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Do analysts know but not say?
The case of going-concern opinions

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ABSTRACT

This study explores whether security analysts recognize firms' going-concern problems and report appropriately to investors. We find that analysts signal their anticipation of the publication of a going-concern modified (GCM) audit report in two ways: 1) they downgrade more aggressively stock recommendations of GCM firms than stock recommendations of control firms as the event date approaches; 2) they are more likely to cease coverage of a GCM firm than a control firm over the one-year period prior to the GCM date. We further show that analysts react to the publication of an actual GCM audit report by stopping coverage of such firms immediately subsequent to the event disclosure. Our results suggest that analysts know that the future viability of GCM firms is jeopardized but do not say it clearly to retail investors, who constitute the main clientele of these firms. Consistent with the SEC concerns about analyst recommendations, we conclude that investors cannot rely solely on analyst recommendations since they are reluctant to report negatively (i.e, "underperform" or "sell") even in this extreme bad news domain. We further conclude that analyst relative pessimism and coverage cessation is likely to be associated with negative expectations about firms' future prospects.

Keywords: analyst behaviour, stock recommendations, bad news announcements, going-concern reports

JEL classification: M41, M42, G14, G24

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1. Introduction

This paper explores whether security analysts anticipate a going-concern audit opinion and report appropriately to investors on such financially distressed firms. This issue is of significant interest given the implications of the questioning of the going-concern assumption for the future viability of the firm, and therefore constitutes an extreme bad news signal to investors. This is further emphasized by the highly negative returns earned by such firms (Kausar et al., 2009).

The main clientele for such small speculative firm stocks consists of unsophisticated investors (Kausar et al., 2009) who primarily rely on the analyst, and, in particular, their stock recommendations for investment advice, in contrast to sophisticated investors (Malmendier and Shantikumar, 2007). Analyst privileged access to information may lead us to believe that their advice is crucial to retail investors since these more naïve investors are not able to produce their own predictions (De Bondt and Thaler, 1990) and because they may lack the time, skill or resources to analyze and interpret financial statements (Beaver, 2002). However, analysts have come under fire from investors, politicians and regulators over recent years as a consequence of their biased behavior. As such, investigating whether analysts report appropriately in the going-concern domain is particularly important to understand if these sophisticated agents provide retail investors with value-relevant information in this context.

There is an extensive literature suggesting analysts are both prone to bias in their judgments and reluctant to report unfavorably on firms. For instance, research shows that the number of "buy" recommendations is systematically higher than the number of "sell" recommendations (e.g., Womack, 1996; Ho and Harris, 1998; Barber et al., 2006).[1] There is also empirical support that analysts are self-selective by start covering firms they view favourably and stop covering firms they view unfavourably (McNichols and O'Brien, 1997). We examine whether such behavior is equally manifest in the case of going-concern uncertainties where the key role played by the analyst is particularly pronounced. This

[1] In one of the recent financial scandals, the Enron case revealed that almost 90% of analysts covering the firm were still recommending the firm's stock as a "buy" or "strong buy" just six weeks before its bankruptcy filing.

paper sets out explicitly to answer four main questions. First, we test whether security analysts anticipate the GCM audit report by: 1) investigating if they downgrade more aggressively their stock recommendations for GCM firms in comparison to similar non-GCM firms within the pre-GCM period; 2) investigating if analysts are more likely to cease coverage of GCM firms than similar non-GCM firms within the pre-GCM period. Second, we explore how security analysts react to the publication of a GCM audit report by: 1) comparing their stock recommendations for GCM firms between the pre- and post-GCM period; 2) testing if security analyst interest in these firms remains after the announcement of such acute bad news.

We find that sell-side analysts recognize the financial deterioration of firms that subsequently receive a GCM audit report. However, and more importantly, analysts do not say what retail investors need to hear to react negatively. Our results show that analysts anticipate the publication of a GCM audit report by downgrading more aggressively stock recommendations of GCM firms (from "buy" to "hold") when compared to similar non-GCM firms (do not change from "buy") as the event date approaches. In addition, analysts are more prone to cease coverage of GCM firms than control firms over the one-year pre-GCM period. These results show that analysts are not interested to report negatively on GCM firms and do not say "underperform" or "sell", which are the recommendations that retail investors recognize as unfavorable. In fact, Malmendier and Shantikumar (2007) show that retail investors follow recommendations literally and, contrary to large investors, do not react negatively to "hold" recommendations. We also find that analyst react to the publication of a GCM audit report by ceasing the coverage of the stock and do not change significantly their recommendations from previous "hold" following the publication of the audit report. We conclude that analysts know that the future viability of these firms is jeopardized but do not say it clearly to retail investors.

The going-concern principle is one of the most important accounting assumptions in the preparation of financial statements. This principle assumes that a company is ordinarily viewed as continuing in business for the foreseeable future. When this assumption is explicitly questioned by external auditors, this is perceived as an acute and unambiguous case of bad news (e.g., Fleak and Wilson, 1994; Carlson, Glezen, and Benefield, 1998; Taffler, Lu, and Kausar, 2004; Kausar, Taffler, and Tan, 2009). The GCM event offers a unique scenario to investigate analyst ability to anticipate bad news announcements 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).

One of the most interesting research agendas in this domain is to explore how analysts deal with the going-concern assumption. Two important ideas contribute to the interest of this research question. First, the marginal contribution of 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 (Kothari, Shu and Wysocki, 2010). As Hong, Lim, and Stein (2000) argue, managers of firms sitting on good news will push the news out the door themselves. For the opposite reason, managers will have few incentives to bring investors up to date quickly when firms are sitting on bad news. Second, 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, 2009). For instance, Kausar, Taffler, and Tan (2009) show that the market underreacts to the publication of a going-concern audit report (bad news) whereas fully anticipating the withdrawal of such a report (good news). Understanding how security analysts deal with the going-concern principle can help us answer the question of whether the inefficient processing of negative information is an exclusive phenomenon of non-sophisticated agents.

Our study also contributes to understand some unclear issues. First, there is mixed evidence about the ability of analysts to anticipate bad news. On the one hand, studies suggest that analysts fail to anticipate earnings declines associated with high accruals (Bradshaw, Richardson, and Sloan, 2001; Teoh and Wong, 2002; Barth and Hutton, 2004) and firm restatements and corrective disclosures (Griffin, 2003). On the other hand, there is evidence that analysts are able to anticipate some types of accounting fraud (e.g., Dechow, Sloan, and Sweeney, 1996; Cotter and Young, 2007) and bankruptcy announcements (Clarke, et al., 2006). Second, security analysts have long been seen as sophisticated processors of financial information who are less likely to misunderstand the implication of such information when compared to naïve investors (Ramnath, Rock, and Shane, 2008). However, there is evidence that analysts activity is biased, a phenomenon that is particularly evident in the bad news domain (e.g., Das, 1998; Easterwood and Nutt, 1999; Brown, 2001, Abarbanell and Lehavy, 2003). Third, regulators are focusing their attention in the behavior of sophisticated agents that play an important role in the functioning of financial markets. In one of their online publications aiming at protecting investors, the SEC is particularly clear when discussing analyst stock recommendations:[2]

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

“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.”

Our research contributes to both the academic literature and to investor understanding. From an academic perspective, we link 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, we provide original evidence about how security analysts deal with a major bad news accounting event. From an investor vantage point, this study provides additional evidence on the usefulness and limitations of analysts’ activities.

The remainder of this study is organized as follows: section 2 describes the sample selection process and provides the descriptive statistics for our sample and section 3 describes our method. Section 4 reports the results of our analyses and section 5 presents additional robustness checks. Section 6 discusses our results and section 7 concludes.

2. Data and descriptives

2.1. Sample selection

Our sample consists of 924 non-finance, non-utility, industry firm-year observations 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 for our purposes.[3] The use of an unbiased GCM sample is particularly important for two main reasons. First, identifying a first-time GCM company is not a straightforward process since existing sources of data are not clean (e.g., Butler, Leone, and Willenborg, 2004; Kausar, Taffler, and Tan, 2009). Second, there is evidence that conflicting results in some of the going-concern literature are due to the use of biased samples (e.g., Asare, 1990; Kausar, Taffler, and Tan, 2009). Table 1 summarizes our

[3] These 924 cases represent 871 companies.

sample construction process. It draws heavily on Kausar, Taffler, and Tan (2009) and is designed to eliminate the number of incorrect cases classified as GCM firms.

We 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 from which we exclude 16,866 cases because 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, 2009), we work exclusively with first-time GCM cases. In particular, we define a GCM audit report as first-time if a firm has not received a GCM opinion in the previous fiscal year. The use of first-time GCM cases is justified by the evidence that the informational value of a continuing going-concern report is less clear than that of a first-time report (Mutchler, Hopwood, and McKeown, 1997) and that a company with a going-concern qualification in a given year is more likely to receive a qualification the next year (Mutchler, 1985). From the 2,296 remaining cases, we delete another 1,017 since there is insufficient accounting or market data for our purposes in the COMPUSTAT or CRSP databases. In particular, we exclude: 1) companies not listed on the NYSE, AMEX and NASDAQ during the 12-months pre-GCM date; 2) companies not trading ordinary common stock; 3) companies with unavailable accounting information for the 2-year period before the GCM year.

Finally, we delete cases that could potentially bias our results due to their specific characteristics. In particular, we remove: 1) companies classified as "utilities" or "financials" according to the 49 industry portfolios defined by Kenneth French;[4] 2) companies classified as foreign to ensure a consistent legal framework; 3) companies classified as in a "development stage" since these companies have unique characteristics and have a considerable chance of failure;[5] 4) companies that file Chapter 11 before the audit report publication date since this filing contaminates the impact of a first-time GCM audit report on market prices.

Table 1 here

[4] This is because "utility" firms are affected by specific regulations and "financial" firms accounting information is not comparable to that of the remaining firms respectively.

[5] 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.

2.2. Control firm selection

Investigating how security analysts deal with the GCM audit report by solely studying GCM firm cases might introduce a selection bias since analysts cannot know ex-ante which firms will receive a GCM audit report. Drawing on Clarke et al. (2006), we 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 our main results, our set of control firms consists of non-GCM firms with similar size and BM ratio to those of our sample firms. This is because size and BM ratio may drive analyst preference for specific firms. For instance, these two characteristics have demonstrated ability to predict stock prices. 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 our setting. 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 this context, "*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*" (Jegadeesh et al., 2004). In addition, the literature suggests that analyst coverage is strongly correlated with firm size (e.g., Bhushan, 1989; Hong, Lim, and Stein, 2000) and shows that analysts tend to favour "growth" stocks compared to "value" stocks (Jegadeesh et al., 2004), highlighting the need to control our results for these two characteristics.

We identify 924 non-GCM control firms by matching each of our sample firms with the company with most similar size and BM ratio. The matching process is as follows. First, for each sample firm, we 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) one year before the GCM announcement.[6] Subsequently, among the match candidates for each sample firm, we identify those with a market value between 70% and 130% of the

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

sample firm. Finally, from this list of candidates, we choose as a control firm the firm which has the closest BM ratio to that of our GCM firm.[7] BM ratio is defined as the book value of equity divided by market capitalization. Book value of equity is taken from the last annual accounts reported before the measurement of market capitalization.

2.3. Descriptive statistics

Table 2 provides sample firms descriptive statistics. Panel A of table 2 shows the annual distribution of the GCM cases and reveals that 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.

Panel B of table 2 shows that our sample is typically composed of small companies with high distress risk. For instance, our sample 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, we find that our 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 (mean leverage ratio = 38%; median leverage ratio = 32%). 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 within the next year. In addition, the mean (median) score of the discriminant model that predicts a forthcoming GCM audit report (PREDGC) is 0.20 (0.01), suggesting that our sample firms are close to the cut off score of 0.01 that we use to distinguish "expected" from "unexpected" GCM audit reports.[8] Panel B of table 2 also indicates that book value per share of sample firms is low relative to the stock price (mean BM ratio = 0.77; median BM ratio = 0.40) and that stock firms have experienced negative returns over the previous 11-months prior to the GCM announcement (mean monthly momentum [t=-12 to -2] = -4%; median momentum = -4%).

[7] 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.
[8] 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 we work exclusively with GCM firms, we 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.

Panel C of table 2 reveals that although 85% of our GCM firms have positive book value of equity only 8% of them report positive earnings in the year preceding the publication of a GCM audit report and that only 2.5% pay dividends. The data analysis also reveals that almost 5% of our sample firms enter into bankruptcy/liquidation (delisting codes: 400, 572, 574) within the one-year period subsequent to the GCM announcement date, but, importantly, no less than 46% of our sample firms are delisted within the same period. On the other hand, almost one in five firms continue to be listed and appear to recover in the following fiscal year with their GCM lifted. Finally, two thirds of firms are audited by the one of the five audit companies that dominate the supply of audit services worldwide (BIG5).

Table 2 here

Table 3 compares the descriptive statistics between our 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 GCM firm. However, there are significant differences in the other variables presented in table 3. 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, our 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 our GCM firms are associated with higher levels of financial distress and have worse past return performance, highlighting the need to control our results for these variables.

Table 3 here

3. Method

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

The overarching research question of this study is whether analysts are providing investors with value-relevant information in the GCM domain. Specifically, we investigate analyst anticipation and reaction to the GCM audit report using one of their most important information transmission vehicles: analysts' recommendations. The use of recommendations to address our research questions can be justified in a number of ways. First, they represent a clear and unequivocal course of action to investors (Elton, Gruber, and Grossman, 1986). Second, recommendations are viewed as the bottom line of the research report (e.g., Shipper, 1991). Finally, recommendations are reported on a simple and finite scale common to all stocks, avoiding ambiguous interpretations of information (McNichols and O'Brien, 1997). As Jegadeesh et al. (2004) highlight, "*recommendations offer a unique opportunity to study analyst judgment and preferences across large samples of stocks*".

Stock recommendations are obtained from the Institutional Broker Estimates System (I/B/E/S) database.[9] For each stock recommendation, we gather the following information: recommendation date; broker identification; analyst identification and I/B/E/S recommendation code. Next, following Zhang (2008), we exclude all recommendations issued before 01.01.1994 and after 31.12.2005 and observations with zero analyst-specific identification code.[10] All recommendations are then sorted by date relative to the GCM announcement day (t=0) and allocated in event-quarters. Event-quarters are defined as periods of 90 calendar days relative to the GCM announcement date.[11] It should be noted that we 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". Because I/B/E/S codes "strong buy" recommendations as 1 and "sell" as 5, more optimistic recommendations have lower numerical values. Our final data consists of 3,395 recommendations issued by 1,289 different security analysts for 463 sample firms between 01.01.1994 and 31.12.2005 from event-quarter -8 to event quarter +4.

[9] The I/B/E/S Recommendations database starts in October 1993 and contains, among other information, recommendations from a wide range of brokerage firms.

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

[11] 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.

3.1.1. Testing analyst anticipation of a GCM audit report

We investigate analyst anticipation of a GCM audit report within the pre-GCM period by testing: 1) if they downgrade more aggressively their stock recommendations for GCM firms in comparison to similar non-GCM firms; 2) if they are more likely to cease coverage of GCM firms than similar non-GCM firms. As such, we focus on two different signals that analysts might use to communicate unfavourable information about a firm before the publication of a GCM audit report: 1) analyst downgrade of stock recommendations; and 2) analyst cessation of stock coverage. If the first message is intuitively understood as negative information, the second one requires more discussion. The association between analyst decision to cease coverage of a firm and negative information is justified by the evidence that analysts are reluctant to issue unfavourable investment advice (McNichols and O'Brien, 1997) and that they generally remain at the same brokerage firm after stopping firm coverage (Clarke et al., 2006).

We conduct two different tests to investigate analyst downgrade of stock recommendations and analyst coverage cessation. In the first case, we test the significance of the differences in analyst mean and median recommendations and percentage of "buy" recommendations over the 8 event-quarters prior to the GCM date between sample and control firms using the two-tailed t-test, the Wilcoxon-Mann-Whitney test and the binomial test, respectively. Secondly, we test if 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. The model is defined as follows:

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

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:

$$z_i = \alpha_0 + \sum_{n=1}^{9} \beta_n X_{ni} + u_i \tag{2}$$

We employ 9 independent variables to estimate equation 2, 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 our 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 shares outstanding times price one year before the GCM announcement. Given that analysts tend to follow larger firms (e.g., Bhushan, 1989; Hong, Lim, and Stein, 2000), we expect 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, we define *ANALY* as the number of analysts following the firm at the end of event-quarter -4. Similarly to *LOGSIZE*, we 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 2.2. 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, we 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 the average monthly raw returns for the prior 11-month period (t-12 to t-2) relative to the GCM announcement month. The inclusion of this variable is justified by the evidence that analysts prefer firms associated with positive momentum (Jegadeesh et al., 2004). As such, we

conjecture 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), we 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), we 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). We 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. Again, we 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 4 provides the correlation between all variables. As can be seen, for the majority of cases, the correlation between independent variables is lower than 20% suggesting that these variables are not strongly correlated. There are some exceptions like LOGSIZE and ANALY which is consistent with the idea that analysts prefer larger firms (e.g., Bhushan , 1989; Hong, Lim and Stein, 2000). Moreover, there is also a considerable degree of association between ZSCORE, PREDGC and LEV as well as between GCMG and some other firm characteristics. In order to ensure that our conclusions are not contaminated by high correlations between independent variables, we estimate different regressions excluding those that could potentially affect the results.

Table 4 here

3.1.2. Testing analyst reaction to the GCM audit report

We investigate analyst reaction to the GCM audit report by testing: 1) if there are significant differences between pre- and post-GCM stock recommendations for GCM firms; 2) if analyst interest in these firms remains after the announcement of such acute bad news. More specifically, we investigate analyst reaction to the GCM audit report by comparing their recommendations for GCM firms between event-quarter -1 and event-quarter +1. We focus our attention on a short period surrounding the GCM announcement date since analyst reaction (if any) should occur as soon as the event becomes publicly known.[12] We test the significance of the difference in analyst mean and median recommendations and percentage of "buy" recommendations for GCM firms between event-quarter -1 and event-quarter +1 using the two-tailed t-test, the Wilcoxon-Mann-Whitney test and the binomial test, respectively. We also use a binary logistic regression model 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. The model is as follows:

$$Pr(CEASE_i = 1 \mid X_i) = \frac{e^w}{1 + e^w} \tag{3}$$

where Pr(*CEASEi =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:

[12] We use one event-quarter following the disclosure of a GCM audit report as reaction period to allow a reasonable number of observations.

$$w_i = \alpha_0 + \sum_{n=1}^{9} \beta_n X_{ni} + u_i \qquad (4)$$

Equation 4 uses 8 of the same 9 explanatory variables defined in equation 2: *GCMG*, *LOGSIZE*, *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. To avoid the potential problem arising from the relationship between delisting firms and analyst decision to drop the coverage of such firms, we exclude all recommendations of firms delisted within event-quarter +1. Again, we pay particular attention to the potential problems arising from the use of independent variables highly correlated.

3.2. Recommendation categories

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. Therefore, we use three recommendation categories to mitigate this problem: a) reported recommendations; b) current recommendations; c) inferred recommendations.

Reported recommendations are those effectively issued by the analyst and are readily available on the I/B/E/S Recommendations – Detail File. We 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*.[13] 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*. Finally, we define firms' average reported recommendations at quarter *q* as follows:

[13] 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.

$$REPREC_q = \frac{1}{M}\sum_{j=1}^{M} REPREC_{j,q} \tag{5}$$

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

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, we assume that the last reported recommendation still applies to the current event-quarter. Specifically, we define analyst i's current recommendation for firm j at event-quarter q ($\text{CURREC}_{i,j,q}$) 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 ($\text{CURREC}_{j,q}$) is then calculated as the average of analyst current recommendations for firm j at event-quarter q. Finally, we define firms' average current recommendations in event-quarter q as follows:

$$CURREC_q = \frac{1}{M}\sum_{j=1}^{M} CURREC_{j,q} \tag{6}$$

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

Inferred recommendations are similar to current recommendations with one difference. When an analyst ceases coverage of a firm, we infer an unfavourable recommendation for that event-quarter and for the subsequent two event-quarters.[14] This aims at capturing the association between analyst decision to cease coverage of a firm and analyst negative expectations about the firm's future prospects as discussed in section 3.1.1. Drawing on Clarke et al. (2006), we define analyst i's inferred recommendation for

[14] We 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).

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

$$INFREC_q = \frac{1}{M}\sum_{j=1}^{M} INFREC_{j,q} \tag{7}$$

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

4. Main results

4.1. Analyst anticipation of the GCM audit report

Table 5 summarizes our results testing analyst anticipation of the GCM audit report by comparing stock recommendations for GCM firms and control firms over the period preceding the bad news disclosure. We find no significant differences between mean and median stock recommendations for GCM and non-GCM firms from event-quarter -8 to event-quarter -5. In addition, 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. These results suggest that analysts are advising investors to buy both GCM and control firm stocks in the most distant event-quarters, a fact emphasised by the high percentage of firms for which the average recommendation is "buy" (above 60% for the large majority of quarters). As such, our results suggest that, approximately two years before the event, analysts do not distinguish GCM from control firms and share similar expectations about both types of firms.

The analysis of the most recent event-quarters reveals a different pattern. Table 5 shows that, starting from event-quarter -4, the average stock recommendation for GCM firms becomes significantly more unfavourable than that of non-GCM firms. In general, analysts downgrade their stock recommendations for GCM firms from “buy” to “hold” while maintaining their previous recommendations for control firms. More importantly, in most cases, the differences in the mean and median stock recommendations between groups are now statistically significant at the 0.1% level. Again, the results are materially the same for all three different recommendations under scrutiny. 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).

Table 5 here

Table 6 reports the results from running the logistic regression model of equation 2 to distinguish between firms for which analysts cease their coverage before the publication of the GCM audit report and those for which analysts continue their coverage. As can be seen, our logistic regression model is highly significant (Wald x^2 = 107.11, p-value<0.0001) and reveals that the going-concern modified group (*GCMG)* variable coefficient is positive and highly significant. This suggests that, ceteris paribus, analysts are more prone to cease coverage of GCM firms than control firms between the event-quarter -4 and event-quarter -1. We also find three significant independent variables, with all coefficients consistent with our initial predictions. For instance, *LOGSIZE* is negatively related to the analyst to stop firm coverage. This indicates that analysts are relatively more prone to cease coverage of small firms, consistent with previous research showing that analyst coverage is strongly related to firms’ size (e.g., Bhushan, 1989; Hong, Lim, and Stein, 2000). Moreover, the coefficients of *BM* and *MOM* suggest that analyst decision to cease coverage of firms is facilitated in the case of value firms and firms with negative momentum, reinforcing the notion that analyst prefer growth stocks and stocks associated with positive momentum (Jegadeesh et al., 2004). Importantly, we find that these conclusions are robust when we re-estimate the model excluding the independent variables that are more correlated with the significant ones. In addition, the sign and significance of these coefficients does not change when we use the stepwise technique to estimate the logistic regression model.

Overall, these results suggest that security analysts recognise and signal the going-concern problems of firms as the GCM date approaches by communicating unfavourable information to the market. First, they downgrade stock recommendations for GCM firms more aggressively than the recommendations for control firms. Second, analysts are more likely to cease the coverage of GCM firms in comparison to non-GCM firms sharing similar size and BM ratio over the one-year period before the GCM date.

Table 6 here

4.2. Analyst reaction to the GCM audit report

Table 7 summarizes our results testing analyst reaction to the publication of a GCM audit report by comparing stock recommendations for GCM firms between event-quarter -1 and event-quarter +1. Panel A (panel B) presents the results for reported (current) recommendations, whereas panel C shows the results when inferred recommendations are considered. As can be seen, there is no statistically significant 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. In addition, we find that, generally, the differences between current and inferred recommendations from event-quarter -1 to event-quarter +1 are not significant at conventional levels. This suggests 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.

Table 7 here

Table 8 shows the results from running the logistic regression model 4 to distinguish between firms for which analysts cease their coverage following the publication of a GCM audit report and those for which analysts continue their coverage. The key finding in this table relates to the positive and highly significant coefficient associated with the *GCMG* variable ($p<0.0001$) suggesting 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. Importantly, our logistic regression model is highly significant (Wald x^2 = 97.87, p-value<0.0001). We also find an additional significant independent variable in our model. Interpreting the negative and significant coefficient associated with *MOM* suggests that, *ceteris paribus*, the analyst's decision to cease coverage of a firm following the disclosure of a GCM audit report is strengthened when firms have negative momentum. Similar to the robustness analysis conducted in section 4.1., we confirm that the conclusions when interpreting regression 4 results are materially the same when we exclude the independent variables that are more correlated with the significant ones as well as when we use the stepwise technique to estimate the logistic regression model.

Overall, our results suggest that security analysts do not ignore the publication of a GCM audit report. However, they do not communicate unfavourable information to the market through a downgrade in stock recommendation following the GCM announcement but prefer to cease coverage of GCM firms. This avoids the need to report negatively on them. Such a result is consistent with the idea that analysts dislike issuing unfavourable recommendations (e.g., McNichols and O'Brien, 1997) and that a coverage cessation is likely to be associated with unfavourable information about the future prospects of the firm (e.g., McNichols and O'Brien, 1997; Griffin, 2003; Clarke et al., 2006).

Table 8 here

5. Additional tests

5.1. Controlling for alternative benchmarks

This section aims at ensuring that our prior results are not due to analysts' preferences for certain stocks nor are they a mere statistical artefact. In effect, analyst behaviour regarding GCM stock recommendations might be related to other firm characteristics than size and the BM ratio, that also have the ability to predict returns (e.g., Fama and French, 1992; Jegadeesh and Titman, 1993; Dichev, 1998). As we show in table 3, GCM firms have significant higher levels of financial distress and worse past return performance. Therefore, particular emphasis will be given to the robustness of our conclusions using alternative sets of control firms that account for these characteristics. Size is used as a match criterion in all benchmarks given its relationship with both future stock returns and level of analyst coverage.

5.1.1. 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 as the GCM date approaches as well as the higher likelihood of coverage cessation before and after the GGM event is related to firms' momentum, we identify a new set of control firms by matching each of our sample firms with the firm with most similar size and momentum. Control firms are identified as follows. First, for each sample firm, we 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.[15] Subsequently, among the match candidates for each sample firm, we identify those with a market value between 70% and 130% of the sample firm. Finally,

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

from this list of candidates, we choose a control firm with the closest momentum to that of the GCM firm. Momentum is defined as in section 3.1.1.

We find that our previous conclusions do not change substantially when we use this matching criterion to define an alternative set of control firms. First, we find significant differences in all categories of analyst stock recommendations between GCM and control firms at event-quarter -1. For instance, the mean (median) inferred recommendation for GCM firms for event-quarter -1 is 3.09 (3.21) whilst the mean (median) inferred recommendation for control firms is 2.86 (3.00), with these differences significant at the 1% and 0.1% level respectively. In addition, only 22% of GCM firms have their average inferred recommendation classified as "buy" in contrast with 30% for control firms (difference significant at the 1% level). However, it should be noted that these differences become significant only after event-quarter -3 and the significance of these differences is now weaker (usually at a 5% level). These results are consistent with those of Jegadeesh et al. (2004) who show that analysts have a predisposition to rate more unfavourably companies with negative momentum. As such, although analysts also downgrade stock recommendations for firms with lower momentum, their downgrade is more aggressive for GCM firms than control firms with similar size and momentum. Second, the results from running logistic regressions 2 and 4 using this new set of control firms does not change the conclusion that analysts are more prone to cease coverage of GCM firms than control firms before and after the publication of a GCM audit report.

5.1.2. 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, we identify a new set of control firms by matching each of our sample firms with firms of the same industry. More specifically, for each sample firm, we 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, we 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.[16] Finally, from this list of

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

candidates, we choose as a control firm the firm which has the closest BM ratio to that of our GCM firm. The BM ratio is defined as in section 2.2.

Our results show that analyst anticipation of a GCM audit report and their reaction to this event is not driven by an industry bias. In fact, the more aggressive downgrade of recommendations for GCM stock recommendations than for control firms remains clear using this new set of control firms. We find that stock recommendations for GCM firms become significantly more unfavourable than non-GCM firms after event-quarter -5. At a more detailed level, mean and median differences between stock recommendations for GCM and control firms as well as the differences in the percentage of firms for which their average recommendation is classified as "buy" are highly significant at the 0.1% level for all recommendation categories for event-quarter -2 and -1. In addition, the coefficients associated with the *GCMG* variable remain positive and highly significant when we run regression 2 and 4 with a set of control firms that account for industry.

5.1.3. 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 our research since GCM firms are highly financially distressed as can be seen in table 2.[17]

To investigate if our previous conclusions are due to the omission of a distress risk factor in the set of control firms, we identify a new set of firms by matching each of our sample firms with the firm with most similar size and z-score. Control firms are identified as follows. First, for each sample firm, we 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) one year before the GCM announcement.[18] Subsequently, among the match candidates for each sample firm, we identify those with a market value between 70% and 130% of the sample firm. Finally, from this list of candidates, we 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

[17] 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.

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

information from the fiscal year ending one year before the GCM announcement date is employed to compute each firm's z-score.

Our results confirm that analysts anticipate the publication of a GCM audit report by downgrading more aggressively their recommendations for GCM firms than control firms as the GCM date approaches. In fact, analyst recommendation trend for control firms is very similar to that presented in table 5 using size and BM ratio as matching criteria. For instance, the mean (median) inferred recommendation for control firms in event-quarter -1 now is 2.55 (2.48) whereas the percentage of control firms for which their average inferred recommendation is classified as "buy" is 50%. Importantly, all differences between GCM and control firm recommendations become significant at conventional levels after event-quarter -4 and highly significant at the 0.1% level at event-quarter -2 and -1. Again, our results show that analysts are more prone to cease coverage of GCM firms than control firms before and after the publication of a GCM audit report.

6. Discussion

This study contributes to understand how analysts deal with the going-concern assumption and whether investors should be aware of analyst behavior in this particular domain. For instance, our results provide further evidence that analysts are able to anticipate non-routine bad news events (e.g., Dechow, Sloan, and Sweeney, 1996; Clarke et al., 2006; Cotter and Young, 2007) through their relative pessimism about GCM firms and their decision to cease coverage of such firms. Moreover, we show that analysts react to the publication of a GCM audit report by ceasing firm coverage thereby providing further evidence that these sophisticated agents are less interested in following companies associated with bad news (e.g., Griffin, 2003), presumably tending to replace these firms with others more associated with good news (e.g., McNichols and O'Brien, 1997; Kecskés and Womack, 2007). At a more detailed level, our result that analysts are more likely to cease coverage of value GCM firms and GCM firms with negative momentum, provides evidence that analyst preference for growth stocks and stocks associated with positive momentum (Jegadeesh et al., 2004) is also demonstrated in the bad news domain.

However, despite the evidence that security analysts anticipate and react to this accounting event, we conclude that the signals they use to communicate unfavorable information are not understood by retail investors, who constitute the main clientele for GCM stocks. Our results demonstrate that analysts downgrade their stock recommendations for GCM firms from "buy" to "hold" while maintaining their previous “buy” recommendations for similar non-GCM firms as the event date approaches. Malmendier and Shanthikumar (2007) show that retail investors follow analyst stock recommendations literally and that, contrary to large investors, they do not react negatively to a “hold” recommendation. These authors conclude that retail investors react negatively only when analysts say “underperform” or “sell”, which is not the case in the going-concern domain. In line with this rationale, Kausar, Taffler and Tan (2010) show a significant decline of mean institutional holdings on GC stocks from 17% to 11% within the same period whereas retail investors increase their holdings from 69% to 74%. As such, analyst recommendations for GCM firms are not providing retail investors with value-relevant information before the publication of such bad news and explain, at least partially, why retail investors reinforce their holdings in these highly distressed stocks.

Consistent with the notion that security analysts are reluctant to issue unfavourable recommendations (e.g., McNichols and O’Brien, 1997; Conrad et al., 2006), we conjecture that analyst coverage cessation explains, at least partially, why the average recommendation on GCM stocks does not reduce from “hold”. In fact, the analyst decision to cease coverage of firms with going-concern problems has important implications in the interpretation of the observable average recommendation for GCM firms. Considering that analysts do not downgrade stock recommendations when they cease coverage of firms (e.g., McNichols and O’Brien, 1997), the lower tail of the recommendation distribution is censored leading to the average observed recommendation being 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’.*”

Our results can be better understood by drawing a distinction between pessimism and relative pessimism. In the sense of McNichols and O’Brien (1997), relative pessimism is a view that is unfavourable relative to a benchmark, such as in the case of an analyst rating a particular stock worse than another stock. Therefore, relative pessimism is an excellent definition to summarise our findings on analyst expectations for a GCM firm. However, we reject the idea that analysts are pessimistic about the future prospects of GCM firms within the pre-event period. Pessimism can be described as a “*view that was too unfavourable in retrospect*” (McNichols and O’Brien, 1997). As such, does a “hold” recommendation represents a pessimistic view about the future prospects of GCM firms immediately before the disclosure of such a bad news? On the contrary, there are reasons to believe that a “hold” recommendation in this context may represent an optimistic view. Typically, brokerage firms (e.g., Credit Suisse, UBS Warburg, Salomon Smith Barney, Morgan Stanley, Merrill Lynch) issue a “hold” recommendation when a stock is perceived to be fairly priced. However, Kausar, Taffler, and Tan (2009) show that, following the publication of a GCM audit report, stock prices of GCM firms underperform by around -14% over the next year.

7. Conclusion

Using a sample of 924 non-finance, non-utility, industry firms with first-time going-concern modified audit reports published between1994 and 2005, we show that security analysts anticipate the publication of a GCM audit report. To be precice, we find that analysts downgrade more aggressively GCM stock recommendations than control firms and are more likely to cease coverage of GCM firms over the one-year period prior to the GCM event. We also demonstrate that analysts react to the publication of a GCM audit report but by being more likely to cease coverage of GCM firms compared with similar non-GCM firms immediately after the disclosure event, not by downgrading their stock recommendations. Importantly, we show that our results are robust to the use of alternative control firms based on size, BM ratio, momentum, industry and distress risk and to the use of different categories of recommendations.

Overall, despite the idea that the marginal contribution of security analysts to investors may be greater in the case of the dissemination of bad news (e.g., Hong, Lim, and Stein, 2000), investors cannot rely on these sophisticated agents as messengers of bad news. In particular, investors should be aware that analysts are reluctant to report negatively on firms, and that the observable recommendations for firms experiencing bad news do not tell the all story as the SEC highlight in their statement about analyst recommendations. Our results suggest the need for investors to read between the lines and pay particular attention to analyst relative pessimism about stocks and to their decision to cease coverage.

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Table 1

Sample Selection Process for the First-Time GCM Audit Report

This table shows how our 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 our 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, we 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. We 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

Table 2

Descriptive Statistics

This table presents the descriptive statistics of our 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: Annual Distribution of the GCM cases

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

Panel B: 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 C: 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).

TABLE 3
Descriptive Statistics – Sample Firms vs. Control Firms

This table compares the descriptive statistics for our sample and control firms. Control firms are selected employing the control firm approach based on size and BM as described in section 2.2. 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
Pearson and Spearman correlations between Independent Variables

This table provides the Pearson (Spearman rank) correlation above (below) the diagonal between all independent variables used to estimate equations 2 and 4 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 our 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 as described in section 2.2.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.

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

TABLE 5
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 our 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 as described in section 2.2.

Section 3.2. 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)

TABLE 6
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 our 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 as described in section 2.2.
The binary logistic regression model is defined in equation 2. 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 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 $p<0.0001$

TABLE 7
Analyst Recommendation around the GCM Audit Report - Sample Firms

This table presents a comparison between quarter -1 and quarter +1 analyst stock recommendations for our 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.
Section 3.2. 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)

TABLE 8
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 our 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 as described in section 2.2.
The binary regression model is defined in equation 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 3: 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