploring how analysts deal with other bad news events in environments characterized by higher levels of analyst coverage is another example of possible complementary work. This may provide clear evidence on whether analyst activity simply does not provide investors with value-relevant information in the bad news domain or if my conclusions are driven by the small number of analysts following GCM firms.

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