Why the going-concern accounting anomaly: gambling in the market?

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ABSTRACT

The market fails to incorporate the adverse information conveyed by the going-concern (GC) opinion in a timely manner. This paper seeks to explain this market-pricing paradox. In particular, we argue that the lottery-like features of GC stocks attract a predominantly retail clientele who use such stocks to gamble in the market. Such trading behavior leads to underreaction to the GC event itself followed by a continuing fall in prices of almost 20% over the next 12 months. Using first time GC firms from 1993 to 2007 we show that GC stocks have extreme lottery-type characteristics. We further demonstrate that retail investors have a proclivity to be net-buyers of these stocks both at the GC event and subsequently, and such contrarian behavior is directly related to the lottery-like nature of GC firms. We test, and rule out, a range of alternative explanations for why retail investors are net-buyers of GC stocks, and conclude that it is their gambling-type behavior that appears to be driving the short-term market reaction to, and the longer-term market response following, the going-concern audit opinion.

Keywords: Market underreaction to bad news; retail investors; lottery stocks

Why the going-concern anomaly: gambling in the market?

1. Introduction

This paper provides an explanation for *why* the market underreacts to going-concern (GC) audit report disclosures. In a recent article in this journal ("The going-concern market anomaly") Kausar, Taffler, and Tan [2009] (henceforth KTT) establish that the GC anomaly, originally identified for the United Kingdom by Taffler, Lu, and Kausar [2004], equally holds in the U.S.. In particular, KTT demonstrate a negative and significant post-event abnormal return of around -14% over the 12-month period following a first-time going-concern bad news announcement, which result is robust to a range of alternative risk-based and other explanations.[1] Thus, despite the clear adverse signals about the firm's continuing financial viability provided by the public domain GC opinion, the active trading observed in GC stocks appears to be taking place at prices inconsistent with fundamental value.

However, although KTT show high trading costs render an arbitrage strategy unprofitable, in theory inhibiting the market underreaction phenomenon they describe being traded away, they do not answer the question of *why* the GC anomaly exists in the first place (Chan [2003]).[2] In particular, we propose that the documented post-GC event drift follows from the inherent nature of GC firm stocks. Specifically, we demonstrate that such stocks have lottery-type characteristics (Kumar [2009]), i.e., they represent cheap bets with negative expected return although a small probability of a high payoff, which make them particularly attractive to a retail investor clientele who trade for speculative reasons. Such investment behavior dominates that of institutional investors

[1] Using a broadly similar set of firms to KTT, we report an equivalent one-year post-GC abnormal return of -19% cumulating returns commencing immediately after the GC event, rather than from the beginning of the following month as in KTT.
[2] The behavioral finance literature points out that the beliefs of rational investors may not dominate stock prices at least in the short run because prices reflect a weighted average of investor beliefs, where the weights depend on the frequencies of different investor types and their risk tolerance levels (e.g., Lee [2001]). Limits to arbitrage may then lead the resulting mispricing to persist (e.g,, Shliefer and Vishny [1997]).

which we show to be more rational.[3] In contrast to these sophisticated investors, retail investors behave in a contrarian manner by *buying* such bad news stocks. We conclude that the established going-concern anomaly can be explained by retail investor trading activity akin to "gambling in the market" (Kumar [2009]).

Specifically, we test whether it is the divergent trading behaviors of individual and professional investors in going-concern stocks that slow down the market reaction to the GC opinion reflected both in their initial overpricing, and subsequent downward drift in price for several months following the GC event. We propose that GC firms constitute lottery-type stocks, and are consequently attractive to retail investors who are likely to be the principal traders in such stocks with a greater propensity to buy than sell them. On this basis we would expect the following market response to the going-concern opinion: (i) the greater the degree of retail investor interest the less negative the immediate market reaction to the GC event, and (ii) the greater the degree of retail investor interest in such stocks at the GC date, the more severe the subsequent market underreaction.

Based on analysis of all first-time going-concern opinions from 1993 to 2007 meeting data availability requirements our results are consistent with our expectations. First, we show that GC firm stocks take on lottery-type features (Kumar [2009]) around the GC event date, and these characteristics become even more pronounced over the following year. Consistent with this, retail investors increase their holdings in these firms, and the volume of their trades. In particular, we find a uniform propensity for the dollar volume of small buy orders, proxying for retail trades, to materially exceed that for small sell orders both at the going-concern announcement date, and over the following year. In contrast to institutional investors, retail investors like to *buy* such unambiguous bad news stocks with such propensity being directly related to their lottery-type characteristics.

Next, we show that the market reaction to the GC announcement depends on whether small buy order volume exceeds small sell order volume. Specifically, in the case of GC

[3] We use the respective terms retail, individual and unsophisticated, and institutional, professional and sophisticated synonymously in this paper.

firms with positive small buy minus sell order imbalance prices fall by only -3.6% on the going-concern announcement. In sharp contrast, GC firms with negative small buy minus sell order imbalance experience a price drop of no less than -9%. It is the net-buying behavior of retail investors that appears to be ameliorating the expected negative market reaction to the release of the bad news conveyed by the GC opinion at the audit report publication date.

Finally, we examine directly whether we can explain the going-concern market anomaly, i.e., the documented significant negative post-event abnormal return, itself in terms of retail investor attraction for GC stocks because of their lottery-type characteristics. In fact, we find that GC firms with dollar volume of small buy orders exceeding dollar volume of small sell orders at the GC date underperform those GC firms with a negative net small order imbalance by no less than -28% over the following one-year period.

Our evidence is consistent with the going-concern market pricing paradox being explained by the "irrational" trading behavior of individual investors akin to gambling in the market as documented by Kumar [2009], and others, in the finance literature.[4] The going-concern audit opinion appears to turn our sample firms into lottery stocks. This helps explain the increased retail holdings of these stocks we find both at, and subsequent to, the GC announcement, and associated increased individual investor propensity to purchase them. Such trading behavior serves to inhibit the timely assimilation of the adverse information conveyed by the GC audit report into market prices.

Although we test alternative explanations including the news attention hypothesis, investor overconfidence, and the naïve investor hypothesis, we find no evidence consistent with any of these potential explanations for the GC anomaly. On this basis we are left with retail investor gambling as the most likely explanation for this market pricing paradox.

[4] We use the terms "rational" and "irrational" in an economic context not as a description of investor psychological utility.

We contribute to the accounting literature by providing a potential explanation for the established going-concern market anomaly, and specifically show why it might arise. In particular, we demonstrate the important role small (or less sophisticated) investors play in the market for such lottery-type stocks, and how their trading behavior leads to the anomalous market pricing of GC firms previously documented by KTT. On this basis we suggest that the lack of timely market reaction to the going-concern announcement is due to the preponderance of individual investors in the stocks of GC firms who trade actively on this extreme bad news event, and are net-buyers. Retail trader interest may be an important determinant of how markets react to adverse accounting news more generally. We speculate that the varying trading patterns of different stock clienteles might also help explain other established market-based accounting anomalies (e.g., Ayers, Li, and Yeung [2011]), and the financial distress anomaly (e.g., Campbell et al. [2008]).

Our results, likewise, have implications for accounting policy standard setters. Prior research demonstrates the inability of retail investors to even process publicly available information (e.g., Battalio and Mendenhall [2005]; Bhattacharya et al. [2007]; Miller [2010]; Ayers, Li, and Yeung [2011]). In such settings as we explore here, enhanced accounting disclosures (i.e., richer accounting information) may have little value to the less sophisticated investors who are, in effect by default, the price setters in such situations, and consequently little impact on market prices resulting in trades taking place at prices inconsistent with fundamental value.

The remainder of this paper is organized as follows: section 2 provides the background and presents our hypotheses. Section 3 describes our sample selection criteria and data. Section 4 investigates whether GC firms have lottery-type features. Section 5 examines who trades on GC news, and section 6 presents evidence that small trader behavior influences both the short-term market reaction to, and the longer-term market response following, the publication of the going-concern audit report. Section 7 relates the trading behavior of small investors to socioeconomic factors to test whether local investor risk attitudes influence retail investor GC stock buying behavior. In section 8 we test alternative explanations to an investor gambling one for the contrarian behavior of small investors. Section 9 concludes.

2. Background and hypotheses

A number of studies demonstrate that institutional, and less sophisticated investors trade in very different ways (e.g., Lee [1992]; Radhakrishan, and Krinsky [2000]; Bhattacharya [2001]; Battalio and Mendenhall [2005]; Bhattacharya et al. [2007]; Ayers, Li, and Yeung [2011]). A key finding of these studies is that professional investors behave in a rational manner while individual investors trade irrationally. For example, Lee [1992] shows that institutional investors react immediately to earnings announcements in their trades, buying stocks on good earnings news, and selling if the news is bad. However, in contrast, retail investors trade actively for a period of time around the earnings announcement date, with an anomalous proclivity to buy such stocks irrespective of the direction of the earnings news. Using an analysis of trade size, Lee concludes that "small money" does not move in lockstep with "big money". Similarly, Battalio and Mendenhall [2005] show that small investors respond in a less-sophisticated way to analyst earnings forecast errors compared with large traders, and suggest that this can help explain the post-earnings announcement drift.

Complementary research in finance is starting to provide some answers to the question of why unsophisticated investors trade differently to sophisticated ones. A new line of research highlights the important role of gambling in investment decisions (e.g., Barberis and Huang [2008]; Kumar [2009]; Kumar, Page, and Spalt [2011]). These studies tell us that a particular class of investor like stocks that have speculative features which make them attractive gambles. In particular, Kumar [2009] shows that such investors find low-priced stocks with high idiosyncratic volatility, and high idiosyncratic skewness very attractive, and classifies firms with such speculative features as "lottery-type stocks".[5]

[5] The theoretical motivation behind this definition of lottery-type stocks is provided by Barberis and Huang [2008] where investors overweight low probability events, and exhibit high preference for stocks with positive skewness. In the context of this paper investors overweight the low probability of earning high returns from investing in firms with going-concern audit reports.

Interestingly, Kumar documents that socioeconomic factors that induce higher expenditures in state lotteries are also associated with greater investments in lottery-type stocks. Kumar, Page, and Spalt [2011] show that religion is similarly associated with gambling in the market, and find that such speculative trading not only affects stock returns but also impacts investors' portfolio choices, as well as corporate decisions. Many recent papers in finance are also supportive of these arguments (e.g., Grinblatt and Keloharju [2009]; Dorn and Sengmueller [2009]; Dorn and Huberman [2010]).

Based on the above arguments, if our GC stocks are lottery-type stocks, and thus attract a predominantly retail investor clientele with the propensity to gamble in the market, then we expect the following market reaction to the GC announcement:

(i) The negative market reaction to the GC disclosure will be attenuated by the contrarian preference of individual investors for GC firm stocks swamping the rational price setting activities of professional investors,[6] and

(ii) Prices of GC stocks will continue to fall over the longer term as institutional investors take advantage of retail investor behavior to exit the market. In a sense, the market catches up with its initial underreaction to the GC announcement over time.

We test the above predictions in the form of the following four hypotheses stated in alternative form:

H1: Going-concern stocks have the characteristics of lottery-type stocks.

H2: Retail investors are the principal traders in GC stocks, and have a greater propensity to buy such stocks than sell them.

[6] We speculate that the decline in prices around the GC event could also itself lead to an increased investor attraction for these stocks as individual investors could become more confident of high payoff outcomes.

H3: The greater the level of individual trader buying interest at the GC date, the less negative the market reaction to the GC announcement, and

H4: The greater the level of individual investor buying interest at the GC date, the more negative the post-event market response to the GC announcement.

3. Sample selection and data descriptives

Our sample consists of first-time going-concern audit opinions from January 1993 to December 2007, and we adopt a similar sample collection procedure as in KTT. To identify firms listed on the NYSE, AMEX or NASDAQ with going-concern modified audit reports for our sample period we use SEC EDGAR, and the Compact Disclosure database. Our initial search yields many thousands of going-concern opinions. We next locate the searched companies on the Center for Research in Security Prices (CRSP) database. Finally, we eliminate those matched firms where their prior year audit report is not clean, or if they are financials, utilities, in a development stage, have filed for Chapter 11 prior to the GC publication date, are delisted in the GC month, are foreign, or have insufficient data in CRSP/COMPUSTAT. This gives us a sample of 1,404 first-time going-concern opinion cases. However, we also require our sample firms to have data available in TAQ (Trades and Quotes database) to conduct our empirical analyses. This additional requirement results in a final sample of 1,214 first-time GC firm-year observations for the 1993-2007 period.[7] For most of our GC firms the 10-K filing date is the GC announcement date. However, some firms disclose GC news a few days before the 10-K filing date (Menon and Williams [2010]). We identify such firms by searching the press releases of all our GC firms in Factiva prior to the filing of their 10-K. For this early disclosure GC sub-sample the press release date constitutes the event date.[8]

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[7] We find no difference in either the firm characteristics or the market reaction of the 197 first-time GC cases for which we have no TAQ data compared to the set of GC cases where we have the TAQ data.

[8] One hundred and thirty four out of our 1,214 GC firms announce their going-concern audit opinion early. These firms are larger in size (measure by market capitalization) than, but no different in terms of their bankruptcy risk (Altman [1968]) to, those firms that first report their GC in their 10-K. Also, consistent

Market data (such as stock returns, market value, bid-ask spread etc.) are taken from the CRSP database. All other financial data are from COMPUSTAT, and analyst coverage from I/B/E/S. Institutional and insider holdings data is collected from Thomson Reuters Financial Network's institutional holding and insider trading data files. Z-scores, measuring bankruptcy risk (Altman [1968]), are computed using data drawn from COMPUSTAT. Following Shumway [1997], and Shumway and Warther [1999], delisting returns are included in daily returns. To abstract from the influence of outliers, extreme observations are set at the 1st and the 99th percentiles, respectively.

To test our gambling hypotheses, we draw on data from a variety of sources. Trading data is obtained from the Trades and Quotes database (TAQ), where small-sized trades (trade size below $5,000) are used to proxy for retail trades. We also use data from a major U.S. discount brokerage house which contains all trades and end-of-month portfolio positions of a set of individual investors during the 1991 to 1996 time period (see Barber and Odean [2000], [2001] for additional details). County level religious adherence data is collected using the American Religion Data Archive (ARDA).[9] During our sample period, the county level religion data are available only for years 1990, and 2000. Following the approach in the recent literature (e.g., Kumar, Page, and Spalt [2011]; Hilary and Hui [2009]), we linearly interpolate the religion data to obtain the values in the intermediate years. We obtain additional county level demographic characteristics from the U.S. Census Bureau.[10]

Table 1 provides descriptive statistics for our sample of 1,214 first-time GC firms. Auditors modify the going-concern status of the firm if there is substantial doubt about the firm's ability to continue as a going-concern for the foreseeable future. Therefore, by definition GC firms have significant financial problems. This is reflected in the

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with Menon and Williams [2010], we find that early announcers experience a significantly lower (more negative) market reaction to the GC news relative to 10-K announcers.

[9] County-level religion data are available at http://www.thearda.com/. Given such data are only available for our purposes for years 1990, and 2000, we linearly interpolate this data to obtain values for intermediate years (Hilary and Hui [2009]; Kumar, Page, and Spalt [2011].

[10] U.S. Census data are available at http://www.census.gov.

characteristics presented in Table 1. GC firms are small (mean market cap. = $53m) poor performing firms (mean return on assets = –46%).[11] These firms are at high risk of failure with average z-score of –1.71 (where z <1.8 indicates a high failure probability). Forty-four percent of GC firms enter bankruptcy or delist in the year following the announcement of the GC audit report which again demonstrates their high risk profile. Also, as one might expect, analyst coverage is low with only 29% of firms being followed by an analyst around the GC date. Seventy-one percent of firms are audited by large audit firms (Big 4/Big 5).

4. Are GC firms lottery-type stocks?

In this section we investigate whether GC stocks have features that prior research shows to be particularly attractive to retail investors. In particular, do GC firms have the characteristics of lottery-type stocks? Kumar [2009] defines lottery-type stocks as those stocks that are in the lowest 50th stock price percentile, the highest 50th idiosyncratic skewness percentile, and the highest 50th idiosyncratic volatility percentile. Stock price is the daily closing price, idiosyncratic skewness is the skewness of the residual obtained from fitting a two-factor model where the two factors are the market factor and the square of the market factor (Kumar [2009]), and idiosyncratic volatility is the standard deviation of the residual obtained from fitting the Fama-French four-factor (Carhart [1997]) model. Both idiosyncratic skewness, and idiosyncratic volatility are estimated using the previous six months of daily returns data. More specifically, we test whether GC firms have low prices, high idiosyncratic skewness, and high idiosyncratic volatility. It is important to point out that all three features are necessary to classify firms as lottery-type stocks because they have to be cheap bets (low price), have the ability to generate extreme positive returns (high stock-specific skewness), and the likelihood of generating extreme returns should also be high (high stock-specific volatility). We also follow Han and Kumar [2013] and construct a lottery stock index which is a composite measure of these three speculative features. This is computed as the sum of the vigintile assignments of

[11] We measure the market capitalization of GC firms one month before the GC announcement date compared to KTT who measure it at the end of the GC month.

stocks according to stock price, idiosyncratic skewness, and idiosyncratic volatility, divided by 60. The lower the value the more the stock has lottery-like characteristics.

Table 2 examines whether our GC firms have lottery stock characteristics. Specifically, it compares the characteristics of our GC firms for the one-year period leading up to GC event, at the GC announcement date, and for the year following the GC event, with the CRSP population over the same time period (1993-2007). As can be seen, the speculative features of our GC firms become increasingly pronounced around the event date, and, in particular, in the post-GC period. For example, whereas in the prior 12-month period GC firms have a mean (median) lottery index of 0.28 (0.25) compared with 0.24 (0.23) for the CRSP population of lottery-type stocks, this falls to 0.24 (0.22) two days before the GC announcement date (day = -2). More interestingly, the mean (median) GC-firm lottery index declines further to 0.21 (0.18) in the post-GC period. Similar behavior is observed in the different components that make up the lottery index: stock price, idiosyncratic skewness, and idiosyncratic volatility. Figure 1 graphs our GC firm lottery index distribution before, at, and after the GC event compared with the lottery index distribution for stocks classified as lottery-like in the CRSP population. As can be seen, GC stocks become more skewed towards the left relative to CRSP lottery stocks at, and in particular after, the GC event suggesting they increasingly become more extreme gambles.

Confirming what these results indicate we also find that the percentage of GC firms strictly classified as lottery stocks, i.e., with price below the population median contemporaneous with idiosyncratic volatility, and idiosyncratic skewness both with values above the respective population medians significantly increases from 64% (at day -2) to 75% in the 12-month period after the GC announcement. This compares with only 23% of such stocks in the CRSP population. Based on this evidence we conclude that following a going-concern audit report GC firms become increasingly lottery-like representing cheap bets with the ability to generate extreme positive returns although at very high risk, as reflected in their high negative systematic skewness. According to rational asset pricing models such stocks would be expected to earn higher future returns

(Harvey and Siddique [2000]). In contrast, GC stocks earn abnormally low future returns (KTT).

Overall, we find that GC firms have all the three characteristics required to classify firms as stocks with speculative features or lottery-type stocks, i.e. the type of stocks that retail traders are attracted to. These findings are strongly supportive of H1. In the next section we test hypothesis 2 which examines whether retail investors are the dominant clientele of GC stocks, and have a proclivity to buy such stocks.

5. Who trades on GC news?

In this section we test hypothesis H2, i.e., that retail investors are the principal traders in GC stocks, and thus implicitly the relevant price setters, and like to *buy* such stocks, by examining who trades the stocks of GC firms, and who buys and sells them. We do this in two ways. First, we analyze the stockholding patterns of various classes of investor. Second, we examine the intraday trading behavior of different types of investor in our GC stocks.

5.1 GC FIRM STOCKHOLDINGS

To understand the trading environment of GC firms we first examine the stockholding patterns of institutions and insiders and, by deduction, retail investors in these stocks from one year prior to one year post the GC audit report publication quarter, i.e., for 9 quarters (four pre-event quarters, the GC quarter, and four post-event quarters). Insider holdings data is available on a period-by-period basis, and can be transformed into monthly holdings, whereas institutional holdings data is only available on a quarterly basis. Therefore, we conduct our analysis on a quarterly basis. Not every firm has data available in each quarter. Where missing, we use the previous quarter's figure. Retail investor holding proportion is calculated as one minus the combined holdings of institutions and insiders.

Table 3 present the respective mean and median institutional, insider, and retail investor percentage holdings in our GC firm stocks for the nine quarters. In particular, it shows that mean (median) retail investor holdings increase from 66% (71%) in the fourth quarter prior to the GC quarter to about 68% (75%) in that quarter, and then to 70% (80%) in the fourth quarter following the GC quarter. All changes are significant at the 1% (1%) level. Importantly, the holding patterns of retail investors over this two-year period would be consistent with the majority of trading in our GC firms being conducted by small (retail) investors with significant increases in their holding positions over this window. In contrast, we observe a sharp and significant reduction in institutional holdings over the nine-quarter period centered on the GC quarter. Mean (median) institutional holdings decline from 17% (8%) in the fourth quarter prior to the GC quarter to about 10% (1.5%) in the fourth quarter following the GC quarter. Institutions appear to behave in a rational manner in reducing their holdings in the face of bad GC news. Insider holdings experience a small but significant mean (median) increase of 3% (2%) over the two-year period, averaging around 19% (12%). We examine the actual trading activities of different classes of investor in the next sub-section.

5.2 TRADING ACTIVITY IN GC FIRMS

At best, our previous analysis can only provide some indirect evidence about who trades in the stock of GC firms. This sub-section addresses this issue more directly by examining intraday trading data to test hypothesis H2.

5.2.1 Proxying retail investor trading activity

A large body of literature uses trade size to differentiate between sophisticated and unsophisticated investors (e.g., Cready [1988]; Cready and Mynatt [1991]; Lee [1992]; Bhattacharya [2001]; Bhattacharya et al. [2007]; Miller [2010]). The general idea is that, on average, professional investors (such as institutions) who are wealthier and more sophisticated are likely to make larger trades, while individual investors who are less wealthy and less sophisticated are likely to make smaller trades (e.g., Easley and O'Hara

[1987]; Hasbrouck [1988], [1991]; Chan and Lakonishok [1993]; Lee and Radhakrishna [2000]; Kumar [2009]). Lee and Radhakrishna [2000] show that a $5,000 trade size cut-off can effectively identify trades initiated by retail investors.[12] Prior research also suggests that although institutional investors may have incentives to engage in medium-sized trades to disguise their private information (e.g., Cornell and Sirri [1992]; Meulbrock [1992]; Barclay and Warner [1993]), nonetheless, Bhattacharaya et al. [2007] point out that they are unlikely to engage in very small trades as significantly reducing their trading profits. This would be due to the associated higher transaction costs, the greater time required to move all the desired shares, and the number of small orders potentially prompting the specialist to increase the spread. As such, we expect small trade size to be an adequate proxy to capture the behavior of individual investors. Chakravarty [2001], and Barclay, Hendershott, and McCormick [2003], specifically provide empirical evidence that supports this notion. Therefore, we use dollar volume of small trades to capture the trading activities of unsophisticated individual investors. Following earlier studies, we classify trades of $5,000 or less as small trades i.e., those likely to be by retail investors, trades between $5,000 and $50,000 as medium trades, and trades greater than $50,000 as large trades, i.e., likely to be by sophisticated professional investors.[13]

However, we also need to establish whether retail (and institutional) investors are mainly net-buyers or net sellers of our GC stocks around, and following, the GC announcement event. To classify transactions as buys or sells we use the algorithm of Lee and Ready [1991]. We also follow Bhattacharya et al. [2007] in calculating our small investor abnormal net-buy (buys minus sells) order imbalance measure for each of our GC firms. This is derived as the average daily abnormal net-buy volume (buy dollar volume minus sell dollar volume) for firm i over n days deflated by average daily non-announcement trading volume.[14] We term this measure NETIMBS (net-buy-order imbalance – small

[12] Several recent studies use the Trades and Quotes (TAQ) database and employ the $5,000 trade size cut-off to identify trades by retail investors (e.g., Battalio and Mendenhall [2005]; Bhattacharya et al. [2007]; Malmendier and Shanthikumar [2007]; Hvidkjaer [2008]; Barber, Odean, and Zhu [2009]; Miller [2010]).

[13] These cutoffs are further justified by the mean and median trade size statistics of individual investors at a major discount brokerage house investing in GC firms, and matched control stocks, reported in §5.2.5 below.

[14] Specifically, this measure is given by small investor average daily net-buy volume over the n-day period of interest for firm i minus small investor average daily non-announcement period net-buy volume for firm

trades). Thus, NETIMBS is a measure of small investor abnormal dollar-volume net-buying activity. We add the subscripts AD = announcement date (-1, 1), and PAP = post-announcement period (2, 252) to distinguish between short- and longer-term abnormal net-buy order imbalance, and to our other trading activity measures described below as appropriate. A positive value for NETIMBS indicates small trader buying activity which is greater than usual. We compute NETIMBL (net-buy-order imbalance – large trades) measures in exactly the same way but using trades above $50,000 in size as discussed above.

We restrict all analyses that employ individual trade data taken from the TAQ (Trades and Quotes) database to the period January 1, 1993 to December 31, 2003. This is because the introduction of decimalized trading in 2001, and subsequent order splitting (program trading) by institutions due to lower transactions costs, makes it difficult to accurately relate small trades to the behavior of individual investors (e.g., Hvidkjaer [2008]; Kumar [2009]; Barber, Odean, and Zhu [2009]; Han and Kumar [2013]). In particular, Hvidkjaer [2008] shows that his small trade proxy experiences a surge in trading volume from 2003 onwards, reflecting a large increase in small size orders by institutions. As such, it is not appropriate to use small trade size to proxy for retail investor trades beyond, at the latest, 2003.[15]

5.2.2 Trading behavior of small and large investors around the GC event

Table 4 describes the trading activity of retail (small) and institutional (large) traders at the GC announcement date in panels A and B, and over the following year in panels C and D. In the first section of panel A, we report retail investor trading activity in GC stocks during the 3-day GC announcement window (-1,1). $NETIMBS_{AD}$, which measures the average daily small trade abnormal net-buy order imbalance over the 3-day event period, has a mean (median) of 3.8% (2.7%) (p=0.00 (p=0.00)). Panel A also provides the percentage, and abnormal percentage, of small trades taking place respectively labeled

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i over the period (-252, -22), where t=0 is the GC announcement date, deflated by the average daily non-announcement period total trading volume for firm i.

[15] Because of this, we work with the restricted set of 1,047 first-time GC opinions published between January 1, 1993 and December 31, 2003 in all analyses involving small trade dollar volumes.

$SM\_TRADE_{AD,}$ and $ABSM\_TRADE_{AD}$. These variables are calculated as the daily average event period trading dollar-volume level, and daily average event period dollar-volume trading level, minus the daily average dollar-volume trading level computed over the pre-event period (-252,-22). As can be seen, small trades of GC stocks account, on average, for 65% of all such trades in dollar-volume terms in the 3-day announcement period, a 12% increase in abnormal trading volume. As such, aggregate small trading frequency increases by no less than 22% around the GC announcement date.[16]

Opposite behavior is observed in the first part of panel B of table 4, which reports the equivalent trading behavior of institutional investors (proxied by large trades) over the 3-day GC event period. Here large investor mean daily net-order imbalance ($NETIMBSL_{AD}$) is -1.0% (p=0.02).[17] Professional investors respond negatively to the GC event, and sell down their holdings in GC stocks in contrast to retail investors who are strong net-buyers. Daily average large trade dollar volume percentage at the GC announcement date (LG_TRADE_{AD}) is, however, only 4%, but average abnormal large trading volume ($ABLG\_TRADE_{AD}$) is -2.8%. As such, the proportion of large trades to all trades in GC stocks falls by 40% suggesting the selling down of these stocks by sophisticated investors, in direct contrast to retail investors who are active net-buyers.

5.2.3 Longer-term trading behavior of retail and institutional investors

The previous sub-section contrasts the contrarian response of small investors to the GC announcement with that of professional investors in terms of their significant increase in buy relative to sell dollar volume, and increased trading activity. However, to test hypothesis H2 fully, we also need to explore retail and institutional behavior subsequent to the GC event. To do this, we derive similar trading activity measures for small and large investors for the one-year period following the going-concern announcement.

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[16] Increase (decrease) in the proportion of small/large trades is computed as $AB(SM/LG)\_TRADE_{AD}$ / $((SM/LG)TRADE_{AD} – AB(SM/LG)\_TRADE_{AD})$.

[17] Median large trades are zero at GC announcement, i.e., the median GC firm has no large trades. As such it is not meaningful to report such median figures.

Panels C and D of table 4 report the trading activity of small and large traders during the one-year post-event period (2,252) respectively. In the first section of panel C we continue to observe abnormal retail investor trading activity in GC stocks. $NETIMBS_{PAP}$, which measures the post-announcement period average daily small trade abnormal net-buy dollar volume order imbalance, has a mean (median) value of 6.7% (4.6%) (p=0.00 (p=0.00)) for these stocks, which is double that at the going-concern announcement date. Panel C also provides the percentage, and abnormal percentage, of small trades taking place over this one-year period respectively labeled $SM\_TRADE_{PAP,}$ and $ABSM\_SMTRADE_{PAP}$. These variables are calculated as the daily average post-event period dollar-volume trading level, and the daily average post-event period dollar-volume trading level minus the daily average dollar-volume trading level, computed over the pre-event period (-252,-22). As can be seen, small trades in GC stocks account on average for 68% of all trades in dollar-volume terms in the year following the GC announcement, a 14.4% increase in abnormal trading volume. As such, small trade dollar volume is 27% greater in the 12-month period post the GC event compared with the prior year.

Similar to the case of short-term trading behavior, panel D of table 4, which reports the trading behavior of institutional investors (proxied by large trades), shows the daily mean net-order imbalance for large investors ($NETIMBL_{PAP}$) over the one-year post-GC event period to be -1.0% (p=0.00). Large trade net-buy order imbalance is negative; professional investors continue to respond negatively to the GC event by continuing to sell down their holdings in such stocks, in contrast to retail investors who remain strong net-buyers. Daily average large trade dollar volume percentage during the post-GC announcement period (LG_TRADE_{PAP}) is, however, only 4.1% with associated average abnormal trading volume ($ABLG\_TRADE_{PAP}$) of -2.9%. As such, the proportion of large trades to all trades falls by 41%. On this basis, “rational” institutional investors appear to lack interest in stocks of GC firms in contrast to retail investors who find such stocks increasingly appealing.

5.2.4 Small investor attraction for GC stocks

This section explores further whether it is the characteristics of GC firm stocks that makes them attractive to small investors, and unappealing to large investors. Specifically, we compare the trading behavior of small and large investors in the stocks of our GC firms with that in matched non-GC stocks, both around the respective 3-day (-1,1) GC, and equivalent 10-K announcement dates, and over the following 12 months.[18] Control firms are pair-matched to GC firms on size and book-to-market. Specifically, we identify an appropriate control firm by matching each GC firm with that non-financial, non-utility, and non-GC firm in the full CRSP population of firms with most similar size, and book-to-market ratio. We first identify all firms with a market value of equity between 70% and 130% of the market value of equity of the firm at the end of the GC fiscal year-end; from this set of firms we choose the firm with the book-to-market ratio closest to that of the sample firm.

The second set of results in each panel of Table 4 provides equivalent abnormal net-buy order imbalance statistics for small and large trades, together with the dollar volume percentages, and abnormal dollar volume percentages, of small and large trades to total trades for our control firms equivalent to the results for our GC firms provided in the first part of each panel. Panel A of Table 4 shows, for example, that small investor abnormal buying behavior differs significantly between GC firm stocks and control firms around the respective event dates. Mean GC firm $NETIMBS_{AD}$ is twice that for the matched control firm sample (p=0.00), and mean GC firm SM_TRADE_{AD} is 35% greater (p=0.00). Similarly, mean GC $ABSM\_TRADE_{AD}$ is no less than seven times that for our control firms (p=0.00).

However, in contrast to small trader behavior, panel B shows large investors are net sellers of GC firm stocks, but not of their matched non-GC firm counterparts. For example, mean GC $NETIMBL_{AD}$ is significantly negative, and much lower than for our control firms (p=0.08). However, more interestingly, GC firm LG_TRADE_{AD} is less than half of that for control firms (p=0.00). As can be observed, panels C and D provide very

[18] Footnote 8 shows that, in almost 90% of GC firm cases the first mention of a going-concern audit report is at the 10-K publication date.

similar results to panels A and B in terms of small and large investor longer-term trading activity in the stocks of GC and non-GC control firms. Thus, both around the GC event, and over the following year, we provide evidence of significantly weaker small trading interest in the stocks of our control group of firms compared with our GC stocks. Such results are consistent with retail investors, in contrast to institutional investors, finding the lottery-type stock characteristics of GC firms highly appealing.

5.2.5 Evidence from actual trades of individual investors

To provide additional support for an individual investor attraction to lottery-type stocks explanation for the market underreaction to the GC event, we use data on the actual trades by retail investors in our going-concern and control firm stocks drawing on data provided by a major discount brokerage house. This database contains all trades and end-of-month portfolio positions for a large set of individual investors between 1991 and 1996. We need first to identify the GC firms within this dataset. In fact, we are able to match 201 GC and control firm pairs with the firms used in the TAQ-data analysis of §§ 5.2.2 to 5.2.4 above with trades taking place within the 12-month period centered on the GC (10-K) date. Mean (median) trade size (in dollar terms) for our discount brokerage house GC (control) firms is $7,503 ($3,450) ($6,617 ($3,100)). We also compute the percentage of net-buys (Buy - Sells / (|Buys| + |Sells|)) for these GC firms and control firms. Consistent with our previous results, we find that the net-buying behavior of these individual investors is significantly more pronounced in the case of GC firms than with their matched control firms. For instance, the mean decimal percentage of net-buys during the 12-month period around the GC (10-K) date for GC firms is 0.13, and for control firms 0.10; with the difference significant at the 1% level.[19]

To test further whether individual investors exhibit a stronger preference for GC stocks than control firm stocks (Kumar [2009]), we examine the relative weightings such investors assign to GC stocks, and control firms, in their portfolios. There are 54,214

[19] We test and confirm that such differences are also significant in a multivariate setting.

investors in our discount brokerage house data who hold common stocks between 1993 to 1996. Given that we only have 201 pairs of GC and control firm stocks held at any time by these investors, the average investor's portfolio is likely to contain only a very small proportion of such equity. In fact, we find that, on average, only 0.44% of individual investor portfolio market capitalization is accounted for by GC firm equity, and 0.28% by control firm equity. Nonetheless, the difference in holding proportions is significant at the 1% level. This again suggests that individual investors exhibit a strong preference for GC stocks relative to control firms; retail investors seem to find GC stocks very attractive indeed.

Overall, this section demonstrates that small (retail) investors are the main clientele of GC stocks and that, additionally, they behave in a contrarian manner compared to large (institutional) investors. Even though the GC opinion highlights bad news regarding firm future viability, small traders, in contrast to sophisticated investors, are net-buyers of such stocks both at the GC announcement date, and over the subsequent 12-month period. This, we show, is due directly to their attraction for lottery-like GC stocks for speculative trading reasons. Such evidence is strongly supportive of hypothesis H2. Retail investors are indeed the main clientele of GC stocks, and continue to be net-buyers of such lottery-type stocks over an extended period.

Taken together with the speculative nature of GC firms, as highlighted in section 4 above, we are now in a position to test hypotheses H3 and H4 in the next two sections. Specifically, we provide a formal explanation for the GC anomaly in terms of retail investor gambling in the market leading both to market underreaction to the GC announcement, and a significant downward drift in prices over an extended period following the GC event.

6. Small trader behavior and GC stock returns

In this section we explicitly test the impact of the abnormal trading behavior of less sophisticated (individual) investors on the short-term market reaction to (H3), and the longer-term market response following (H4), the publication of the GC opinion. $NETIMBS_{AD}$, which captures the abnormal net-buy behavior of small traders at the GC announcement date, is our main independent variable of interest. Based on hypotheses H3 and H4 we expect (i) a positive association between short-term market reaction to the GC announcement, and $NETIMBS_{AD}$, and (ii) a negative association between longer-term market response, and $NETIMBS_{AD}$.

6.1 RETURN GENERATING MODEL

In this sub-section, we describe how we test hypotheses H3 and H4 controlling for factors that might potentially impact our results. We calculate the short-term stock market reaction to the GC announcement as the 3-day (-1,1) buy-and-hold abnormal return (BHAR). Longer-term BHARs are measured over four separate trading-day periods, i.e., (2,62), (2,124), (2,186), and (2,252) respectively. The size, and book-to-market matched control firms of §5.2.4 above are used as the market benchmark.

We test for any association between stock market reaction to the GC announcement, and trading activity of small traders around the GC opinion date using multiple regression analysis. The key variable of interest is the independent variable $NETIMBS_{AD}$ which captures the trading behavior of individual investors associated with firm i''s going-concern announcement. If the contrarian trading behavior of small traders delays the assimilation of GC news into stock prices, then we expect the coefficient on $NETIMBS_{AD}$ to be positive and significant in the short term (H3), and negative and significant in the longer term (H4). The following ordinary least-squares multiple regression model we employ to test H3 and H4, controlling for other variables that could explain the market reaction to the first-time GC opinion, with dependent variable $BHAR(t_1,t_2)$, is given by equation 1:[20]

[20] In additional tests we also control for the passage of the Sarbanes Oxley Act in 2002 by including the dummy variable SOX (=1 if year of GC reporting is 2002 or later; 0 otherwise). There are arguments in the

$$BHAR(t_1,t_2)_i = \lambda_0 + \lambda_1 NETIMBS_{ADi} + \lambda_2 LNSIZE_i + \lambda_3 BM_i + \lambda_4 PRRET_i + \lambda_5 Z_i + \lambda_6 LEV_i + \lambda_7 CHEAR_i + \lambda_8 ROA_i + \lambda_9 ANALYST_i + \lambda_{10} BIG_i + \lambda_{11} TRVOL_i + \lambda_{12} BIDASK_i + u_i \quad (1)$$

For our short-term market reaction tests t_1 = day -1, and t_2 = day 1, relative to the GC announcement day (t = 0), whereas for our longer-term tests t_1 = day 2 and t_2 = days{62, 124, 186, 252}. Mutchler [1986] suggests that auditors will issue going-concern modifications more often to smaller firms. Therefore, issuance of the GC opinion to larger firms may come as a surprise to the market. On the other hand, larger firms have a richer information environment in terms of higher analyst following and institutional ownership. Thus, we have no prior expectation about the sign of the relation between firm size, and abnormal returns around the GC announcement date. We use natural log of market capitalization (SIZE) as a proxy for firm size.

Other important variables which might potentially explain cross-sectional abnormal returns are the book-to-market (BM) ratio, and prior returns (PRRET). High book-to-market firms tend to have higher returns (e.g., Fama and French [1992]), therefore, we expect the sign to be positive. PRRET controls for returns prior to issuance of the audit report.[21] Market expectations of a GC opinion are likely to be higher for firms with more negative prior returns; therefore, we expect the sign to be positive.

Our next set of control variables relate to firm financial distress. Z-score (Z) (Altman [1968]) proxies for bankruptcy risk. We expect a positive relation between Z and stock returns in our GC firm context. This is because firms with lower Z have a greater

literature suggesting that by mandating higher, and more stringent, disclosure requirements the firm information environment is enhanced (Engel, Haynes, and Wang [2007]; Leuz [2007]) leading to a more negative market reaction on the more timely release of bad news. We find the SOX dummy to be statistically insignificant. This could be because many of our firms are unlikely to have been accelerated filers as firms with market capitalization less than $75 million were not required to comply fully with the Sarbanes Oxley Act until 2007 (http://www.sec.gov/rules/final/2006/33-8760fr.pdf).

[21] PRRET is defined as prior 6-month (-126, -2) buy-and-hold raw return where t=0 is the GC event day.

probability of bankruptcy. We also use firm leverage (LEV) to control for the potential influence of default risk on returns. Firms that have higher leverage are similarly expected to have a more negative stock market reaction to the GC announcement.

Going-concern audit reports are often associated with contemporaneous negative earnings surprises (e.g., Taffler, Lu and Kausar [2004]; KTT; Menon and Williams [2010]). We thus need to control for earnings expectations. We proxy earnings expectations by earnings change (CHEAR) in the 12-month period leading up to the GC announcement, and expect the coefficient on this variable to be positive. GC firms with positive earnings surprise are expected to have higher stock returns, and *vice versa* (Bernard and Thomas [1989]). Earnings change is defined as annual earnings change derived as $(EBITDA_t - EBITDA_{t-1})/|EBITDA_t|$, where t is the GC year. We also use return on assets (ROA) to control for return differences attributable to variation in the operating performance of our GC firms. We expect market reaction to be positively associated with financial performance.

Next, we proxy the information environment of our sample firms in terms of analyst coverage represented by the dummy variable ANALYST indicating whether the firm is followed by one or more analysts or not (=1 if number of analysts > 0; 0 otherwise). We expect a negative sign on the variable on the basis that analyst coverage is likely to be associated with greater market interest, and thus more rapid impounding of GC news into stock prices.

Prior research (DeAngelo [1981]; Francis and Krishnan [1999]) suggests that Big 4/5 auditors provide “higher quality” audits. On this basis, we speculate that issuance of a GC audit report by a quality auditor will be relatively more timely, and thus less expected. Therefore, we expect the sign on our AUDITOR (=1 if Big 4/5; 0 otherwise) variable to be negative.

Our final two control variables proxy for GC firm liquidity. Trading volume (TRVOL) is calculated as number of shares traded each day divided by number of shares in issue averaged over the six-month period (-126,-2) prior to the GC event date (t=0). We expect GC firms with higher TRVOL to be more liquid, and hence experience a more pronounced market reaction to the going-concern opinion. We also control for bid-ask spread (BIDASK) to take into account transaction costs. We expect higher transaction costs to be associated with a less negative market reaction to the GC event as selling costs will be greater. $\lambda_0,\ldots,\lambda_{12}$ are the regression parameter estimates, and u_i is a mean zero stochastic error term.

6.2 PRICE REACTION TESTS

Hypotheses H3 tests whether the greater the retail buying interest at the GC announcement date, the less negative the market reaction, and H4 whether the associated post-GC market response is more negative.

6.2.1 Small investor trades and short-term market reaction

Our starting off point here is that in untabulated results we find the short-term (-1,1) stock market reaction to the GC announcement to be significantly negative with mean (median) abnormal market reaction of -5% (-3%) (p=0.00 (p=0.00)). This result is consistent with prior literature (e.g., Menon and Williams [2010]). To assess how the market reaction to the bad news conveyed by the going-concern disclosure varies with the abnormal trading behavior of small investors, we start by comparing the stock market response to the GC event for firms with positive, and negative, abnormal small trade net-buy order imbalance on a univariate basis. Differences in individual firm characteristics are also examined. We then conduct multiple regression analysis to explore the relation between short-term market reaction to the GC event, and retail trading behavior in more detail, controlling for other factors. Based on hypothesis H3, our expectation is that GC firms with positive small trade abnormal net-buy order imbalance will experience a less negative market reaction to the GC announcement than firms where small investor abnormal sell dollar volume exceeds abnormal buy dollar volume.

Table 5 presents the differences in firm characteristics across firms with positive $NETIMBS_{AD}$, and firms with negative $NETIMBS_{AD}$. Consistent with our lottery stock argument the percentage of GC firms with small trade net-buy behavior is much greater than the percentage with net-sell behavior (63% v 37%). Panel A presents the differences in short-term market reaction, and trading statistics across the two sub-samples.[22] We observe a clear difference in the market reaction to the going-concern announcement between positive, and negative $NETIMBS_{AD}$ groups. For instance, negative $NETIMBS_{AD}$ firms suffer a mean BHAR(-1,1) of around -9.0% (p=0.00), whereas positive $NETIMBS_{AD}$ firms experience a mean BHAR(-1,1) of only -3.6% (p=0.00), with the 5.4% difference highly significant (p=0.00). Such findings are clearly consistent with retail investor attraction for GC stocks that are more lottery-like, for example, as demonstrated by the significant difference in mean (median) lottery index between positive and negative $NETIMBS_{AD}$ GC firms (p=0.00 (p=0.00)).[23] In parallel, positive $NETIMBS_{AD}$ stocks have a significantly higher small trade dollar-volume percentage (SM_TRADE_{AD}), and abnormal small trade dollar-volume percentage ($ABSM\_TRADE_{AD}$), than negative $NETIMBS_{AD}$ firms. This, again, serves to highlight their greater attraction for retail investors. Panel B of table 5 shows that the main differences in firm characteristics are that positive $NETIMBS_{AD}$ firms are smaller in size, have lower prior returns, lower stock prices, lower trading volume (mean only), higher bid-ask spreads (median only), and are more likely to delist. On the other hand, we do not observe any differences in such firm fundamentals as profitability, leverage, bankruptcy risk, and analyst coverage etc.

Table 6 examines the association between short-term market reaction, and retail investor behavior controlling for potential confounding factors using equation (1). The first regression model which excludes our key variable of interest ($NETIMBS_{AD}$) shows that other factors only account for about 3% of variation in stock returns around the GC

[22] To assess the robustness of our results, we also split our GC sample by median $NETIMBS_{AD}$. These results are very similar to those reported in the paper and are available from the authors upon request.
[23] In untabulated analysis, we find a significant positive correlation between $NETIMBS_{AD}$, and the lottery index across our GC firms. This is consistent with the more a GC stock has the characteristics of a lottery, the greater the propensity of retail investors to be net-buyers of these stocks.

announcement date. However, in the second regression where we introduce $NETIMBS_{AD}$ as an independent variable, its coefficient is positive and highly significant (0.25 (p=0.00)). This suggests that the greater the retail investor interest in GC stocks, the less negative the market reaction is at the GC date. Also, adjusted-R^2 increases from 2.5% to 6.5% suggesting that the abnormal trading behavior of small investors significantly influences the market reaction to GC news. That is, $NETIMBS_{AD}$ seems to be an important determinant of stock returns around the GC announcement date.

Overall, these results are consistent with our hypothesis H3 that small investors slow down the market reaction to the GC disclosure event because of their attraction for such lottery-type stocks. In the next sub-section, we test whether small investor abnormal trading behavior, which we have shown leads to market underreaction to the GC announcement event, also explains the documented post-GC drift.

6.2.2 Small trades and longer-term market response

KTT show that subsequent to the GC event month the prices of GC stocks continue to drift downwards over the following year. This they term the going-concern market anomaly. We first replicate and confirm the findings of KTT on our data. Our one-year (6-month) mean size and book-to-market control firm-adjusted GC firm BHARs of -19% (-13%), statistically significant at conventional levels, are very similar to those reported by KTT.[24] Parallel results are obtained using the Fama-French four-factor (Carhart [1997]) model. First-time GC audit report disclosures are followed by substantial negative abnormal returns, and this downward drift persists for, at least, up to one year after the GC announcement date.

To test whether the post-GC event downward drift in the stock prices of GC firms is driven by small investor abnormal buying behavior (H4), we form two portfolios based on positive, and negative, $NETIMBS_{AD}$ GC firms. We expect the underreaction anomaly

[24] Our buy-and-hold abnormal returns are somewhat more negative compared with KTT's -14% (-12%) because we cumulate returns from day +2 following the GC announcement date (t=0), whereas KTT cumulate returns from the beginning of the month following the GC month.

to be concentrated in those GC stocks where retail investors are making abnormal net purchases i.e., positive $NETIMBS_{AD}$ GC cases. In fact, in untabulated analysis, we find that positive $NETIMBS_{AD}$ GC firms have a mean one-year (6-month) BHAR of -28% (-21%) (p=0.00 (p=0.00)). In comparison, mean negative $NETIMBS_{AD}$ GC firm BHAR over the same period is only -2% (1%), which result is statistically insignificant (p=0.82 (p=0.88)). The difference in mean one-year (6-month) BHAR between the positive and negative $NETIMBS_{AD}$ GC firm portfolios is also statistically significant (p=0.03 (p=0.01)). Such results also hold in a multivariate setting.[25] Thus, it appears that the propensity for retail investors to be net-buyers of the stocks of GC firms also slows down the subsequent market reaction to the GC opinion, leading to significant downward drift in the prices of GC firms over the following year, as predicted by H4. We thus conclude that the going-concern market anomaly can be explained by retail investor attraction for going-concern stocks because of their lottery-like nature, and thus the opportunity they provide to "gamble in the market".

7. Small trades and socioeconomic factors

So far, we have shown that individual investors are net-buyers of GC stocks which leads to the slow assimilation of GC information into stock prices and an associated downward drift. We further argue that it is the lottery-like nature of GC stocks that attract retail investors to such stocks. In order words, we propose that it is the gambling-like behavior of individual investors which explains the market underreaction to GC news. An additional way of testing this proposition is to examine whether local gambling/risk attitudes influence the buying behavior of retail investors. Specifically, we investigate whether the retail preference for GC stocks varies with the socioeconomic characteristics of local investors. This conjecture is motivated by prior literature suggesting that people's risk-taking propensity in one setting predicts risky behavior in other settings (e.g., Kumar [2009]; Grinblatt and Keloharju [2009]). For example, Kumar [2009] demonstrates that socioeconomic factors that induce greater expenditure in lotteries are also associated with greater investment in lottery-type stocks. We exploit this argument, and relate the net

[25] Detailed empirical results are available from the authors on request.

abnormal buying behavior of small investors with local county level socioeconomic factors.

Hilary and Hui [2009] find that firms located in counties with higher levels of religiosity are more risk averse. McGuire, Omer, and Sharp [2012] also present results consistent with this idea. Further. Kumar [2009] demonstrates that socioeconomic factors such as being married or older renders an investor less likely to engage in gambling-like activities. On the other hand, if investors are male, or part of racial minority, then they are more likely to exhibit gambling-type behavior. We test these propositions by identifying the county where the GC firm is headquartered. We expect a negative relation between the net-buying behavior of small traders in GC stocks, and the percentage of the population in the county where the GC firm has its head office that is religious, older, and married. On the other hand, we expect a positive relation between small trader net-buying behavior if the area where the GC firm is headquartered has a higher proportion of its population that are male, or belong to minority groups.

To test these propositions directly, we regress small trader abnormal net-buy order imbalance around the GC date, $NETIMBS_{AD}$, separately against a number of different socioeconomic variables controlling for other factors that might affect retail investor trading activity. Our county-based socioeconomic variables are religiosity, defined as the total number of religious adherents in the county as a proportion of its total population (REL), male-female ratio (MALE), proportion of households with a married couple (MARRIED), median age (AGE), and minority population percentage (proportion of the county that is non-white) (MINORITY). Control variables are as in equation (1), but also include county education level (percentage of county residents above age 25 that has completed a bachelor's degree or higher) (EDU), natural log of county population (LNPOP), and average per capita income (PERCAP). Table 7 presents the regression results, and shows that retail investor abnormal buying behavior is significantly related with these socioeconomic factors as predicted. For example, religion, marriage, and age variables are negatively associated with $NETIMBS_{AD}$ (p=0.01 or better), and male and minority percentage figures are positively related to $NETIMBS_{AD}$ (p=0.02 or better).

Such results are consistent with Kumar's [2009] argument that socioeconomic factors help to drive the risk appetite of individual investors. Overall, these findings are supportive of the idea that the gambling-like proclivities of investors in GC firms drive the market reaction to GC news.

8. Alternative Explanations

We test for three potential alternative explanations to our main gambling story for the abnormal net-buying activity of small (retail) investors of GC stocks.

8.1 ATTENTION-GRABBING HYPOTHESIS

Barber and Odean [2008] argue that individual investors are more likely to buy rather than sell those stocks that catch their attention. This is based on the idea that such investors have to search through thousands of stocks when making stock purchase decisions. In contrast, when selling, they are restricted in choice to the few stocks they own. On this basis, individual investors will be more prone to buying attention-grabbing stocks, which simplifies their search task considerably, than to selling them. Whilst it is possible such an argument could explain the anomalous retail investor trading behavior observed in the case of GC firms, it is not very obvious that this would be the case. The general idea is that, in contrast to institutional investors who have access to the necessary technology to monitor stocks on a systematic basis, ,individual investors require a screening mechanism to reduce the number of stocks they need to consider to a manageable number.. Searching for stocks with lottery-like features might be a way for retail investors to decide on which stocks to buy. In fact, Kumar [2009] points out that as individual investors would most likely extrapolate past extreme returns into the future, it might be easier for such investors to discriminate stocks based on low prices, high idiosyncratic skewness, and high idiosyncratic volatility. Furthermore, studies suggest that media attention or press coverage may enhance stock market efficiency (e.g., Kothari et al. [2009]; Fang and Peress, [2009]; Bushee et al. [2010]). Therefore, *a priori*, it is not at all clear that an attention-grabbing story will hold for GC stocks.

To test this alternative news-attention explanation for our results we need a way of identifying attention-grabbing stocks. To do this we follow Barber and Odean [2008], and construct three observable measures that are likely associated with attention-grabbing events. The first proxies for media coverage (news), the second relates to abnormal trading volume, and our final measure extreme returns. We measure news disclosure over the 3-day GC announcement period (-1,1) where day 0 is the actual GC date. In particular, we search each GC stock in Factiva, and count the total number of news stories, ignoring replications, published during this 3-day period. Our media measure (MEDIA_MENTION) is then calculated as (1 + ln(number of media mentions)).[26] Our second attention-grabbing proxy (AV_{-2}), which is the abnormal volume on day -2, is defined as day -2 stock i trading volume divided by its mean daily trading volume over the previous one year (i.e., 252 trading days). Our final variable (RET_{-2}) is day -2 GC firm return.[27]

Table 8 reports the results of these tests. If the attention-grabbing story holds, then we expect a significant positive relation between $NETIMBS_{AD,}$ and our attention-grabbing proxies. As can be seen, results are not consistent with an attention-grabbing story. Two of our three news attention measures, AV_{-2} and RET_{-2} are insignificant.[28] Also, although our news coverage measure (MEDIA_MENTION) is significant, its sign is in the opposite direction to what the attention-grabbing hypothesis predicts, indicating an inverse relation between media mention, and small investor abnormal GC firm net-buying behavior. As such we find no support for the idea that attention-grabbing events trigger small investor interest in GC stocks.

[26] Seventy five percent of GC stocks are mentioned at least once have at least once around the GC event date.

[27] In untabulated tests, we also construct dummy variables for each of our attention-grabbing proxies. We set each dummy variable = 1 if a GC firm is ranked within the top quartile, and 0 otherwise. We also experiment with different event periods in computing abnormal volume, and extreme returns. In particular, instead of using day -2, we employ pre-event windows (-2,-1), (-3,-1), and (-5, -1). In all cases, results are similar to those reported in Table 8.

[28] The regression model includes past 6-month trading volume (TRVOL) as a control variable. However, excluding this variable has no impact on the AV_{-2} variable which remains statistically insignificant.

8.2 INVESTOR OVERCONFIDENCE

In this sub-section, we examine the possibility that the abnormal net-buying behavior of GC stocks by retail investors could be due to investor overconfidence rather than their gambling-driven attraction for lottery-type stocks. Prior research suggests that the higher level of valuation uncertainty associated with low priced stocks, or lottery-type stocks could induce greater overconfidence (e.g., Daniel, Hirshleifer, and Subramanyan, [1998], [2001]; Kumar, [2009]).

To test whether overconfidence might explain the trading behavior of small investors in our GC firm setting, we examine whether it is the more actively traded GC stocks that drive the buying behavior of retail investors. Prior research shows that overconfident investors tend to trade excessively (e.g., Barber and Odean [2000], [2001]), and that trading volume increases when investors are overconfident (e.g., Odean [1998]). Thus, in our first test we proxy investor overconfidence by trading volume. Under the overconfidence hypothesis we would expect a positive relation between trading volume, and the buying behavior of small investors. To test this proposition, we regress $\text{NETIMBS}_{\text{AD}}$ against our trading volume, and the same set of control variables as in equation 1. We define trading volume both as (i) normal trading volume, and (ii) abnormal trading volume. Normal trading volume is given by mean daily trading volume over the one-month period leading up to the GC date (-22,-2), and abnormal trading volume as normal trading volume divided by mean daily trading volume over the previous 11-month period (-252,-23). In untabulated analysis, we find an insignificant relation between GC stock trading volume, and the associated stock buying behavior of retail investors.[29] These results are not consistent with our investor overconfidence argument.

In a second test of our overconfidence hypothesis we use our discount brokerage house database to examine whether individual investors in GC stocks trade more actively than

[29] As a robustness test we also measure abnormal trading volume over periods (-62,-2), and (-124,-2). Again, there is no association between small investor GC firm net-buying behavior and trading volume.

those not holding any GC firms in their stock portfolios. In fact, we find that retail investors who invest in GC stocks during the 1993-1996 sample period actually trade less frequently than non-GC investors. This is consistent with Kumar [2009] who observes similar trading behavior by retail investors who buy lottery-type stocks. Once again, these results are not supportive of an investor overconfidence explanation for retail investor GC stock net-buying behavior.

8.3 NAÏVE INVESTOR HYPOTHESIS

Our gambling explanation for the GC anomaly suggests that small investors like GC stocks because of their lottery-like characteristics. A third alternative hypothesis might be that naïve (retail) investors select stocks on the basis of a single firm characteristic which happens to be correlated the with lottery-type features of GC stocks, resulting in the impression that small investors exhibit gambling-type behavior. Table 5 shows that negative $NETIMBS_{AD}$ GC firms are significantly smaller, have lower stock price, and also more negative prior returns compared to GC firms with positive $NETIMBS_{AD}$. We hypothesize that individual investors could select stocks based on firm size, stock price, or prior returns. To test this naïve investor-based explanation for our results, we explicitly control for each of these firm characteristics by adopting a matched-firm approach. Specifically, we separately match each negative $NETIMBS_{AD}$ GC firm with the positive $NETIMBS_{AD}$ GC firm which is closest to it in terms of size, stock price, or prior returns. We then run separate regressions of BHAR(-1,1) against each of these three variables, $NETIMBS_{AD}$, and our standard set of control variables as in equation (1), to test whether the difference in market reaction to the GC event between positive and negative $NETIMBS_{AD}$ GC firms can be explained by these variables. In untabulated tests we show that $NETIMBS_{AD}$ continues to be a significant determinant of abnormal returns around the GC event in all three regressions, although none of our three proxies for naïve investor behavior, firm size, stock price, and prior returns, is significant. On this basis we have no evidence consistent with a naïve investor hypothesis explanation for the GC anomaly.

Overall, in this section, we can find no alternative explanation for the market underreaction to the going-concern announcement to that of retail investor gambling behavior.

9. Conclusion

Kausar, Taffler, and Tan [2009] show that the market underreacts to the publication of the going-concern (GC) audit report for up to a year following its publication. However, they do not examine the market reaction to the GC announcement itself nor, more importantly, *why* the going-concern market anomaly exists. In this paper, we link the return predictability of going-concern stocks directly to retail investor gambling behavior (Kumar [2009]). First, we test whether going-concern stocks have lottery-like characteristics, and then whether retail investors are the main clientele of such stocks, and find them particularly attractive to invest in. Next, we explore whether, as we expect, the more interesting such stocks are to individual investors, as proxied by their net-buying behavior at the GC event, the less the market price falls on the announcement of going-concern uncertainties. Finally, we consider whether similar retail investor attraction to such stocks inhibits the impounding of the adverse consequences of the going-concern bad news disclosure into market prices in a timely manner leading to the documented downward post-GC drift. We also explore the influence of socioeconomic factors in determining the lottery-type behavior of retail investors and their investment in GC stocks. Finally, we test for alternative explanations to retail investor gambling for the existence of GC anomaly.

Using 1,214 first-time GC cases listed on NYSE, AMEX and NASDAQ from 1993 to 2007, we first demonstrate that our GC stocks have characteristics that are, in fact, very similar to the lottery-type stocks of Kumar [2009]. Kumar points out that if investors are searching for "cheap bets" they are likely to find low-priced, high idiosyncratic volatility, and high idiosyncratic skewness stocks very attractive, perceiving such stocks as akin to lottery tickets. Next, our results show that going-concern stocks are the domain of retail (small) investors who are the main holders of these stocks, and also responsible for most of their trades. There is a uniform propensity for small investor buy order dollar volume to materially exceed sell order dollar volume in these stocks at the going-concern event date, and subsequently in the one-year period following the publication of the GC opinion. Small investor buy propensity is significantly correlated with the lottery features of GC stocks.

We further show that firms with positive net-buy order imbalance of small trades experience significantly less negative market reaction to the GC announcement. This result is consistent with the idea that speculative buying of the stocks of these firms by retail investors ameliorates the negative market reaction to the GC bad news event in a major way. Moreover, we examine whether such retail investor trading propensity can explain the going-concern market anomaly; our evidence is consistent with such an explanation for this market-pricing paradox. The more positive the net-buy (buy minus sell) abnormal dollar volume order imbalance of small trades (proxying for retail investor trading behavior) at the GC event date, the more negative is the longer-term market response following the publication of the GC audit report.

Our test of the association between retail investors' GC firm stock buying behavior, and their socioeconomic characteristics, further confirm our gambling story. We find that retail investor attraction to going-concern stocks is significantly related to local investor socioeconomic characteristics,, such as county level religiosity, gender breakdown, percentage married, minority status, and average age, as predicted. Importantly, this result is consistent with the growing literature that suggests socioeconomic factors can explain investor risk preferences (e.g., Hilary and Hui [2009]; Kumar [2009]; Kumar, Page, and Spalt [2011]; McGuire, Omer, and Sharp [2012]).

Finally, we are unable to find empirical support for competing explanations to our retail investor gambling hypothesis for the going-concern anomaly, such as attention-grabbing, investor overconfidence, and the naïve investor hypothesis. We conclude that the anomalous pricing of GC stocks can be explained by retail investor buying and selling activity which is akin to "gambling in the market" (Kumar [2009]).

Our results may also be of interest to regulators and standard-setters. Prior research demonstrates the inability of retail investors to even process publicly available information appropriately (e.g., Battalio and Mendenhall [2005]; Bhattacharya et al. [2007]; Miller [2010]; Ayers, Li, and Yeung [2011]). In our GC context, enhanced accounting disclosures, such as those in FASB's [2008] Proposed Statement of Financial Accounting Standards on Going Concern, may have little impact on the appropriate pricing of going-concern firms. This is because retail investors are the price setters of such stocks and, as we have shown in this paper, unable to respond to the unambiguous bad news signal conveyed by the GC opinion in a rational manner. We speculate that such issues may equally pertain in other accounting disclosure environments where retail traders constitute the main investor clientele leading to trades taking place at prices inconsistent with fundamental value. Our findings suggest that retail trading behavior may be an important determinant of how markets react to adverse accounting news more generally.

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TABLE 1

Data Summary Statistics

Variable	Mean	Median	Std. Dev.
SIZE	53.26	16.86	239.09
BM	0.43	0.31	1.49
PRRET	-0.28	-0.38	0.52
Z	-1.51	-0.45	5.64
LEV	0.69	0.66	0.45
CHEAR	-0.16	-0.23	1.50
ROA	-0.75	-0.47	0.90
PRICE	2.64	1.50	4.11
ANALYST	0.29	0.00	NA
AUDITOR	0.72	1.00	NA
TRVOL	161.69	93.36	215.30
BIDASK	8.25	6.04	8.24
DELIST	0.45	0.00	NA

This table presents summary statistics relating to our population of 1,214 nonfinance, nonutility industry firms listed on NYSE, AMEX or NASDAQ receiving first-time going-concern audit reports between January 1, 1993 and December 31, 2007. SIZE = market value measured by market capitalization in $ million one month before the GC event date, BM = book-to-market ratio, PRRET = 6-month holding period raw returns leading up to the GC announcement (-126, -2), where t=0 is the GC publication date, Z = financial distress z-score (Altman [1968]), LEV = leverage proxy defined as total liabilities/total assets, CHEAR = annual earnings change derived as $(EBITDA_t – EBITDA_{t-1})/|EBITDA_t|$, where t denotes the GC year, ROA = return on assets (net income/total assets), PRICE = stock price in $ as one month before the GC announcement date, ANALYST = analyst coverage dummy (1 if number of analysts issuing earnings forecasts on IBES > 0; 0 otherwise), AUDITOR = audit quality proxy dummy (1 if Big 4/5; 0 otherwise), TRVOL = daily equity trading volume expressed as the number of shares traded in the 6-month period leading up to the GC date as a percentage of the numbers of shares in issue (reported on an annual basis), BIDASK = daily bid-ask spread as a percentage of stock price averaged over the 6-month period leading up to the GC date, and DELIST = delist dummy (1 if the firm is delisted within one year of the audit report date; 0 otherwise).

TABLE 2

GC firms as lottery-type stocks

Panel A: Means

	GC firms			CRSP stocks		
Stock characteristic	**Prior 12 months**	**Day=-2**	**Post 12 months**	**Lottery**	**Nonlottery**	**Other**
Lottery Index	0.28	0.24	0.21	0.24	0.79	0.54
Stock Price	$3.87	$2.35	$2.12	$4.50	$31.14	$17.68
Total Skewness	0.69	0.88	0.95	1.18	-0.20	0.31
Systematic Skewness	-10.44	-8.39	-9.18	-13.72	-3.47	-7.69
Idiosyncratic Skewness	0.68	0.87	0.94	1.21	-0.25	0.35
Total Volatility	0.07	0.09	0.10	0.06	0.02	0.04
Idiosyncratic Volatility	0.07	0.08	0.10	0.06	0.02	0.03
Market Beta	0.81	0.63	0.75	0.85	0.88	0.90
Firm Size	72.01	39.60	36.48	105.26	3404.45	1109.51
SMB Beta	0.88	0.97	0.83	0.90	0.45	0.75
Book-To-Market	0.67	1.11	0.53	0.64	0.57	0.63
HML Beta	0.25	0.19	0.37	0.19	0.28	0.18
Percentage Without Analyst Coverage	0.76	0.67	0.59	0.53	0.17	0.29
Mean Number of Analysts	2.00	2.00	2.60	3.42	8.42	5.90

Panel B: Medians

Stock characteristic	GC firms: Prior 12 months	GC firms: Day=-2	GC firms: Post 12 months	CRSP stocks: Lottery	CRSP stocks: Nonlottery	CRSP stocks: Other
Lottery Index	0.25	0.22	0.18	0.23	0.80	0.53
Stock Price	$2.58	$1.37	$1.06	$3.50	$26.19	$12.99
Total Skewness	0.63	0.71	0.81	0.90	-0.04	0.30
Systematic Skewness	-6.31	-6.70	-7.31	-8.80	-0.99	-3.64
Idiosyncratic Skewness	0.63	0.69	0.80	0.92	-0.05	0.35
Total Volatility	0.07	0.08	0.10	0.06	0.02	0.03
Idiosyncratic Volatility	0.07	0.08	0.09	0.05	0.02	0.03
Market Beta	0.79	0.63	0.62	0.78	0.88	0.86
Firm Size	27.91	15.23	11.57	34.54	687.41	155.69
SMB Beta	0.79	0.86	0.72	0.84	0.40	0.65
Book-To-Market	0.52	0.80	0.46	0.48	0.52	0.52
HML Beta	0.27	0.22	0.34	0.20	0.30	0.22
Percentage Without Analyst Coverage	0.76	0.67	0.59	0.53	0.17	0.29
Median Number of Analysts	1.00	1.00	2.00	2.00	7.00	4.00

This table presents mean (median) lottery-stock type characteristics for our population of 1,214 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ that published a GC opinion for the first-time between January 1, 1993 and December 31, 2007. For comparison we also report the equivalent mean and median characteristics of CRSP stocks classified as lottery stocks, nonlottery stocks and other. All variables are computed as in Kumar (2009) or Han and Kumar (2013) using data from 1993 to 2007. Kumar defines lottery-type stocks as those stocks that are in intersection set of lowest 50^{th} stock price percentile, highest 50^{th} idiosyncratic skewness percentile, and highest 50^{th} idiosyncratic volatility percentile firms. Nonlottery stocks are those stocks that are in the intersection set of highest 50^{th} stock price percentile, the lowest 50^{th} idiosyncratic skewness percentile, and the lowest 50^{th} idiosyncratic volatility percentile firms. Other stocks are those that neither fall in the lottery stock category nor in the nonlottery stock category. Panel A present the means while panel B the medians. Lottery Index is defined as in Han and Kumar (2013) as the sum of the vigintile assignments based on stock price, idiosyncratic skewness, and idiosyncratic volatility measures, divided by 60. Stock Price is the stock price, Total Volatility is the standard deviation of daily stock returns, Idiosyncratic Volatility is standard deviation of the residual from a four-factor model, Total Skewness measures the third moment of daily stock returns, Idiosyncratic Skewness measures third moment of the residual obtained by fitting a two-factor model, Systematic Skewness is the coefficient of the squared market factor in the skewness regression, Firm Size is the market capitalization (price × shares outstanding), Book-To-Market ratio is book-value of equity divided by the market capitalization of the firm. Market, SMB, and HML Betas are the loadings on RMRF, SMB, and HML factors in a three-factor model respectively. Percentage Without Analyst Coverage is the proportion of firms without analyst coverage, and Number of Analysts is the number of analysts providing earnings estimates for the stock as reported in I/B/E/S at any time during the 12 months prior to the GC announcement, 3 months prior to the GC announcement, and 12 months post-GC, respectively. Market measures are computed using data for the prior 6-month period.

TABLE 3

First-time going-concern audit report institutional, insider, and retail investor holding patterns

	Quarter								
	-4	-3	-2	-1	0	1	2	3	4
Institutional									
Mean (%)	16.9	16.8	15.5	14.7	13.2	11.5	10.2	9.9	9.6
p-value					0.00				0.00
Median (%)	8.4	8.8	7.4	7.4	5.9	4.0	2.6	1.9	1.5
p-value					0.00				0.00
Insider									
Mean (%)	17.6	17.8	18.2	18.2	18.9	19.5	19.9	20.6	20.7
p-value					0.00				0.00
Median (%)	10.0	10.5	10.7	10.8	11.3	11.8	11.9	12.2	11.9
p-value					0.04				0.12
Retail (by deduction)									
Mean (%)	65.6	65.6	66.5	67.2	68.2	69.4	70.5	70.2	70.4
p-value					0.00				0.00
Median (%)	71.4	71.1	72.5	73.1	75.0	76.3	78.6	78.9	80.0
p-value					0.00				0.00

This table presents mean and median percentage institutional, insider, and, by deduction, retail holding patterns for our 1,214 first-time going-concern audit report (GC) nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ with such audit opinions published between January 1, 1993 and December 31, 2007. Results for 9 quarters are provided, four quarters prior to the GC quarter, four quarters subsequent to, and the GC quarter itself (0). p-values reported shows the statistical significance of annual change in holdings i.e., from quarter -4 to quarter 0, and from quarter 0 to quarter 4. Retail holding, and trading percentages are calculated by subtracting the respective institutional plus insider percentages for those stocks where the relevant percentage figures are available from 100%.

TABLE 4

Trading statistics

Panel A: Small investors' trading activity at the GC/10-K event date (t= -1, 1)

Variable	GC Firms Mean	GC Firms p-value	GC Firms Median	GC Firms p-value	Control Firms Mean	Control Firms p-value	Control Firms Median	Control Firms p-value	Mean difference p-value	Median difference p-value
$NETIMBS_{AD}$	0.038	0.00	0.027	0.00	0.017	0.00	0.002	0.43	0.00	0.00
SM_TRADE_{AD}	0.652	0.00	0.693	0.00	0.476	0.00	0.438	0.00	0.00	0.00
$ABSM\_TRADE_{AD}$	0.116	0.00	0.109	0.00	0.017	0.02	0.005	0.18	0.00	0.00

Panel B: Large investors' trading statistics at the GC/10-K event date (t= -1, 1)

Variable*	GC Firms Mean	GC Firms p-value			Control Firms Mean	Control Firms p-value			Mean difference p-value	
$NETIMBL_{AD}$	-0.010	0.02			-0.004	0.28			0.08	
LG_TRADE_{AD}	0.042	0.00			0.094	0.00			0.00	
$ABLG\_TRADE_{AD}$	-0.028	0.00			0.002	0.41			0.00	

TABLE 4 (Cont.)

Variable	GC Firms Mean	GC Firms p-value	GC Firms Median	GC Firms p-value	Control Firms Mean	Control Firms p-value	Control Firms Median	Control Firms p-value	Mean difference p-value	Median difference p-value
Panel C: Small investors' trading activity in the year following the GC/10-K announcement										
NETIMBS$_{PAP}$	0.067	0.00	0.046	0.00	0.020	0.00	0.003	0.39	0.00	0.00
SM_TRADE$_{PAP}$	0.680	0.00	0.734	0.00	0.497	0.00	0.488	0.00	0.00	0.00
ABSM_TRADE$_{PAP}$	0.144	0.00	0.139	0.00	0.037	0.00	0.034	0.00	0.00	0.00
Panel D: Large investors' trading activity in the year following the GC/10-K announcement										
Variable*	Mean	p-value			Mean	p-value				
NETIMBL$_{PAP}$	-0.009	0.00			-0.003	0.33			0.06	
LG_TRADE$_{PAP}$	0.041	0.00			0.092	0.00			0.00	
ABLG_TRADE$_{PAP}$	-0.029	0.00			0.000	0.99			0.00	

This table presents mean and median statistics relating to the trades of small and large investors in GC firms and control firms at, and subsequent to, the GC or 10-K announcement date. The population of firms covered consists of the 1,047 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which published a going-concern audit report (GC) for the first time between January 1, 1993 and December 31, 2003. Control firms consists of the 1,047 non-GC, nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which are individually matched with the GC firms on the basis of size and book-to-market. NETIMBS = net small trade order imbalance derived as daily average abnormal imbalance of small trades (<= $5,000), and computed as net-buy volume of small investors over the period of interest minus the non-announcement period net-buy volume scaled by non-announcement period total volume, SM_TRADE = percentage of small trades given by daily average percentage of small trades to total trades over the period of interest, ABSM_TRADE = abnormal percentage of small trades calculated as daily average percentage of small trades over the period of interest minus the non-announcement period daily average percentage of small trades to total trades, NETIMBL = net large trade order imbalance derived as daily average abnormal net imbalance of large trades (> $50,000), and computed as net-buy volume of large investors over the period of interest minus the non-announcement period net-buy volume scaled by non-announcement period total volume, LG_TRADE = percentage of large trades given by daily average percentage of large trades to total trades over the period of interest, and ABLG_TRADE = abnormal percentage of large trades calculated as daily average percentage of large trades to total trades over the period of interest minus non-announcement period daily average percentage of large trades to total trades. Subscript AD = announcement date i.e., the 3-day period (-1, 1) centered on the GC report day (t=0), and subscript PAP = post-announcement period defined as the one-year period following the GC event (2, 252), where t=0 is the GC event date. Non-announcement period is (-252, -22). *The median GC firm has no large trades at, and subsequent to, the GC period. Thus it is not meaningful to report median figures.

TABLE 5

Univariate tests of differences in stock market reaction, trading statistics, and firm characteristics conditional on negative and positive abnormal net-buy small trade order imbalance

Panel A: Differences in short-term market reaction, and trading statistics around the GC event

	Positive $NETIMBS_{AD}$ (N=663)		Negative $NETIMBS_{AD}$ (N=384)		Difference	
	Mean	Median	Mean	Median	Mean p-value	Median p-value
BHAR(-1,1)	-0.036	-0.020	-0.090	-0.066	0.00	0.00
LOTTINDEX	0.224	0.200	0.255	0.240	0.00	0.00
$NETIMBS_{AD}$	0.120	0.079	-0.104	-0.048	0.00	0.00
SM_TRADE_{AD}	0.689	0.759	0.591	0.621	0.00	0.00
$ABSM\_TRADE_{AD}$	0.142	0.144	0.075	0.077	0.00	0.00
$NETIMBL_{AD}$	-0.012		-0.006		0.63	
LG_TRADE_{AD}	0.034		0.054		0.00	
$ABLG\_TRADE_{AD}$	-0.028		-0.030		0.72	

Panel B: Differences in firm characteristics

	Positive $NETIMBS_{AD}$ (N=663)		Negative $NETIMBS_{AD}$ (N=384)		Difference	
Variable	Mean	Median	Mean	Median	Mean p-value	Median p-value
SIZE	29.014	12.359	59.414	22.178	0.00	0.00
BM	0.438	0.308	0.435	0.301	0.97	0.95
PRRET	-0.361	-0.460	-0.216	-0.282	0.00	0.00
Z	-1.771	-0.636	-1.151	-0.451	0.15	0.11
LEV	0.696	0.668	0.700	0.658	0.86	0.92
CHEAR	-0.168	-0.234	-0.119	-0.265	0.62	0.93
ROA	-0.795	-0.489	-0.695	-0.463	0.11	0.14
PRICE	2.068	1.313	2.975	1.694	0.00	0.00
ANALYST	0.255	0.000	0.299	0.000	0.12	0.12
AUDITOR	0.728	1.000	0.789	1.000	0.03	0.03
TRVOL	1.414	0.921	1.747	0.981	0.01	0.42
BIDASK	0.093	0.074	0.093	0.062	0.92	0.02
DELIST	0.498	0.000	0.414	0.000	0.02	0.02

This table presents tests of differences in stock market reaction, trading statistics, and firm characteristics between firms with positive, and negative small trade net-order imbalance at the GC date for our population of 1,214 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which published a going-concern audit report (GC) for the first time between January 1, 1993 and December 31, 2003. BHAR(-1,1) is the 3-day size and book-to-market control firm adjusted buy-and-hold abnormal return centered on the GC date (t=0), LOTTINDEX (lottery index) is defined as in Han and Kumar (2013) as the sum of vigintile assignments based on stock price, idiosyncratic skewness, and idiosyncratic volatility measures, divided by 60, NETIMBS = net small trade order imbalance derived as daily average abnormal imbalance of small trades (<= $5,000), and computed as net-buy volume of small investors over the period of interest minus the non-announcement period net-buy volume scaled by non-announcement period total volume, SM_TRADE = percentage of small trades given by daily average percentage of small trades to total trades over the period of interest, ABSM_TRADE = abnormal percentage of small trades calculated as daily average percentage of small trades over the period of interest minus the non-announcement period daily average percentage of small trades to total trades, NETIMBL = net large trade order imbalance derived as daily average abnormal net imbalance of large trades (> $50,000), and computed as net-buy volume of large investors over the period of interest minus the non-announcement period net-buy volume scaled by non-announcement period total volume, LG_TRADE = percentage of large trades given by daily average percentage of large trades to total trades over the period of interest, and ABLG_TRADE = abnormal percentage of large trades calculated as daily average percentage of large trades to total trades over the period of interest minus non-announcement period daily average percentage of large trades to total trades. Subscript AD = announcement date i.e., the 3-day period (-1,1) centered on the GC report day (t=0). Non-announcement period is (-252,-22). The median GC firm has no large trades at, and subsequent to, the GC period. Thus it is not meaningful to report medians for $NETIMBL_{AD}$, LG_TRADE_{AD}, and $ABLG\_TRADE_{AD}$. SIZE = market value measured by market capitalization in $ million one month before the GC event date, BM = book-to-market ratio, PRRET = 6-month holding period raw returns leading up to the GC announcement (-126,-2), where t=0 is the GC publication date, Z = financial distress z-score (Altman [1968]), LEV = leverage proxy defined as total liabilities/total assets, CHEAR = annual earnings change derived as $(EBITDA_t - EBITDA_{t-1})/|EBITDA_t|$, where t denotes the GC year, ROA = return on assets (net income/total assets), PRICE = stock price in $ one month before the GC announcement date, ANALYST = analyst coverage dummy (1 if number of analysts issuing earnings forecasts on IBES > 0; 0 otherwise), AUDITOR = audit quality proxy dummy (1 if Big 4/5; 0 otherwise), TRVOL = daily equity trading volume expressed as the number of shares traded in the 6-month period leading up to the GC date as a percentage of the numbers of shares in issue (reported on an annual basis), BIDASK = daily bid-ask spread as a percentage of stock price averaged over the 6-month period leading up to the GC date, and DELIST = delist dummy (1 if the firm is delisted within one year of the audit report date; 0 otherwise).

TABLE 6

Multivariate analysis of short-term market returns and small trader abnormal net-buy order imbalance

Dependent Variable		BHAR(-1,1)		BHAR(-1,1)	
Independent Variables	Prediction	Coeff.	p-value	Coeff.	p-value
$NETIMBS_{AD}$	+			0.253	0.000
LNSIZE	?	-0.017	0.012	-0.012	0.061
BM	+	0.001	0.833	0.002	0.713
PRRET	+	0.015	0.235	0.022	0.080
Z	+	0.000	0.808	0.001	0.693
LEV	-	0.000	0.996	0.001	0.974
CHEAR	+	0.012	0.007	0.013	0.003
ROA	+	-0.002	0.849	-0.002	0.872
ANALYST	-	0.002	0.884	0.008	0.648
AUDITOR	-	-0.033	0.046	-0.029	0.068
TRVOL	-	-0.001	0.839	0.000	0.992
BIDASK	+	0.065	0.491	0.079	0.392
INTERCEPT		0.019	0.529	-0.008	0.773
F significance (p-value)		0.00		0.00	
Adjusted R-squared		0.025		0.065	
No of cases		1,047		1,047	

This table presents the results of regressing GC announcement date abnormal returns on small investor abnormal net-buy volume ($NETIMBS_{AD}$), and control variables for our population of 1,047 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which published a going-concern audit report for the first time between January 1, 1993 and December 31, 2003. p-values are computed using robust standard errors. $NETIMBS_{AD}$ = net small trade order imbalance derived as daily average abnormal imbalance of small trades (<= $5,000), and computed as net-buy volume of small investors at the announcement date (-1,1) minus the non-announcement period net-buy volume scaled by non-announcement period total dollar volume, LNSIZE = natural log of market value measured by market capitalization in $ million one month before the GC event date, BM = book-to-market ratio, PRRET = 6-month holding period raw returns leading up to the GC announcement (-126, -2), where t=0 is the GC publication date, Z = financial distress z-score (Altman [1968]), LEV = leverage proxy defined as total liabilities/total assets, CHEAR = annual earnings change derived as $(EBITDA_t – EBITDA_{t-1})/|EBITDA_t|$, where t denotes the GC year, ROA = return on assets (net income/total assets), ANALYST = analyst coverage dummy (1 if number of analysts issuing earnings forecasts on IBES > 0; 0 otherwise), AUDITOR = audit quality proxy dummy (1 if Big 4/5; 0 otherwise), TRVOL = daily equity trading volume expressed as the number of shares traded in the 6-month period leading up to the GC date as a percentage of the numbers of shares in issue (reported on an annual basis), and BIDASK = daily bid-ask spread as a percentage of stock price averaged over the 6-month period leading up to the GC date.

TABLE 7

GC firm small investor abnormal trading behavior and socioeconomic factors

		$NETIMBS_{AD}$		$NETIMBS_{AD}$		$NETIMBS_{AD}$		$NETIMBS_{AD}$		$NETIMBS_{AD}$	
Independent Variables	Prediction	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
REL	-	-0.159	0.000								
MALE	+			0.367	0.008						
MARRIED	-					-0.168	0.007				
AGE	-							-0.007	0.002		
MINORITY	+									0.107	0.014
EDU		0.001	0.353	0.000	0.952	0.000	0.757	0.000	0.736	0.000	0.875
LNPOP		0.000	0.989	-0.007	0.505	-0.002	0.821	-0.008	0.396	-0.012	0.247
PERCAP		-0.049	0.817	-0.117	0.580	0.009	0.967	-0.108	0.609	-0.106	0.616
LNSIZE		-0.016	0.003	-0.015	0.005	-0.015	0.006	-0.015	0.006	-0.015	0.005
BM		-0.010	0.029	-0.008	0.078	-0.010	0.037	-0.008	0.092	-0.009	0.051
PRRET		-0.040	0.000	-0.040	0.000	-0.039	0.000	-0.040	0.000	-0.039	0.000
Z		0.001	0.512	0.001	0.557	0.001	0.697	0.000	0.788	0.001	0.541
LEV		0.043	0.050	0.042	0.059	0.038	0.089	0.037	0.092	0.042	0.061
CHEAR		-0.008	0.019	-0.008	0.023	-0.008	0.024	-0.008	0.023	-0.007	0.034
ROA		-0.005	0.624	-0.007	0.482	-0.005	0.592	-0.007	0.449	-0.006	0.551
ANALYST		-0.020	0.131	-0.020	0.131	-0.020	0.127	-0.018	0.169	-0.020	0.133
AUDITOR		-0.011	0.365	-0.013	0.294	-0.009	0.456	-0.013	0.307	-0.011	0.370
TRVOL		0.001	0.686	0.001	0.854	0.001	0.773	0.001	0.754	0.000	0.865
BIDASK		0.018	0.825	0.012	0.887	-0.004	0.962	-0.015	0.858	0.011	0.893
INTERCEPT		0.112	0.435	-0.210	0.243	0.169	0.252	0.390	0.027	0.191	0.205
Adj. R-Squared			0.051		0.045		0.046		0.048		0.045
Model Significance (p-			0.000		0.000		0.000		0.000		0.000

value)

This table presents the results of regressing GC announcement date abnormal net-buy volume ($NETIMBS_{AD}$) on state socioeconomic factors, and control variables for our population of 1,047 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which published a going-concern audit report for the first time between January 1, 1993 and December 31, 2003. p-values are computed using robust standard errors. $NETIMBS_{AD}$ = net small trade order imbalance derived as daily average abnormal imbalance of small trades (<= $5,000), and computed as net-buy volume of small investors at the announcement date (-1,1) minus the non-announcement period net-buy volume scaled by non-announcement period total dollar volume, REL = religiosity of the county defined as the total number of religious adherents in the county as a proportion of the total population in the county, MALE = male-female ratio in the county, MARRIED = the proportion of households in the county with a married couple, AGE = the median age of the county, MINORITY = the proportion of the county population that is non-white, EDU = proportion of the county population above age 25 that has completed a bachelor's degree or higher, LNPOP = natural log of the total population of the county, PERCAP = average per capita income of county residents, LNSIZE = natural log of market value measured by market capitalization in $ million one month before the GC event date, BM = book-to-market ratio, PRRET = 6-month holding period raw returns leading up to the GC announcement (-126, -2), where t=0 is the GC publication date, Z = financial distress z-score (Altman [1968]), LEV = leverage proxy defined as total liabilities/total assets, CHEAR = annual earnings change derived as ($EBITDA_t$ – $EBITDA_{t-1}$)/|$EBITDA_t$|, where t denotes the GC year, ROA = return on assets (net income/total assets), ANALYST = analyst coverage dummy (1 if number of analysts issuing earnings forecasts on IBES > 0; 0 otherwise), AUDITOR = audit quality proxy dummy (1 if Big 4/5; 0 otherwise), TRVOL = daily equity trading volume expressed as the number of shares traded in the 6-month period leading up to the GC date as a percentage of the numbers of shares in issue (reported on an annual basis), and BIDASK = daily bid-ask spread as a percentage of stock price averaged over the 6-month period leading up to the GC date.

TABLE 8
Attention-grabbing regressions

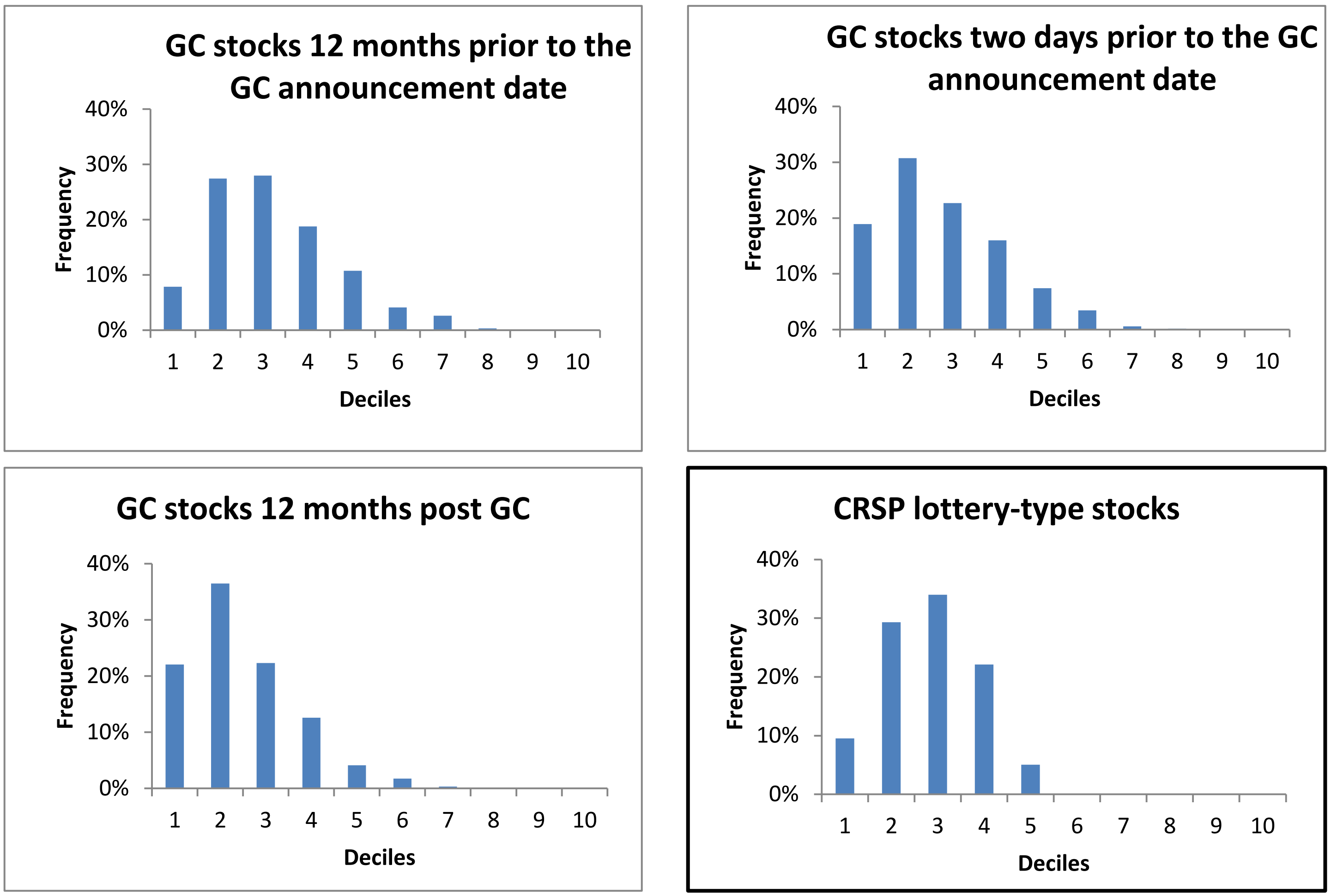
Dependent Variable		NETIMBS(-1,1)		NETIMBS(-1,1)		NETIMBS(-1,1)	
Independent Variables	Prediction	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
MEDIA_MENTION	+	-0.007	0.072				
AV_{-2}	+			0.003	0.381		
RET_{-2}	+					0.042	0.308
LNSIZE		-0.015	0.013	-0.017	0.006	-0.016	0.006
BM		-0.005	0.221	-0.005	0.237	-0.005	0.222
PRRET		-0.030	0.005	-0.031	0.004	-0.030	0.005
Z		-0.001	0.481	-0.001	0.487	-0.001	0.466
LEV		0.003	0.841	0.001	0.972	0.000	0.983
CHEAR		-0.003	0.396	-0.003	0.432	-0.003	0.434
ROA		0.002	0.819	0.001	0.878	0.002	0.806

ANALYST	-0.021	0.155	-0.021	0.155	-0.021	0.161
AUDITOR	-0.019	0.166	-0.018	0.194	-0.019	0.179
TRVOL	-0.002	0.433	-0.002	0.437	-0.002	0.427
BIDASK	-0.032	0.717	-0.031	0.727	-0.032	0.718
INTERCEPT	0.106	0.000	0.098	0.000	0.103	0.000
Model Significance (p-value)	0.000		0.000		0.000	
Adj-R-Squared	0.035		0.032		0.032	

This table presents the results of regressing GC announcement date abnormal net-buy volume (NETIMBS) on attention-grabbing proxies, and control variables for our population of 1,047 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which published a going-concern audit report for the first time between January 1, 1993 and December 31, 2003. p-values are computed using robust standard errors. NETIMBS(-1,1) = net small trade order imbalance derived as daily average abnormal imbalance of small trades (<= $5,000), and computed as net-buy volume of small investors at the announcement date (-1,1) minus the non-announcement period net-buy volume scaled by non-announcement period total dollar volume, MEDIA_MENTION is the natural log of one plus the number of times the firm is mentioned in the media at the GC announcement date (-1,1), AV_{-2} = abnormal volume at day t=-2 relative to the GC announcement date (t=0), where abnormal volume is measured at the trading volume at day t=-2 divided by the average daily trading volume over the prior 12 months (252 days), RET_{-2} is GC firms returns on day t=-2, LNSIZE = natural log of market value measured by market capitalization in $ million one month before the GC event date, BM = book-to-market ratio, PRRET = 6-month holding period raw returns leading up to the GC announcement (-126,-2), where t=0 is the GC publication date, Z = financial distress z-score (Altman [1968]), LEV = leverage proxy defined as total liabilities/total assets, CHEAR = annual earnings change derived as $(EBITDA_t – EBITDA_{t-1})/|EBITDA_t|$, where t denotes the GC year, ROA = return on assets (net income/total assets), ANALYST = analyst coverage dummy (1 if number of analysts issuing earnings forecasts on IBES > 0; 0 otherwise), AUDITOR = audit quality proxy dummy (1 if Big 4/5; 0 otherwise), TRVOL = daily equity trading volume expressed as the number of shares traded in the 6-month period leading up to the GC date as a percentage of the numbers of shares in issue (reported on an annual basis), and BIDASK = daily bid-ask spread as a percentage of stock price averaged over the 6-month period leading up to the GC date.

FIGURE 1

Lottery index distribution of GC stocks compared with CRSP lottery-type stocks



This figure presents the lottery index distribution of GC firms averaged over the 12-month period prior to, two days before, and averaged over the 12-month period post GC announcement date for our population of 1,214 nonfinance, nonutility industry firms listed on the NYSE, AMEX or NASDAQ which published a going-concern audit report for the first time between January 1, 1993 and December 31, 2007 compared with the lottery index distribution for stocks classified as lottery-like in the CRSP population. The lottery index measure used is defined as in Han and Kumar (2013) as the sum of the vigintile assignments based on stock price, idiosyncratic skewness, and idiosyncratic volatility measures, divided by 60.