A cross-country examination of auditor reporting for going-concern uncertainty

Elizabeth Gutierrez
Universidad de Chile

Jake Krupa
University of Miami

Miguel Minutti-Meza*
University of Miami

Maria Vulcheva
Florida International University

August 2015

Abstract

The audit opinion includes an assessment of the client's going concern uncertainty. Using data from several countries, previous studies show a wide gap between going concern opinions (GCOs) and subsequent bankruptcies. This gap is often attributed to GCOs having low information content and to auditors failing to provide timely warning to investors about bankruptcies. We use a large sample of opinions from 17 countries to determine whether GCOs are better predictors of subsequent corporate defaults, including bankruptcies, than a comprehensive *ex ante* estimate of probability of default (PD), based on accounting and market data. Despite country-level differences in the predictability of defaults, on average, GCOs and PDs *independently* have similar predictive accuracy. However, GCOs and PDs do not have perfect overlap and using them *together* results in incremental predictive accuracy. Considering the inherent difficulties in forecasting defaults, our results suggest that GCOs contain useful information in predicting defaults across countries.

Keywords: going concern opinions; audit quality.

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

Authors thank Pietro Bianchi, Khrystyna Bochkay, Lauren Cunningham, Mark Maffett, Dhananjay Nanda, Peter Wysocki, and seminar participants at University of Chicago and University of Miami. Authors also thank the excellent research assistance of Yaomin Hao and Taylor Wiesen. *Corresponding author: mminutti@bus.miami.edu

I. INTRODUCTION

This study examines auditor reporting for going concern uncertainty across countries. More specifically, we use large a sample of audit opinions from 17 countries to determine whether going concern opinions (GCOs) are better predictors of subsequent corporate defaults, including bankruptcies, than a comprehensive *ex ante* estimate of probability of default (PD), based on publicly-available accounting and market data.

Under the U.S. and international audit standards the auditor is required to evaluate the going concern assumption. Both sets of 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 GCO.[1] The AICPA Statement on Auditing Standards 341 describes the auditor's responsibility with respect to evaluating going concern. Section 341.02 (formerly SAS No. 59 AICPA 1988) state that:

> *"The auditor has a responsibility to evaluate whether there is substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time, not to exceed one year beyond the date of the financial statements being audited (hereinafter referred to as a reasonable period of time). 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."*

Furthermore, the auditor's responsibility is limited with respect to predicting future events. Section 341.04 states that:

> *"The auditor is not responsible for predicting future conditions or events. The fact that the entity may cease to exist as a going concern subsequent to receiving a report from the*

[1] For examples of going concern modification paragraphs see Appendix B.

auditor that does not refer to substantial doubt, even within one year following the date of the financial statements, does not, in itself, indicate inadequate performance by the auditor.”[2]

GCOs have been a topic of constant debate, particularly in time periods when the number of corporate bankruptcies rises due to bad economic conditions.[3] In contrast with the restricted auditor's responsibility prescribed in the auditing standards, the financial press has raised some concerns with the auditor's responsibility in warning investors about potential business failures. For example, Chasan (2013) highlights that “Investors are growing more frustrated with so-called “going-concern” opinions from corporate auditors that have failed to warn them of bankruptcies.” Similarly, McKenna (2011) points out that none of the banks that failed, were bailed out, or were effectively nationalized during 2007 and 2008 received GCOs; and, also that there are hundreds of companies in the U.S. “that had ‘going concern' qualification for their financials statements several times”, and asks why “are the criteria so imprecise that auditors can have significant doubt, year after year that a company can survive the next twelve months only to be proven wrong, over and over again?”

Regulators have been recently concerned with the auditors' 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 (PCAOBa 2012, p. 3)”. On August 27, 2014, the FASB issued ASU 2014-15, providing guidance on determining when

[2] Similar responsibilities and limitations are described in the International Standard on Auditing 570 (Sections 570.6 and 570.7).

[3] For example, in 2009 the IAASB issued a Staff Audit Practice Alert “to raise auditors' awareness about matters relevant to the consideration of the use of the going concern assumption in the preparation of the financial statements in the current environment (IAASB 2009, p.1).”

and how to disclose going-concern uncertainties in the financial statements. The new standard requires management to perform interim and annual assessments of an entity's ability to continue as a going concern within one year of the date the financial statements are issued. 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).[4]

A large body of research has studied the drivers of the auditor's decision to issue a GCO and the literature often uses GCOs as a proxy for audit quality.[5] In particular, a stream of the literature focuses on whether the auditor is "accurate" about the client's future business failure.[6] These studies compare the auditor's opinion, using a 1/0 categorization for GCOs, versus the client's subsequent bankruptcy. In the U.S., historical data shows that approximately half of the companies going bankrupt do not receive a prior GCO. In contrast, over two thirds of companies with a GCO do not subsequently go bankrupt (e.g., Carson, Fargher, Geiger, Lennox, Raghunanadan and Willekens 2013). Outside the US, previous studies also document a gap between GCOs and subsequent bankruptcies (e.g., Carson, Simnett and Tronnes 2012). This gap, observed across countries, is often attributed to GCOs having low information content and to

---

[4] The Sub Advisory Group's suggested a number of issues with the Audit Standard AU 341, including: (1) lack of specific objectives that the auditor should achieve, (2) the auditor is not required to design their audit specifically to look for evidence with respect to going concern; (3) there is no requirement for auditor to communicate with the audit committee about going concern issues; and, (4) the auditor is not required to consider public domain information that is contrary to evidence management has presented (PCAOBb 2012). The new going concern disclosure standard is a substantial modification to the assessment of the going concern assumption, previously defined in SAS No. 59 issued in 1988 (AICPA 1988).

[5] Please see Carson et al. (2013) for a thorough review of the papers in the GCO literature. For examples of using auditor's propensity to issue 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.

[6] For examples of these studies using U.S. data, see Geiger, Raghunandan and Rama (2005); Geiger and Rama (2006); Feldmann and Read (2010); Myers, Schmidt, and Wilkins (2014); and, also studies using non-U.S. data see Lennox (1999); Martin (2000); Carey, Geiger and O'Connell (2008); Carcello, Vanstraelen and Willenborg (2009); Carey, Kortum and Moroney (2012); Carson, Simnett and Tronnes (2012), and Sormunen, Jeppesen, Sundren and Svanstrom (2013).

auditors failing to provide timely warnings to investors about impending bankruptcy. However, this interpretation conflicts with studies demonstrating that investors react negatively to the announcement of GCOs (e.g., Menon and Williams 2010). In addition, extant studies compare bankruptcies and auditor opinions that happen at different points in time and do not necessarily evaluate the auditor's decision against the *ex ante* probability of default when the GCO was issued (i.e., whether the auditor adequately considers the set of *existing* conditions at year-end).

This study examines the information content of GCOs from a different perspective, comparing a one-year default prediction model using GCOs versus a comprehensive *ex ante* estimate of probability of default within 12 months (PD). In other words, our research design compares the accuracy of the auditor's professional judgment versus the accuracy a statistical decision model based on the client's year-end financial condition. In our main analyses, we use PD estimates and cross-country data on corporate defaults from the database of the Credit Research Initiative (CRI) of the Risk Management Institute at National University of Singapore. The CRI determines its PD estimates following a comprehensive credit risk model by Duan, Sun and Wang (2012). The CRI's PD estimates are notably good in forecasting various forms of corporate defaults, including bankruptcy (CRI 2013).[7] The PD estimates are based on publicly available information from economy-level indicators and firm-specific variables, including: stock index return, short term interest rate, volatility-adjusted leverage, liquidity, cash and short term investments, profitability, relative size, market valuation, and idiosyncratic volatility.

[7] The prediction accuracy of the CRI PD forecasts has been tested in-sample using Accuracy Ratio (AR) and area under the receiver operating characteristic curve (AUC). The range of possible AR values is in the interval [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. Similarly, AUC, with possible values in the interval [0.5,1], is mostly greater than 0.8 at the one-year horizon for most of the countries in the estimation sample.

Our sample is unique to the GCO literature. We examine 43,726 auditor reports, with 5,680 GCOs from 17 countries for the years 2000 to 2012. Relatively few studies examine GCO frequencies across multiple countries because of data limitations with respect to GCO and subsequent defaults. We compare the predictive power of GCOs and PDs independently in terms of the predictive accuracy of two logistic regression models, one including GCOs and one including PDs. Our main measure of predictive accuracy is the area under the receiver operating characteristic curve (AUC). The AUC summarizes the model's ability to correctly classify default observations for all probability cut-off thresholds. The range of possible AUC values is in the interval [0.5,1], where 0.5 is a poor performance and 1 is a perfect performance.

On average, we find that GCOs and PDs independently have similar predictive accuracy in forecasting subsequent defaults. For example, using aggregate data at the global level, the AUC of a model that predicts defaults one-year ahead using GCOs, controlling for company characteristics (e.g., profitability, leverage, liquidity, and auditor type), including country, industry, and year fixed effects, is 0.854. In contrast, the AUC of a similar model using PDs is 0.860. The difference between these models' AUCs is not statistically significant (at the 10 percent level). We find a similar pattern after aggregating similar countries and also at the country level, despite country-specific differences in the ability to predict future defaults. For example, the AUCs of the country-level default models using GCOs are 0.734 for China and 0.872 for the U.S.

We also find that GCOs and PDs do not have perfect overlap and using them *together* results in incremental predictive accuracy. The predictive accuracy of a model combining both indicators is greater than the predictive accuracy of using each indicator alone. The AUC of the global-level default model using both GCOs and PDs is 0.874.

Our study contributes to the literature by providing evidence that, after considering the inherent difficulties in forecasting corporate defaults, on average GCOs are generally as good as a statistical PD estimate in predicting default. However, the imperfect overlap between GCOs and PDs suggest that GCOs provide useful incremental information in precisely predicting defaults across countries. The imperfect overlap can be attributed to auditors' professional judgment involving somewhat different criteria than the statistical PD model, including private information, in issuing GCOs. Our results suggest that auditors, on average, have lower false-positive rates compared to a statistical decision rule. We hope that this study will enhance our understanding of the observed gap between the number of clients with GCOs and the number of *ex post* bankruptcies. Also, our results may foster discussion about whether standards on GCOs should suggest auditors to use statistical models as additional criteria in assessing going concern uncertainty. Finally, our study fits within the growing literature examining auditor quality across countries (e.g., Francis, Michas and Seavey 2013; Carson 2009; Francis and Wang 2008) and we encourage other cross-country studies to also use the PD estimates employed in this study.

II. LITERATURE REVIEW AND STANDARDS ON GOING CONCERN

2.1 Incidence and accuracy of GCOs in the U.S.

The incidence of GCOs is influenced by client and auditor characteristics and has changed over time in the U.S. Some historical changes impacting the incidence of GCO's were the issuance of SAS No. 59 "Auditor's consideration of an entity's ability to continue as a going concern", the passing of the Private Securities Litigation Reform Act in 1995, and the passing of Sarbanes-Oxley act in 2002. Butler, Leone and Willenborg (2004) show that in the period from 1980 to 1999, 33% of all opinions had some auditor qualification. 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 GCO. Carson et al. (2013) show that the incidence of GCOs has steadily increased from 9.8% in 2000 to 17% in 2010.

A number of extant studies examining the auditor's propensity to issue a GCO focus on whether the auditor is "accurate" in predicting future default. These studies compare the auditor's opinion, using a 1/0 categorization for GCOs, versus client *ex post* bankruptcy, using a 1/0 categorization for clients that went bankrupt in the following year after the auditor's opinion. These studies define two types of reporting misclassifications. 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. These studies benchmark the actual incidence of GCOs versus an ideal 100 percent rate among clients with *ex post* bankruptcy.

In general, approximately half of the companies going bankrupt in the U.S. 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% in the period between 2000 and 2003. Geiger and Rama (2006) find a type II misclassification of 51% and a type I misclassification of 88% in the period between 1990 and 2000. Feldmann and Read (2010) find a type II misclassification of 41% in the period between 2000 and 2007. Myers et al. (2014) find a type II misclassification of 32% and a type I misclassification of 20% 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, p. 366) note 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). In addition, prior studies compare bankruptcies and auditor opinions that happen at different points in time and do not necessarily evaluate the auditor's decision against the *ex ante* probability of default when the GCO was issued (i.e., whether the auditor adequately considers the set of *existing* conditions at year-end).

2.2 Incidence and accuracy of GCOs outside the U.S.

Outside the US, some studies have examined cross-country and time-related variation in the incidence of GCOs and there is also evidence of a gap between GCOs and subsequent bankruptcies. Martin (2000) shows that in the period from 1987 to 1991, the U.S. had a higher incidence of GCOs compared to Germany and France. A recent study by Carson et al. (2012) tabulates rates for GCOs in five countries: Australia, U.K., U.S., France and Germany. Carson et al. (2012) document that among loss firms the GCO rates are 23% in Germany, 21% in Australia and the U.S., 14% in the U.K., and 11% in France in the period between 2001 and 2009. In addition, GCO rates increased in the U.K., Australia, and France in 2008. Moreover, examining the ratio of GCO relative to the number of net loss firms reveals that auditors appear to be least conservative at reflecting financial distress in France, followed by the U.S., U.K., with Germany and Australia being the most conservative by issuing the highest proportion of GCOs.

Among the non-U.S. studies examining GCO misclassification rates are Lenox (1999), using U.K. data from 1987 to 1994; Carey et al. (2008), using Australian data from 1994 to 1997; Carcello et al. (2009), using Belgian data from 1995 to 2002; Carey et al. (2012), using Australian data from 1995, 1996, 2004 and 2005; and, Sormunen et al. (2013), using data from Denmark, Finland, Norway and Sweden from 2007 to 2011. These studies also find high Type II and I misclassification rates for GCOs. For example, in the U.K. the proportion of firms that do not go bankrupt in the year subsequent to a GCO is approximately 80 percent (Lennox 1999) and in Australia the proportion of firms with GCOs that do not subsequently go bankrupt is 88 percent based on first-time GCOs (Carey et al. 2008).

2.3 Standards on GCOs

Under the U.S. (AICPA Statement on Auditing Standards AU 341) and international standards (AISB International Standard on Auditing ISA 570) the auditor is required to evaluate the going-concern assumption. Both sets of 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 or lower than "substantial doubt" (AU 341.02) or "significant doubt" (ISA 570.09), which would trigger an opinion modified for going-concern uncertainty. However, there is not an exact definition of what constitutes significant 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 either intends to liquidate the entity or to cease operations, or has no realistic alternative but to do so.

The auditing standards suggest some events that may indicate going concern uncertainty but 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. ISA 570.A2 describes events or conditions in the following three categories: financial, operating, and other. Nevertheless, both sets of auditing standards are unclear as to how the auditor is to interpret and assess these events or conditions. 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.

Only until recently, under the U.S. standards there was no guidance about management's responsibilities in evaluating or disclosing going concern uncertainties. On August 27, 2014, the FASB issued ASU 2014-15, providing guidance on determining when and how to disclose going-concern uncertainties in the financial statements. The new standard requires management to perform interim and annual assessments of an entity's ability to continue as a going concern within one year of the date the financial statements are issued. 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).

The International Accounting Standard (IAS) 1, "Presentation of Financial Statements" requires management to make an assessment of an entity's ability to continue as a going concern. Second, the period of assessment may be comparatively longer under the international standard. ISA 570 requires the auditor to consider the same period as that used by management in making its assessment, a period of at least, but not limited to, 12 months from the balance sheet date. AU 341 requires the auditor to evaluate whether there is "substantial doubt" for a reasonable period of time, not to exceed one year beyond the date of the financial statements being audited.

III. RESEARCH QUESTIONS AND METHODOLOGY

In this section, we discuss the methodology we use to compare the predictive value of GCOs and PDs independently in terms of the predictive accuracy of a logistic regression model including these determinants. Our main research question is what is the accuracy of the auditor's judgment versus a statistical decision model based on year-end existing conditions? We begin by estimating separately the two following logistic regression models, with clustered standard errors by company:

$$P(DEFAULT_{i,t+1}) \quad = \quad f(GCO_{i,t}\ , Client\ Characteristics_{i,t}, Fixed\ Effects_{i,t}, \varepsilon_{it} \qquad \textbf{(1)}$$

$$P(DEFAULT_{i,t+1}) \quad = \quad f(HIGH\_PD_{i,t}\ , Client\ Characteristics_{i,t}, Fixed\ Effects_{i,t}, \varepsilon_{it} \qquad \textbf{(2)}$$

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; $HIGH\_PD_{i,t}$ is an indicator variable equal to one if the estimated PD for the next 12 months at fiscal year-end in the CRI database for firm i is in the top three deciles by country and year t, and 0 otherwise; *Client Characteristics* include several determinants of GCOs from the literature (Carson et al. 2013), $ROA_{i,t}$ defined as net income divided by total assets, $CFO_{i,t}$ defined as cash flow from operations divided by total assets, $LEVERAGE_{i,t}$ defined as total leverage divided by total assets, $CASH_{i,t}$ defined as cash and cash equivalent holdings divided by total assets, $SIZE_{i,t}$ defined as the natural logarithm of total assets, $NEGEQUITY_{i,t}$ an indicator variable equal to one if the company has negative equity and 0 otherwise, and $BIG4_{i,t}$ an indicator variable equal to one if the company has a Big 4 auditor, and 0 otherwise; and $Fixed\ Effects_{i,t}$ depend on the level of the analysis. We perform (a) global-level analyses and include in the models year, industry (1-digit SIC Code), and country fixed effects;

(b) grouping similar countries and include in the models year, industry (1-digit SIC Code), and country fixed effects; and, (3) country-level analyses and include in the models year fixed effects.

Following, we examine the relative predictive ability of logistic regressions (1) and (2). Our main measure of 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., 1-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 study we are specifically interested in the accuracy of a logistic model in default prediction, where one-year ahead default is coded as 1/0. After fitting the logistic model, we compute estimated probabilities that each observation *i* belongs to the default =1 group, given GCO and other control variables. Next, after choosing a specific probability threshold, such as 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.[8]

A model with perfect discrimination has a 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, the higher the overall accuracy of the model (e.g., Janes, Longton and Pepe 2009). Therefore, there

[8] 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.

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, Longton and Janes 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), 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 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 1000 replications), where the null hypothesis is that both AUC values are equal (Janes et al. 2009).[9]

Finally, our second research question is whether GCOs and PDs together are incrementally informative in predicting defaults. In other words, whether the predictive accuracy of a model combining both indicators is greater than the predictive accuracy of using each indicator alone. We compare the AUCs of models (1) and (2) above, versus the AUC of a third combined logistic regression model:

$$P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, HIGH\_PD_{i,t}, Client\ Characteristics_{i,t}, Fixed\ Effect_{i,t}, \varepsilon_{it} \quad \textbf{(3)}$$

[9] 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).

IV. DATA DESCRIPTION

4.1 Sample selection

Our sample is the intersection of the Thomson Reuters Database and the public companies covered by Credit Research Initiative (CRI) of the Risk Management Institute at National University of Singapore. We start with the population of public companies covered by the CRI from 1990 to the present. The CRI is a non-profit organization that operates on a proprietary database covering macroeconomic, financial and default related information. The population that CRI covers consists of firms from 106 economies in six groups: Developed Asia-Pacific, North America, Europe, emerging markets, China and India.

We merge the CRI database with the Thomson Reuter Database using SEDOL and ISIN number. Furthermore, we limit our analysis to firms from 17 major economies with the largest number of default events and audit reports that we could obtain and translate (in alphabetical order): Australia, Canada, China, Denmark, France, Germany, Italy, Malaysia, Netherlands, Norway, Philippines, Singapore, Sweden, Taiwan, Thailand, United Kingdom (U.K.), and United States (U.S.). We only include non-financial firms and we require non-missing Total Assets, Net Income, and Auditor Opinion from Thomson Reuters. Hopwood, McKeown, and Mutchler (1994) demonstrate that the auditor's decision environment is different for distressed firms. Our final sample includes 43,726 observations.[10]

4.2 Going concern opinions

We manually collect GCOs from annual reports, since neither Reuters Fundamentals, Worldscope, or Compustat Global explicitly identify the existence of a GCO in the audit report.

[10] We include observations from Canada only after 2010. Before the adoption of the International Auditing Standards in 2010, Canadian auditors did not issue a GCO when the client adequately disclosed going concern uncertainties in the annual report (Bedard, Brousseau and Vaenstraelen 2014).

However, these databases indicate whether a report departs from a "clean" opinion. We eliminate any firm-year in which the three auditor opinion variables, Reuters Fundamentals Worldscope, or Compustat Global are missing. We search annual reports for firms with at least one of the three sources of auditor opinion indicating an audit report with a departure from a "clean" opinion, including: (1) unqualified opinion with explanation paragraph, (2) qualified opinion, (3) additional disclaimer, or (4) adverse opinion. This procedure is similar to the one used by Ogneva and Subramanyam (2007, p.441) to identify GCOs in Australia. We download all available annual reports for the selected non-U.S. firms from Mergent Online, Thomson One Banker, or Datastream to identify GCOs and we use Audit Analytics for the U.S. firms, as well as EDGAR for those observations that we could not match to Audit Analytics.

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" (ISA 571 and AU 341). In addition, examining only bankruptcy cases would limit the scope of our study to countries with formal bankruptcy procedures (e.g., U.S. Chapter 11).[11]

We identify default events, including bankruptcies, using the CRI database. The database includes a thorough list of default events for more than 4,000 firms since 1990, originating from

[11] According to ASU 2014-15 (FASB 2015), the default events identified in our sample are related to two specific types of relevant events that suggest that an entity may not meet its obligations (a) negative financial trends, for example, recurring operating losses, working capital deficiencies, negative cash flows from operating activities, and other adverse key financial ratios; and (b) other indications of possible financial difficulties, for example, default on loans or similar agreements, arrearages in dividends, denial of usual trade credit from suppliers, a need to restructure debt to avoid default, noncompliance with statutory capital requirements, and a need to seek new sources or methods of financing or to dispose of substantial assets

Bloomberg, Compustat, CRSP, Moody's, TEJ, exchange websites, and news sources. CRI classifies default events into hard and soft defaults. Hard defaults are permanent defaults from which the company cannot recover. Such defaults are administrations, arrangements, Chapter 11 proceedings, and liquidation, among others. Soft defaults are defaults from which the company could reemerge and usually are related to debt defaults; for example, coupon and/or principal payment defaults, debt restructuring, loan payment defaults, etc. We include both hard and soft defaults in our analyses. Moreover, CRI identifies other events such as delisting, change in industry, and merger and acquisitions ("Non-Default exits") for the firms in the database. From these other events, we include delistings with subsequent bankruptcy, liquidations, and reorganizations as default indicators. If a company has multiple default events, we use the date of the first event as the beginning of the default period. In the descriptive statistics Section we provide a summary of the default events in our final sample.

4.4 Probability of default (PD)

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 1-year PD's to make it comparable to the auditor's horizon in assessing going concern uncertainty.

The forward intensity model is a reduced-form model in which the default of the firms is signaled by a jump in a Poisson process, which in turn is determined by the intensity of the process as a function of the input variables at the time the prediction is being made. The possibility of a different type of exit (non-default exit) is determined by the intensity of a separate Poisson process. The model assumes that if a simultaneous jump is produced by both Poisson processes, this is a default event. Therefore, the firm has three mutually exclusive options during a specific time interval – survival, default exit, and non-default exit.

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 firms-specific variables used in the model are measures of volatility-adjusted leverage, liquidity, profitability, relative size, market misvaluation/future growth opportunities, and volatility idiosyncratic volatility. The economy level variables in the model are stock index returns and interest rate. Appendix A provides a more detailed explanation of the model estimation and the variables used in its calibration.

We use PDs as the benchmark in predicting default/bankruptcy events since the performance of the Duan et al. (2012) model is notably good. 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 in [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.

4.5 Other control variables and country classifications

We collect financial statement variables, market capitalization and industry from Thomson Financial (Worldscope). We obtained the auditor (Auditor Code) from Reuters Fundamentals since this database provides historical information for the auditor of the company. Despite the size of our dataset, corporate defaults are relatively infrequent events and performing country-level analyses, including year and industry fixed effects, results in the loss of observations in country-year-industry clusters without variation in the dependent variable (i.e., defaults). Thus, we aggregate the 17 countries in our data within five groups (1) U.S. alone; (2) other common law countries: Australia, Canada, and U.K.; (3) Continental Europe: France, Germany, Italy, and Netherlands; (4) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand. Our country groupings are based on geographic regions and also have somewhat similar levels of institutional development based on legal system, rule of law and regulatory quality. La Porta, Lopez-de-Silanes, Shleifer and Vishny (1998) indicate that country legal rules and the quality of their enforcement affect institutional features of financial market.

V. RESULTS

5.1 Descriptive statistics

Figure 1, Panel A presents descriptive statistics on the frequencies of GCOs and defaults by year for our full sample. Our final sample consists of 43,726 loss firm-years and there are 5,680 observations with GCOs during the period from 2000 to 2012 (13 percent of the sample). The annual frequency of GCOs ranges from 10.1 to 16.4 percent. The highest frequency of GCOs is clustered in the period between 2008 and 2012. In general, our sample consists of relatively large firms with data on Worldscope and the CRI database, 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 794 default observations during the period from 2000 to 2012 (1.8 percent of the sample). The incidence of defaults is highest during the economic crisis periods, 2000 and 2001, as well as 2007 to 2008. Figure 1, Panel B shows the frequency of GCOs and defaults by country. There is considerable cross-country variation sample size as well as in the incidence of GCOs and defaults. The U.S. is the country with the largest number of observations (15,044). The U.S. sub-sample has a frequency of GCOs of 10.5 percent and a frequency of defaults of 2.6 percent. Some countries have very low frequencies of GCOs and defaults, such as Sweden and Denmark. While other countries have relatively high frequencies of GCOs and low frequencies of default, such as Australia and Canada. Figure 1, Panel C shows the types of defaults included in our sample. The most common types are bankruptcy filings, including U.S. Chapter 11 and other bankruptcy procedures. The second most common types are related to loan payments and debt restructuring.

Table 1, Panel A provides the full-sample descriptive statistics for the variables used in our analyses. First, we provide descriptive statistics for continuous PD estimates, as in the CRI database ($CONT\_PD_{i,t}$), as well as for an indicator variable for high PD estimates in the top three deciles in each country and year ($HIGH\_PD_{i,t}$). In our main analyses we use the high PD indicator, aiming to compare GCOs versus another 1/0 variable, but we also report results using the continuous PD estimates in the Sensitivity analyses section. The average return on assets and cash flow from operations ($ROA_{i,t}$ and $CFO_{i,t}$) are negative (at -0.55 and -0.18, respectively) as a result of including in our sample only loss firm-years. The mean leverage is 71.4 percent ($LEVERAGE_{i,t}$) and 5.8 percent of the firm-years have negative equity ($NEGEQUITY_{i,t}$). Approximately 59 percent of the observations have a Big 4 auditor ($BIG_{i,t}$).

Table 1 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 PDs than observations without GCOs ($GCO_{i,t}$ =0), 59 percent of the observations with GCOs have PD estimates in the top three deciles in each country and year, compared to 25.6 percent of the observations without GCOs. Only 6.4 percent of the GCO firms in our sample default a year after the auditor report ($DEFAULT_{i,t+1}$), while defaults in the non-GCO group average just 1.1 percent. The $GCO_{i,t}$ =1 group also has comparatively (a) lower return on assets, cash flow from operation, and levels of cash holdings; (b) smaller firms and frequency of Big 4 auditors; and (3), higher leverage and frequency of negative equity. As expected, our descriptive statistics indicate that firms with GCOs exhibit generally worse financial conditions than firms without GCOs.

5.2 Predictive accuracy of GCOs

Table 2, Panel A shows the results for the GCO logistic model (1), aggregating data at the global-level and by country groupings. Column 1 shows the global-level estimates. The $GCO_{i,t}$ variable has a positive coefficient of 1.875 (statistically significant at the one percent level). All the control variables are associated with subsequent defaults, except for $ROA_{i,t}$, arguably because we limit our sample to loss years. $CFO_{i,t}$, $CASH_{i,t}$, and $BIG4_{i,t}$ are negatively related to subsequent default, while $LEVERAGE_{i,t}$, $SIZE_{i,t}$, and $NEGEQUITY_{i,t}$, are positively related to subsequent default. The AUC for the model is 0.854. Columns 2 to 6 show the estimates for our country groupings: (1) U.S. alone; (2) other common law countries: Australia, Canada, and U.K.; (3) Continental Europe: France, Germany, Italy, and Netherlands; (4) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand. For all country groupings, except Scandinavian countries, the $GCO_{i,t}$ variable has positive and statistically significant coefficients (at the one percent level), ranging from 1.040 to 2.727. However, for all country groupings the AUC is greater than 0.78.

Table 2, Panel B shows the country-level results. It is not possible to determine reliable estimates for all countries due to low incidence of defaults. We only show results for countries with more than 10 defaults in the sample. Our country-level results generally support the aggregate result in Panel A. The $GCO_{i,t}$ variable has positive and statistically significant coefficients (at the five percent level) for the U.S., other common law countries (Australia and U.K.), Germany, and two of the Asia-Pacific countries (China and Malaysia). For all countries in Panel B the AUC is greater than 0.73.

5.3 Predictive accuracy of PDs

Table 3, Panel A shows the results for the PD logistic model (2), aggregating data at the global-level and by country groupings. Column 1 shows the global-level estimates. The $HIGH\_PD_{i,t}$ variable has a positive coefficient of 1.476 (statistically significant at the one percent level). All the control variables are associated with subsequent defaults, except for $ROA_{i,t}$ and $LEVERAGE_{i,t}$, arguably because we limit our sample to loss years and variation in these variables is captured by the PD estimates. $CFO_{i,t}$, $CASH_{i,t}$, and $BIG4_{i,t}$ are negatively related to subsequent default, while $SIZE_{i,t}$ and $NEGEQUITY_{i,t}$, are positively related to subsequent default. The AUC for the model is 0.860. Columns 2 to 6 show the estimates for our country groupings. For all country groupings the $HIGH\_PD_{i\ i,t}$ variable has positive and statistically significant coefficients (at the one percent level), ranging from 1.016 to 1.914. For all country groups the AUC is greater than 0.79.

Table 3, Panel B shows the country-level results. Our country-level results generally support the aggregate result in Panel A. The $HIGH\_PD_{i\ i,t}$ variable has positive and statistically significant coefficients (at the five percent level) for the U.S., Australia, Germany, and four of the Asia-Pacific countries (Singapore, Taiwan, Thailand, and Malaysia). For all countries in Panel B the AUC is greater than 0.72.

5.4 Combined predictive accuracy of GCOs and PDs

Finally, Table 4, Panel A shows the results for the combined GCO and PD logistic model (3). Column 1 shows the global-level estimates. Both $GCO_{i,t}$ and $HIGH\_PD_{i,t}$ variables have a positive coefficient of 1.552 and 1.216 (statistically significant at the one percent level). This result provides initial evidence that both indicators are incrementally informative in predicting defaults. Similar to Tables 3 and 4, all the control variables are associated with subsequent defaults, except for $ROA_{i,t}$ and $LEVERAGE_{i,t}$, arguably because we limit our sample to loss years and variation in these variables are captured by the PD estimates. $CFO_{i,t}$, $CASH_{i,t}$, and $BIG4_{i,t}$ are negatively related to subsequent default, while $SIZE_{i,t}$ and $NEGEQUITY_{i,t}$, are positively related to subsequent default. The AUC for the model is 0.874. Columns 2 to 6 show the estimates for our country groupings. The results are consistent with the independent GCO and PD models in Tables 2 and 3, Panel A. For all country groupings the AUC is greater than 0.80.

Table 4, Panel B shows the results at the country-level. Our country-level results further support the aggregate results in Panel A, as well as the independent GCO and PD models in Tables 2 and 3, Panel B. The only difference is that, after including both PD and GCO, the Philippines has a positive and statistically significant coefficient (at the ten percent level) for $HIGH\_PD_{i,t}$.

5.5 Comparison of AUCs across models

Table 5 summarizes the comparison of AUCs across all models in Tables 2 to 4. We highlight that there is variation in the ability to forecast defaults aggregating countries and at the country-level. For example, raking the country groupings (Column 1), the AUC of the U.S. sample using the GCO model is 0.877, the other common law countries is 0.870, the Continental Europe countries is 0.867, Scandinavian countries is 0.839, and Asia-Pacific countries is 0.788.

Column 4 provides evidence about our first research question. This column shows the p-value of the difference in AUC between the GCO and PD models. At the global-level the difference between the GCO and PD models' AUCs is not statistically significant (at the 10 percent level). Moreover, we find a similar pattern after aggregating similar countries and also at the country level, despite country-specific differences in the ability to predict future defaults. Only in the U.S. the GCO model has a small statistically significant (at the one percent level) difference between the AUC of the GCO model (0.872 Column 1) and the AUC of the PD model (0.870 Column 2).

These results suggest that, on average, GCOs and PDs *independently* have similar predictive accuracy in forecasting subsequent defaults.

In contrast, Columns 5 and 6 provide evidence about our second research question. These columns show the p-values of the difference in AUC between the combined GCO-PD versus GCO models (Column 5), and combined GCO-PD versus PD models (Column 6). These results demonstrate that GCOs and PDs together are incrementally informative in predicting defaults. At the global-level and also for all country groupings, the predictive accuracy of the logistic model combining both indicators is greater than the predictive accuracy of using only one indicator. The differences are statistically significant (at the ten percent level or higher). Using country-level data we only document a statistically significant improvement (at the one percent level) for the U.S. Figure 2 provides similar evidence, illustrating the ROC plots for the data at the global-level for the GCO, PD and combined models. The figure demonstrates how the combined model is consistently nearer to the upper left region of the graph, indicating a larger AUC and greater predictive power than the two separate models.

The imperfect overlap between GCOs and PDs suggest that GCOs provide useful incremental information in predicting defaults across countries. The imperfect overlap can be attributed to auditors using generally different criteria than the PD model, including private information, in issuing GCOs. A way to illustrate the imperfect overlap is by examining separate two-by-two contingency tables between subsequent defaults ($DEFAULT_{i,t+1}$) and $HIGH\_PD_{i,t}$ and subsequent defaults and $GCO_{i,t}$. Table 6 compares the contingency tables for GCOs and PDs. It is important to highlight that forecasting defaults is difficult due to the rarity of these events. Even among the loss firms in our sample, the true default rate is 1.8 percent. In general, auditors give GCOs to firms that subsequently default in 0.8 percent of the cases, while PDs are in the top three deciles for firms that subsequently default in 1.3 percent of the cases. In contrast, auditors give inaccurate GCOs to firms that do not subsequently default in 12.2 percent of the cases, while PDs are in the top three deciles by country and year for firms that do not subsequently default in 28.6 percent of the cases. Ideally, the false positive rate should be close to zero. This evidence suggests that, on average, auditors are careful about false positives.

VI. ADDITIONAL AND SENSITIVITY ANALYSES

6.1 Using a continuous PD estimate

In our main analyses we use a 1/0 variable for high levels of PD estimates. As a sensitivity test, we repeat our analyses using the continuous PD estimates from the CRI database. Table 7 summarizes the comparison of AUCs across all models as in Table 5. Column 4 shows the p-value of the difference in AUC between the GCO and PD models. At the global-level the difference between the GCO and PD models' AUCs indicates that the AUC of the GCO model is greater than the AUC of the PD model (at the 10 percent level), but we only find a similar pattern after aggregating similar countries for the Scandinavian country group. These results suggest that, on average, GCOs and PDs *independently* are very similar, with small differences indicating that GCOs may be more informative in predicting defaults than a continuous PD estimate.

In contrast, Columns 5 and 6 provide evidence about our second research question. These columns show the p-values of the difference in AUC between the combined GCO-PD versus GCO models (Column 5), and combined GCO-PD versus PD models (Column 6). These results demonstrate that GCOs and PDs together are incrementally informative in predicting defaults. At the global-level and also for all country groupings, the predictive accuracy of the logistic model combining both indicators is greater than the predictive accuracy of using only one indicator. The differences are statistically significant (at the ten percent level or higher). Using country-level data we only document a statistically significant improvement for the U.S (at the one percent level) and Australia (at the ten percent level).

VI. CONCLUSION

GCOs have been a topic of constant debate, particularly in time periods when the number of corporate bankruptcies 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 with the auditor's responsibility in warning investors about potential business failures. Previous studies, using data from several countries, show a wide gap between going concern opinions (GCOs) and subsequent bankruptcies. This gap is often attributed to GCOs having low information content and to auditors failing to provide timely warning to investors about impending bankruptcy.

In this study we investigate the accuracy of the auditor's judgment versus a statistical decision model based on year-end existing conditions. We compare the predictive value of GCOs and PDs independently in terms of the predictive accuracy of a logistic regression model including these determinants. We use data from 43,726 auditor reports, with 5,680 GCOs from 17 countries for the years 2000 to 2012. We find that, on average, GCOs and PDs independently are equally informative in predicting defaults.

We also examine the incremental predictive accuracy of both indicators together in a combined model. We find that GCOs and PDs together are incrementally informative in predicting defaults. The imperfect overlap between GCOs and PDs suggest that GCOs provide useful incremental information in predicting defaults across countries. The imperfect overlap can be attributed to auditors using generally different criteria than the PD model, including private information, in issuing GCOs. Our results suggest that auditors, on average, have lower false positive rates compared to a statistical decision rule. We hope that this study will foster our understanding of the observed gap between the number of clients with GCOs and the number of *ex post* bankruptcies.

The auditing standards suggest some events that may indicate going concern uncertainty but are silent about the use of statistical models in assessing going concern uncertainty. 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. Our results, showing that GCOs and PD together are incrementally informative, may foster discussion about whether standards on GCOs should suggest auditors to use statistical models as additional criteria in assessing going concern uncertainty

We note that our findings have some limitations. First, we focus on a sample of relatively large firms with losses and available data in Worldscope and the CRI database, with lower average incidence of GCOs than the full population of listed firms. Second, our results rely on our codification of GCOs from annual reports available in Mergent Online, Thomson One Banker, Thomson Reuters, and other country-specific online resources. Third, in our main analyses we rely on the PD estimates provided by the CRI.

References

American Institute of Certified Public Accountants (AICPA). 1988. *The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern.* Statement on Auditing Standards (SAS) No. 59. New York, NY: AICPA.

Bedard, J., C. Brosseau, and A. Vanstraelen. 2014. The Informative Value of Auditors' Going-Concern Emphasis of Matter: Evidence from a Quasi-Natural Experiment. Working Paper, Laval University and Maastricht University.

Butler, M., A. J. Leone, and M. Willenborg, 2004. An Empirical Analysis of Auditor Reporting and its Association with Abnormal Accruals. *Journal of Accounting & Economics* 37 (2): 139–165.

Carcello, J. V., A. Vanstraelen, and M. Willenborg. 2009. Rules Rather than Discretion in Audit Standards: Going-Concern Opinions in Belgium. *The Accounting Review* 84 (5): 1395–1428.

Carey, P. J., M. A. Geiger, and B. T. O'Connell. 2008. Costs Associated with Going-Concern Modified Audit Opinions: An Analysis of the Australian Audit Market. *Abacus* 44 (1): 61–81.

Carey, P. J., S. Kortum, and R. A. Moroney. 2012. Auditors' Going Concern Modified Opinions After 2001: Measuring Reporting Accuracy. *Accounting and Finance* 52 (1): 1041–1059.

Carson, E. 2009. Industry Specialization by Global Audit Firm Networks. *The Accounting Review* 84 (2): 355–382.

Carson, E., N. Fargher, M. Geiger, C. Lennox, K. Raghunandan, and M. Willekens. 2013. Audit Reporting for Going-Concern Uncertainty: A Research Synthesis. *Auditing: A Journal of Theory and Practice* 32 (Supplement 1): 353–384.

Carson, E., R. Simnett, and P. Tronnes. 2012. International Consistency in Audit Reporting Behaviour: Evidence from Going Concern Modifications. Report to International Auditing and Assurance Standards Board. Available at: http://files.iaaer.org/research/IAASB_Report_Final_working_version_9_January_2012.pdf?1406556333

Chasan, E. 2012. Going Concern Opinions on Life Support With Investors. *The Wall Street Journal CFO Report* 12 September.

Cleves, M. A. 2002. From the Help Desk: Comparing Areas under Receiver Operating Characteristic Curves from Two or More Probit or Logit Models. *The Stata Journal* 2 (3): 301–313.

Credit Research Initiative (CRI). 2013. NUS-RMI Credit Research Initiative Technical Report. Version 2013: 2013 Update 2b. *Global Credit Review* 3 (1): 77–167.

DeLong, E. R., D. M. DeLong, and D. L. Clarke-Pearson. 1988. Comparing the areas Under Two or More Correlated Receiver Operating Characteristic Curves: A nonparametric approach. *Biometrics* 44 (1): 837–845.

Duan, J-C., J. Sun, and T. Wang. 2012. Multiperiod Corporate Default Prediction: A Forward Intensity Approach. *Journal of Econometrics* 170 (1): 191-209.

Fawcett, T. 2006. An Introduction to ROC Analysis. *Pattern Recognition Letters* 27 (1): 861–874.

Financial Accounting Standards Board. (FASB). 2014. *Disclosures about an entity's ability to continue as a going concern.* Accounting Standards Update No. 2014-15. Norwalk, CT: FASB.

Feldmann, D., and W. Read. 2010. Auditor Conservatism after Enron. *Auditing: A Journal of Practice & Theory* 29 (1): 267–278.

Francis, J. R., and D. Wang. 2008. The Joint Effect of Investor Protection and Big 4 Audits on Earnings Quality around the World. *Contemporary Accounting Research* 25 (1): 157– 191.

Francis, J. R. 2011. A Framework for Understanding and Researching Audit Quality. *Auditing: A Journal of Practice & Theory* 30 (2): 125–152.

Francis, J. R., P. N. Michas, and S. E. Seavey. 2013. Does Audit Market Concentration Harm the Quality of Audited Earnings? Evidence from audit markets in 42 countries. *Contemporary Accounting Research* 30 (1): 325-355.

Geiger, M. A., and D. V. Rama. 2006. Audit Firm Size and Going-Concern Reporting Accuracy. *Accounting Horizons* 20 (1): 1–17.

Geiger, M. A., K. Raghunandan, and D. V. Rama. 2005. Recent Changes in the Association Between Bankruptcies and Prior Audit Opinion. *Auditing: A Journal of Practice & Theory* 24 (1): 21–35.

Hopwood, W., J. C. McKeown, and J. F. Mutchler. 1994. A Reexamination of Auditors Versus Model Accuracy Within the Context of the Going-Concern Opinion Decision. *Contemporary Accounting Research* 10 (2): 409–431.

International Accounting Standards Board (IASB). 2007. *Presentation of Financial Statements.* International Accounting Standards (IAS) No. 1. London, United Kingdom: IASB.

International Auditing and Assurance Standards Board (IAASB). 2009. *International Standard on Auditing 570 Going Concern*. International Standards on Auditing (ISA) No. 570. New York, NY: IAASB.

International Auditing and Assurance Standards Board (IAASB). 2009. *Audit Considerations in Respect of Going Concern in the Current Economic Environment*. Staff Audit Practice Alert. New York, NY: IAASB.

Janes, H., G. Longton, and M.S. Pepe. 2009. Acommodating Covariates in Receveir Operating Characteristic Analysis. *The Stata Journal* 9 (1): 17–39.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. W. Vishny. 1998. Law and Finance. *Journal of Political Economy* 106 (6): 1113–1155.

Larcker, D., and A. Zakolyukina. 2012. Detecting Deceptive Discussions in Conference Calls. *Journal of Accounting Research* 50 (2): 495–540.

Lennox, C. 1999. The Accuracy and Incremental Information Content of Audit Reports in Predicting Bankruptcy. *Journal of Business, Finance and Accounting* 26 (5–6): 757–778.

Martin, R. D. 2000. Going-concern uncertainty disclosures and conditions: A comparison of French, German, and U.S. practices. *Journal of International Accounting, Auditing and Taxation* 9 (2): 137–158.

McKenna, F. Going, Gone: Too Many "Going Concern" Warnings May Be As Bad As Too Few. *Forbes* 27 July.

Menon, K., and D. Williams. 2010. Investor Reaction to Going Concern Audit Reports. The Accounting rrview 85 (6): 2075–2105.

Minutti-Meza, M. 2013. Does Auditor Industry Specialization Improve audit Quality? *Journal of Accounting Research* 51 (4): 779–817.

Myers, L.A., J. J. Schmidt, and M. S. Wilkins. 2014. An Investigation of Recent Changes in Going Concern Reporting Decisions among Big N and Non-Big N Auditors. *Review of Quantitative Finance and Accounting* (43) 155–172.

Ogneva, M., and K. R. Subramanyam. 2007. Does the Stock Market Under-React to Going Concern Opinions? Evidence from The U.S. and Australia. *Journal of Accounting and Economics* 43 (2–3): 439–452.

Pepe, M.S., G. Longton, and H. Janes. 2009. Estimation and Comparison of Receiver Operating Characteristic Curves. *The Stata Journal* 9 (1): 1 –16.

Public Company Accounting Oversight Board (PCAOB). 2012a. *Going Concern Considerations and Recommendations*. Washington, DC: PCAOB.

Public Company Accounting Oversight Board (PCAOB). 2012b. *Presentation of the PCAOB's Investor Advisory Group Working Group on Going Concern*. Washington, DC: PCAOB.

Sormunen, N., K. K. Jeppesen, S. Sundgren, and T. Svanstrom. 2013. Harmonisation of audit practice: Empirical evidence from going-concern reporting in the Nordic countries. *International Journal of Auditing* 17 (1): 308–326.

APPENDIX A
CRI PD Model Estimation

NUS-RMI Credit Initiative Technical report (2013 Update 2b) [12] describes the modeling framework, the methodology to compute PDs, the model calibration, as well as details about the parameter estimation. In this Appendix we present an extract from the technical report on the modeling framework and the input variables.

A.1 Modeling Framework

CRI produce PDs based on a reduced-form approach based on forward intensity model to estimate firm's default probabilities for different horizons. In the forward intensity model, a firm's default is signaled by a jump in a Poisson process. The probability of a jump in the Poisson process is determined by the intensity of the Poisson process. The forward intensity model draws an explicit dependence of intensities at time periods in the future (that is, forward intensity) to the value of predictor variables at the time of the prediction. The CRI model takes into account not only defaults/bankruptcy events, but that considers other types of firms exits such as mergers and acquisitions, delisting events due to reasons other than default. In order to take into accounts, defaults and other exits are modeled as two independent Poisson processes. While defaults and exits classified as non-defaults are mutually exclusive by definition, the assumption of independent Poisson processes does not pose a problem since the probability of a simultaneous jump in the two Poisson processes is negligible. In the discrete time framework, the probability of simultaneous jumps in the same time interval is non-zero. As a modeling assumption, a simultaneous jump in the same time interval by both the default Poisson process and the non-default type exit Poisson process is considered as a default. In this way, there are three mutually exclusive possibilities during each time interval: survival, default and non-default exit. As with defaults, the forward intensity of the Poisson process for other exits is a function of the input variables.

[12] http://d.rmicri.org/static/pdf/2013update2.pdf

There are three possible paths for a firm at each time point. Either the firm survives for the next time period Δt, or it defaults within Δt, or it has a non-default exit within Δt. Information about firm i is known up until time $t = m\Delta t$.

Let's consider possibilities in the future between $t = (n-1)\Delta t$ and $(n+1)\Delta t$. Here, m and n are integers with $m < n$. The probability of each path are, for example: $p_i(m,n)$ the conditional probability viewed from $t = m\Delta t$ that firm i will default before $(n+1)\Delta t$, conditioned on firm i surviving up until $n\Delta t$. Likewise $\bar{p}_i(m,n)$ is the conditional probability viewed from $t = m\Delta t$ that firm i will have a non-default exit before $(n+1)\Delta t$, conditioned on firm i surviving up until $n\Delta t$. With the conditional default and other exit probability of firm i is $1 - p_i(m,n) - \bar{p}_i(m,n)$.

Hence, the probability that a particular path will be followed is the product of the conditional probabilities along the path. For example, the probabilities at time $t = m\Delta t$ of firm i surviving up until $(n-1)\Delta t$ and defaulting between $(-1)\Delta t$ and $n\Delta t$ is:

$$Prob_{t=m\Delta t}[\tau_i = n, \tau_i < \bar{\tau}_i] = p_i(m,n) \prod_{j=m}^{n-2}[1 - p_i(m,j) - \bar{p}_i(m,j)] \qquad \textbf{(1)}$$

Here, τ_i is the default time for firm i measured in units of months, $\bar{\tau}_i$ is the other exits time measured in units of months, and the product is equal to 1 if there is no term in the product. The condition $\tau_i < \bar{\tau}_i$ is the requirement that the firm defaults before it has a non-default type of exit.

Using Equation (1), cumulative default probabilities can be computed. At $m\Delta t$ the probability of firm i defaulting at of before $n\Delta t$ and not having other exit before $t = n\Delta t$ is obtained by taking the sum of all of the paths that lead to default at of before $n\Delta t$

$$Prob_{t=m\Delta t}[m < \tau_i \leq n, \tau_i < \bar{\tau}_i] = \sum_{k=m}^{n-1}\left\{p_i(m,k) \prod_{j=m}^{k-1}[1 - p_i(m,j) - \bar{p}_i(m,j)]\right\} \textbf{(2)}$$

The forward intensity for the default of firm i that is observed at time $t = m\Delta t$ for the forward time interval from $t = n\Delta t$ to $(n+1)\Delta t$, is denoted by $h_i(m,n)$, where $m \leq n$. The corresponding forward intensity model for a non-default exit is denoted by $\bar{h}_i(m,n)$.

Because default is signaled by a jump in a Poisson process, its conditional probability is a simple function of its forward intensity:

$$p_i(m,n) = 1 - \exp[-\Delta t h_i(m,n)] \quad \textbf{(3)}$$

Since joint jumps in the same time interval are assigned as defaults, the conditional other exit probability needs to take this into account:

$$\bar{p}_i(m,n) = \exp[-\Delta t\, h_i(m,n)]\{1 - \exp[-\Delta t\, \bar{h}_i(m,n)]\} \quad \textbf{(4)}$$

The conditional survival probabilities in Equations (1) and (2) are computed as the conditional probability that the firm does not default in the period and the firm does not have a non-default exit either:

$$Prob_{t=m\Delta t}[\tau_i\,, \bar{\tau}_i > n+1 \mid \tau_i, \bar{\tau}_i > n] = \exp\{-\Delta t\,[h_i(m,n) + \bar{h}_i(m,n)]\} \quad \textbf{(5)}$$

The forward intensities need to be positive so that the conditional probabilities are non-negative. A standard way to impose this constraint is to specify the forward intensities as exponentials of a linear combination of the input variables:

$$h_i(m,n) = \exp[\beta(n-m) * Y_i(m)] \quad \textbf{(6)}$$

$$\bar{h}_i(m,n) = \exp[\bar{\beta}(n-m) * Y_i(m)]$$

Here, β and $\bar{\beta}$ are coefficient vectors that are functions of the number of months between the observation date and the beginning of the forward period$(n-m)$, and $Y_i(m) = (1, X_i(m))$ where $X_i(m)$ is the input variables associated with i^{th} firm. $X_i(m) = (W(m), U_i(m))$ Here, $W(m)$ is a vector of variables that is common to all firms in the economy and $U_i(m)$ is a vector of variables specific to firm i. The unit element allows the linear combination in the argument of the exponentials in Equation (6) to have a non-zero intercept.

Before expressing the probabilities in Equation (1) and (2) in terms of the forward intensities, a notation H is introduced for the forward intensities so that it becomes clear which parameters the forward intensity depends on:

$$H\big(\beta(m-n), X_i(m)\big) = \exp[\beta(n-m) * Y_i(m)] \quad \textbf{(7)}$$

This is the forward default intensity. The corresponding notation for the forward other exit intensity is then just $H\big(\beta(m-n), X_i(m)\big)$. So, the probability in Equation (1) is expressed in terms of the forward intensities, using Equation (3) as the conditional default probability and Equation (5) as the conditional survival probability:

$$
\begin{aligned}
&Prob_{t=m\Delta t}[\tau_i = n, \tau_i < \bar{\tau}_i] \\
&\qquad = \{1 - \exp[-\Delta t \, H(\beta(n-1-m), X_i(m))]\} \\
&\qquad \times \prod_{j=m}^{n-2} exp\left\{-\Delta t \, \left[H(\beta(j-m), X_i(m)) + H\left(\bar{\beta}(j-m), X_i(m)\right)\right]\right\} \\
&\qquad = \{1 - \exp[-\Delta t \, H(\beta(n-m-1), X_i(m))]\} \\
&\qquad \times exp\left\{-\Delta t \sum_{j=m}^{n-2} [H(\beta(j-m), X_i(m)) + H\left(\bar{\beta}(j-m), X_i(m)\right)]\right\}
\end{aligned}
$$

The cumulative default probability given in Equation (2) in terms of the forward intensities is then:

$$
\begin{aligned}
&Prob_{t=m\Delta t}[m < \tau_i \leq n, \tau_i < \bar{\tau}_i] \\
&\qquad = \sum_{k=m}^{n-1} \left\{ \{1 - \exp[-\Delta t \, H(\beta(k-m), X_i(m))]\} \right. \\
&\qquad \left. \times exp\left\{-\Delta t \sum_{j=m}^{k-1} [H(\beta(j-m), X_i(m)) + H\left(\bar{\beta}(j-m), X_i(m)\right)]\right\} \right\}
\end{aligned}
$$

This formula is used to compute the main output of the CRI: an individual firm's PD within various time horizons. The β and $\bar{\beta}$ parameters are obtained when the firm's economy is calibrated, and using those together with the firm's input variables yields the firm's PD.

The empirical data set used for calibration data set used for calibration can be described as follows. For the economy as a whole, there are N end month observations, indexed as $n = 1, \ldots, N$. Of course, not all firms have observations for each of the N months. There are a total of I firms in the economy, and they are indexed as $i = 1, \ldots, I$. The input variables for the i^{th} firm at the end of the n^{th}

month is $X_i(n)$. The set of all observations for all firms is denoted by X. The calibration of the β and $\bar{\beta}$ parameters is done by maximizing a pseudo-likelihood function for the horizon l:

$$L_l\left(\beta, \bar{\beta}, \tau, \bar{\tau}, X\right) = \prod_{m=1}^{N-1} \prod_{i=1}^{I} P_{\min(N-m,l)}(\beta, \bar{\beta}, \tau, \bar{\tau}, X_i(m)) \tag{10}$$

$P_{\min(N-m,l)}$ is a probability for the i^{th} firm, with the nature of the probability depending on what happens to the firm during the period from month m to month $m + \min(N - m, l)$.

A.2 Input Variables

In Duan et al. (2012), different variables that are commonly used in the literature were tested as candidates for the elements of $W(n)$ and $U_i(n)$. Two common variables and ten firm-specific variables, as described below, were selected as having the greatest predictive power for corporate defaults in the United States.

Common variables

The vector $W(n)$ contains two elements, which are:

1. Stock index return: the trailing one-year simple return on a major stock index of the economy;
2. Interest rate: a representative 3-month short term interest rate.

Firm-specific variables

The ten firm-specific input variables are transformations of measures of six different firm characteristics. The six firm characteristics are:

1. Volatility-adjusted leverage: Level and Trend of DTD in a Merton-type model.
2. Liquidity: Level and Trend of (Cash + Short Term Investment) / Total Assets
3. Profitability: Level and Trend of Net Income / Total Assets
4. Relative Size: Level and Trend of log (Firm Market capitalization / Economy's median capitalization)
5. Market misvaluation/future growth opportunities: Current value of (Market Capitalization + Total Liabilities) / Total Assets.

6. Idiosyncratic volatility: Current value of Sigma. Sigma is computed by regressing the daily returns of the firm's market capitalization against the daily returns of the economy's stock index, for the previous 250 days. Sigma is defined to be the standard deviation of the residuals of this regression.

Level is computed as the one-year of the measure and trend is computed as the current value of the measure minus average of the measure.

APPENDIX B
Examples of going concern modification (GCO) paragraphs

Germany – Travel24com – Annual Report 2001

With the exception of the following qualification our audit did not lead to any objections:

The consolidated financial statements were prepared assuming that the Company is still a going concern although the company has so far posted negative cash flows from the business activity The plans for the continuation of the Company's business activities require additional cash in the form of equity capital or borrowed funds. Should the Company not succeed in procuring the required financial means within the necessary timeframe, the Company's existence is in jeopardy. The essence of the financial statements assumes the continued existence of the Company and as such they do not contain any amendments which reflect any uncertainty over its future.

With this qualification, the annual financial statements present fairly, in all material respects, a true and fair view of the net worth, financial position, earnings and cash flows of the Company. The management report presents an accurate view of the position of the Company and accurately presents the risks from future developments.

Munich, 28 March 2002

Haarmann, Hemmelrath & Partner GmbH
Wirtschaftsprüfungsgesellschaft
Steuerberatungsgesellschaft

Zelger Wirtschaftsprüfer	ppa. Komm Wirtschaftsprüfer

Solarvalue AG – 2008 Annual Report

Not intended to qualify our opinion we refer to the indications under financial risks in the management report. There is explained that the present liquid assets of the Company are probably sufficient to prove the process ability of the production process which is currently under development. However, for the proof, great technical challenges have to be met. For the planned ramp up of the industrial production additional liquid assets are necessary. In case that it would not be possible to procure these liquid assets through Solarvalue AG, insolvency could occur and therefore endanger the going concern of Solarvalue AG."

Berlin, June 30, 2009	UHY Deutschland AG Wirtschaftsprüfungsgesellschaft
(ppa. Kulla) Wirtschaftsprüferin [German Public Auditor]	(Lauer) Wirtschaftsprüfer [German Public Auditor]

France

Club Mediterranne – 2003 Financial report

- Club Méditerranée's ability to meet its financing needs as of October 31, 2003 was dependent on the banks agreeing to keep in place a €324 million credit facility with short-term drawing rights. In the expectation that it would breach one of the covenants associated with this facility at that date, the Company entered into negotiations with its banks to avoid the debt becoming callable. As explained in note 11 to the consolidated financial statements, in December 2003 the Company renegotiated the terms of the facility. The revised facility is for an amount of €220 million and will expire in June 2005. The accompanying consolidated financial statements have therefore been prepared on a going concern basis.
- Deferred tax assets of €76 million have been recognized in the consolidated balance sheet at October 31, 2003. As explained in notes 1.2.5 and 3.8 to the consolidated financial statements, the Company has drawn up a three-year business plan, validated by an independent expert. The business plan projections served as the basis for the analyses performed by us, the result of which provided us with reasonable assurance regarding the recoverability of these assets.

In addition, we have verified the information given in the report entitled "Management's Discussion and Analysis". We are satisfied that the information is fairly stated and agrees with the consolidated financial statements.

Paris and Neuilly-sur-Seine, January 23, 2004

The Statutory Auditors

Ernst & Young Audit
Pascal Macioce

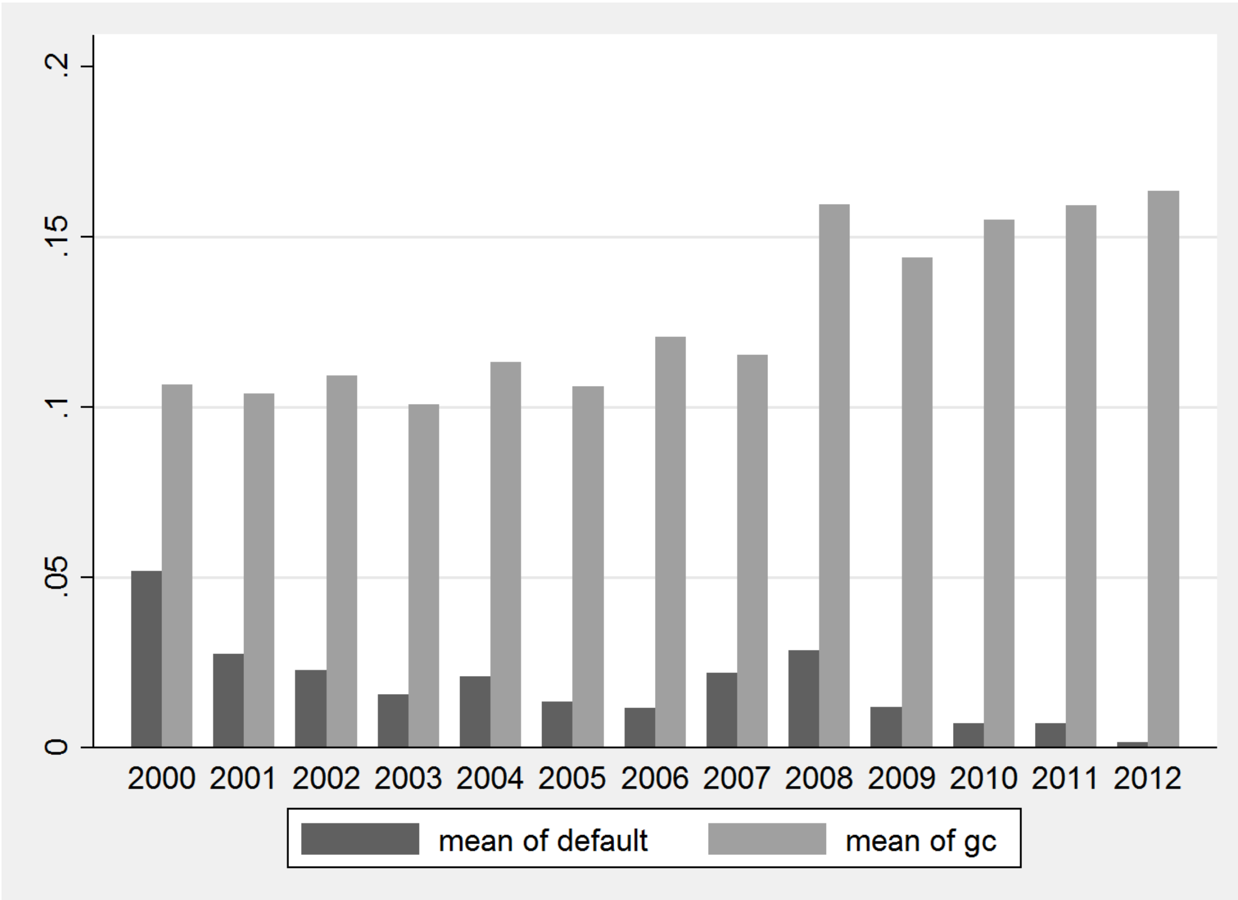
Deloitte Touche Tohmatsu - Audit
Hervé Pouliquen Alain Pons

APPENDIX C
Variable Definitions

Variable		*Definition*	*Source*
$DEFAULT_{i,t+1}$	=	indicator variable equal to one if a company *i* has a default event 12 months following fiscal year-end *t* and 0 otherwise;	CRI 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 for US firms, hand-collected from annual reports downloaded from Mergent and Datastream for non-US firms
$HIGH\_PD_{i,t}$	=	Indicator variable equal to one if the estimated PD for the next 12 months at fiscal year-end in the CRI database for firm *i* is in the top three deciles by country and year *t*, and 0 otherwise;	CRI database, country-level ranking calculated for our sample
$CONT\_PD_{i,t}$	=	Estimated PD for the next 12 months at fiscal year-end in the CRI database for firm *i* in fiscal-year *t*;	CRI database
$ROA_{i,t}$	=	Net Income/Total Assets;	Thomson Financial
$CASH_{i,t}$	=	Cash and Cash Equivalents/ Total Assets;	Thomson Financial
$CFO_{i,t}$	=	Cash Flow from Operating activities/Total Assets;	Thomson Financial
$LEVERAGE_{i,t}$	=	Total Liabilities/Total Assets;	Thomson Financial
$SIZE_{i,t}$	=	Logarithm(Total Assets);	Thomson Financial
$NEGEQUITY_{i,t}$	=	Indicator variable equal to one if Total Liabilities exceed Total Assets, and 0 otherwise; and,	Thomson Financial
$BIG4_{i,t}$	=	Net Income/Total Assets.	Thomson Financial

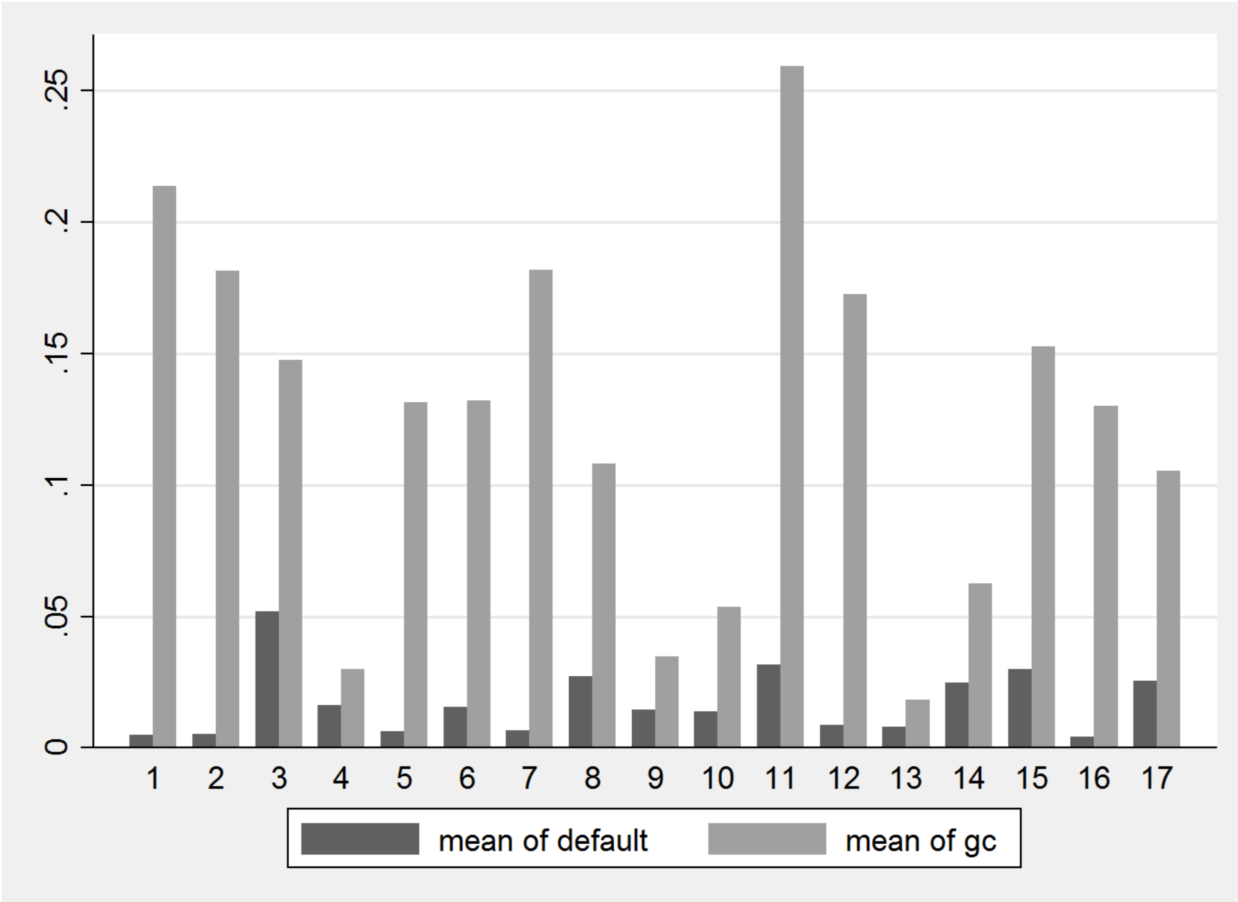
Figure 1 – Frequencies of GCOs and defaults

Panel A: Frequency of GCOs and defaults by year



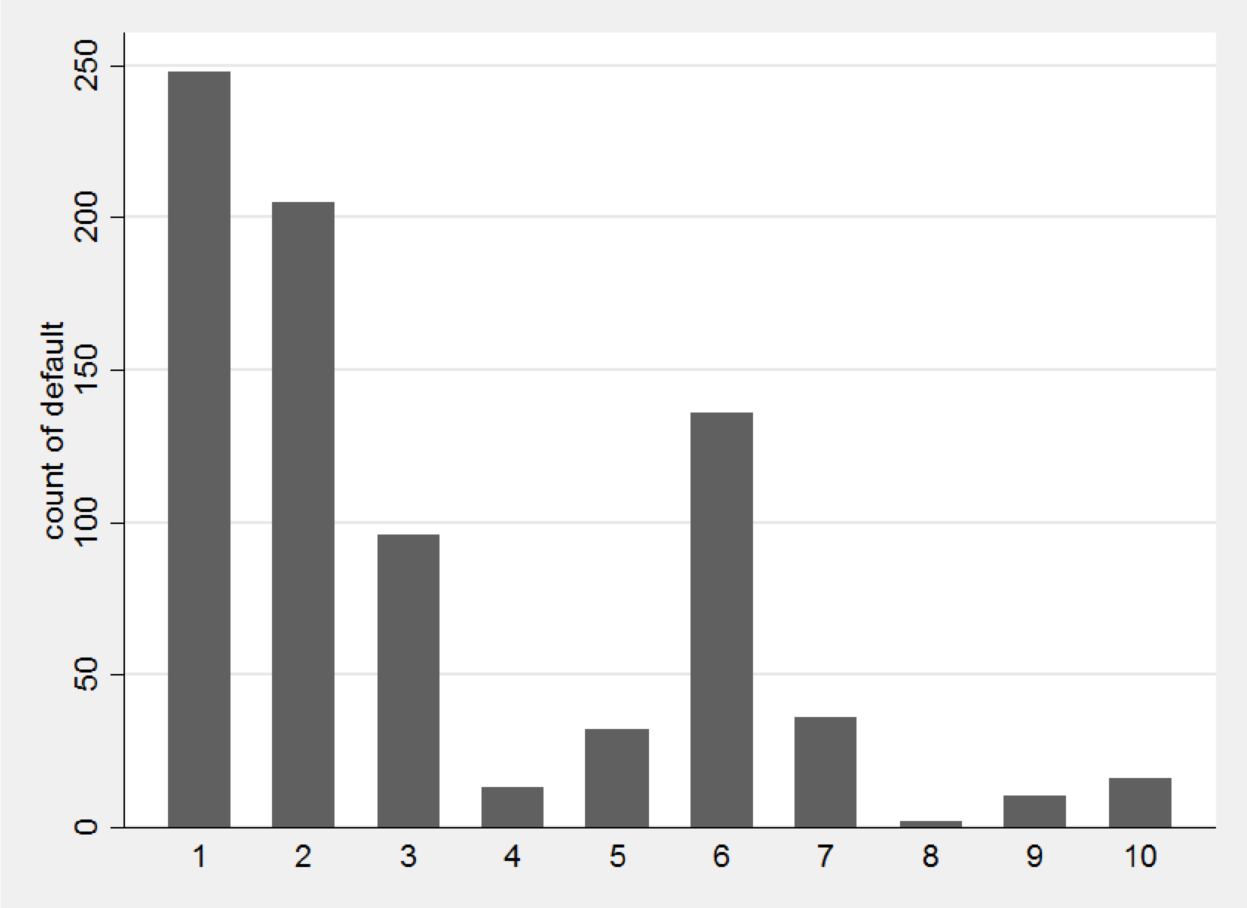
Year	*$GCO_{i,t}$ N. Obs.*	*$GCO_{i,t}$ Freq.*	*$DEFAULT_{i,t}$ N. Obs.*	*$DEFAULT_{i,t}$ Freq.*	*Total N. Obs.*
2000	283	0.107	138	0.052	2,651
2001	377	0.104	100	0.028	3,623
2002	380	0.109	79	0.023	3,474
2003	303	0.101	47	0.016	3,003
2004	309	0.113	57	0.021	2,723
2005	310	0.106	40	0.014	2,921
2006	367	0.121	36	0.012	3,040
2007	373	0.116	71	0.022	3,229
2008	660	0.160	119	0.029	4,134
2009	594	0.144	50	0.012	4,120
2010	534	0.155	25	0.007	3,444
2011	571	0.159	26	0.007	3,581
2012	619	0.164	6	0.002	3,783
Total	5,680	0.130	794	0.018	43,726

Panel B: Frequency of GCOs and defaults by country



	Country	$GCO_{i,t}$ N. Obs.	$GCO_{i,t}$ Freq.	$DEFAULT_{i,t}$ N. Obs.	$DEFAULT_{i,t}$ Freq.	Total N. Obs.
1	*Australia*	1,694	0.214	38	0.005	7,928
2	*Canada*	172	0.182	5	0.005	947
3	*China*	261	0.147	92	0.052	1,770
4	*Denmark*	13	0.030	7	0.016	433
5	*France*	183	0.132	9	0.006	1,391
6	*Germany*	297	0.132	35	0.016	2,245
7	*Italy*	138	0.182	5	0.007	758
8	*Malaysia*	233	0.108	59	0.027	2,151
9	*Netherlands*	12	0.035	5	0.014	345
10	*Norway*	35	0.054	9	0.014	651
11	*Philippines*	98	0.259	12	0.032	378
12	*Singapore*	216	0.173	11	0.009	1,251
13	*Sweden*	25	0.018	11	0.008	1,353
14	*Taiwan*	201	0.063	80	0.025	3,208
15	*Thailand*	87	0.153	17	0.030	570
16	*U.K.*	430	0.130	14	0.004	3,303
17	*U.S.*	1,585	0.105	385	0.026	15,044
	Total	5,680	0.130	794	0.018	43,726

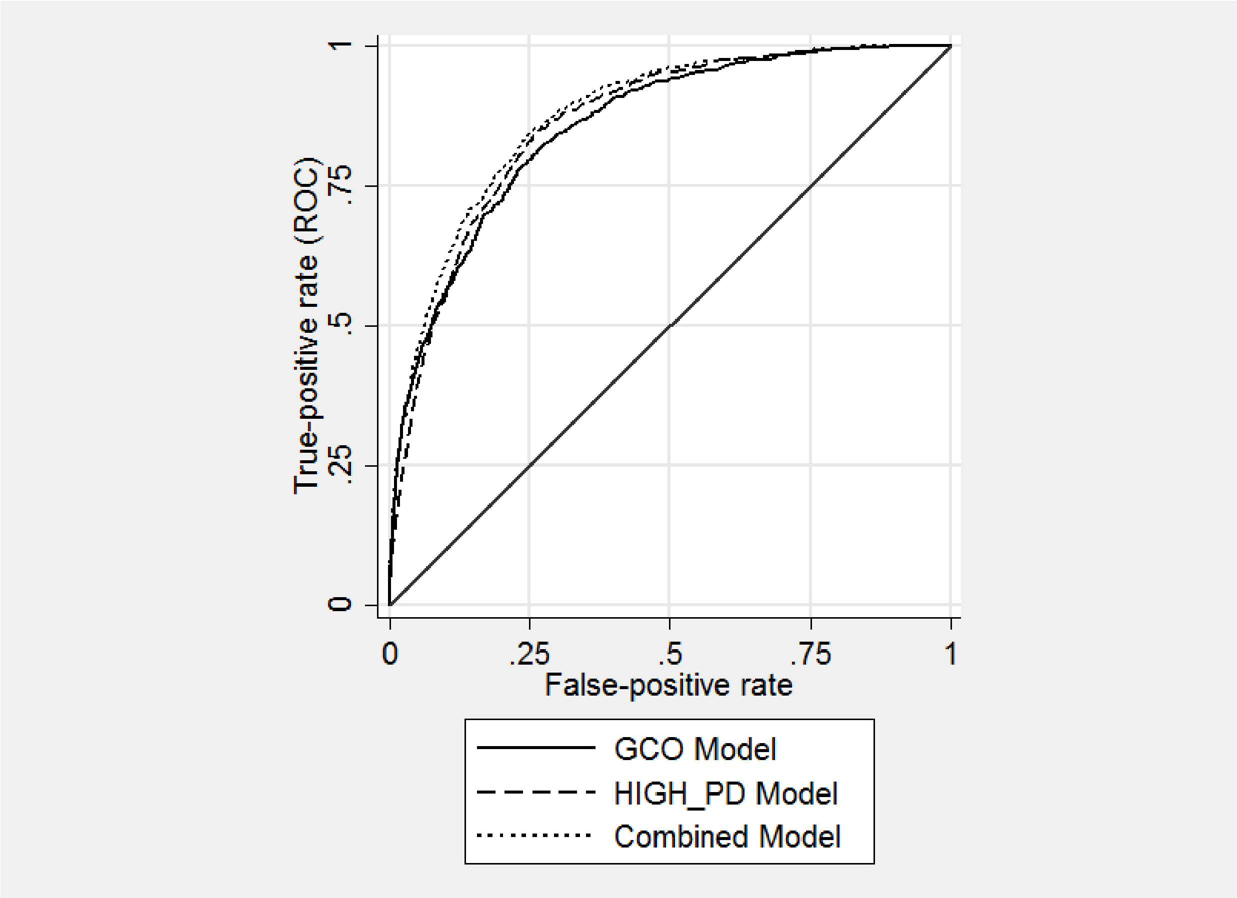
Panel C: Frequency of default events by type



Default Types	*Default N. Obs.*	*Default Freq.*
Bankruptcy Filing		
1. *Chapter 11*	248	0.006
2. *Other*	205	0.005
Default Corporate Action		
3. *Loan Payment Default*	96	0.002
4. *Subsidiary Default*	13	0.000
5. *Debt Restructuring*	32	0.001
6. *Other*	136	0.003
Delisting & Subsequent Hard Defaults		
7. *Delisted by Exchange*	36	0.001
8. *Merger/Acquisition*	2	0.000
9. *Liquidated*	10	0.000
10. *Other*	16	0.000
Total	794	0.018

The Figures in Panels A to C show descriptive statistics about the GCOs and defaults in our sample. Panel A shows the frequency of these variables over time. Panel B shows the frequency of these variables by country. Panel C shows the frequency of various default events. Variable definitions are included in Appendix C.

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



This figure shows the ROC curve for all three models: (1) *GCO*, (2) *HIGH_PD*, and (3) combined model shown in Column 1 of Tables 2, 3 and 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., 1-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 AUROC is the area under the depicted curves.

Table 1 –Descriptive statistics

Panel A: Full sample

Variable	*Mean*	*S.D.*	*25 Perc.*	*Median*	*75 Perc.*
$DEFAULT_{i,t+1}$	0.018	0.134	0.000	0.000	0.000
$GCO_{i,t}$	0.130	0.336	0.000	0.000	0.000
$HIGH\_PD_{i,t}$	0.299	0.458	0.000	0.000	1.000
$CONT\_PD_{i,t}$	0.014	0.038	0.001	0.004	0.011
$ROA_{i,t}$	-0.546	24.208	-0.327	-0.118	-0.041
$CFO_{i,t}$	-0.182	5.479	-0.162	-0.029	0.039
$LEVERAGE_{i,t}$	0.714	18.360	0.191	0.440	0.678
$CASH_{i,t}$	0.248	0.262	0.047	0.141	0.378
$SIZE_{i,t}$	10.968	2.042	9.619	10.881	12.224
$NEGEQUITY_{i,t}$	0.058	0.234	0.000	0.000	0.000
$BIG4_{i,t}$	0.589	0.492	0.000	1.000	1.000
N. Obs. = 43,726					

Panel B: Partition by GCO

	GCO = 0			*GCO = 1*		
Variable	*Mean*	*S.D.*	*Median*	*Mean*	*S.D.*	*Median*
$DEFAULT_{i,t+1}$	0.011	0.106	0.000	0.064	0.245	0.000
$GCO_{i,t}$	0.000	0.000	0.000	1.000	1.000	1.000
$HIGH\_PD_{i,t}$	0.256	0.436	0.000	0.590	0.492	1.000
$CONT\_PD_{i,t}$	0.011	0.028	0.003	0.033	0.073	0.009
$ROA_{i,t}$	-0.434	25.602	-0.103	-1.300	10.970	-0.342
$CFO_{i,t}$	-0.123	5.429	-0.021	-0.579	5.785	-0.118
$LEVERAGE_{i,t}$	0.490	2.515	0.423	2.214	50.500	0.618
$CASH_{i,t}$	0.257	0.264	0.151	0.190	0.239	0.085
$SIZE_{i,t}$	11.118	2.012	11.023	9.957	1.957	9.900
$NEGEQUITY_{i,t}$	0.039	0.193	0.000	0.189	0.391	0.000
$BIG4_{i,t}$	0.608	0.488	1.000	0.463	0.499	0.000
N. Obs. =	38,046			5,680		

The table includes descriptive statistics for the variables in our analysis. Panel A uses all observations in our sample. Panel B partitions the sample for $GCO_{i,t}$ =0 and $GCO_{i,t}$ =1 firms. Variable definitions are included in Appendix C.

Table 2 – Logistic regression model using $GCO_{i,t}$ as a predictor of subsequent defaults

Panel A: Global-level and country-groupings analysis

	Dependent Variable = $DEFAULT_{i,t+1}$					
Variables	*Global level* (1)	*U.S. Only* (2)	*Common Law* (3)	*Cont. Europe* (4)	*Asia Pacific* (5)	*Scandinavia* (6)
$GCO_{i,t}$	1.875***	2.727***	1.443***	1.454***	1.040***	0.591
	[18.45]	[17.13]	[4.18]	[4.03]	[5.86]	[0.60]
$ROA_{i,t}$	-0.057	0.101	-0.220	-0.588	-0.975***	-0.576
	[-0.74]	[0.66]	[-1.63]	[-1.22]	[-4.07]	[-1.28]
$CFO_{i,t}$	-0.391**	-0.402	-0.040	-2.198**	-0.864	-0.176
	[-2.57]	[-1.50]	[-0.16]	[-2.55]	[-1.39]	[-0.21]
$LEVERAGE_{i,t}$	0.153**	1.106***	0.160	-0.238	-0.086	2.249*
	[2.36]	[4.92]	[1.37]	[-0.51]	[-0.75]	[1.77]
$CASH_{i,t}$	-1.749***	-0.867***	-0.895	-3.693**	-3.219***	-1.824
	[-6.64]	[-2.74]	[-1.06]	[-2.28]	[-3.86]	[-1.12]
$SIZE_{i,t}$	0.247***	0.333***	0.408***	0.300***	0.146***	0.177
	[9.98]	[8.71]	[4.35]	[3.47]	[2.83]	[1.24]
$NEGEQUITY_{i,t}$	0.745***	0.085	0.926*	0.671	0.514*	0.764
	[5.43]	[0.35]	[1.95]	[1.11]	[1.71]	[0.77]
$BIG4_{i,t}$	-0.195**	-0.102	-0.263	-0.604*	-0.267*	-0.964**
	[-2.00]	[-0.64]	[-0.72]	[-1.91]	[-1.79]	[-2.07]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-7.033***	-7.906***	-9.249***	-20.813***	-4.325***	-5.459***
	[-21.24]	[-14.90]	[-6.85]	[-13.92]	[-6.11]	[-3.28]
N. Obs.	43,287	15,030	12,105	3,796	8,245	1,683
Pseudo-R^2	0.204	0.274	0.184	0.200	0.126	0.191
AUC	0.854	0.877	0.870	0.867	0.788	0.839

Panel B: Country level analysis

	Dependent Variable = $DEFAULT_{i,t+1}$										
	U.S.	*Australia*	*U.K.*	*Germany*	*China*	*Philippines*	*Singapore*	*Taiwan*	*Thailand*	*Malaysia*	*Sweden*
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
$GCO_{i,t}$	2.741***	1.132***	1.863***	1.313**	0.731**	0.522	1.549	0.228	0.511	1.610***	1.463
	[16.90]	[2.62]	[3.04]	[2.48]	[2.41]	[0.69]	[1.60]	[0.51]	[0.67]	[4.82]	[0.90]
$ROA_{i,t}$	0.113	-0.357**	0.586**	-0.356	-0.022	2.047	-0.571	-3.880***	-2.929	-0.616	0.306
	[0.78]	[-2.19]	[2.35]	[-0.80]	[-0.07]	[0.99]	[-0.98]	[-5.57]	[-1.61]	[-1.48]	[0.59]
$CFO_{i,t}$	-0.345	0.070	-0.755*	-1.854**	0.344	-8.011*	0.434	-3.114***	1.289	-0.503	-1.549*
	[-1.34]	[0.23]	[-1.79]	[-1.98]	[0.33]	[-1.71]	[0.42]	[-2.75]	[0.44]	[-0.25]	[-1.66]
$LEVERAGE_{i,t}$	1.138***	0.281	0.577**	-0.538	-0.085	0.009	0.222	2.466***	2.606	0.288	0.740
	[5.16]	[1.44]	[2.22]	[-0.70]	[-0.78]	[0.01]	[0.57]	[4.24]	[1.28]	[1.00]	[0.44]
$CASH_{i,t}$	-0.941***	-1.024	-3.481	-3.644**	-1.362	-35.619**	-2.404	-1.157	-2.329	-8.310***	-0.779
	[-2.83]	[-1.10]	[-1.14]	[-2.01]	[-1.00]	[-2.03]	[-0.64]	[-0.93]	[-0.59]	[-2.65]	[-0.48]
$SIZE_{i,t}$	0.353***	0.405***	0.304	0.196	-0.069	0.615	0.389	0.233***	-0.164	0.142	0.384***
	[9.49]	[3.80]	[1.64]	[1.42]	[-0.67]	[1.64]	[1.49]	[2.61]	[-0.50]	[1.28]	[2.66]
$NEGEQUITY_{i,t}$	0.056	0.916	-0.094	-0.857	1.137**	1.300	0.641	-2.652***	2.556*	-0.922	2.695
	[0.23]	[1.22]	[-0.07]	[-0.66]	[2.53]	[0.97]	[0.60]	[-2.78]	[1.88]	[-1.23]	[1.25]
$BIG4_{i,t}$	-0.166	-0.191	0.095	-0.708	-2.097**	0.404	-0.378	-0.001	1.056	-0.132	-1.530**
	[-1.01]	[-0.48]	[0.11]	[-1.63]	[-2.06]	[0.31]	[-0.58]	[-0.01]	[1.46]	[-0.47]	[-2.09]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-8.147***	-8.760***	-23.020***	-4.389***	-1.391	-9.707**	-8.586**	-6.385***	-5.211	-4.496***	-7.676***
	[-16.81]	[-5.89]	[-14.97]	[-2.59]	[-1.03]	[-2.26]	[-2.35]	[-5.24]	[-1.55]	[-3.60]	[-4.03]
Observations	15,034	6,272	1,796	1,358	1,326	277	415	2,166	429	1,955	843
Pseudo R^2	0.267	0.216	0.163	0.143	0.105	0.199	0.180	0.198	0.375	0.137	0.111
AUC	0.872	0.886	0.852	0.792	0.734	0.832	0.842	0.856	0.914	0.783	0.802

This table includes results from the logistic regression including $GCO_{i,t}$ (Eq. 1): $P(DEFAULT_{i,t+1}) = f(GCO_{i,t}$, *Client Characteristics*$_{i,t}$, *Fixed Effects*$_{i,t}, e_{it})$. Panel A shows estimates at the global-level and country-grouping. Panel B shows country-level estimates. Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significant at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix C. In Panel A, country groupings in columns (2) to (6) are as follows: (2) U.S. alone; (3) other common law countries: Australia, Canada, and U.K.; (4) Continental Europe: France, Germany, Italy, and Netherlands; (5) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand.

Table 3 – Logistic regression model using $HIGH\_PD_{i,t}$ as a predictor of subsequent default

Panel A: Global-level and country-groupings analysis

	Dependent Variable = $DEFAULT_{i,t+1}$					
Variables	*Global level (1)*	*U.S. Only (2)*	*Common Law (3)*	*Cont. Europe (4)*	*Asia Pacific (5)*	*Scandinavia (6)*
$HIGH\_PD_{i,t}$	1.476***	1.914***	1.401***	1.016***	0.953***	1.850***
	[17.29]	[13.49]	[4.16]	[3.18]	[6.76]	[3.42]
$ROA_{i,t}$	-0.090	0.026	-0.183	-0.526	-1.040***	-0.321
	[-1.30]	[0.19]	[-1.50]	[-1.24]	[-4.17]	[-0.78]
$CFO_{i,t}$	-0.532***	-0.691***	-0.126	-2.598***	-1.060*	-0.219
	[-3.71]	[-2.65]	[-0.54]	[-3.36]	[-1.72]	[-0.28]
$LEVERAGE_{i,t}$	0.100	1.097***	0.097	-0.271	-0.119	1.741
	[1.61]	[4.90]	[0.92]	[-0.63]	[-1.01]	[1.47]
$CASH_{i,t}$	-1.507***	-1.025***	-0.492	-3.798**	-2.160***	-0.908
	[-5.66]	[-3.07]	[-0.61]	[-2.33]	[-2.65]	[-0.63]
$SIZE_{i,t}$	0.181***	0.165***	0.332***	0.317***	0.151***	0.246
	[7.59]	[4.74]	[3.78]	[3.75]	[3.06]	[1.62]
$NEGEQUITY_{i,t}$	0.915***	0.223	1.049**	0.713	0.680**	0.846
	[7.02]	[0.94]	[2.17]	[1.19]	[2.45]	[0.88]
$BIG4_{i,t}$	-0.166*	-0.113	-0.294	-0.502	-0.199	-1.017**
	[-1.73]	[-0.74]	[-0.83]	[-1.56]	[-1.33]	[-2.12]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-6.529***	-5.935***	-8.814***	-21.345***	-4.657***	-6.987***
	[-20.99]	[-12.34]	[-7.24]	[-14.24]	[-6.80]	[-3.88]
N. Obs.	43,287	15,030	12,105	3,796	8,245	1,683
Pseudo-R^2	0.192	0.232	0.181	0.191	0.130	0.241
AUC	0.860	0.878	0.879	0.853	0.796	0.876

Panel B: Country-level analyses

	Dependent Variable = $DEFAULT_{i,t+1}$										
	U.S.	*Australia*	*U.K.*	*Germany*	*China*	*Philippines*	*Singapore*	*Taiwan*	*Thailand*	*Malaysia*	*Sweden*
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
$HIGH\_PD_{i,t}$	1.911***	1.556***	0.817	1.050**	0.171	1.362	3.158***	0.767**	1.576**	1.038***	1.522
	[13.55]	[3.68]	[1.39]	[2.51]	[0.62]	[1.64]	[3.26]	[2.39]	[2.34]	[3.67]	[1.61]
$ROA_{i,t}$	0.051	-0.313**	0.347	-0.364	-0.106	2.837	-0.438	-3.663***	-2.456	-0.664*	0.392
	[0.38]	[-2.08]	[1.56]	[-1.01]	[-0.35]	[1.30]	[-0.69]	[-5.17]	[-1.28]	[-1.78]	[0.70]
$CFO_{i,t}$	-0.682***	0.000	-0.644*	-1.915**	0.094	-8.592*	-0.131	-3.081***	0.069	-0.875	-1.645**
	[-2.67]	[0.00]	[-1.77]	[-2.43]	[0.09]	[-1.87]	[-0.11]	[-2.71]	[0.02]	[-0.44]	[-2.03]
$LEVERAGE_{i,t}$	1.124***	0.197	0.338	-0.426	-0.080	-0.342	-0.008	1.742***	2.376	0.254	0.133
	[5.08]	[1.07]	[1.43]	[-0.61]	[-0.70]	[-0.31]	[-0.01]	[2.77]	[1.06]	[0.90]	[0.08]
$CASH_{i,t}$	-1.197***	-0.180	-3.604	-3.159*	-1.129	-34.805*	0.592	-0.437	-0.591	-8.201**	-0.193
	[-3.63]	[-0.21]	[-1.19]	[-1.80]	[-0.75]	[-1.94]	[0.19]	[-0.35]	[-0.14]	[-2.55]	[-0.11]
$SIZE_{i,t}$	0.194***	0.342***	0.249	0.222	-0.058	0.606	0.485*	0.251***	-0.273	0.165	0.511***
	[5.92]	[3.53]	[1.27]	[1.55]	[-0.54]	[1.33]	[1.91]	[2.85]	[-0.85]	[1.57]	[2.68]
$NEGEQUITY_{i,t}$	0.229	1.041	-0.047	-0.959	1.436***	1.356	0.766	-2.452**	2.647*	-0.542	2.821
	[0.98]	[1.47]	[-0.03]	[-0.71]	[3.46]	[0.88]	[0.80]	[-2.47]	[1.83]	[-0.74]	[1.51]
$BIG4_{i,t}$	-0.163	-0.263	0.140	-0.661	-2.143**	0.152	-0.704	0.048	1.285*	0.171	-1.484**
	[-1.06]	[-0.67]	[0.15]	[-1.50]	[-2.12]	[0.11]	[-0.97]	[0.18]	[1.80]	[0.60]	[-2.04]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-6.432***	-8.847***	-21.641***	-5.204***	-1.558	-10.134*	-11.505***	-6.563***	-4.441	-5.154***	-9.549***
	[-15.40]	[-6.53]	[-9.51]	[-2.79]	[-1.09]	[-1.95]	[-3.09]	[-5.36]	[-1.34]	[-4.26]	[-3.29]
Observations	15,034	6,272	1,796	1,358	1,326	277	415	2,166	429	1,955	843
Pseudo R^2	0.224	0.226	0.118	0.143	0.0963	0.230	0.257	0.207	0.407	0.119	0.136
AUC	0.870	0.899	0.824	0.784	0.724	0.851	0.893	0.859	0.931	0.782	0.799

This table includes results from the logistic regression including $HIGH\_PD_{i,t}$ (Eq. 2): $P(DEFAULT_{i,t+1}) = f(HIGH\_PD_{i,t}, Client\ Characteristics_{i,t}, Fixed\ Effects_{i,t}, e_{it})$. Panel A shows estimates at the global-level and country-grouping. Panel B shows country-level estimates. Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significant at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix C. In Panel A, country groupings in columns (2) to (6) are as follows: (2) U.S. alone; (3) other common law countries: Australia, Canada, and U.K.; (4) Continental Europe: France, Germany, Italy, and Netherlands; (5) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand.

Table 4 – Logistic regression model using $GCO_{i,t}$ and $HIGH\_PD_{i,t}$ together as a predictors of subsequent default

Panel A: Global-level and country-groupings analysis

	Dependent Variable = $DEFAULT_{i,t+1}$					
Variables	*Global level (1)*	*U.S. Only (2)*	*Common Law (3)*	*Cont. Europe (4)*	*Asia Pacific (5)*	*Scandinavia (6)*
$GCO_{,t}$	1.552***	2.275***	1.189***	1.300***	0.873***	0.614
	[15.33]	[14.51]	[3.40]	[3.61]	[4.94]	[0.71]
$HIGH\_PD_{i,t}$	1.216***	1.502***	1.165***	0.868***	0.852***	1.855***
	[13.55]	[9.86]	[3.29]	[2.66]	[5.88]	[3.43]
$ROA_{i,t}$	-0.022	0.212	-0.184	-0.470	-0.944***	-0.263
	[-0.29]	[1.42]	[-1.39]	[-0.98]	[-3.87]	[-0.61]
$CFO_{i,t}$	-0.426***	-0.507*	-0.077	-2.351***	-1.019	-0.258
	[-2.79]	[-1.90]	[-0.30]	[-2.72]	[-1.64]	[-0.33]
$LEVERAGE_{i,t}$	0.095	0.893***	0.149	-0.318	-0.144	1.637
	[1.47]	[4.01]	[1.32]	[-0.68]	[-1.22]	[1.33]
$CASH_{i,t}$	-1.129***	-0.389	-0.170	-3.440**	-1.914**	-0.931
	[-4.29]	[-1.18]	[-0.20]	[-2.15]	[-2.41]	[-0.65]
$SIZE_{i,t}$	0.252***	0.327***	0.403***	0.326***	0.155***	0.249
	[10.08]	[8.60]	[4.24]	[3.73]	[3.07]	[1.60]
$NEGEQUITY_{i,t}$	0.595***	0.095	0.782*	0.575	0.384	0.873
	[4.47]	[0.41]	[1.65]	[0.99]	[1.33]	[0.90]
$BIG4_{i,t}$	-0.193**	-0.150	-0.322	-0.581*	-0.229	-1.027**
	[-1.96]	[-0.94]	[-0.89]	[-1.82]	[-1.52]	[-2.15]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-7.613***	-8.268***	-9.672***	-20.961***	-4.792***	-6.924***
	[-22.67]	[-15.46]	[-7.34]	[-14.29]	[-6.76]	[-3.82]
	1.552***	2.275***	1.189***	1.300***	0.873***	0.614
N. Obs.	43,287	15,030	12,105	3,796	8,245	1,683
Pseudo-R^2	0.229	0.307	0.201	0.214	0.141	0.243
AUC	0.874	0.900	0.891	0.872	0.807	0.880

Panel B: Country level analysis

	Dependent Variable = $DEFAULT_{i,t+1}$										
	U.S.	*Australia*	*U.K.*	*Germany*	*China*	*Philippines*	*Singapore*	*Taiwan*	*Thailand*	*Malaysia*	*Sweden*
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
$GCO_{i,t}$	2.281***	0.867**	1.743***	1.174**	0.722**	0.326	1.054	0.139	0.182	1.394***	1.450
	[14.33]	[2.06]	[2.58]	[2.30]	[2.36]	[0.46]	[1.13]	[0.32]	[0.25]	[4.12]	[0.97]
$HIGH\_PD_{i,t}$	1.502***	1.379***	0.553	0.958**	0.130	1.315*	2.981***	0.759**	1.543**	0.799***	1.534
	[9.88]	[3.27]	[0.85]	[2.35]	[0.46]	[1.67]	[2.89]	[2.34]	[2.42]	[2.72]	[1.60]
$ROA_{i,t}$	0.239*	-0.316**	0.562**	-0.239	-0.032	2.889	-0.549	-3.639***	-2.516	-0.632	0.631
	[1.68]	[-1.99]	[2.30]	[-0.58]	[-0.11]	[1.29]	[-0.86]	[-5.21]	[-1.29]	[-1.55]	[1.07]
$CFO_{i,t}$	-0.474*	0.026	-0.709*	-1.842**	0.271	-8.776*	-0.149	-3.091***	0.082	-0.606	-1.781**
	[-1.83]	[0.09]	[-1.82]	[-2.07]	[0.26]	[-1.81]	[-0.13]	[-2.72]	[0.03]	[-0.29]	[-1.97]
$LEVERAGE_{i,t}$	0.918***	0.229	0.530**	-0.681	-0.089	-0.270	-0.149	1.681***	2.360	0.208	0.003
	[4.20]	[1.18]	[2.12]	[-0.84]	[-0.81]	[-0.26]	[-0.32]	[2.63]	[1.06]	[0.71]	[0.00]
$CASH_{i,t}$	-0.488	-0.024	-3.166	-3.187*	-1.105	-34.831*	0.813	-0.433	-0.537	-7.058**	-0.116
	[-1.42]	[-0.03]	[-1.07]	[-1.79]	[-0.76]	[-1.90]	[0.26]	[-0.35]	[-0.13]	[-2.30]	[-0.06]
$SIZE_{i,t}$	0.344***	0.393***	0.295	0.228*	-0.055	0.621	0.460*	0.255***	-0.270	0.149	0.515***
	[9.47]	[3.69]	[1.53]	[1.65]	[-0.51]	[1.31]	[1.71]	[2.85]	[-0.84]	[1.36]	[2.59]
$NEGEQUITY_{i,t}$	0.073	0.830	-0.140	-0.870	1.108**	1.194	0.319	-2.422**	2.598*	-1.014	2.839
	[0.32]	[1.17]	[-0.10]	[-0.71]	[2.49]	[0.79]	[0.31]	[-2.47]	[1.81]	[-1.44]	[1.41]
$BIG4_{i,t}$	-0.204	-0.252	0.065	-0.704	-2.089**	0.187	-0.721	0.047	1.303*	-0.059	-1.495**
	[-1.27]	[-0.64]	[0.07]	[-1.64]	[-2.05]	[0.13]	[-1.01]	[0.18]	[1.80]	[-0.21]	[-2.11]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-8.545***	-9.399***	-20.671***	-5.084***	-1.623	-10.358*	-11.299***	-6.576***	-4.505	-4.943***	-9.485***
	[-17.75]	[-6.47]	[-11.27]	[-2.84]	[-1.14]	[-1.85]	[-3.00]	[-5.36]	[-1.32]	[-3.94]	[-3.21]
Observations	15,034	6,272	1,796	1,358	1,326	277	415	2,166	429	1,955	843
Pseudo R^2	0.300	0.237	0.168	0.163	0.105	0.232	0.276	0.207	0.407	0.150	0.145
AUC	0.896	0.902	0.871	0.801	0.737	0.853	0.906	0.858	0.932	0.797	0.808

This table includes results from the logistic regression including $GCO_{i,t}$ and $HIGH\_PD_{i,t}$ (Eq. 3): $P(DEFAULT_{i,t+1}) = f(GCO_{i,t}, HIGH\_PD_{i,t}, Client\ Characteristics_{i,t}, Fixed\ Effects_{i,t}, e_{it})$. Panel A shows estimates at the global-level and country-grouping. Panel B shows country-level estimates. Robust z-statistics are shown in the brackets. Standard errors are clustered by company. ***, **, and * indicate statistical significant at 0.01, 0.05, and 0.10 levels, respectively. Variable descriptions are included in Appendix C. In Panel A, country groupings in columns (2) to (6) are as follows: (2) U.S. alone; (3) other common law countries: Australia, Canada, and U.K.; (4) Continental Europe: France, Germany, Italy, and Netherlands; (5) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand.

Table 5 – Comparison of the predictive ability based on AUC of models in Tables 2 to 4

Aggregation Level	*(1) GCO Model*	*(2) PD Model*	*(3) Combined Model*	*(4) Ho: No Diff. (2)-(1)*	*(5) Ho: No Diff. (3)-(1)*		*(6) Ho: No Diff. (3)-(2)*		*No. Obs.*
	AUC			*p-value*					
Global	0.854	0.860	0.874	0.238	0.000	***	0.000	***	43,287
Country Groupings:									
U.S.	0.877	0.878	0.900	0.898	0.000	***	0.000	***	15,030
Common Law	0.870	0.879	0.891	0.586	0.034	**	0.179		12,105
Cont. Europe	0.867	0.853	0.872	0.293	0.479		0.046	**	3,796
Asia-Pacific	0.788	0.796	0.807	0.360	0.002	***	0.018	**	8,245
Scandinavia	0.839	0.876	0.880	0.107	0.074	*	0.306		1,683
Country:									
U.S.	0.872	0.870	0.896	0.778	0.000	***	0.000	***	15,034
Australia	0.886	0.899	0.902	0.297	0.139		0.552		6,272
U.K.	0.852	0.824	0.871	0.594	0.153		0.245		1,796
Germany	0.792	0.784	0.801	0.730	0.577		0.295		1,358
China	0.734	0.724	0.737	0.455	0.181		0.297		1,326
Philippines	0.832	0.851	0.853	0.381	0.351		0.760		277
Singapore	0.842	0.893	0.906	0.356	0.139		0.384		415
Taiwan	0.856	0.859	0.858	0.663	0.670		0.798		2,166
Thailand	0.914	0.931	0.932	0.303	0.272		0.624		429
Malaysia	0.783	0.782	0.797	0.941	0.212		0.225		1,955
Sweden	0.802	0.799	0.808	0.941	0.886		0.440		843

This table includes the AUC comparison for the logistic models in Tables 2 to 4

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

Column 4 shows p-values of the non-parametric Wald test to assess the differences in AUCs between the models in columns 1 and 2. Column 5 indicates p-values of the non-parametric Wald test to assess the differences in AUCs between the models in columns 1 and 3. Column 6 indicates p-values of the non-parametric Wald test to assess the differences in AUCs between the models in columns 2 and 3. In columns 4, 5, and 6, ***, **, and * indicate statistical significant at 0.01, 0.05, and 0.10 levels, respectively. Country groupings are as follows: (1) U.S. alone; (2) other common law countries: Australia, Canada, and U.K.; (3) Continental Europe: France, Germany, Italy, and Netherlands; (4) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand.

Table 6 - Two-by-two contingency tables between subsequent default and $GCO_{i,t}$, and subsequent default and $HIGH\_PD_{i,t}$

Panel A: $GCO_{i,t}$ and subsequent default

		$DEFAULT_{i,t+1}$		
		=0	=1	
$GCO_{i,t}$	=0	86.0%	1.0%	87.0%
	=1	12.2%	0.8%	13.0%
		98.2%	1.8%	100.0%

Sensitivity (0.8% / 1.8%) = 45.7%
Specificity (86.0% / 98.2%) = 87.6%

Panel B: $HIGH\_PD_{i,t}$ and subsequent default

		$DEFAULT_{i,t+1}$		
		=0	=1	
$HIGH\_PD_{i,t}$	=0	69.5%	0.5%	70.1%
	=1	28.6%	1.3%	29.9%
		98.2%	1.8%	100.0%

Sensitivity (1.3% / 1.8%) = 71.2%
Specificity (69.5% / 98.2%) = 70.8%

This table displays two-by-two contingency tables comparing subsequent default to GCOs and subsequent default to HIGH_PDs in the global-level sample. In the table, the frequencies, sensitivity and specificity of each outcome are displayed. The overall frequency of subsequent default is 1.8%, frequency of GCOs is 13% and by construction 30% of the observations are in the top three deciles of PD by country and year.

Table 7 - Comparison of the predictive ability based on AUC of GCO, PD and combined models using a continuous PD estimate

Aggregation Level	*(1) GCO Model*	*(2) Cont. PD Model*	*(3) Combined Model*	*(4) Ho: No Diff. (2)-(1)*		*(5) Ho: No Diff. (3)-(1)*		*(6) Ho: No Diff. (3)-(2)*		*No. Obs.*
	AUC			p-value						
Global	0.854	0.846	0.862	0.063	*	0.000	***	0.000	***	43,287
<u>*Country Groupings:*</u>										
U.S.	0.877	0.867	0.884	0.150		0.000	***	0.010	***	15,030
Common Law	0.870	0.853	0.872	0.174		0.051	*	0.127		12,105
Con. Europe	0.867	0.854	0.875	0.278		0.152		0.059	*	3,796
Asia-Pacific	0.788	0.777	0.790	0.104		0.021	**	0.040	**	8,245
Scandinavia	0.839	0.858	0.863	0.096	*	0.014	**	0.415		1,683
<u>*Country:*</u>										
U.S.	0.872	0.854	0.879	0.028	**	0.000	***	0.002	***	15,034
Australia	0.886	0.883	0.891	0.772		0.061	*	0.372		6,272
U.K.	0.852	0.813	0.851	0.339		0.698		0.355		1,796
Germany	0.792	0.789	0.807	0.871		0.307		0.319		1,358
China	0.734	0.720	0.733	0.259		0.466		0.280		1,326
Philippines	0.832	0.832	0.840	1.000		0.528		0.407		277
Singapore	0.842	0.834	0.847	0.862		0.470		0.763		415
Taiwan	0.856	0.856	0.856	0.765		0.788		0.872		2,166
Thailand	0.914	0.921	0.922	0.617		0.533		0.401		429
Malaysia	0.783	0.775	0.798	0.685		0.142		0.112		1,955
Sweden	0.802	0.779	0.802	0.395		0.878		0.404		843

This table includes the AUC comparison for the GCO, PD and combined models using a countinuous PD estimate:

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

Column 4 shows p-values of the non-parametric Wald test to assess the differences in AUCs between the models in columns 1 and 2. Column 5 indicates p-values of the non-parametric Wald test to assess the differences in AUCs between the models in columns 1 and 3. Column 6 indicates p-values of the non-parametric Wald test to assess the differences in AUCs between the models in columns 2 and 3. In columns 4, 5, and 6, ***, **, and * indicate statistical significant at 0.01, 0.05, and 0.10 levels, respectively. Country groupings are as follows: (1) U.S. alone; (2) other common law countries: Australia, Canada, and U.K.; (3) Continental Europe: France, Germany, Italy, and Netherlands; (4) Scandinavian countries: Denmark, Norway, and Sweden; and, (5) Asia-Pacific countries: China, Malaysia, Philippines, Singapore, Taiwan, and Thailand.