How useful are auditors' going concern opinions as predictors of default?

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Abstract

A landmark study by Hopwood, McKeown, and Mutchler (1994) demonstrates that auditors' going concern opinions (GCO) are just as good predictors of bankruptcy as a statistical model based on key accounting ratios. Regulatory and economic conditions, default prediction models, and available data have evolved since the 1990's, while the usefulness of GCOs continues to be questioned. We examine whether GCOs are better predictors of defaults, including bankruptcies, than *ex ante* statistical models of probability of default (PD), based on a comprehensive set of accounting, market, and macroeconomic variables available at the opinion's date. We demonstrate that GCOs and the PDs *independently* have similar overall predictive accuracy. Nevertheless, GCOs and PDs do not have perfect overlap. Using GCOs and the PDs *combined* results in small, although statistically significant, incremental predictive accuracy. We also compare GCOs against changes in public credit ratings and find that GCOs have statistically greater predictive power. Our findings highlight that GCOs impound public information and an incrementally predictive component. Thus, GCOs constitute a useful signal for investors. However, there is an area of opportunity in implementing data-driven and comprehensive statistical models as part of routine going concern assessments.

Keywords: audit quality; bankruptcy; credit ratings; going concern opinions; predictive accuracy.

Data Availability: Data is obtainable from the sources described in the text and is available upon request.

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1. INTRODUCTION

Under U.S. audit standards, the auditor is required to evaluate the going concern assumption. The existing standards rely on principles to guide the auditor's interpretation of what constitutes a going concern issue and when the client's financial condition warrants a going concern opinion (GCO). The auditor's evaluation is based on his or her knowledge of relevant conditions and events that *exist at or have occurred prior to the date of the auditor's report* (AICPA Statement on Auditing Standards 341, formerly SAS No. 59 AICPA 1988). We examine the usefulness of the auditor's GCO as an indicator of a client's probability of default (i.e., bankruptcy and market delisting followed by bankruptcy). Seminal research on this topic produced mixed results. Early studies documented that statistical models using financial ratios –such as return on assets, liquidity, and leverage ratios- were superior to GCOs as predictors of bankruptcy (Altman and McGough 1974; Altman 1982; Levitan and Knoblett 1985; Koh 1991). However, a landmark study by Hopwood, McKeown, and Mutchler (1994) examined bankruptcy data from 1975 to 1985 and overturned the previous inferences, demonstrating that GCOs were as good as a statistical model in predicting bankruptcy.[1]

Several conditions have changed since the publication of Hopwood et al. (1994) and earlier related studies. First, the past 20 years have witnessed a significant evolution in the auditors' regulatory landscape and changes to the economic environment (e.g., the passage of the Private Securities Litigation Reform Act of 1995 and the Sarbanes-Oxley Act of 2002; the creation of the Public Company Accounting Oversight Board in 2002; and, two stock market crises in 2002-2003

[1] The Hopwood et al. (1994) study examined 134 bankrupt firms and 160 non-bankrupt firms. This study's statistical prediction model is based on six key financial ratios and firm size. The two main takeaways are that inferences in previous studies were attributable to using (a) non-representative samples, with 50 percent bankrupt and 50 percent non-bankrupt companies; and, (b) mixed samples with both distressed and non-distressed companies. This study is a widely used methodological reference to focus on distress companies for GCO research and has been cited over 360 times.

and 2007-2008).[2] Second, the literature on default prediction has proposed increasingly powerful models and there are new computational techniques to assess a model's predictive power (e.g., Shumway 2001; Pepe, Longton, and Janes 2009; Duan, Sun, and Wang 2012). Third, the existing data to address this research question has grown considerably, due to the availability of large databases with auditor's opinions and bankruptcy events and to recent developments in text-mining techniques. We believe that these changes are substantial enough to warrant a comprehensive reexamination of the predictive accuracy of GCOs. In this study, we investigate whether GCOs provide incremental predictive power in forecasting a client's default over that of statistical models that incorporate existing accounting, market, and macroeconomic data. Next, we examine the usefulness of a *joint model* that includes inputs from *both the GCOs and existing data*. This is a possibility that was not examined by Hopwood et al. (1994). In addition, we compare the predictive value of GCOs versus credit ratings, another publicly available signal of companies' financial distress.

Comparing the auditor's judgment to a statistical (mechanical) model is not without significant tension. There are reasons to believe that an auditor may or may not have an edge over a statistical model. First, auditors have access to private information about the client. Second, auditors are able to consider qualitative criteria that cannot be quantified nor is captured in financial ratios or market variables. These two conditions should give GCOs incremental predictive accuracy. On the other hand, auditors are subject to constrained processing power and time. In other words, there is only so much information that auditors can incorporate into their decision making. Furthermore, behavioral research has demonstrated that people are unrealistically optimistic, overestimating the probability of positive outcomes for themselves

[2] Also, in the aftermath of the 2007-2008 crisis, investors and regulators have questioned the auditors' role in warning the public about clients' potential default (e.g., McKenna 2011; Chasan 2012; PCAOB 2012).

while underestimating the probability of negative outcomes (Weinstein 1980; Odean 1998a, 1998b). Specific to auditors as experts, previous studies show that experts exhibit the same biases in assessing the probability of uncertain events. Griffin and Tversky (1992) highlight that experts display higher levels of overconfidence bias when the evidence is more ambiguous and the event predictability is more uncertain. Moreover, the audit literature has shown that variation in auditors' expertise and independence affects the incidence of going concern opinions (Carson, Fargher, Geiger, Lennox, Raghunanadan and Willekens 2013). In contrast, a statistical model is not limited by behavioral biases or independence issues. Auditors typically use a checklist approach and individual judgement (e.g., more likely than not) to determine the threshold that will trigger a GCO. Even if an auditor and a model use the same inputs for a given client, a model can systematically aggregate large amounts of historical data to generate a specific prediction and a confidence interval (i.e., a specific probability than can be used to rank a company among a population of distress firms).

In our main analyses, we examine a large sample of distressed U.S. companies during the period from 1996 to 2013.[3] We obtain data on corporate defaults from multiple databases, including Credit Research Initiative (CRI)[4], CRSP, Compustat, Bankruptcy.com, and UCLA-LoPucki Bankruptcy Research Database. Overall, bankruptcy and other forms of defaults are very rare events. In our main sample, as illustrated in Figure 1, we find that only 1.5 percent of distressed companies at fiscal year-end default in the subsequent year. Within the companies that default in year *t+1*, approximately 55 percent receive a GCO in year *t*, and within the (majority of) distressed

[3] We limit our main analysis to 2013 since we require one year ahead corporate default events and our default data ends in 2014. We are presently working on extending our sample with default data through 2016.
[4] CRI database is provided by the Risk Management Institute (RMI) at the National University of Singapore. RMI is a non-profit organization that operates on a proprietary database covering macroeconomic, financial, and default-related information.

firms that do not default in *t+1*, 91.8 percent do not receive a GCO. For each year, we compare the sensitivity (the percentage of subsequent defaults predicted correctly) and specificity (the percentage of non-default predicted correctly) of (i) companies with a GCO, versus (ii) companies in the highest three deciles of the predicted probability of default (PD) based on basic financial ratios.[5] For each year, these results can be seen as a discrete contingency table, indicating the percentage of cases correctly and incorrectly classified by each signal, the GCO and high PD. We find that the statistical model outperforms GCOs in sensitivity in some years. However, GCOs consistently outperform the statistical model in specificity in every year. These results illustrate that there is a tradeoff between Type I and Type II errors in issuing GCOs, which must be taken into consideration when assessing predictive accuracy.

Next, we compare five incremental logistic models that predict default, ranging from the most simplistic model, which only predicts default using GCOs, to the most comprehensive model, which predicts default using GCOs, financial ratios, and market variables (e.g., stock returns). Our main criterion of predictive accuracy is the in-sample area under the receiver operating characteristic curve (AUC). The AUC criterion has two useful properties (i) it summarizes a model's sensitivity and specificity in a straightforward indicator that ranges between 0.5 and 1.0, and (ii) there are well-defined statistical tests to compare two models' AUCs.[6] We document four main findings. First, consistent with Hopwood et al. (1994), we do not find a statistical difference between the simple model with GCOs and the model with six key financial ratios. Second, a model which includes *both* GCOs and financial ratios has a statistically significantly higher AUC than

[5] The PD is calculated for all distressed companies annually, using a discrete-time hazard model that includes financial ratios, estimated over a year's prior three-year rolling windows. The highest three deciles is an arbitrary threshold for "high" PD, selected for illustration purposes.

[6] In addition, to compare the models' out-of-sample predictive accuracy we employ a K-fold cross-validation approach (e.g., Witten and Frank 2005; Larcker and Zakolyukina 2012; Kim and Skinner 2012). This approach allows for calculating a mean out-of-sample AUC and mitigates the problem of over-fitting a dataset. We find strong predictive accuracy among all five models, similar to those results of our in-sample AUC analyses.

either of the two independent models. Third, a comprehensive model using GCOs, financial ratios, and market variables has the highest AUC, which is statistically different than the AUCs of all other models ($p < 0.01$). Specifically, the inclusion of GCOs in a model including financial ratios and market variables increases the AUC by 0.014. Fourth, we find a similar pattern of results when we compare the performance of the individual and combined models after partitioning our sample by several cross-sectional characteristics (i.e., size, Big N auditors, years of distress, first-year GCOs, and time periods). Our combined evidence suggests that GCOs provide incremental information over financial ratios and market variables.

We also compare the predictive power of GCOs versus third-party generated firm-level probabilities of default (PDs) that consider market and economy-wide factors, while controlling for financial ratios and other client characteristics. We obtained these PDs from the Credit Research Initiative (CRI) database of the Risk Management Institute (RMI) at the National University of Singapore. The RMI computes these PDs using state-of-the-art methodology on default prediction, following the model in Duan, Sun, and Wang (2012). Similar to our previous analyses, we find that GCOs and the CRI PDs independently have a similar ability to forecast subsequent defaults. However, the AUC of the model using both GCOs and the CRI PDs is higher than the AUC of the models including GCOs and PDs independently.

It is inherently difficult to separate the GCOs' informational role from the GCOs' potential effect as a default trigger, and we note that our findings could be partially attributable to a "self-fulfilling prophecy" effect (e.g., Louwers, Messina, and Richard 1999; Vanstraelen 2003). However, from an outsider perspective, we argue that GCOs have incremental predictive value as straightforward indicators of subsequent default (i.e., relatively simple 1/0 signal). We conducted two sets of analyses to examine this possibility. First, we compare the predictive power of auditors'

GCO to changes in public credit ratings, another indicator which could induce a self-fulfilling prophecy effect. We find that GCOs have greater prediction accuracy than credit rating downgrades in the same fiscal year as the GCO. Our results suggest that auditors already compound the public information content of a decrease in credit rating in their GCO assessments, complementing the findings of Funcke (2014). Second, we also examine the association between GCOs and subsequent defaults for a matched sample of GCO and non-GCO distressed clients. Essentially, we isolate firms that are in very similar financial conditions and yet an auditor chooses to issue a GCO to one firm, but not to another matched firm. In our matched sample, the odds of subsequent default are 4.2 times higher when a distressed company receives a GCO.

Our study contributes to the literature by providing evidence that auditors' GCOs remain useful in predicting defaults. Our approach benchmarks the information content of the GCOs against *existing* information at the time of the opinion. Our findings highlight that GCOs impound public information and an incrementally predictive component. Thus, GCOs constitute a useful signal for investors. Auditors, on average, have lower false-positive rates, but also lower true-positive rates, compared to statistical models. The imperfect overlap may be attributed to auditors' professional judgment, access to private information, and even inherent human limitations (e.g., potential behavioral biases in the use of accounting and market data). Using GCOs *together* with financial ratios and market variables (as well as with the CRI PDs) results in a small, although statistically significant, incremental predictive accuracy above all other types of models that we examine in this study. We hope that this study will enhance our understanding of the gap between the number of clients with GCOs and the number of *ex post* bankruptcies, which are inherently difficult to predict. Our results may foster discussion about whether standards on GCOs should suggest auditors and management to incorporate data-driven and comprehensive statistical models as additional criteria in routinely assessing going concern uncertainty.

2. LITERATURE REVIEW AND STANDARDS ON GCO

2.1 Standards on GCOs

Under U.S. standards, the auditor is required to evaluate the going concern assumption (AICPA Statement on Auditing Standards AU 341). Existing standards rely on principles to guide the auditor's interpretation of what constitutes a going concern issue and when this warrants the inclusion of a going concern modification in the audit opinion. The auditor's responsibility involves assessing the probability of a client not continuing as a going concern within the foreseeable future, and whether this probability is higher than "substantial doubt" (AU 341.02), which would trigger an opinion modified for going concern uncertainty. However, there is no exact definition of what constitutes substantial doubt. The going concern assumption is not appropriate if the entity is unable to meet its obligations as they become due without substantial disposition of assets outside the ordinary course of business, restructuring of debt, externally forced revisions of its operations, or similar actions. Moreover, this assumption may not be met if management intends either to liquidate the entity or to cease operations.

The auditing standards suggest some events that may indicate going concern uncertainty, but the standards are silent about the use of statistical models in assessing going concern uncertainty. AU 341.06 includes four categories of events that may indicate substantial doubt about the continuation as a going concern: negative trends, other indications of possible financial difficulties, internal matters, and external matters. Nevertheless, the auditing standard is unclear as to how the auditor is to interpret and assess these events. Thus, auditors must rely on their own judgment when assessing whether a firm's probability of not continuing as a going concern is sufficiently high to justify issuing a GCO.

Regulators have expressed concerns with auditors' accuracy in their assessment of the going concern assumption and the client's own responsibility to disclose going concern uncertainties. For example, the PCAOB Investors Sub Advisory Group's recommendations state that "going concern reports have failed to show up sufficiently early to warn investors" (PCAOB 2012a, 3). Importantly, on August 27, 2014, the FASB issued ASU 2014-15, providing guidance on determining when and how management must disclose going concern uncertainties in the financial statements (independently from the auditor's assessment). An entity must provide certain disclosures if "conditions or events raise substantial doubt about [the] entity's ability to continue as a going concern". The ASU applies to all entities and is effective for annual periods ending after December 15, 2016 (FASB 2014). A related study by Mayew, Sethuraman, and Venkatachalam (2015) examines management's opinion about going concern reported in the MD&A and the linguistic tone of the MD&A and finds that these two signals together provide significant explanatory power in predicting whether a firm will cease as a going concern.

2.2 Incidence and accuracy of GCOs in the United States

A large body of research has studied the drivers of the auditor's decision to issue a GCO, and the literature often uses the presence of GCOs as a proxy for audit quality.[7] The incidence of GCOs is influenced by client and auditor characteristics and has changed over time in the United States. Some historical changes impacting the incidence of GCOs were the issuance of SAS No. 59 "Auditor's consideration of an entity's ability to continue as a going concern", the passing of

[7] For examples of studies using the presence of GCOs as a proxy for audit quality, see Francis (2011). Given two auditors and two clients with equally poor financial condition (i.e., high uncertainty that the client meets the going concern assumption), the auditor that issues a GCO is considered more "strict" and deemed to be of comparatively higher quality.

the Private Securities Litigation Reform Act in 1995, and the passing of the Sarbanes-Oxley act in 2002. Butler, Leone, and Willenborg (2004) show that in the period from 1980 to 1999, 33 percent of all opinions had some auditor qualification (i.e., GCO or other qualifications). In addition, after extensively collecting information about qualified reports, they document that in the period from 1994 to 1999, about half of all qualified reports were GCOs. Carson et al. (2013) show that the incidence of GCOs has steadily increased from 9.8 percent in 2000 to 17 percent in 2010.

A number of studies examining the incidence of GCOs focus on whether an auditor is "accurate" in predicting the client's subsequent default. These studies benchmark the actual incidence of GCOs versus an ideal 100 percent rate among clients with *ex post* bankruptcy. A type I misclassification arises if the auditor issues a GCO and the client does not subsequently fail. A type II misclassification arises when the auditor does not issue a GCO and the client subsequently fails. In particular, previous accuracy studies examine type II misclassifications, focusing on a sample of *ex post* bankrupt firms. In general, approximately half of the companies going bankrupt in the United States do not receive a prior GCO. In contrast, over two thirds of companies with a GCO do not subsequently go bankrupt. Geiger et al. (2005) find a type II misclassification of 46 percent in the period between 2000 and 2003. Geiger and Rama (2006) find a type II misclassification of 51 percent and a type I misclassification of 88 percent in the period between 1990 and 2000. Feldmann and Read (2010) find a type II misclassification of 41 percent in the period between 2000 and 2007. Myers et al. (2014) find a type II misclassification of 32 percent and a type I misclassification of 20 percent in the period between 2000 and 2006. The relatively large type II and I error rates documented in the literature are often attributed to GCOs having low information content. The review study by Carson et al. (2013, 366) notes that "the issue of interest for regulators, creditors, lawyers, and other financial statement users is why auditors have failed to provide warning of impending bankruptcy for companies going bankrupt." However, this interpretation conflicts with studies demonstrating that investors react negatively to the announcement of GCOs (e.g., Menon and Williams 2010).[8]

2.3 Comparing the auditor's judgement versus a statistical model

Previous studies evaluating the auditor's decision against an *ex ante* probability of default model document mixed evidence. Generally, these studies examine whether the auditor adequately considers the set of *existing* conditions at the time of the opinion. On one hand, studies in the 70s, 80s, and early 90s (Altman and McGough 1974; Altman 1982; Levitan and Knoblett 1985; Koh 1991) show that statistical models are superior to auditors' opinions as predictors of corporate bankruptcy. These studies reported that statistical models predicted bankruptcy correctly in around 85 percent of the cases, while the auditor's going concern opinion was correct in around 45 percent of them. However, subsequent studies (Hopwood et al. 1994; Mutchler et al. 1997) provide evidence that overturns this notion: in other words, there is no significant difference between auditors' opinions and statistical models as predictors of corporate bankruptcy. The collective evidence in these studies is limited to datasets ending in 1994 at the latest, and the statistical models they use are based only on accounting variables and the analysis of hand-collected bankrupt companies along with a similar (small) number of non-bankrupt companies.

Comparing auditors' judgment to a statistical model is not without significant tension. There are reasons to believe that auditors may or may not have an edge over a statistical model. First, auditors have access to private information about the client. Second, arguably auditors are able to consider qualitative criteria that cannot be quantified or is not captured in financial ratios

[8] Outside the United States, previous studies also document a discrepancy between GCOs and subsequent bankruptcies (e.g., Lennox 1999; Carson, Simnett, and Tronnes 2012).

or market variables. These two conditions should give GCOs incremental predictive accuracy. On the other hand, auditors are subject to constrained processing power and time. In other words, there is only so much information that auditors can incorporate into their decision making.

The accuracy of GCOs may be affected by optimism bias (also known as overconfidence bias) as it relates to assessing probabilities of uncertain events like defaults (Weinstein 1980). This overconfidence bias has also been documented among investors (Odean 1998a, 1998b). One potential driver of this overconfidence has been the subject of a stream of psychology research in "calibration", which suggests that people inherently believe the information and knowledge they possess is more accurate than others (Keren 1991; Yates 1990). Along a similar vein, there is also the confirmation bias, which affects how people compound new information into their beliefs about future uncertainties. Confirmation bias arises from people tending to overweight evidence in support of their prior beliefs, or interpreting ambiguous evidence in a favorable manner to their prior beliefs, while disregarding contradictory evidence as arising due to luck or flawed data (Gilovich 1991). These biases lead to mispricing and irrational actions in financial markets and asset pricing. For instance, Forsythe, Nelson, Neumann, and Wright (1992) provides experimental evidence that individuals with higher levels of confirmation bias tend to lose money in markets. Hirshleifer (2001) provides a detailed review of the applicable psychology and asset pricing literature regarding these and other behavioral biases.

As it relates to auditors as experts, research has shown that experts exhibit these same biases in assessing the probability of uncertain events. Griffin and Tversky (1992) highlight that experts display higher levels of overconfidence bias when the evidence is more ambiguous and the event predictability is lower. Given that defaults are low frequency events and the evidence considered in going concern assessments is ambiguous (i.e. there are no explicitly defined criteria for when reasonable doubt exists as to a firm's ability to continue as a going concern), it is quite possible that auditors display these same psychological biases in their going concern assessments. Auditors may overweigh evidence in favor of their belief about the ability of a firm to continue as a going concern and disregard evidence to the contrary, believing that their private information about the client is more accurate than the information of outsiders. Statistical models of defaults are not subject to behavioral biases.

Presently, audit firms do not generally use statistical models as a tool in their going concern assessment. The most common approaches are based on a checklist of criteria (including the conditions suggested by the GCO standard) that indicate a client's financial distress. However, even if an auditor and a model use the same inputs for a given client, a model can systematically aggregate large amounts of historical data to generate a specific prediction and a confidence interval (i.e., a specific probability than can be used to rank a company among a population of distress firms).

3. RESEARCH QUESTIONS AND METHODOLOGY

3.1 Predictive ability of GCOs and statistical models in terms of AUC

In this section, we discuss the methodology we use to compare the predictive value of GCOs and statistical models, both independently and together, in terms of the predictive accuracy of alternative logistic regression models. The logistic regression estimates are similar to a discrete-time hazard model (Shumway 2001; Mayew, Sethuraman, and Venkatachalam 2015). Our first research question is *what is the accuracy of the auditor's judgment versus a statistical model based on key financial ratios?* We begin by estimating the three following logistic regression models, with standard errors clustered by company:

$$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \textit{Fixed Effects}_{i,t}, \varepsilon_{i,t}) \quad \textbf{(1)}$$

$$P(DEFAULT_{i,t+1}) = f(\textit{Financial Ratios}_{i,t}, \textit{Fixed Effects}_{i,t}, \varepsilon_{i,t}) \quad \textbf{(2)}$$

$$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \textit{Financial Ratios}_{i,t}, \textit{Fixed Effects}_{i,t}, \varepsilon_{i,t}) \quad \textbf{(3)}$$

where, $DEFAULT_{i,t+1}$ is an indicator variable equal to one if company *i* defaults in year *t* + 1 and 0 otherwise; $GCO_{i,t}$ is an indicator variable equal to one if the auditor issues a going concern opinion for firm *i* in year *t*, and 0 otherwise. The *Financial Ratios* include several measures used in bankruptcy models plus determinants of GCOs from the auditing and bankruptcy literature (Hopwood et al. 1994; Shumway 2001; Mayew et al. 2015; Carson et al. 2013). $ROA_{i,t}$ is defined as net income divided by total assets, $LEVERAGE_{i,t}$ is defined as total liabilities divided by total assets, $WCAP_{i,t}$ is defined as current assets minus current liabilities (working capital) divided by total assets, $CURRENT_{i,t}$ is calculated as current assets divided by current liabilities, $CASH_{i,t}$ is defined as cash and cash equivalent holdings divided by total assets, $CFO_{i,t}$ is defined as cash flow from operations divided by total assets, $SIZE_{i,t}$ is defined as the natural logarithm of total assets, $NEGEQUITY_{i,t}$ is an indicator variable equal to one if the company has negative equity and 0 otherwise, and $BIGN_{i,t}$ is an indicator variable equal to one if the company has a Big 4 auditor and 0 otherwise. $\textit{Fixed Effects}_{i,t}$ are Fama-French 12 industry classification and year fixed effects.

Our second research question is *are GCOs incrementally informative over financial ratios and the market variables identified in Shumway (2001)?* We compare the AUCs of models (1), (2), and (3) above, versus the AUC of the logistic regression models including market variables:

$$P(DEFAULT_{i,t+1}) = f(\textit{Market Variables}_{i,t}, \textit{Financial Ratios}_{i,t}, \textit{Fixed Effects}_{i,t}, \varepsilon_{i,t}) \quad \textbf{(4)}$$

$$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \textit{Market Variables}_{i,t}, \textit{Financial Ratios}_{i,t}, \textit{Fixed Effects}_{i,t}, \varepsilon_{i,t}) \quad \textbf{(5)}$$

where all the variables are as defined above with the addition of three market variables from Shumway (2001). $REL\_MKTCP_{i,t}$ is defined as the logarithm of the firm's market capitalization at time t to the index's total market capitalization at time t; $EX\_RET_{i,t}$ is defined as the excess cumulative returns of firm i compared to the cumulative returns of the market over the 12 months leading up to the filing date for the year t; and $SIGMA_{i,t}$ is defined as standard deviation of the residuals from a monthly return model of monthly firm returns on market returns for the 12 months leading up to the filing date for year t.

We examine the relative predictive ability of logistic regressions (1) to (5). Our main criterion for predictive ability is the area under the receiver operating characteristic curve (AUC). The receiver operating characteristic curve (ROC) is a plot of the true positive rate (i.e., sensitivity) versus the false positive rate (i.e., specificity) for different cut-off thresholds. Each point on the ROC plot represents a sensitivity and specificity pair corresponding to a particular decision threshold. In order to generate the ROC plot, we compute estimated probabilities that each observation i belongs to the default =1 group after fitting each logistic model. Next, after choosing a specific probability threshold – as an example we chose 0.6 – it is possible to classify all observations with an estimated probability greater than 0.6 as default =1 and below 0.6 as default =0. Given that the estimated model is not perfect, applying the 0.6 threshold will result in some classification errors with respect to actual outcomes, and it is possible to determine the true and false positive rates at this given 0.6 threshold (i.e., create a two-by-two contingency table). After repeating these steps over many probability thresholds, it is also possible to create a smooth ROC curve by plotting the true versus false positive rates.[9]

A model with perfect discrimination has an ROC plot that passes through the upper left corner (100 percent sensitivity and specificity). The closer the ROC plot is to the upper left corner,

[9] Note that there is no specific cut-off probability threshold prescribed by the auditing standards. An auditor is required to evaluate the going concern uncertainty after concluding that there is substantial doubt about the entity's ability to continue as a going concern for a reasonable period.

the higher the overall accuracy of the model (e.g., Pepe et al. 2009). Therefore, there is a relation between the overall rates of correct classification and the area under the ROC. The AUC is the most popular summary statistic when comparing models predicting discrete outcomes, also known as classifiers (Fawcett 2006; Pepe et al. 2009). The AUC has also been previously used in the accounting literature to evaluate the predictive ability of deceptive language in restatement cases (Larcker and Zakolyukina 2012), the predictive ability of industry versus other determinants of litigation (Kim and Skinner 2012), as well as an alternative statistic to pseudo-R^2 in models of auditor choice (Minutti-Meza 2013).

The AUCs' possible values are in the interval [0.5, 1], where a value of 0.5 indicates no predictive ability, and a value of 1 indicates perfect predictive ability. The AUC can be interpreted as the probability that a randomly chosen default =1 observation is rated or ranked as more likely to default than a randomly chosen default =0 observation. If defaulting firms had been assigned to the *GCO* =1 group before they defaulted, then auditors have discriminated well between healthy and distressed firms and the value of the AUC is high. We assess the statistical significance of the difference in AUCs between our models using a non-parametric Wald test (based on bootstrap with 1,000 replications), where the null hypothesis is that both AUC values are equal (Janes et al. 2009).[10]

We then turn to our third research question *are GCOs incrementally informative over financial ratios and the PD estimates from CRI?* To answer this question, we compare the AUC from equation (3) to:

[10] We use the Stata command rocreg to compare AUCs. This command calculates standard errors based on bootstrap and does not assume that the ROCs are independent. This command is a modification of roccomp (Cleves 2002) that estimates standard errors following DeLong, DeLong, and Clarke-Pearson (1988). As noted by Kim and Skinner (2012), although AUC has advantages, a disadvantage is that it naturally increases as predictors are added to the model, in a manner analogous to unadjusted R-squares. There is no well-accepted way of adjusting for this problem. However, our models all have the same number of predictors. Thus, the number of predictors is not likely to drive the variation in the AUC across models.

$$P(DEFAULT_{i,t+1}) \quad = \quad f(CONT\_PD_{i,t}, \ Financial\ Ratios_{i,t}, \ Fixed\ Effects_{i,t}, \varepsilon_{i,t}) \tag{6}$$

$$P(DEFAULT_{i,t+1}) \quad = \quad f(GCO_{i,t}\ , \ CONT\_PD_{i,t}, \ Financial\ Ratios_{i,t}, \ Fixed\ Effects_{i,t}, \varepsilon_{i,t}) \tag{7}$$

where all the variables are as defined above with the addition of the *CONT_PDi,t* which is defined as the estimated PD for the next 12 months calculated at the closest month-end before the audit opinion date in the CRI database for firm *i*.

3.2 Predictive ability of GCOs and PDs out of sample using cross-validation

To assess the out-of-sample predictive accuracy of each model, we employ a K-fold cross-validation approach, a methodology from data mining (Witten and Frank 2005) that has been previously implemented in accounting studies examining out-of-sample predictive accuracy (Kim and Skinner 2012; Larcker and Zakolyukina 2012). In order to perform K-fold cross-validation, the observations are first divided into subsets called folds using random sampling without replacement from our whole sample. The choice of the number of folds is arbitrary; however, ten folds have been widely used in practice (Witten and Frank 2005). As such, we divide our sample into ten folds, with each fold containing roughly 2,719 observations from our full sample. Next, we fit each of our models on nine out of the ten folds, excluding the *k*th fold. Then, we use the fitted models and predict the *k*th fold that was left out. This step of fitting a model on nine folds and estimating the *k*th fold is repeated nine additional times so that each fold has been left out and estimated once. We then compute the AUC for each fold of out-of-sample predictions. This methodology creates an out-of-sample AUC prediction for each of our ten folds in our sample. Following Kim and Skinner (2012), we report the mean out-of-sample AUC to further assess the predictive ability of our models in our main analysis.

4. DATA DESCRIPTION

4.1 Sample selection

Our sample is the intersection of Compustat North America, CRSP, and Audit Analytics. We start with the population of public companies covered by Compustat North America from 1996 to 2013 and require a valid link to both CRSP and Audit Analytics (using CIK numbers). We only keep non-financial companies (i.e., delete companies with SIC codes between 6000 and 6999) and observations with non-missing financial variables and market variables required to construct our ratios defined above. We then limit our analysis to distressed firms, defined as those companies with negative net income or negative cash flow from operations (following DeFond, Raghunandan, and Subramanyam 2002). Table 1 shows a detailed summary of the number of observations at each step of the data selection and merging process. Our final dataset spans the years from 1996 to 2013 and includes 27,189 firm-year observations.

4.2 Going concern opinions

We employ text scraping techniques in order to isolate audit opinions prior to the release of Audit Analytics, which begins tracking going concern opinions in 2000. Following the technique in Butler et al. (2004), we first isolate audit opinions from 1996 to 2013 from 10-K filings on the SEC EDGAR website. Once we have isolated audit opinions, our algorithm searched for the key words "going concern", "bankruptcy", or "material business uncertainty" (Butler et al. 2004). Audit opinions that mentioned these key words received a 1 for the GCO variable, and a 0 otherwise. In order to assess the validity of our algorithm, we compared the results of the text mining program to Audit Analytics GCO variable. For the years of overlap (from 2000 to 2013), there was a 0.95 correlation between our codification and the Audit Analytics' codification of GCOs. Thus, in our final sample, the $GCO_{i,t}$ variable is comprised of the results from our text mining algorithm for the years prior to 2000, and then we use Audit Analytics for the year 2000 and afterwards.

4.3 Corporate default events

This paper focuses on default events, including but not limited to filing for bankruptcy, because these events are likely to challenge the going concern assumption. The auditing standards do not specifically refer to bankruptcy as the only event that constitutes an exception to the ability to realize an entity's assets and discharge its liabilities in the "normal course of business" (AU 341). As such, we include both bankruptcies and other default events (e.g. delistings) in our analysis. We identify default events – including bankruptcies – using a combination of datasets, namely CRI, Compustat, CRSP, Bankruptcy.com, and CRSP, Compustat, Bankruptcy.com, UCLA-LoPucki Bankruptcy Research Database. If a company has multiple default events across the datasets, we use the date of the first event as the beginning of the default period. Our final sample includes 404 subsequent default events. In the descriptive statistics section, we provide a summary of the types of default events in our final sample.

4.4 Probability of default (PD) estimated by CRI

We also compare the predictive power of GCOs versus a third-party generated firm-level probability of default (PD) that considers market and economy-wide factors, while controlling for financial ratios and company characteristics. We employ the PDs from the CRI database generated by the Risk Management Institute at National University of Singapore.[11] The RMI is a non-profit organization that operates on a proprietary database covering macroeconomic, financial, and default-related information. This imposes an additional restriction on our sample for those analyses, namely that the company be covered by CRI. For these analyses, the merge is conducting using Compustat Global, relying on SEDOL and ISIN as identifiers. Our final sample for CRI PD

[11] National University of Singapore, Risk Management Institute, CRI database. Available at: http://rmicri.org [Accessed 27 January 2017]

analyses includes 19,243 firm-year observations and spans the period from 2000 to 2011 due to the availability of data from CRI.

CRI computes PD estimates for public companies over different time horizons (1 month to 5 years) based on a forward-intensity probability model developed by Duan et al. (2012). We use one-year PD's at the closest month-end to the audit opinion date to make the estimates comparable to the auditor's horizon in assessing going concern uncertainty. The forward intensity model is implemented by maximizing a pseudo-likelihood function. It includes a combination of ten firm-specific and two economy-level variables. The firm-specific variables used in the model are measures of volatility-adjusted leverage, liquidity, profitability, relative size, market misvaluation/future growth opportunities, and idiosyncratic volatility. The first four firm characteristics enter the model as both level and trend variables. The economy level variables in the model are stock index returns and interest rate.

By considering exits other than bankruptcy, Duan et al. (2012) overcome the censoring bias inherent in the more sophisticated logit, probit, and hazard models used in Chava and Jarrow (2004), Campbell, Hilscher, and Szilagyi (2008), Bharath and Shumway (2008), and Hillegeist, Keatin, Cram, and Lundsedt (2004). Additionally, unlike prior research that focuses on firm-level financial ratios, the Duan et al. (2012) model also includes firm-level market characteristics and economy-wide risk factors. The model can link a default which will occur a number of periods in the future to the values of the variables at the present moment (Duan and Fulop 2013). Also, an important improvement is the use in the Duan et al. (2012) model of both state variables and trend effects, both of which have highly significant impacts on the results (Duan and Wang 2012).

We use PDs as a comprehensive benchmark in predicting default/bankruptcy events, since the performance of the Duan et al. (2012) model is notably good and constitutes one of the latest developments in default prediction models. The prediction accuracy of the RMI PD forecasts has been tested in-sample using Accuracy Ratio (AR) and ROC (CRI 2013). The range of possible AR values is [0, 1], where 0 is completely random system and 1 is a perfect rating system. The model used by CRI achieves AR results mostly greater than 0.7 at the one-year horizon for many of the countries covered by CRI. The model also performs well in terms of ROC; the CRI documentation shows that in most countries in their estimation sample the ROC is greater than 0.8 at the one-year horizon.

5. RESULTS

5.1 Descriptive statistics and sensitivity-specificity rates over time

Figure 1 presents descriptive statistics on the frequencies of GCOs and defaults by year for our full sample. Our final sample consists of 27,189 distressed firm-years, and there are 2,429 observations with GCOs during the period from 1996 to 2013 (8.9 percent of the sample). The annual frequency of GCOs ranges from 6.5 to 12.9 percent. The highest frequency of GCOs is clustered between 2000 and 2002 and between 2007 and 2008, coinciding with periods of economic downturns. In general, our sample consists of relatively large firms with data on Compustat, CRSP, and Audit Analytics databases, with lower average incidence of GCOs than the full population of U.S. listed firms (Carson et al. 2012). In contrast, throughout the entire period the frequency of default is comparatively low. There are 404 subsequent default observations during the period from 1997 to 2014 (1.9 percent of the sample). The incidence of defaults is highest during the economic downturn periods, 2000 and 2001, as well as 2007 to 2008.

Table 2, Panel A provides the full-sample descriptive statistics for the variables used in our analyses. We provide descriptive statistics for continuous PD estimates, as in the CRI database ($CONT\_PD_{i,t}$), which is for our limited sample of 19,243 firm-year observations instead of the full sample. In our main analyses, the average return on assets and cash flow from operations ($ROA_{i,t}$ and $CFO_{i,t}$) are negative (at -0.271 and -0.127, respectively) as a result of including in our sample only distressed firm-years. The mean leverage is 49.1 percent ($LEVERAGE_{i,t}$), and 5.8 percent of the firm-years have negative equity ($NEGEQUITY_{i,t}$). Approximately 77 percent of the observations have a Big 4 auditor ($BIGN_{i,t}$).

Table 2, Panel B presents descriptive statistics separately for $GCO_{i,t}$ =0 and $GCO_{i,t}$ =1 observations. Observation with GCOs ($GCO_{i,t}$ =1) have higher calculated PDs – with a mean of 5.0 percent – compared to observations without GCOs ($GCO_{i,t}$ =0), which have a mean PD of 1.2 percent. Approximately 9.1 percent of the firms that receive a GCO in our sample default a year after the auditor report ($DEFAULT_{i,t+1}$), while defaults in the non-GCO group average just 0.7 percent. The $GCO_{i,t}$ =1 group also has comparatively (a) lower return on assets, cash flow from operation, working capital, and current ratios, and levels of cash holdings; (b) smaller size and lower frequency of Big 4 auditors; and (3) higher leverage and higher frequency of negative equity. These differences in means are all statistically significant at the 1% level. As expected, our descriptive statistics indicate that firms with GCOs exhibit generally worse financial conditions than firms without GCOs.

Table 2, Panel C presents descriptive statistics separately for $DEFAULT_{i,t+1}$ =0 and $DEFAULT_{i,t+1}$ =1 observations. Among defaulting firm-years 54.5 percent get a going concern opinion (GCO = 1), while among non-defaulting firm-years only 8.2 percent get a going concern opinion. Observations that default also have significantly higher PDs, lower return on assets, smaller cash flows, higher leverage, and lower current and working capital ratios. More of the defaulting firm-years have negative equity, and fewer are audited by a Big 4 auditor. Interestingly, firm-years that default are significantly larger in size even in the year leading up to the default.

Table 3 presents the results from a descriptive analysis regarding the sensitivity and specificity rates over time of GCOs and a logit model including financial ratios. The Naïve GCO columns present the percentage of default events in year *t+1* which received a GCO in year *t* (i.e. the sensitivity of GCOs) and the percentage of non-default events in year *t+1* which did not receive a GCO in year *t* (i.e. the specificity of GCOs). The Financial Ratios columns are the resulting specificity and sensitivity from a logit model specified as equation (2) above. The logit model was fit on three-year rolling windows and the resulting estimates were then used to predict the probability of default for the subsequent year. If the resulting predicted probability was in the top three deciles of predicted probabilities for that year, it was assigned as having a predicted default equal to one. The sensitivity and specificity were then calculated using these predicted defaults. The Difference in Ratios columns compare the statistical difference between the two respective sensitivity and specificity ratios for the Naïve GCOs and the Financial Ratios columns.

As a result of this descriptive analysis, it is clear that the tradeoff between type I and type II errors is of great importance in this comparison. In terms of sensitivity (i.e. true-positives), there are a handful of years where the financial ratios model outperforms the naïve GCO. However, the naïve GCO outperforms the financial ratios model in every year when considering specificity (i.e. true-negatives). While the financial ratios model may seem more accurate at times when it comes to true-positives, there is a large number of false-positives which drive down the specificity rate. Without knowing the true cost of the large number of false-positives generated by the financial ratios model, it is unclear whether this is an acceptable tradeoff for slightly more accurate true-positive hits. As such, we compare the AUC of each model in our analyses, which is a more appropriate method to analyze the sensitivity-specificity tradeoff as detailed above.

5.2 Predictive accuracy of GCOs, financial ratios, and market variable models

Table 4, Panel A, Columns (1) to (5) show the results for the logistic models specified in equations (1) to (5) above. In Column (1), the $GCO_{i,t}$ variable alone has a positive coefficient of 2.600 (statistically significant at the 1 percent level). The AUC for the GCO standalone model is 0.835. In Column (2), we find that $LEVERAGE_{i,t,}$ $CURRENT_{i,t,}$ and $SIZE_{i,t}$ are positively associated with subsequent defaults (statistically significant at the 1 percent level). The AUC for the model is 0.847. In Column (3) which combines GCO and the financial ratios, the $GCO_{i,t}$ variable has a positive coefficient of 2.496 (statistically significant at the 1 percent level), and the financial ratios retain their statistical significance. The AUC for the model is 0.879. In Column (4), market variables are introduced to the financial ratios model. We find that $REL\_MKTCP_{i,t}$ and $EX\_RET_{i,t}$ are negatively associated with subsequent defaults (statistically significant at the 1% level). The AUC for the model is 0.895. Lastly, in Column (5), the combined model with the GCO, market variables, and financial ratios is presented. The $GCO_{i,t}$ variable has a positive coefficient of 1.844 (statistically significant at the 1 percent level), and the association of financial ratios and market variables with subsequent defaults still has statistical significance. These findings show that GCOs, financial ratios, and market variables all have incremental power with respect to each other in predicting subsequent defaults. The AUC for the model is 0.909.

Table 3, Panel A also reports the mean out of sample AUCs resulting from the k-fold cross validation to assess the out of sample predictive accuracy of the models. All mean out of sample AUCs are above 0.8 indicating generally excellent predictive classification (Hosmer and Lemeshow 2000, p. 162). Table 3, Panel B assesses the differences in AUCs between the models in Panel A. First, we do not find evidence of a statistically significant difference in predictive accuracy between the simple GCO model and the financial ratio model. As shown in Column (3), the difference in AUCs between (2) and (1) is 0.012, not statistically significant at the 10 percent level. This is in line with the results of Hopwood et al. (1994). However, we do find that the combined GCO and financial ratios model has comparatively higher predictive accuracy than both the individual GCO model and financial ratio model; both differences are statistically significant at the 1 percent level as shown in Column (3). Figure 2 illustrates the ROC plots for the GCO model, the financial ratio model, and the combined GCO and financial ratio model. The figure demonstrates how the combined model is slightly closer to the upper left region of the graph, indicating a larger AUC and greater predictive power than the other two models.

Our next AUC comparison is between the model which includes both market and financial ratios (most similar to the Shumway 2001 model). The AUC of this model is greater than both the AUC of the standalone GCO model and the GCO and financial ratio model, statistically significant at the 1 percent and 5 percent level respectively. Overall, this suggests the inclusion of market variables yields a substantial increase in predictive accuracy over and above that of the GCO and financial ratio models.

As such, our final AUC comparison is between the full model, which includes the GCO, the financial ratios, and the market variables, and other models. Overall, the full model has a greater AUC than any other model, statistically significant at the 1 percent level. The significant difference between the full model and just the market variable and financial ratios model is most notable. If the auditors’ GCO itself did not contain incremental information to the market variables or financial variables, then the AUC difference would not be statistically significant. However, the pure inclusion of the auditors’ GCO in the model yields a 0.014 increase in AUC, statistically significant at the 1 percent level.

5.3 Cross-sectional partitions based on client characteristics

As additional analyses, aiming to determine whether there is cross-sectional variation in the relative predictive power of GCOs versus PDs, we partition our sample using various characteristics. Table 5 shows the comparison between AUCs for our GCO and financial ratio model (eq. 3), our market variables and financial ratios model (eq. 4), and our full model that combines all of them (eq. 5) in subsamples resulting from partitioning the main sample by size (highest and lowest quartile of total assets), Big 4 versus non-Big 4 auditor, consecutive versus non-consecutive years of distress, a GCO in the prior year versus no GCO in the prior year, and the three years *pre* and *post* the 2008 financial crisis. We do find evidence that auditors have similar predictive accuracy in certain subsamples of our data (Column 4). For example, for firms which have a GCO in the prior year, the auditors do just as well as the market model. Additionally, the differing results among the size subsamples and BigN subsamples suggest that there is little incremental information in auditors' GCOs for small firms and non-BigN auditors (Column 6), but also there is larger overlap in the information content of the GCO and market variables as there is no statistical difference in the AUCs (Column 4). In terms of the financial crisis, GCOs leading up to the financial crisis appear to be beaten by the market variables, but this effect dissipates in the years after the financial crisis. This could be an indication that the purely statistical models exhibit more discipline, which aids their predictive accuracy during a time of much uncertainty. The findings overall confirm the results from our main sample.

5.4 Predictive accuracy of GCOs and the CRI PDs

Table 6, Panel A, Columns (1) to (3) show the results for the logistic models including the variables $GCO_{i,t}$, $CONT\_PD_{i,t}$, and both combined. In Column (1) the $GCO_{i,t}$ variable has a positive coefficient of 2.288 (statistically significant at the 1 percent level). We also find that $LEVERAGE_{i,t}$ and $SIZE_{i,t}$ are positively associated with subsequent defaults (statistically significant at the 1 percent level). The AUC for the model is 0.871. In Column (2) the $CONT\_PD_{i,t}$ variable has a positive coefficient of 13.738 (statistically significant at the 1 percent level). We also find that $LEVERAGE_{i,t}$ and $SIZE_{i,t}$ are positively associated with subsequent defaults (statistically significant at the 1 percent level). The AUC for the model is 0.878. In Column (3) the $GCO_{i,t}$ variable has a positive coefficient of 1.726, and the $CONT\_PD_{i,t}$ variable has a positive coefficient of 10.812 (statistically significant at the 1 percent level). These findings show that both GCOs and PDs have incremental power with respect to each other in predicting subsequent defaults. We also find that $LEVERAGE_{i,t}$ and $SIZE_{i,t}$ are positively associated with subsequent defaults (statistically significant at the 1 percent level). The AUC for the model is 0.891.

Table 4, Panel B assesses the differences in AUCs between the models in Panel A. We do not find evidence of a statistically significant difference in predictive accuracy between the $GCO_{i,t}$ and $CONT\_PD_{i,t}$ models; as shown in Column 4, the difference in AUCs between (2) and (1) is 0.007, which is not statistically significant at the 10 percent level. However, we find that the combined $GCO_{i,t}$ and $CONT\_PD_{i,t}$ model has comparatively higher predictive accuracy; as shown in Column 5, the difference between (3) and (1) is 0.023, and in Column 6 the difference between (3) and (2) is 0.015. Both differences are statistically significant at levels of 1 percent and 5 percent, respectively.

5.5 GCOs compared to changes in credit ratings

We also compare the auditor's GCO to changes in credit ratings. Arguably, changes in credit ratings –and specifically ratings downgrades- are an interesting benchmark for GCOs, given that credit ratings could also have a "self-fulfilling prophecy" effect. We use three variables to capture the effect of credit rating changes: $DOWN_{i,t}$ is an indicator variable, equal to one if the Standard & Poor's (S&P) credit rating for firm *i* has been downgraded in the 12 months of fiscal year *t*, and zero otherwise; $DOWN\_LVL_{i,t}$ is a count variable, indicating the number of levels in credit ratings that firm *i* has been downgraded in the 12 months of fiscal year *t*; and $INVST\_CH_{i,t}$ is an indicator variable, equal to one if the S&P credit rating for firm *i* has been downgraded from investment grade to non-investment grade (BB or higher to B or lower) in the 12 months of fiscal year *t*, and zero otherwise. For this analysis, we generate our sample beginning with our main sample spanning from 1996 to 2013. We then remove firms with no S&P credit rating in the Compustat North America database to compute our credit rating changes variables defined above. Our final credit rating sample is comprised of 3,507 observations. Table 8, Panel A shows a summary of our sample selection process.

Table 7, Panel B provides descriptive statistics for the variables used in these analyses. The incidence of subsequent default in this sample is 3.5 percent and the incidence of GCOs is 4.2 percent. Table 7, Panel C shows the GCO frequency and the subsequent default frequency for each level of credit rating. The highest percentage of GCOs and defaults is in the B and CCC rating levels, approximately 2.0 and 1.3 percent, respectively. Table 7, Panel D, Columns (1) to (7) show the results for the logistic models including the variables $GCO_{i,t}$, $DOWN_{i,t}$, $DOWN\_LVL_{i,t}$, and $INVST\_CH_{i,t}$, and each credit rating variable combined with $GCO_{i,t}$.

Table 7, Panel E compares the predictive ability of the models in Panel D. The results of these analyses indicate that GCOs have higher predictive accuracy than the variables for credit rating downgrades (Column 4). The AUC of the $GCO_{i,t}$ model is between 0.035 and 0.044 higher than the AUC of any of the three credit rating downgrade models (the difference is statistically significant at the 1 percent level for the INVST_CH Models and at the 5 percent level for the DOWN Models and the DOWN_LVL Models). The incremental predictive accuracy of using both GCOs and credit rating downgrades results primarily from adding GCOs (see Column 6).

However, we note that these analyses are subject to the caveat that GCOs are given after the credit rating downgrades. Arguably, auditors use credit rating downgrades in their GCO judgments as documented by Funcke (2014).

5.6 Matching companies with and without GCOs on size, profitability, default, and other relevant characteristics.

As Table 2, Panel B shows, audit clients that receive and do not receive a GCO differ significantly on a number of firm-level characteristics. Although we include those characteristics as firm-level controls in our logistic models, we also conduct an additional analysis meant to estimate the association between GCOs and subsequent default after isolating these characteristics. To do so, we match observations with and without GCOs using propensity score matching. Table 8, Panel A shows the estimation of a logistic model of the probability of receiving a GCO, in which we include the estimated PD as a determinant. Table 8, Panel B shows the descriptive statistics of the full and matched samples. The matched sample (Columns 3 and 4) has 1,418 $GCO_{i,t}$ =1 and 1,418 $GCO_{i,t}$ =0 observations. The matched sample shows balance in client characteristics (i.e., the *t*-statistic of the difference in means between $GCO_{i,t}$ =1 and $GCO_{i,t}$ =0 observations is statistically insignificant at the 10 percent level for all variables in the GCO model). Most importantly, in the matched sample, the incidence of subsequent default for $GCO_{i,t}$ =1 is 7.1 percent compared to 2 percent for $GCO_{i,t}$ =0.

Table 8, Panel C shows a multivariate analysis of the association between GCOs and subsequent defaults using the matched sample. The coefficient on $GCO_{i,t}$ is 1.492 (statistically significant at the 1 percent level). In terms of odds ratios (untabulated), a distressed company with $GCO_{i,t}$ =1, compared to another company with $GCO_{i,t}$ =0, but similar in other characteristics, is 4.5 times more likely to default in the subsequent year. We note that this association could be partially attributable to a “self-fulfilling prophecy” effect. Previous studies by Vanstraelen (2003) and Louwers et al. (1999) document that the initial year after receiving a GCO is significantly more risky in terms of bankruptcy filing for a financially troubled firm, and that this risk declines substantially in later years. A recent study by Gerakos, Hahn, Kovrijnykh, and Zhou (2016), modeling the joint probability of GCO and subsequent bankruptcy, finds support for both the prediction and inducement effect of GCOs. It is inherently difficult to separate the GCOs’ informational role from the GCOs’ potential effect as default triggers. However, from an outsider perspective, GCOs have incremental predictive value as a clear 1/0 indicator of potential subsequent default.

6. ADDITIONAL AND SENSITIVITY ANALYSES

6.1 Comparing GCOs to a different PD estimation date, and using a high PD indicator variable

As a sensitivity analysis, we repeat our analyses using the 12-month continuous PD estimates, but we vary the calculation date of the PD. Specifically, we use the 12-month PDs calculated at fiscal year-end for each firm-year observation, as opposed to the PD calculated closest to the opinion date. This new calculation date specifically aligns the end date of the 12-month PD horizon with the end date of the auditor’s horizon for assessing the going concern assumption, which is 12 months after fiscal year-end. In untabulated results, we confirm our main findings and do not find evidence of a statistical difference between the AUC of the GCO model and the PD model; similarly, the combined model has an AUC that is marginally higher than the AUC of the GCO and PD models independently. The difference between the AUCs is statistically significant (at the 1 percent level). Thus, we find that our results are robust to varying the chosen calculation date for PD estimates.

Additionally, we repeat our analyses using an indicator variable for high PD estimates from the CRI database ($HIGH\_PD_{i,t}$). In untabulated results, we do not find evidence of a difference in predictive accuracy between the $GCO_{i,t}$ and $HIGH\_PD_{i,t}$ models. However, we similarly find that the combined $GCO_{i,t}$ and $HIGH\_PD_{i,t}$ model has comparatively higher predictive accuracy than the models using $GCO_{i,t}$ and $HIGH\_PD_{i,t}$ independently.

6.2 Full sample of distressed and non-distressed companies

We also conduct additional analyses using both distressed and non-distressed companies. Our pooled sample of distressed and non-distressed firms is generated using the intersection of Compustat North America and Audit Analytics from 2000 to 2011. Again, we merge the CRI Default Events into this dataset. Then, we remove from our sample firms that are defined as financial and firms that have missing financial information to compute control variables. We then remove firms with no PD data from CRI. Our final pooled sample is comprised of 40,116 observations. In this sample there are 0.9 percent defaults and 4.8 percent GCOs (untabulated). We find a statistically significant difference in predictive accuracy between the $GCO_{i,t}$ and $CONT\_PD_{i,t}$ models. The $CONT\_PD_{i,t}$ model has an AUC of 0.913, compared to an AUC of 0.894 for the $GCO_{i,t}$ model. The difference is 0.019 (statistically significant at the 1 percent level). These findings are similar to those discussed by Hopwood et al. (1994). Arguably, the auditor's judgment is different for distressed and non-distressed clients, and thus Hopwood et al. (1994) recommend comparing GCOs versus bankruptcy prediction models only for the subsample of distressed clients.

7. CONCLUSION

The usefulness of GCOs constitutes a topic of constant debate, particularly in time periods when the number of corporate defaults rises due to bad economic conditions. In contrast with the restricted auditor's responsibility prescribed in the auditing standards, the financial press, regulators, and researchers have raised some concerns regarding the auditor's responsibility for warning investors about potential business failures. A landmark study by Hopwood, McKeown, and Mutchler (1994), examining data from bankruptcies that occurred between 1974 to 1985, demonstrated that in predicting bankruptcy GCOs were as good as a statistical model based on key financial ratios and firm size. Several conditions have changed since the publication of Hopwood et al. (1994), including the evolution of the regulatory landscape, changes in the economic environment, improvements to default prediction models, and increases in data availability. We believe that these changes are significant enough to warrant a comprehensive reexamination of the predictive accuracy of GCOs. We investigate whether GCOs provide incremental predictive power in forecasting a client's default compared to statistical models that rely on existing accounting, market, and macroeconomic data. Next, we examine the usefulness of a *joint model* that includes inputs from *both auditor's GCOs and existing data*, a possibility that was not within the scope of Hopwood et al. (1994). Lastly, we also compare the predictive value of GCOs versus credit ratings, another publicly available signal of companies' financial distress.

We examine a U.S. large sample of distressed companies during the period from 1996 to 2013. Overall, bankruptcy and other forms of defaults are very rare events. In our sample, only 1.5 percent of distressed companies at fiscal year-end default in the subsequent year. Only approximately 55 percent of bankrupt firms receive a GCO in the prior year. Our findings demonstrate that there is a tradeoff between Type I and Type II errors in issuing GCOs, which must be taken into consideration when assessing predictive accuracy. Next, we compare five progressively complex logistic models that predict default, ranging from the most simplistic model, which only predict default using GCOs, to the most comprehensive model, which predicts default using GCOs, financial ratios, and market variables. Our main criterion for each model's predictive accuracy is the in-sample area under the receiver operating characteristic curve (AUC). We document four primary findings. First, consistent with Hopwood et al. (1994), we do not find a statistical difference between the simple model with GCOs and the model with six key financial ratios. Second, a model which includes *both* the GCO and financial ratios has a statistically significantly higher AUC than either of the two independent models. Third, a comprehensive model using GCOs, financial ratios, and market variables has the highest AUC. Fourth, we find a similar pattern of results when we compare the performance of the models partitioning our sample by several cross-sectional characteristics. Our combined evidence suggests that GCOs provide incremental information over financial ratios and market variables.

We also compare the predictive power of GCOs versus third-party generated firm-level probabilities of default (PDs) that consider market and economy-wide factors, while controlling for financial ratios and company characteristics. We obtained these PDs from the database of the Credit Research Initiative (CRI) of the Risk Management Institute at the National University of Singapore. Similar to our previous analyses, we find that GCOs and the CRI PDs independently have a similar ability to forecast subsequent defaults. However, the AUC of the model using both GCOs and the CRI PDs is higher than the AUC of the models including GCOs and PDs independently. Next, we also compare the predictive power of auditors' GCO to changes in public credit ratings, another construct which could induce a self-fulfilling prophecy. We find that GCOs have greater prediction accuracy than credit rating downgrades in the same fiscal year as the GCO. Finally, we examine the association between GCOs and subsequent defaults for a matched sample of GCO and non-GCO distressed clients. In our matched sample, the odds of subsequent default are 4.2 times higher when a distressed company receives a GCO.

Our study contributes to the literature by providing evidence that auditors' GCOs remain useful in predicting defaults. We extend the results in Hopwood et al. (1994) results and demonstrate that GCOs have incremental predictive accuracy when included in a comprehensive statistical model hat also incorporates financial ratios and market variables. Our findings highlight that auditors are compounding unique information, which is orthogonal to the information included in statistical models proposed by the literature, and thus provide investors with a useful and straightforward (1/0) signal in the form of GCOS. We hope that this study will enhance our understanding of the gap between the number of clients with GCOs and the number of *ex post* bankruptcies, which are inherently difficult to predict. Our results may foster discussion about whether standards on GCOs should suggest auditors and management to incorporate statistical models as additional criteria in assessing going concern uncertainty.

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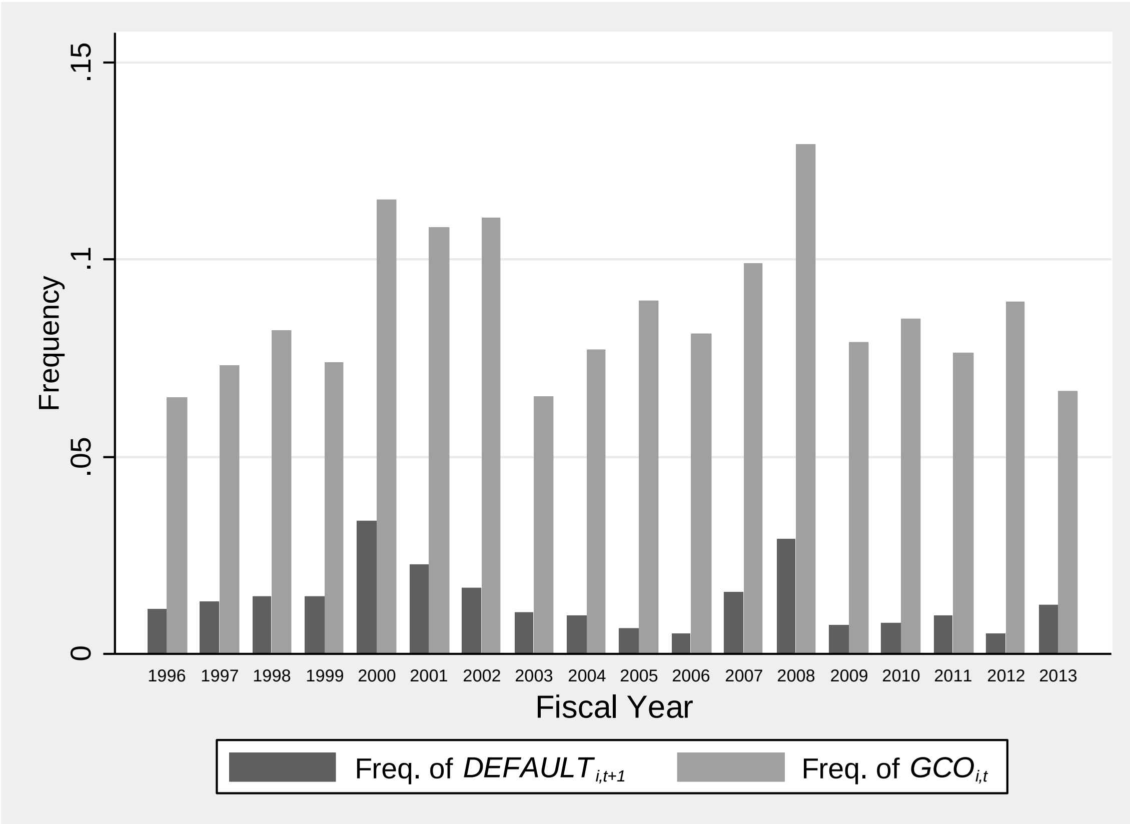
APPENDIX A
Variable Definitions

Variable		*Definition*	*Source*
$DEFAULT_{i,t+1}$	=	indicator variable equal to one if company *i* has a default event 12 months following fiscal year-end *t* and 0 otherwise;	CRI, CRSP, Compustat, Bankruptcy.com, UCLA-LoPucki Bankruptcy Research Database
$GCO_{i,t}$	=	indicator variable equal to one if a company *i* has a GCO in fiscal year-end *t*, and 0 otherwise;	Audit Analytics and text mined SEC 10-K Filings
$CONT\_PD_{i,t}$	=	Estimated PD for the subsequent 12 months for firm *i* calculated at the closest month-end before the signature date of the audit opinion for fiscal year *t*;	CRI database
$REL\_MKTCP_{i,t}$	=	Log (Firm Market Capitalization / Index Market Capitalization);	CRSP
$EX\_RET_{i,t}$	=	Cumulative Firm Returns – Cumulative Market Returns over the 12 months leading up to the filing date for year *t*;	CRSP
$SIGMA_{i,t}$	=	Standard deviation of the residuals from a monthly return model of firm returns on market returns for the 12 months leading up to the filing date for year *t*;	CRSP
$ROA_{i,t}$	=	Net Income / Total Assets;	Compustat North America
$LEVERAGE_{i,t}$	=	Total Liabilities / Total Assets;	Compustat North America
$WCAP_{i,t}$	=	(Current Assets – Current Liabilities) / Total Assets;	Compustat North America
$CURRENT_{i,t}$	=	Current Assets / Current Liabilities;	Compustat North America
$CASH_{i,t}$	=	Cash and Cash Equivalents / Total Assets;	Compustat North America
$CFO_{i,t}$	=	Cash Flow from Operating Activities / Total Assets;	Compustat North America
$SIZE_{i,t}$	=	Log(Total Assets);	Compustat North America
$NEGEQUITY_{i,t}$	=	Indicator variable equal to one if Total Liabilities exceed Total Assets, and 0 otherwise; and	Compustat North America

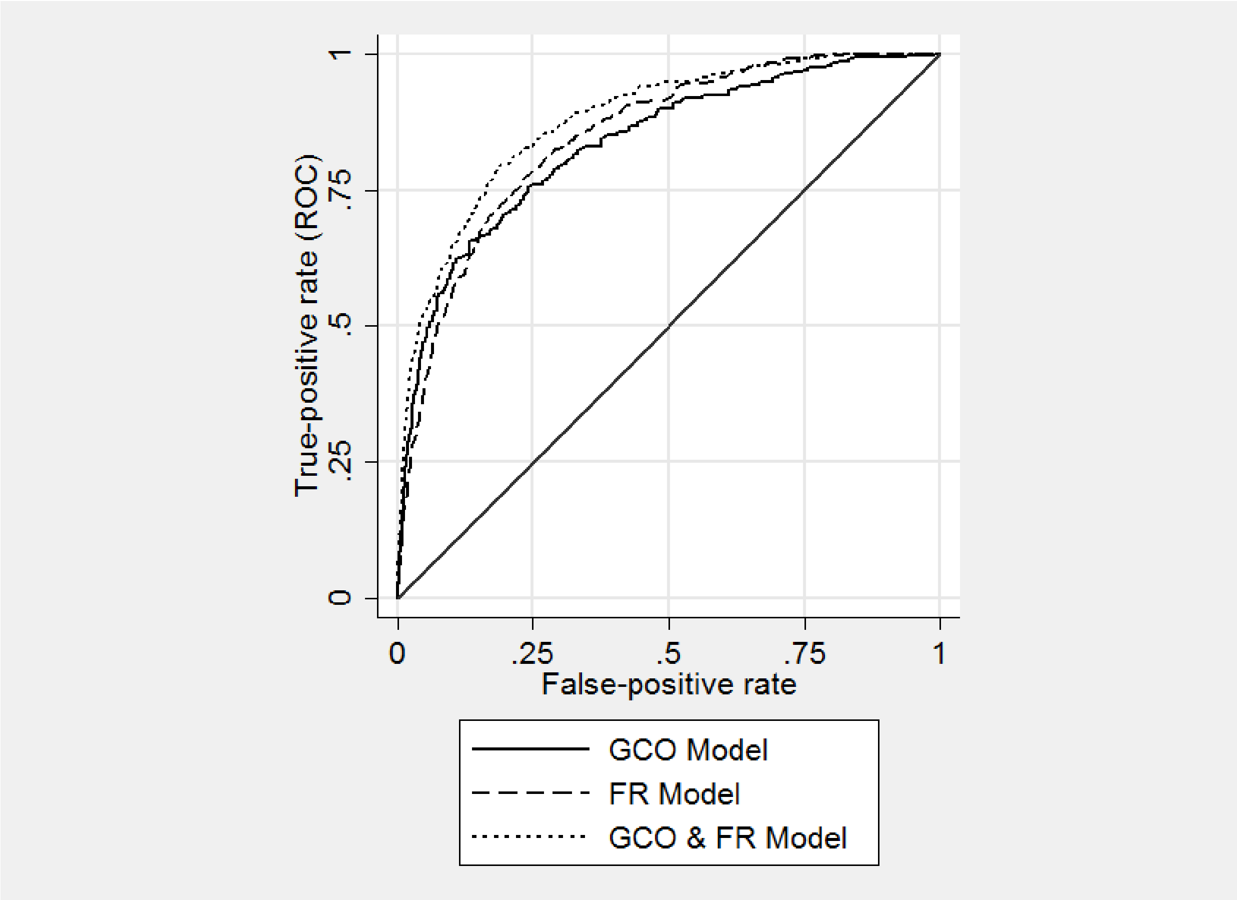
Variable		*Definition*	*Source*
$BIGN_{i,t}$	=	Indicator variable equal to one if the company has a Big 4 auditor, and 0 otherwise.	Audit Analytics and Compustat (pre-2000)
$DOWN_{i,t}$	=	Indicator variable equal to one if the S&P credit rating for firm *i* has been downgraded during the 12 months of fiscal year *t*;	Compustat North America
$DOWN\_LVL_{i,t}$	=	Count variable indicating the number of levels in credit ratings that firm *i* has been downgraded during the 12 months of fiscal year *t*;	Compustat North America
$INVST\_CH_{i,t}$	=	Indicator variable equal to one if the S&P credit rating for firm *i* has been downgraded from investment grade to non-investment grade during the 12 months of fiscal year *t*;	Compustat North America

Figure 1 – Frequency of GCOs and defaults by year among distressed firms



Year	$GCO_{i,t}$ *N. Obs.*	$GCO_{i,t}$ *Freq.*	$DEFAULT_{i,t+1}$ *N. Obs.*	$DEFAULT_{i,t+1}$ *Freq.*	*Total N. Obs.*
1996	80	0.065	14	0.011	1,231
1997	95	0.073	17	0.013	1,299
1998	107	0.082	19	0.015	1,307
1999	132	0.074	26	0.015	1,789
2000	263	0.115	77	0.034	2,286
2001	235	0.108	49	0.023	2,174
2002	225	0.111	34	0.017	2,034
2003	106	0.065	17	0.010	1,627
2004	110	0.077	14	0.010	1,429
2005	125	0.089	9	0.006	1,398
2006	112	0.081	7	0.005	1,380
2007	140	0.099	22	0.016	1,417
2008	208	0.129	47	0.029	1,611
2009	121	0.079	11	0.007	1,530
2010	99	0.085	9	0.008	1,166
2011	87	0.076	11	0.010	1,140
2012	103	0.089	6	0.005	1,153
2013	81	0.067	15	0.012	1,218
Total	2,429	0.089	404	0.015	27,189

Figure 2 – ROC curves for equations (1), (2), and (3)



This figure shows the ROC curve for all three equations: (1) *GCO* Model, (2) Financial Ratio Model, and (3) GCO and Financial Ratio model shown in Table 4, Panel A. The receiver operating characteristic curve (ROC) is a plot of the true positive rate (i.e., sensitivity) versus the false positive rate (i.e., specificity) for different cut-off thresholds. Each point on the ROC plot represents a sensitivity and specificity pair corresponding to a particular decision threshold. In this analysis, a model with perfect predictive power will produce curves near the upper left corner, while a random guess will be on the diagonal line. The AUC is the area under the depicted curves.

Table 1 – Sample selection

	Total Obs.	$GCO_{i,t}$	$DEFAULT_{i,t+1}$
Intersection of Compustat, CRSP, & Audit Analytics	87,738	3,299	614
- Firms defined as financial	(19,361)	(244)	(64)
- Firms with missing data to compute variables	(3,266)	(501)	(115)
- Firms not defined as distressed	(37,922)	(125)	(31)
Main Sample	27,189	2,429	404
- Firm with missing CRI data	(7,946)	(645)	(139)
CRI Analysis Sample	19,243	1,784	265

This table shows the sample selection for the observations in the main analysis using financial and market variables. Then, the sample selection is shown for our analyses using CRI's probability of default measure. Distressed firms are defined as companies with either negative net income or negative operating cash flows following DeFond et al. (2002). Financial firms are defined as those firms having SICs between 6000 and 6999.

Table 2 – Descriptive statistics

Panel A: Full sample

Variable	*Mean*	*S.D.*	*25 Perc.*	*Median*	*75 Perc.*
$DEFAULT_{i,t+1}$	0.015	0.121	0.000	0.000	0.000
$GCO_{i,t}$	0.089	0.285	0.000	0.000	0.000
$REL\_MKTCP_{i,t}$	-11.872	1.715	-13.081	-11.907	-10.740
$EX\_RET_{i,t}$	-0.009	0.868	-0.502	-0.224	0.165
$SIGMA_{i,t}$	0.047	0.031	0.026	0.039	0.060
$CONT\_PD_{i,t}$†	0.016	0.034	0.001	0.004	0.013
$ROA_{i,t}$	-0.271	0.440	-0.339	-0.111	-0.025
$LEVERAGE_{i,t}$	0.491	0.321	0.236	0.450	0.681
$WCAP_{i,t}$	0.303	0.307	0.081	0.287	0.530
$CURRENT_{,t}$	3.696	4.466	1.312	2.203	4.100
$CASH_{i,t}$	0.293	0.286	0.047	0.187	0.489
$CFO_{i,t}$	-0.127	0.300	-0.179	-0.032	0.040
$SIZE_{,i,t}$	4.802	1.804	3.506	4.600	5.915
$NEGEQUITY_{i,t}$	0.058	0.233	0.000	0.000	0.000
$BIGN_{i,t}$	0.774	0.418	1.000	1.000	1.000
N. Obs. =	27,189				

Panel B: Partition by going concern

	$GCO_{i,t} = 0$			$GCO_{i,t} = 1$			*Difference*
Variable	*Mean*	*S.D.*	*Median*	*Mean*	*S.D.*	*Median*	*in Means*
$DEFAULT_{i,t+1}$	0.007	0.086	0.000	0.091	0.287	0.000	-0.083***
$REL\_MKTCP_{i,t}$	-11.734	1.687	-11.763	-13.279	1.307	-13.319	1.545***
$EX\_RET_{i,t}$	0.024	0.873	-0.195	-0.345	0.729	-0.519	0.369***
$SIGMA_{i,t}$	0.045	0.029	0.038	0.070	0.038	0.061	-0.025***
$CONT\_PD_{i,t}$†	0.012	0.026	0.003	0.050	0.064	0.022	-0.038***
$ROA_{i,t}$	-0.220	0.357	-0.095	-0.792	0.756	-0.556	0.572***
$LEVERAGE_{i,t}$	0.470	0.301	0.434	0.703	0.421	0.656	-0.233***
$WCAP_{i,t}$	0.330	0.285	0.310	0.025	0.376	0.017	0.306***
$CURRENT_{,t}$	3.877	4.555	2.330	1.847	2.842	1.048	2.030***
$CASH_{i,t}$	0.299	0.287	0.196	0.233	0.266	0.116	0.066***
$CFO_{i,t}$	-0.097	0.250	-0.025	-0.432	0.519	-0.233	0.335***
$SIZE_{,i,t}$	4.922	1.774	4.717	3.583	1.656	3.324	1.339***
$NEGEQUITY_{i,t}$	0.044	0.205	0.000	0.195	0.396	0.000	-0.151***
$BIGN_{i,t}$	0.786	0.410	1.000	0.646	0.478	1.000	0.141***
N. Obs. =	24,760			2,429			

†Denotes a variable constructed using CRI data which has a sample size of 19,243. Refer to Table 1.

Panel C: Partition by default

	$DEFAULT_{i,t+1} = 0$			$DEFAULT_{i,t+1} = 1$			Difference in Means
Variable	*Mean*	*S.D.*	*Median*	*Mean*	*S.D.*	*Median*	
$GCO_{i,t}$	0.082	0.275	0.000	0.545	0.499	1.000	-0.462***
$REL\_MKTCP_{i,t}$	-11.858	1.715	-11.892	-12.787	1.388	-12.856	0.929***
$EX\_RET_{i,t}$	-0.001	0.869	-0.216	-0.537	0.546	-0.613	0.536***
$SIGMA_{i,t}$	0.047	0.031	0.039	0.067	0.038	0.059	-0.020***
$CONT\_PD_{i,t}$†	0.015	0.032	0.004	0.086	0.077	0.054	-0.071***
$ROA_{i,t}$	-0.267	0.436	-0.110	-0.496	0.633	-0.228	0.228***
$LEVERAGE_{i,t}$	0.485	0.317	0.445	0.839	0.373	0.817	-0.354***
$WCAP_{i,t}$	0.308	0.304	0.292	-0.002	0.355	0.003	0.309***
$CURRENT_{,t}$	3.722	4.470	2.225	1.915	3.792	1.009	1.807***
$CASH_{i,t}$	0.295	0.286	0.190	0.156	0.228	0.062	0.139***
$CFO_{i,t}$	-0.126	0.299	-0.032	-0.207	0.384	-0.051	0.081***
$SIZE_{,i,t}$	4.795	1.803	4.592	5.292	1.810	5.217	-0.497***
$NEGEQUITY_{i,t}$	0.054	0.227	0.000	0.270	0.444	0.000	-0.215***
$BIGN_{i,t}$	0.774	0.418	1.000	0.772	0.420	1.000	0.002
N. Obs. =	26,785			404			

This table includes descriptive statistics for the variables in our analysis. Panel A uses all observations in our sample. Panel B and C partitions the sample by going concern and by default, respectively, and reports the difference in means. Throughout the table, ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively, and the symbol † denotes a variable constructed using CRI data which has a sample size of 19,243 firm-years with 1,784 firm-years having a GCO and 265 firm-years having default events as shown in Table 1. Refer to Appendix A for variable definitions.

Table 3 – Sensitivity and specificity of GCOs compared to model using financial ratios overtime

		Sensitivity *(Percentage of Defaults Predicted Correctly)*				Specificity *(Percentage of Non-Defaults Predicted Correctly)*		
Year	Defaults	Naïve Going Concern	Financial Ratios	Difference in Ratios	Non-Defaults	Naïve Going Concern	Financial Ratios	Difference in Ratios
1999	26	34.6%	88.5%	-53.8% ***	1,789	93.0%	70.9%	22.1% ***
2000	77	48.1%	67.5%	-19.5% **	2,286	89.8%	71.3%	18.4% ***
2001	49	57.1%	77.6%	-20.4% **	2,174	90.3%	71.1%	19.2% ***
2002	34	61.8%	67.6%	-5.9%	2,034	89.8%	70.7%	19.2% ***
2003	17	52.9%	88.2%	-35.3% ***	1,627	94.0%	70.6%	23.4% ***
2004	14	50.0%	92.9%	-42.9% ***	1,429	92.7%	70.7%	22.0% ***
2005	9	77.8%	55.6%	22.2%	1,398	91.5%	70.2%	21.3% ***
2006	7	14.3%	71.4%	-57.1% **	1,380	91.9%	70.2%	21.7% ***
2007	22	54.5%	54.5%	0.0%	1,417	90.8%	70.4%	20.4% ***
2008	47	68.1%	63.8%	4.3%	1,611	88.7%	71.0%	17.7% ***
2009	11	81.8%	90.9%	-9.1%	1,530	92.6%	70.4%	22.2% ***
2010	9	77.8%	88.9%	-11.1%	1,166	92.0%	70.5%	21.5% ***
2011	11	36.4%	81.8%	-45.5% **	1,140	92.6%	70.5%	22.1% ***
2012	6	50.0%	66.7%	-16.7%	1,153	91.3%	70.3%	21.0% ***
2013	15	53.3%	73.3%	-20.0%	1,218	93.9%	70.6%	23.4% ***
Overall	354	54.8%	72.9%	-18.1% ***	23,352	91.5%	70.7%	20.8% ***

This table compares the sensitivity and specificity results from using the naïve GCO in year *t* as a predictor of default in year *t+1* versus using financial ratios in year *t* as predictors of default in year *t+1*. The naïve Going Concern column displays the sensitivity (specificity) in year *t* which is the percentage of firms which default (do not default) in year *t+1*, the variable $DEFAULT_{i,t+1}$=1 (=0), that also receive a GCO in year *t*, the variable $GCO_{i,t}$=1 (=0). The financial ratios column displays the sensitivity (specificity) in year *t* which is the percentage of firms which default (do not default) in year *t+1*, the variable $DEFAULT_{i,t+1}$=1 (=0), that also are in the top three deciles of the predicted probability of default for year *t* from a three year rolling window logistic regression using financial ratios. The model is estimated using the three years prior (years t-3 to t-1), and is specified as:

$$P(DEFAULT_{i,t+1}) = f(ROA_{i,t}, LEVERAGE_{i,t}, WCAP_{i,t}, CURRENT_{i,t}, CASH_{i,t}, CFO_{i,t}, SIZE_{i,t}, NEGEQUITY_{i,t}, BIGN_{i,t}, Industry\ Fixed\ Effects_{i,t}, e_{it})$$

The resulting estimated coefficients were then used to predict a probability of default in year *t+1* based upon the financial ratios for year *t*. The sensitivity and specificity of the resulting probability of default was determined using whether the predicted probability fell within the top three deciles of all predicted probabilities for year *t*. In this table, ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Refer to Appendix A for variable definitions.

Table 4 – Comparison of GCOs to financial ratios and market variables

Panel A: Logistic regression results

	Dependent Variable = $DEFAULT_{i,t+1}$				
	GCO	*Fin Ratios (FR)*	*GCO & FR*	*Market & FR*	*Full Model*
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
$GCO_{i,t}$	2.600***		2.496***		1.844***
	[24.37]		[16.18]		[10.95]
$REL\_MKTCP_{i,t}$				-0.495***	-0.435***
				[-10.92]	[-9.09]
$EX\_RET_{i,t}$				-1.842***	-1.420***
				[-5.34]	[-4.50]
$SIGMA_{i,t}$				2.029	-0.264
				[1.09]	[-0.13]
$ROA_{i,t}$		-0.294*	-0.086	-0.096	0.013
		[-1.86]	[-0.52]	[-0.59]	[0.08]
$LEVERAGE_{i,t}$		1.346***	1.458***	1.214***	1.305***
		[4.81]	[5.46]	[4.38]	[4.73]
$WCAP_{i,t}$		-2.086***	-0.417	-1.598***	-0.428
		[-6.91]	[-1.53]	[-5.71]	[-1.57]
$CURRENT_{i,t}$		0.068***	0.055***	0.074***	0.070***
		[3.44]	[2.66]	[3.49]	[3.17]
$CASH_{i,t}$		0.345	0.000	0.742*	0.382
		[0.92]	[0.00]	[1.94]	[1.00]
$CFO_{i,t}$		-0.730***	-0.643**	-1.238***	-1.119***
		[-2.91]	[-2.57]	[-4.84]	[-4.36]
$SIZE_{i,t}$		0.226***	0.355***	0.635***	0.667***
		[7.55]	[10.69]	[12.96]	[12.59]
$NEGEQUITY_{i,t}$		-0.032	-0.133	-0.067	-0.125
		[-0.12]	[-0.53]	[-0.28]	[-0.52]
$BIGN_{i,t}$		-0.230	-0.290**	-0.228	-0.293**
		[-1.56]	[-1.98]	[-1.54]	[-1.99]
Constant	-4.770***	-5.985***	-7.279***	-14.933***	-14.552***
	[-14.06]	[-15.04]	[-17.31]	[-19.33]	[-17.37]
Industry & Year FEs	Yes	Yes	Yes	Yes	Yes
N. Obs.	27,189	27,189	27,189	27,189	27,189
Pseudo-R^2	0.189	0.168	0.243	0.257	0.297
AUC	0.835	0.847	0.879	0.895	0.909
Mean out-of-sample AUC	0.822	0.830	0.866	0.883	0.898

Panel B: Comparison of the predictive ability based on AUC

	AUC (1)	(2)	*Difference* (3)
(1) GCO vs. (2) FR	0.835	0.847	0.012
(1) GCO vs. (3) GCO&FR	0.835	0.879	0.044***
(2) FR vs. (3) GCO&FR	0.847	0.879	0.032***
(1) GCO vs. (4) Market&FR	0.835	0.895	0.060***
(3) GCO&FR vs. (4) Market&FR	0.879	0.895	0.016**
(1) GCO vs. (5) Full Model	0.835	0.909	0.074***
(3) GCO&FR vs. (5) Full Model	0.879	0.909	0.030***
(4) Market&FR vs. (5) Full Model	0.895	0.909	0.014***

Panel A includes results from the logistic regressions including:

$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, Fixed\ Effects_{i,t}, e_{it})$ (Column 1)
$P(DEFAULT_{i,t+1}) = f(Financial\ Ratios_{i,t}, Fixed\ Effects_{i,t}, e_{it})$ (Column 2)
$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, Financial\ Ratios_{i,t}, Fixed\ Effects_{i,t}, e_{it})$ (Column 3)
$P(DEFAULT_{i,t+1}) = f(Market\ Variables_{i,t}, Financial\ Ratios_{i,t}, Fixed\ Effects_{i,t}, e_{it})$ (Column 4)
$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, Market\ Variables_{i,t}, Financial\ Ratios_{i,t}, Fixed\ Effects_{i,t}, e_{it})$ (Column 5)

Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix A.

Panel B includes the AUC comparison for the logistic models presented in Panel A. Columns 1 and 2 display the resulting AUC values from the identified models. Column 3 indicates the difference in AUCs between the two models and ***, **, and * indicate statistical significance of the AUC differences resulting from the non-parametric Wald test at 0.01, 0.05, and 0.10 levels, respectively.

Table 5 – Comparison of the predictive ability based on AUC of various cross-sections

Cross-section	*(1) GCO&FR Model*	*(2) Market&FR Model*	*(3) Full Model*	*(4) Cols. (2)-(1)*	*(5) Cols. (3)-(1)*	*(6) Cols. (3)-(2)*	*No. Obs.*
		AUC			*Differences*		
Small firms[a]	0.888	0.886	0.896	-0.002	0.008	0.010	6,798
Large firms[a]	0.919	0.937	0.945	0.018*	0.026***	0.008**	6,798
BigN Auditor	0.894	0.913	0.924	0.019**	0.030***	0.011***	21,058
Non-BigN Auditor	0.873	0.882	0.887	0.009	0.014	0.005	6,131
Consecutively Distressed	0.876	0.893	0.904	0.017**	0.028***	0.011***	20,292
Non-consecutively Distressed	0.928	0.926	0.946	-0.002	0.018**	0.020*	5,980
GCO in prior year	0.836	0.857	0.867	0.021	0.032*	0.010	1,251
No GCO in prior year	0.888	0.904	0.916	0.016*	0.028***	0.012***	25,938
Fiscal year ended 2006-2008	0.844	0.892	0.900	0.047***	0.056***	0.008	4,408
Fiscal year ended 2009-2011	0.931	0.951	0.955	0.020	0.023*	0.004	3,836

This table includes the AUC comparison for the identified cross-sections. The AUC's were calculated from performing the following logistic regressions from Table 4, Panel A on the identified subset of the sample:

$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \text{Financial Ratios}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 3)

$P(DEFAULT_{i,t+1}) = f(\text{Market Variables}_{i,t}, \text{Financial Ratios}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 4)

$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \text{Market Variables}_{i,t}, \text{Financial Ratios}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 5)

Column 4 indicates the difference in AUCs between the models in Columns 1 and 2. Column 5 indicates the difference in AUCs between the models in Columns 1 and 3. Column 6 indicates the difference in AUCs between the models in Columns 2 and 3. In Columns 4, 5, and 6, ***, **, and * indicate statistical significance of the AUC differences resulting from the non-parametric Wald test at 0.01, 0.05, and 0.10 levels, respectively.

[a] Size is calculated as the log of total assets of a firm. Firms that are in the lower quartile of size in our sample – that is, below $33.3 million in assets – are classified as small firms. Firms that are in the upper quartile of size in our sample – that is, above $370.6 million in total assets – are classified as large firms.

Table 6 – Comparison of GCOs to CRI probability of default

Panel A: Logistic regression results

	Dependent Variable = $DEFAULT_{i,t+1}$		
	GCO Model	*PD Model*	*Combined Model*
Variables	*(1)*	*(2)*	*(3)*
$GCO_{i,t}$	2.288***		1.726***
	[12.09]		[8.55]
$CONT\_PD_{i,t}$		13.738***	10.812***
		[15.07]	[10.83]
$ROA_{i,t}$	-0.178	0.139	0.172
	[-0.91]	[0.70]	[0.87]
$LEVERAGE_{i,t}$	0.881***	0.766**	0.850***
	[2.78]	[2.31]	[2.64]
$WCAP_{i,t}$	-0.634*	-1.512***	-0.451
	[-1.89]	[-4.42]	[-1.34]
$CURRENT_{i,t}$	0.053**	0.062***	0.054**
	[2.40]	[2.81]	[2.40]
$CASH_{i,t}$	0.395	0.863**	0.565
	[0.98]	[2.08]	[1.36]
$CFO_{i,t}$	-0.572*	-1.119***	-0.942***
	[-1.89]	[-3.70]	[-3.13]
$SIZE_{i,t}$	0.313***	0.159***	0.251***
	[7.59]	[3.86]	[5.75]
$NEGEQUITY_{i,t}$	0.182	0.089	0.073
	[0.60]	[0.30]	[0.25]
$BIGN_{i,t}$	-0.419**	-0.425**	-0.460***
	[-2.51]	[-2.48]	[-2.69]
Constant	-7.244***	-6.357***	-7.256***
	[-14.17]	[-12.90]	[-13.89]
Year & Industry FEs	Yes	Yes	Yes
N. Obs.	19,243	19,243	19,243
Pseudo-R^2	0.217	0.223	0.255
AUC	0.871	0.878	0.891

This panel includes results from the logistic regressions including:

$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \text{Client Characteristics}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 1)
$P(DEFAULT_{i,t+1}) = f(CONT\_PD_{i,t}, \text{Client Characteristics}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 2)
$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, CONT\_PD_{i,t}, \text{Client Characteristics}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 3)

Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix A.

Panel B: Comparison of the predictive ability based on AUC

	(1) GCO Model	*(2) PD Model*	*(3) Combined Model*	*(4) Cols. (2)-(1)*	*(5) Cols. (3)-(1)*	*(6) Cols. (3)-(2)*	*No. Obs.*
	AUC			*Differences*			
Main Sample	0.871	0.878	0.891	0.007	0.020***	0.013**	19,243

This panel includes the AUC comparison for the logistic models presented in Panel A. Columns 1 through 3 display the resulting AUC values from each model. Column 4 indicates the difference in AUCs between the GCO and PD models. Column 5 indicates the difference in AUCs between the GCO and Combined models. Column 6 indicates the difference in AUCs between the PD and Combined models. In Columns 4, 5, and 6, ***, **, and * indicate statistical significance of the AUC differences resulting from the non-parametric Wald test at 0.01, 0.05, and 0.10 levels, respectively.

Table 7 – Analysis of the predictive power of GCOs versus credit ratings downgrades

Panel A: Sample Selection

	Total Obs.	$GCO_{i,t}$	$DEFAULT_{i,t+1}$
Main Sample			
	27,189	2,429	404
- Firms missing credit rating data	(23,682)	(2,280)	(280)
Credit Rating Sample	3,507	149	124

Panel B: Descriptive Statistics

Variable	*Mean*	*S.D.*	*25 Perc.*	*Median*	*75 Perc.*
$DEFAULT_{i,t+1}$	0.035	0.185	0.000	0.000	0.000
$GCO_{i,t}$	0.042	0.202	0.000	0.000	0.000
$DOWN_{i,t}$	0.157	0.364	0.000	0.000	0.000
$DOWN\_LVL_{i,t}$	0.182	0.472	0.000	0.000	0.000
$INVST\_CH_{i,t}$	0.039	0.194	0.000	0.000	0.000
$ROA_{i,t}$	-0.094	0.189	-0.109	-0.040	-0.013
$LEVERAGE_{i,t}$	0.754	0.250	0.594	0.730	0.882
$WCAP_{i,t}$	0.116	0.177	0.010	0.097	0.208
$CURRENT_{i,t}$	1.874	1.822	1.061	1.526	2.158
$CASH_{i,t}$	0.097	0.122	0.019	0.054	0.129
$CFO_{i,t}$	0.036	0.084	-0.003	0.042	0.079
$SIZE_{i,t}$	7.503	1.262	6.542	7.463	8.404
$NEGEQUITY_{i,t}$	0.129	0.336	0.000	0.000	0.000
$BIGN_{i,t}$	0.951	0.216	1.000	1.000	1.000
N. Obs. = 3,507					

Panel C: GCOs and defaults by credit ratings

Rating	$GCO_{i,t}$ *N. Obs.*	$GCO_{i,t}$ *Freq.*	$DEFAULT_{i,t+1}$ *N. Obs.*	$DEFAULT_{i,t+1}$ *Freq.*	*Total N. Obs.*
AAA	0	0.000	0	0.000	0
AA	0	0.000	0	0.000	11
A	1	0.000	1	0.000	111
BBB	0	0.000	3	0.001	467
BB	14	0.004	17	0.005	1,023
B	71	0.020	68	0.019	1,648
CCC	46	0.013	31	0.009	210
CC	6	0.002	2	0.001	12
C	0	0.000	0	0.000	0
D	11	0.003	2	0.001	25
Total	149	0.042	124	0.035	3,507

Panel D: Logistic regression results

	Dependent Variable = $DEFAULT_{i,t+1}$						
	GCO Model	*DOWN Model*		*DOWN_LVL Model*		*INVST_CH Model*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
$GCO_{i,t}$	3.018***		2.922***		2.964***		3.032***
	[9.91]		[9.23]		[9.24]		[9.95]
$DOWN_{i,t}$		0.960***	0.708***				
		[4.04]	[2.59]				
$DOWN\_LVL_{i,t}$				0.461***	0.142		
				[3.33]	[0.74]		
$INVEST\_CH_{i,t}$						-0.213	-0.498
						[-0.43]	[-0.89]
$ROA_{i,t}$	-0.792**	-0.567*	-0.625	-0.691**	-0.765**	-0.723**	-0.802**
	[-2.24]	[-1.84]	[-1.62]	[-2.40]	[-2.11]	[-2.54]	[-2.28]
$LEVERAGE_{i,t}$	0.596	0.431	0.538	0.406	0.568	0.531	0.625
	[0.94]	[0.67]	[0.84]	[0.62]	[0.89]	[0.83]	[0.99]
$WCAP_{i,t}$	-0.488	-3.418***	-0.347	-3.371***	-0.422	-3.795***	-0.494
	[-0.56]	[-4.60]	[-0.39]	[-4.31]	[-0.47]	[-5.17]	[-0.56]
$CURRENT_{i,t}$	-0.161	-0.047	-0.185	-0.070	-0.179	-0.013	-0.160
	[-0.60]	[-0.26]	[-0.67]	[-0.35]	[-0.64]	[-0.08]	[-0.59]
$CASH_{i,t}$	-2.370	-0.154	-1.820	-0.384	-2.202	-0.844	-2.429
	[-1.48]	[-0.10]	[-1.10]	[-0.24]	[-1.35]	[-0.53]	[-1.51]
$CFO_{i,t}$	-4.394**	-5.596***	-4.064**	-5.670***	-4.274**	-6.181***	-4.429**
	[-2.55]	[-3.47]	[-2.35]	[-3.54]	[-2.49]	[-3.79]	[-2.56]
$SIZE_{i,t}$	0.043	-0.141	0.015	-0.144*	0.029	-0.102	0.059
	[0.52]	[-1.60]	[0.17]	[-1.66]	[0.33]	[-1.19]	[0.71]
$NEGEQUITY_{i,t}$	0.481	0.600	0.505	0.582	0.480	0.536	0.469
	[1.06]	[1.36]	[1.09]	[1.31]	[1.05]	[1.21]	[1.03]
$BIGN_{i,t}$	-0.463	-0.036	-0.454	-0.068	-0.460	-0.064	-0.468
	[-1.10]	[-0.08]	[-1.06]	[-0.15]	[-1.09]	[-0.14]	[-1.11]
Constant	-3.539***	-2.605**	-3.385***	-2.443**	-3.416***	-2.818**	-3.645***
	[-3.21]	[-2.31]	[-3.04]	[-2.14]	[-3.02]	[-2.49]	[-3.28]
Industry & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs.	3,507	3,507	3,507	3,507	3,507	3,507	3,507
Pseudo-R^2	0.329	0.236	0.336	0.230	0.330	0.221	0.330
AUC	0.897	0.862	0.905	0.860	0.899	0.853	0.899

Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix A.

Panel E: Comparison of the predictive ability based on AUC

	(1) GCO Model	*(2) Credit Var Models*	*(3) Combined Model*	*(4) Cols. (2)-(1)*	*(5) Cols. (3)-(1)*	*(6) Cols. (3)-(2)*	*No. Obs.*
	AUC			*Differences*			
DOWN Models	0.897	0.862	0.905	-0.035**	0.008	0.043***	3,507
DOWN_LVL Models	0.897	0.860	0.899	-0.037**	0.002*	0.039***	3,507
INVST_CH Models	0.897	0.853	0.899	-0.044***	0.002	0.046***	3,507

This panel includes the AUC comparison for the logistic models in Panel D:

$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \text{Client Characteristics}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 1)
$P(DEFAULT_{i,t+1}) = f(\text{Credit Variables}, \text{Client Characteristics}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 2)
$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, \text{Credit Variables}, \text{Client Characteristics}_{i,t}, \text{Fixed Effects}_{i,t}, e_{it})$ (Column 3)

Column 4 indicates the difference in AUCs between the models in Columns 1 and 2. Column 5 indicates the difference in AUCs between the models in Columns 1 and 3. Column 6 indicates the difference in AUCs between the models in Columns 2 and 3. In Columns 4, 5, and 6, ***, **, and * indicate statistical significance of the AUC differences resulting from the non-parametric Wald test at 0.01, 0.05, and 0.10 levels, respectively.

Table 8 – Matching companies with and without GCOs on client characteristics

Panel A: Probability of receiving a GCO

	Dependent Variable = $GCO_{i,t}$
Variables	*(1)*
$CONT\_PD_{i,t}$	15.319***
	[21.55]
$ROA_{i,t}$	-0.169*
	[-1.91]
$LEVERAGE_{i,t}$	-0.243
	[-1.53]
$WCAP_{i,t}$	-3.575***
	[-20.38]
$CURRRENT_{i,t}$	0.024*
	[1.81]
$CASH_{i,t}$	-0.278
	[-1.35]
$CFO_{i,t}$	-1.791***
	[-12.79]
$SIZE_{i,t}$	-0.459***
	[-17.00]
$NEGEQUITY_{i,t}$	-0.083
	[-0.53]
$BIGN_{i,t}$	0.189**
	[2.46]
Constant	-0.510**
	[-1.99]
Industry & Year FEs	Yes
N. Obs.	19,243
Pseudo-R^2	0.363

This panel includes results from the logistic regression:

$$P(GCO_{i,t}) = f(CONT\_PD_{i,t}, Client\ Characteristics_{i,t}, Fixed\ Effects_{i,t}, e_{it}) \qquad \text{(Column 1)}$$

Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix A.

Panel B: Matched sample characteristics

	Unmatched		*Matched*		
Variable	$GCO_{i,t}$=1	$GCO_{i,t}$=0	$GCO_{i,t}$=1	$GCO_{i,t}$=0	*t-statistic*
$DEFAULT_{i,t+1}$	0.080	0.007	0.071	0.020	-6.627***
$CONT\_PD_{i,t}$	0.051	0.012	0.039	0.040	-0.680
$ROA_{i,t}$	-0.806	-0.230	-0.676	-0.643	-1.310
$LEVERAGE_{i,t}$	0.704	0.466	0.633	0.616	1.210
$WCAP_{i,t}$	0.025	0.329	0.095	0.100	-0.450
$CURRENT_{i,t}$	1.851	3.879	2.068	1.950	1.100
$CASH_{i,t}$	0.237	0.306	0.246	0.231	1.470
$CFO_{i,t}$	-0.443	-0.098	-0.370	-0.358	-0.690
$SIZE_{i,t}$	3.588	4.962	3.661	3.570	1.530
$NEGEQUITY_{i,t}$	0.197	0.045	0.138	0.118	1.630
$BIGN_{i,t}$	0.625	0.771	0.628	0.611	0.930
N. Obs. =	1,784	17,459	1,418	1,418	

This panel provides the sample means of the key variables for the unmatched and matched samples. The t-statistic reports the difference in means between the treated and control groups of the matched sample. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Variable definitions are included in Appendix A.

Panel C: Matched logistic regression results

	Dependent Variable = $DEFAULT_{i,t+1}$
Variables	*(1)*
$GCO_{i,t}$	1.492***
	[6.20]
$CONT\_PD_{i,t}$	9.687***
	[6.51]
$ROA_{i,t}$	0.081
	[0.35]
$LEVERAGE_{i,t}$	0.435
	[0.98]
$WCAP_{i,t}$	-0.982**
	[-2.25]
$CURRENT_{i,t}$	0.098***
	[3.17]
$CASH_{i,t}$	0.823
	[1.45]
$CFO_{i,t}$	-0.955***
	[-2.64]
$SIZE_{i,t}$	0.340***
	[4.55]
$NEGEQUITY_{i,t}$	0.239
	[0.63]
$BIGN_{i,t}$	-0.304
	[-1.26]
Constant	-7.720***
	[-8.24]
Industry and Year FEs	Yes
N. Obs.	2,836
Pseudo-R^2	0.218

This panel includes results from the logistic regressions including:

$$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, CONT\_PD_{i,t}, Client\ Characteristics_{i,t}, Fixed\ Effects_{i,t}, e_{it}) \quad \text{(Column 1)}$$

Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix A.