AUDITING: A JOURNAL OF PRACTICE & THEORY
Vol. 35, No. 2
May 2016
pp. 23–51

American Accounting Association
DOI: 10.2308/ajpt-51290

There's No Place Like Home: The Influence of Home-State Going-Concern Reporting Rates on Going-Concern Opinion Propensity and Accuracy

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SUMMARY: Prior research has had success identifying client financial characteristics that influence auditors' going-concern reporting decisions. In contrast, relatively little research has addressed whether auditors' circumstances and surroundings influence their propensities to issue modified opinions. We investigate whether auditors' decisions to issue GC opinions are affected by the rate of GC opinions being given in their proximate area. Controlling for factors that prior research associates with going-concern opinions and state-level economics, we find that non-Big 4 auditors located in states with relatively high first-time going-concern rates in the prior year are up to 6 percent more likely to issue first-time going-concern opinions. The results from our state-based GC measure casts doubt that this increased propensity is explained by economic factors and suggests that psychological factors may explain this behavior among auditors. Interestingly, this higher propensity increases auditors' Type I error rates without decreasing their Type II error rates, further suggesting economics alone do not explain these results. Such evidence challenges the generally accepted notion that a higher propensity to issue a going-concern opinion always reflects higher audit quality.

Keywords: auditor reporting; going-concern opinion; audit quality; Type I error; Type II error.

JEL Classifications: M41; M42.

Data Availability: All data are available from public sources.

INTRODUCTION

For a financially distressed client, the auditor's decision to modify the audit report related to doubt about the firm's ability to continue as a going-concern (GC; hereafter referred to as GC opinions, or GC reporting) is generally considered the first public signal of imminent financial failure based on relatively private information (Kida 1980). Furthermore, a modified audit opinion is the auditor's only means of informing outsiders of the organization's financial condition (AICPA 2010). As a result, two important characteristics of GC opinions emerge. First, GC opinions can provide significant firm-specific information to financial statement users (Kausar, Taffler, and Tan 2009; Menon and Williams 2010; Blay, Geiger, and North 2011). Second, an auditor's willingness to issue a GC opinion can signal both that the auditor is independent and that the audit is of high quality (DeFond, Raghunandan, and Subramanyam 2002). Considerable research corroborates and relies upon both characteristics (Carson et al. 2013).

The authors appreciate the helpful comments and suggestions from Justin Leiby, Kathy Rupar, Nadine Funcke, Marshall Geiger, Dana Wallace, participants at the 2013 AAA Annual Meeting, and workshop participants at the University of Florida and Florida State University.

Editor's note: Accepted by Jeffrey R. Cohen, under senior editorship of W. Robert Knechel.

Submitted: December 2013
Accepted: September 2015
Published Online: September 2015

Despite extensive research favoring these interpretations, reasons exist to question whether the issuance of a GC opinion is always an indication of high auditor independence and audit quality. First, financially failing clients unlikely provide substantial future audit fees in the event that the auditor withholds a GC opinion, challenging the theoretical link between auditor independence and the issuance of GC opinions. Second, prior research documents that, in addition to client economic condition (e.g., financial distress), other factors (e.g., client press coverage) influence auditors' GC reporting (Mutchler, Hopwood, and McKeown 1997; Joe 2003). Third, research on the accuracy of a GC opinion using the association between GC opinions and bankruptcy cannot be interpreted with normative thresholds. Research repeatedly finds that GC opinions precede only half of all bankruptcies, suggesting a 50 percent Type II error rate (Hopwood, McKeown, and Mutchler 1989; Raghunandan and Rama 1995; Geiger, Raghunandan, and Rama 2005).[1] Analogously, only 10 percent of the firms receiving a GC opinion file for bankruptcy within one year, indicating a 90 percent Type I error rate (Mutchler and Williams 1990; Nogler 1995). With significant economic losses being associated with both Type I and Type II errors there is an enduring interest among market participants, regulators, and standard setters in research that investigates factors associated with reporting accuracy (Carson et al. 2013). Carson et al. (2013) suggest that novel approaches, such as including nonfinancial measures, are needed to help researchers understand how auditors assess going-concern uncertainty and assess the resulting accuracy of their decisions.

We introduce a novel nonfinancial measure and evaluate its effect on auditors' propensities to issue GC opinions. Specifically, we examine whether recent GC reporting decisions in geographic proximity to the auditor influence auditors' issuances and accuracies of their first-time GC opinions. There are several reasons to posit that recent GC decisions in an auditor's home state may represent a useful variable in models of auditors' GC reporting. First, recent GC reporting decisions of auditors in their home state may proxy for macroeconomic information not considered in prior GC reporting research but nonetheless important to auditors' decisions, such as unemployment rates, state GDP, etc. To the extent that firm characteristics fail to capture these important economic conditions, recent GC decisions for other companies may serve as a useful proxy for otherwise omitted but relevant economic information. Second, a high rate of modified opinions in the auditor's proximate area may reflect the auditor's assessment of litigation risk and hence increase the perceived cost of a Type II error. Because auditors can protect against litigation through the issuance of GC opinions (Kaplan and Williams 2013), higher rates of GC reporting may proxy for otherwise unidentifiable litigation risk. Both of these economic-based arguments—omitted state-level economic conditions and litigation risk—likely lead to an increased propensity to issue GC opinions in areas with higher rates of prior-year GC reporting.

Prior research also investigates psychological reasons for auditors' behaviors. One such behavior is reluctance to issue GC opinions due to their possible self-fulfilling prophecy effects (Kida 1980). Prior research also finds that auditor GC opinions can be influenced by salient information not directly relevant to the decision. Mutchler et al. (1997) document that negative press coverage of a client increases the likelihood of GC reporting. In an experimental setting, Joe (2003) corroborates this result and examines the rationale. She concludes that, consistent with the representativeness heuristic (Kahneman and Tversky 1972), over-weighting redundant, negative information provided in press coverage rather than increases in assessments of litigation risk explains the effect of press coverage on auditors' GC reporting. Along the same lines, seminal psychology research finds that easy-to-retrieve information overly influences probability judgments, even when such information is not relevant to the decision (Tversky and Kahneman 1973). Thus, knowledge of redundant, and even irrelevant, information associated with recent, proximate modified opinions could lead to an increase in GC reporting.[2] In contrast to economic-based arguments, a psychological bias could result in reduced GC reporting accuracy. However, such a bias requires auditors to be either more aware of or more influenced by opinions within their proximate area.

There are many reasons to believe that some auditors are more aware of and more influenced by GC opinions within their state. Research on social networking and social ties indicates that information flows related to stocks disseminate through local sources and social interactions (Coval and Moskowitz 1999; Hong, Kubik, and Stein 2004). In addition, Granovetter (1973) argues that weak social ties, often associated with local connections, facilitate the transfer of information, and subsequent research indicates that these weak local ties are an efficient source of new information (Reagans and McEvily 2003; Wasserman and Faust 1994). Further, state borders establish meaningful boundaries to information flow, as demonstrated by prior research. For example, locally transmitted information contributes strongly to price discovery and liquidity of local stocks in financial markets (Loughran and Schultz 2004; Shive 2012; Peress 2014). Finally, Brown, Stice, and White (2015) document that when states implement distracted driving laws, trading volume on stocks headquartered in the state decrease. They attribute their finding to decreased social information flows within the state.

[1] Type I errors occur when an auditor modifies the opinion for GC uncertainty, but the client subsequently remains viable. Type II errors occur when an auditor fails to modify the opinion for GC uncertainty, but the client does not remain viable.

[2] In this scenario, the redundant information incorrectly increases an auditor's assessment of the likelihood of failure, but the modification threshold determined by error costs remains constant, leading to over-modification of audit reports.

To gain initial insight into the potential effects of state-based information, we interview partners and managers from a wide variety of accounting firms to ascertain whether they are aware of GC reporting in their proximate area, whether they are *more* aware of proximate reporting than reporting in other areas, and whether they believe that they consider recent proximate reporting in making their GC reporting decisions. Our interviews indicate that nearly all auditors are aware of GC opinions for other public companies in geographic proximity to them. Further, non-Big 4 auditors indicate that they are more likely to focus on proximate geographic areas, whereas Big 4 auditors maintain a more comprehensive and national focus. Non-Big 4 auditors also indicate that they consider geographically proximate GC opinions to be relevant to their decisions more often than their Big 4 counterparts. Thus, our interview evidence suggests that non-Big 4 auditors are likely more influenced by prior GC opinions within their state. Accordingly, we focus our subsequent analyses on non-Big 4 firms.[3]

To measure the rate of proximate GC opinions, we analyze 22,862 audit reports of financially distressed clients for the period 2001–2011. We define a home-state GC opinion variable based on the rate of first-time GC opinions in the auditor's state in the prior year and test its relation with current GC reporting. We choose the auditor's state as the level of analysis for several reasons. First, there is a long-standing notion that there are economic boundaries to information flows (Marshall 1920; Krugman 1991; Singh and Marx 2013) and prior research also finds state-level information flows and clustering occur at a significant level (Audretsch and Feldman 1996; Bernile, Kuman, and Sulaeman 2015; Brown et al. 2015). Second, auditors organize and operate to a significant degree at the state level. CPA certification is at the state level, and qualitative evidence from our interviews with audit practitioners indicates that communication with other auditors within the home state is far greater than communication outside of the home state, especially in the case of non-Big 4 practitioners.[4] Third, theory suggests closer levels of proximity will have stronger effects (see, for example, Pool, Stoffman, and Yonker 2015), but a practical trade-off exists between alternative measures of proximity and sample size. This trade-off occurs because bankruptcy and financial distress have low base rates so the more localized the analysis (such as city/office) the less likely adequate sample sizes and numbers of distressed firms will be identified to provide meaningful data.[5] Thus, we choose the auditor's home state as the most meaningful measure of proximity with sufficient data. Our results suggest that current-year first-time GC reporting exhibits a strong, positive relation with the rate of prior-year GC opinions in the auditor's home state. To assess the degree to which this result relates to other state-specific factors, such as the economy and legal environment, we control for an extensive collection of additional variables, including many not previously discussed in the GC reporting literature. We continue to find that prior-year first-time GC reporting at the state level is significantly and positively related to current-year first-time GC reporting.[6] Further, the economic magnitude of this relation is significant, as a one standard deviation increase in prior-year state-GC issuance correlates with a nearly 6 percent increase in the likelihood of a GC opinion, *ceteris paribus*. The magnitude of this home-state effect compares favorably with other well-known GC determinants, such as firm size and cash flows.

We also study whether auditors' Type I and Type II GC opinion errors are affected by their home-states' prior-year going-concern rates. This is especially important given the costly consequences of both types of errors.[7] Our results document that GC reporting accuracy decreases significantly with increases in the state rate of GC opinions. In fact, the increased issuance of GC opinions leads to increases in Type I error rates without a decrease in Type II error rates. Depending on the circumstances, evidence suggests that Type II errors actually increase, even as Type I errors increase. Our results are consistent with non-Big 4 auditors succumbing to psychological information biases, but even our Type I and II results cannot fully rule out economic explanations given the archival nature of our study.

Our study has several implications for academic researchers. First, many prior studies equate greater propensity to issuing a going-concern opinion with greater auditor independence and higher audit quality (e.g., DeFond et al. 2002; Blay and Geiger 2013). Our study provides evidence that, for non-Big 4 auditors, a higher incidence of prior-year GC opinions in an auditor's state corresponds to lower GC reporting accuracy in the current year. This suggests that the link between the issuance of a GC opinion and high audit quality can be tenuous, circumstantial, and even contradictory in certain predictable manners. Second, prior research documents many situations where proximity provides informational advantages to both auditors and investors (Choi et al. 2012; Ayers, Ramalingegowda, and Yeung 2011; Baik, Kang, and Kim 2010), but our study identifies a scenario

[3] We also consider Big 4 firms in supplemental analysis.

[4] One common setting for communication among auditors comes from training. While Big 4 firms are more likely to provide in-house training, auditors from smaller firms more commonly attend third-party provided continuing professional education courses, and these courses generally include auditors from the same state.

[5] Two studies do examine audit quality as a function of proximity, but (1) their measure of proximity—physical distance between auditor and client—ignores the effects of borders that we describe above, (2) neither study examines GC opinions or the effects of proximity on Type I/II error rates, and (3) neither study examines the effects of nonclient firms on auditors' decisions (Choi, Kim, Qiu, and Zang 2012; Kedia and Rajgopal 2011).

[6] Because clients are more likely to receive a repeat GC opinion, we limit all our analyses to first-time GC recipients for a stronger test. All results presented hold (and are stronger in significance) if we include all GC opinions.

[7] As noted by Carson et al. (2013), "misclassification" does not mean that the audits were necessarily substandard. However both types of "error rates" entail potential costs, and classification accuracy is widely studied.

where geographic proximity to information appears to be a disadvantage to non-Big 4 auditors. Proximity to recent GC opinions can lead to increased Type I and II error rates. Finally, our results indicate that at least one geographic characteristic—prior-year GC reporting rates—significantly influences the propensity of non-Big 4 auditors to issue GCs. Future research examining GC issuance and accuracy may be improved by identifying other important factors and by controlling for state-level environmental factors.

Our findings also have important implications for practitioners. Our results indicate that increased home-state GC rates lead to lower GC reporting accuracy for non-Big 4 auditors. Lower GC reporting accuracy imposes economic costs on the client and the auditor (Carson et al. 2013). While it is reasonable that auditors consider local information when making GC opinion decisions, our reporting accuracy results suggest that prior GC rates may be weighted too heavily.

In the next section, we discuss GC reporting, review the relevant literature, discuss preliminary interviews conducted with practitioners, and develop hypotheses. The third section presents the research design. In the fourth section, we present the sample and descriptive statistics. The fifth section documents our results, the sixth section presents additional analyses and sensitivity tests, and the seventh section concludes and provides suggestions for future research.

BACKGROUND AND HYPOTHESIS DEVELOPMENT

Carson et al. (2013) classify GC reporting research into three primary areas: research identifying determinants of report modification (Kida 1980; Mutchler 1985; Carcello and Palmrose 1994; Hopwood, McKeown, and Mutchler 1994; Mutchler et al. 1997; DeFond et al. 2002; Blay and Geiger 2013), research investigating the accuracy of GC reporting (Hopwood et al. 1994; Carcello, Hermanson, and Huss 1995; Raghunandan and Rama 1995; Geiger et al. 2005; Geiger and Rama 2006), and research examining consequences of the reporting decision to both auditors (Kida 1980; Mutchler 1984; Geiger, Raghunandan, and Rama 1998; Carcello and Palmrose 1994) and clients (Louwers, Messina, and Richard 1999; Pryor and Terza 2001; Carcello and Neal 2003; Carey, Geiger, and O'Connell 2008). The general tenor of this extensive body of research is that auditors issue GC opinions to financially struggling clients, but with significant Type I and II error rates. Regardless, the auditor's willingness to issue a GC opinion is accepted as a measure of high auditor independence and audit quality (DeFond et al. 2002; Basioudis, Papanastasiou, and Geiger 2008; Blay and Geiger 2013).

We investigate the question of whether the rate of GC opinions in an auditor's proximate area affects decision making and, as an extension, the quality of those decisions.[8] Prior research suggests that, in addition to a client's financial condition, outside economic factors such as stock market returns and volatility, and psychological factors such as representativeness and motivated reasoning, affect auditors' propensities to issue first-time GC opinions (DeFond et al. 2002; Joe 2003; Blay 2005). Prior research also shows that proximity improves the monitoring effectiveness of auditors, analysts, mutual fund managers, and bankers (Malloy 2005; Baik et al. 2010; Ayers et al. 2011). Auditors' decisions to issue GC opinions may be similarly affected by proximity. However, evidence of psychological biases in auditors' GC decision-making processes may suggest otherwise (Joe 2003; Blay 2005). We posit that psychological and economic factors that affect GC opinions may produce an effect whereby the frequency of prior-year GC opinions affects current GC reporting decisions. We next discuss the mechanism by which auditors are likely aware of proximate GC reporting.

Social Networking and Auditor Information Flows within States

Social network theory posits that information is transmitted between individuals who are tied socially, and that easily communicated ideas are spread most effectively through weak ties (Granovetter 1973).[9] Further, research on information networks provides evidence that information spreads more efficiently within borders and borders impede information flow (Audretsch and Feldman 1996; Bernile et al. 2015; Singh and Marx 2013; Reagans and McEvily 2013). Research also documents that financial information is often transmitted relatively easily within state borders (Coval and Moskowitz 1999; Hong et al. 2004; Brown et al. 2015). Auditor reports represent a specialized type of information and thus we expect audit report information to spread relatively easily within state borders or networks.

Ultimately, the importance of state borders in an auditor and audit report setting is an empirical issue, but *a priori* there are reasons to expect that auditors have networks defined by state boundaries. CPA licenses are at the state level, and states have CPA societies with local chapter meetings. Further, training is often conducted at the state and local level particularly for smaller and mid-tier firms. Auditors obtain CPE through conferences offered by state CPA societies, and many smaller and

[8] Consistent with Geiger and Raghunandan (2006), we associate the quality of GC decision making with the Type I and Type II accuracy of the opinions.

[9] Granovetter (1973) defines weak ties as "acquaintance" relationships, as opposed to close friends. The theory of weak ties proposes that individuals with fewer weak ties are deprived of information from more distant parts of the social system.

mid-tier firms host leadership training at state and regional offices. In contrast, Big 4 firms often have their own training where participation is limited to auditors from that one particular firm who travel from a large number of states and even multiple countries. As a result, Big 4 auditors are privy to more information from outside state borders and are less likely to rely as heavily on information from within state borders. Consequently, we conjecture that although all auditors have social ties (including local ones), auditors with smaller and mid-tier firms are more likely limited to weak-tie interactions with auditors from other firms at the local and state level. Social networking theory would posit that these auditors would obtain less information from outside their network, and thus be more likely to rely on information from within their state network. To provide initial support for this conjecture, we conduct interviews with auditors from a variety of firms and locations.

Interviews with Practicing Auditors

As previously discussed, we contend that (1) auditors know about GC opinions of other auditors in their home state, (2) auditors know more about these opinions than opinions in other states, and (3) this proximate knowledge is more apparent in non-Big 4 auditors because of fewer weak-tie relationships with auditors outside of their home state. To support these expectations, we conducted semi-structured interviews with eight practicing auditors identified through the authors' professional contacts. The auditors were partners and senior managers from three of the Big 4, two second-tier, and three small firms, each registered with the PCAOB. We conducted our interviews with practitioners from both larger and smaller states, including California, Colorado, Connecticut, Florida, Georgia, Michigan, New York, and Tennessee. Six of the interviews were conducted face-to-face and two were conducted via phone. The responses were collected via computerized notes. The interviews consisted of up to 15 questions developed by the authors and were designed to answer three specific questions: (1) Are auditors aware of GC opinions of other companies? (2) Is this knowledge concentrated within state? (3) Does this influence their GC opinion decisions? The questions were also designed to provide evidence about what economic factors influence the GC reporting decision. All interviews began with the same question, but subsequent questions were only asked if they were relevant based on the responses to prior questions. Appendix A lists the 15 potential questions. Subsequent to the interviews, two co-authors categorized the responses into the three primary questions to determine yes or no answers for each auditor interviewed. Appendix A also outlines the coded responses to our three primary questions asked and the representative responses given.

Interview responses almost universally confirmed our expectations. Seven of eight auditors interviewed indicated that they were aware of GC opinions issued to public (issuer) clients within their state and further indicated that they were more aware of local and home-state GC opinions. As noted by one auditor when asked about the extent to which he knows about other auditors' GC decisions in his area, he stated:

> Everyone knows about issuers, but not non-issuers [in my area]. (Partner, Second-Tier Firm)

Another auditor also indicated he considers GC reporting for other firms:

> When we are considering issuing a GC opinion, yes. I talk with risk management and they give me feedback on the public space. (Partner, Big 4)

Of particular interest, another second-tier firm partner noted that he always looked at the financial statements of public companies within his area because:

> We use prior financials to identify prospective clients. We definitely know financial conditions and GC outcome of public companies. (Partner, Second-Tier Firm)

When asked how he learned about the information, another auditor (from Michigan) responded:

> In my geography, I learn about it through the press. I don't usually know about, say, California. (Senior Manager, Big 4)

In addition, many second-tier firm and small firm auditors indicated they interacted more with local and state peers. As one small firm auditor stated:

> My area is a pretty closed network. (Senior Manager, Small Firm)

In contrast, Big 4 auditors indicated they operated on a more national level. When asked about typical interactions, one Big 4 senior manager indicated:

> I interact with people from my firm anywhere in the world within my industry group. (Senior Manager, Big 4)

In responding to the same question, a small firm partner with prior Big 4 experience stated:

> In my role, I am more involved with local accountants. But ten years ago [with a Big 4 firm], I would have said national. (Partner, Small Firm)

Finally, another Big 4 auditor confirmed that proximate reporting was not necessarily the focus when considering GC opinions within his firm, stating:

> Risk management considers both local and national [factors]. (Partner, Big 4)

Although auditors were consistent in indicating that state and local economic conditions were important and that they were aware of GC opinions for companies in their local areas and states, auditors did not uniformly indicate that they considered other GC opinions to be relevant information to their decisions. However, the lack of uniformity appears to be related to audit firm size. According to a Big 4 partner:

> It isn't something I think about specifically. (Partner, Big 4)

However, a small firm partner indicated:

> That [state and local GC reporting] is a very important part of it. What else might lead them to fail? (Partner, Small Firm)

Only two partners, one from a small firm and one from a second-tier firm indicated that they specifically consider recent GC opinions within their state. As stated by one senior manager:

> From a client perspective, no one wants to be the first [to receive a GC opinion]. (Senior Manager, Small Firm)

Based on responses to our interviews, we conclude that auditors are generally aware of GC opinions among issuers in their proximate areas, but Big 4 firms communicate on a more comprehensive and national basis. Further, small and second-tier auditors appear to consider local and state economics more than national economics, and only non-Big 4 auditors stated that they specifically consider recent GC opinions within their state or local area. For this reason, we conclude that the interviews provide support for our conjecture that non-Big 4 auditors are most likely to be influenced by recent GC opinions within their home state and thus we focus our analysis on non-Big 4 auditors.

Recent Proximate GC Opinions and Information Availability

Our interviews with practitioners provide initial evidence that auditors are more aware of and influenced by prior GC opinions within their home state in making their reporting decisions. In addition to providing economically relevant information, it is also possible that recent proximate GC modified opinions influence auditors' perceptions of the level of financial distress facing their clients. Tversky and Kahneman (1973) document that people tend to judge the probability of an event occurring based on the ease of recall of relevant or irrelevant information. This availability heuristic can lead to over or underestimation of the likelihood of an event, but it can also lead to more accurate decisions when the more available information is consistent with the actual underlying probability distribution (Nelson 1993; Wolfe and Pennington 2000; Bonner 2008).

Prior research in accounting documents that more available information influences decisions. Investor participants explicitly asked to identify reasons that would lead or not lead to an earnings increase later provide directionally congruent probability estimates of the likelihood of an earnings increase (Moser 1989). Similarly, Kida, Smith, and Maletta (1998) find that reactions to information are recalled more easily than the information itself and that this bias lowers decision quality. In auditing, Lindberg and Maletta (2003) experimentally find that auditors are more likely to incorrectly attribute information from one client to another client when the information is more consistent with the other client's situation. However, Anderson, Kaplan, and Reckers (1992) do not find a similar availability bias in auditor judgments about the probability of an error.

Recent and salient events are more likely to influence probability judgments when the base rate of occurrence is low (Nisbett and Ross 1980). GC opinions and client bankruptcy are relatively low-frequency events and, therefore, are more likely to be influenced by recent, salient events such as the issuance of a GC opinion by other firms in proximity to the auditor. Indeed, Mutchler et al. (1997) find that increased press coverage of a client's debt default increased the likelihood of a client receiving a GC opinion. In an experimental follow-up, Joe (2003) documented that press coverage of a client can lead to an overstatement of the likelihood of client failure and an increase in the rate of GC reporting without any increase in the auditor's assessment of litigation risk.

Information proximity and barriers to knowledge spillover have also been shown to influence information availability and decision making in other financial decisions. Brown et al. (2015) document a decrease in trading volume of home-state stocks when states implement mobile communication driving restrictions. This decrease does not flow over to nonstate stocks, indicating that in-state information flows matter significantly in stock markets. This in-state versus out-of-state contrast is consistent with information proximity influencing not only the availability of information, but also its usefulness, for more than

brief periods of time. Further, investors have been shown to have a home bias with portfolios overweighed with local investments. Pool, Stoffman, and Yonker (2012) document that institutional investors overweigh stocks from the manager's home state by 12 percent, and this rises to 37 percent for team-managed funds. Pool et al. (2015) extend this finding to demonstrate that the closer the social ties and proximate location of fund managers, the greater the home bias. Bernile et al. (2015) link home bias to information in 10-K filings and document that institutions overweigh stocks that mention the investor's home state more often in the 10-K. Singh and Marx (2013) document that citations in patent applications are driven not only by proximate distance, but also by clear state "border effects" that cannot be explained by distance, and that this may limit knowledge spillover and innovation.

Based on our interviews, prior GC opinions within the auditor's home state represent salient and available information that auditors are more aware of compared with GC opinions not within the auditor's home state. This greater awareness leads to a higher ability to recall the recent and salient outcomes and, in line with Joe (2003), potentially influences probability judgments beyond the economic information captured by the prior GC opinions. In addition, prior research from other fields (e.g., Singh and Marx 2013) further documents that state-level information transfers more easily and is more heavily weighted. Given this result, we predict that prior-period proximate (i.e., state) first-time GC reporting relates positively to current GC reporting.

H1: Non-Big 4 auditors are more likely to issue first-time GC opinions when the rate of recent first-time GC opinions is higher in the auditor's state relative to areas where the state rate is lower, even after controlling for proximate economic conditions.

Despite our reasons for expecting a positive relation, the auditors interviewed also believed that state-level economic information is critically important to assessing the likelihood of survival for a distressed client. As a result, it is possible that prior rates of GC reporting within a state do not provide auditors any additional information beyond identifiable state-level economic data, leading to no significant relation between prior-year proximate GC reporting rates and current GC opinions.

GC Reporting Accuracy

In the GC reporting setting, there are two types of misclassifications relevant to reporting accuracy (Hopwood et al. 1994; Raghunandan and Rama 1995; Geiger et al. 2005). Type I errors occur when an auditor modifies the opinion for GC uncertainty, but the client subsequently remains viable. Type II errors occur when an auditor fails to modify the opinion for GC uncertainty, but the client does not remain viable. Prior accounting research generally considers bankruptcy filing within one year as evidence of lack of client viability and documents Type II error rates of approximately 50 percent and Type I error rates of nearly 90 percent (Raghunandan and Rama 1995; Geiger et al. 2005; Geiger and Rama 2006).

Both reporting misclassifications carry associated costs that are important determinants of auditor reporting decisions (Kida 1980; Geiger et al. 2005). Type I errors are commonly associated with auditor changes (Raghunandan and Rama 1995), whereas Type II errors are generally presumed to increase the likelihood of auditor litigation (Mutchler 1984) and result in larger litigation payments by the auditor (Carcello and Palmrose 1994). Further, issuing a GC opinion to distressed clients protects auditors from large litigation judgments (Kaplan and Williams 2013).

The indifference probability of failure threshold, p^*, that results in the issuance of a GC opinion is defined by a ratio of the costs of a Type I error, C_I, and the costs of a Type II error, C_{II} (Raghunandan and Rama 1995; Geiger et al. 2005). We define p^* based on prior research as:

$$p^* = 1/[1 + (C_{II}/C_I)] \tag{1}$$

Thus, as the cost of a Type II error increases, or the cost of a Type I error decreases, auditors will be more likely to issue a GC opinion (Geiger et al. 2005; Geiger and Rama 2006).

The majority of prior research, as well as legislation, focuses exclusively on Type II misclassifications (e.g., Private Securities Litigation Reform Act (PSLRA), U.S. Congress 1995; Geiger et al. 2005; Geiger and Rama 2006). In this study, we focus on both types of misclassifications to provide more complete evidence about whether prior-year state-level GC reporting rates influence current-year auditor accuracy. Based on Equation (1), a comparison of the level of Type I and Type II errors between higher and lower propensity lagged first-time GC rates can help distinguish the reasons for any reporting frequency differences we find. If economics, such as higher levels of financial distress in a proximate geographic area, drive higher propensities of prior-year GC reporting, then we would expect to see similar accuracy levels across states with higher versus lower prior-period GC frequencies. We would expect this because bankruptcy rates should be correlated with economic conditions. Thus, if economic conditions are worse, then bankruptcy rates should increase with GC rates, and Type I error rates should not increase, nor should Type II error rates decrease. Alternatively, if higher Type II error costs (such as higher perceived litigation risk) drive increased GC modification, then Equation (1) suggests higher Type I error rates and decreased Type II error rates in states with higher GC frequencies. Finally, if overweighing of salient, proximate information drives higher

GC reporting frequencies, then this would result in less accurate reporting, implying higher Type I error rates without a consummate reduction in Type II error rates.

In line with the above discussion of competing possibilities, we state our second two hypotheses in null form:

H2a: Type I misclassification rates for non-Big 4 auditors are not affected by prior-year state-level first-time GC rates.

H2b: Type II misclassification rates for non-Big 4 auditors are not affected by prior-year state-level first-time GC rates.

RESEARCH DESIGN

Measuring Going-Concern Proximity Rates and Type I/II Errors

We require a rate of recent first-time GC opinions in proximity to the auditor. As discussed previously, we choose the auditor's state as our level of analysis for several reasons, including boundaries to information flows, state licensing of CPAs, and CPA firm organizational structure. Therefore, we define proximity as the state in which the auditor's office is located, but we consider alternative proximity definitions in the "Additional Analyses and Robustness Tests" section. We choose the auditor's state, as opposed to the client's state, because our predictions are based on information salient to the auditor, which is more likely related to opinions in the auditor's state than the client's state.

To compute proximity-based reporting rates, we group firms by auditor-state and divide the number of firms receiving a first-time GC opinion in a given fiscal year by the number of distressed observations in the same period. We exclude repeat GC opinions from our sample and from the base rate because prior research argues that repeat GC opinions contain little information content and are not as difficult a decision for an auditor (Hopwood et al. 1994; Blay et al. 2011). If a state has no valid observations in year *t,* then it is not included in our analyses since the GC rate denominator (and numerator) is 0. Furthermore, since we require the prior-year state GC rate and quartile ranking, states must have two consecutive years of observations to be included in our analyses.[10] We label this lagged state-level rate of first-time GC opinions as *STATEGC* and use this measure in our multivariate tests.[11]

We also determine whether each GC opinion (lack of GC modification) constituted a Type I (Type II) error. Type I errors are defined as those firms receiving a GC opinion in year t ($GC = 1$) and not declaring bankruptcy in the 12 months following the audit opinion date. We define Type II errors as those firms receiving a clean opinion in year t ($GC = 0$) but going bankrupt in the 12 months following the opinion (Geiger et al. 2005; Geiger and Rama 2006). To be included in our Type I error analysis, the observation must receive a GC modification in year *t,* and to be included in our Type II error analysis, the firm must go bankrupt in year $t+1$.

To test H2a and H2b, we sort our sample into quantiles based on *STATEGC* so we can examine how accuracy rates differ across these partitions. Specifically, we sort the sample into observation-based quartiles, and for purposes of robustness testing (e.g., to prevent smaller states from unduly influencing our results) we repeat the procedure using terciles and quintiles. Specifically, we sort the states in ascending order by *STATEGC* in year $t-1$. We then assign firms to the highest GC quantile until the percentage of observations in the quantile is greater than or equal to 33 percent, 25 percent, or 20 percent of the total year's observations for terciles, quartiles, and quintiles, respectively. Once that threshold is exceeded, the observations are assigned to quantile two until the 67 percent, 50 percent, or 40 percent observation has been assigned. This procedure is repeated for the remaining quantiles.[12] Using observation-based quantiles alleviates concerns that results could be driven by very small states. To test for the effects of lagged GC rates on reporting accuracy, we match the quantile assignment from year $t-1$ to observations in year t. We use the quartile classification to test GC accuracy rates and to evaluate differences in economic variables between high- and low-quantile states.

GC Prediction Model

In our first analysis, we examine whether the lagged first-time GC rate in the state of a firm's auditor affects the likelihood of that firm receiving a GC modification. Specifically, we extend the DeFond et al. (2002) GC prediction model by adding a

[10] For example, our original data had five observations audited by audit offices in Alaska. There was one observation with a 2006 opinion year, two with 2009, one with 2010, and one with 2011. Given that we require prior-year state-level data, the observations in 2006 and 2009 are excluded from our analyses, while 2010 and 2011 are retained.

[11] Using the current-year quantile or rate would result in a mechanical association between the dependent variable and variable of interest since we use the GC rate to identify high GC states.

[12] To illustrate, consider the following scenario: there are 100 first-time GC observations in a given year divided among eight states. States are sorted in ascending order by GC rate so that State A (H) is the state with the lowest (highest) GC rate. Assume States A through D have 10, 4, 12, and 30 observations, respectively. Under our quartile methodology, states A through C would be assigned to Quartile 1 (since 25 percent of 100 is 25, and $10 + 4 + 12 = 26$). State D would be the lone state assigned Quartile 2 (since 50 percent of 100 is 50, and $26 + 30 = 56$).

lagged prior GC opinion rate (*STATEGC*) to the model. A positive coefficient on this variable indicates support for H1. This probit model is expressed as (subscripts i and t denote firm and year, respectively):

$$P(GC_{i,t} = 1) = \Phi(\beta_0 + \beta_1 STATEGC_{i,t-1} + Controls_{i,t}) \quad (2)$$

where:

$\Phi(\cdot)$ = standard normal cumulative distribution function;
$GC_{i,t} = 1$ if the firm receives a first-time going-concern opinion in year t, and 0 otherwise; and
$STATEGC_{i,t-1}$ = the percentage of firms receiving a GC opinion in the auditor's state, as defined in the prior section.

We estimate Equation (2) using various combinations of control variables, all of which are defined in Appendix B. Our various specifications attempt to balance sample size against properly controlling for GC determinants. We discuss these control variables next.

Control Variables

We begin with basic controls identified by prior research that require only Compustat or Audit Analytics data. Because financial distress is the primary reason for the issuance of a GC opinion, we include Altman's (1968) *ZSCORE* to control for factors that would lead to client failure. We include the log of client assets (*LNASSETS*) because larger firms are more likely to avoid bankruptcy through negotiation with creditors (Reynolds and Francis 2000). We include financial factors such as leverage (*LEV*), change in leverage (*CHLEV*), and the incidence of loss (*LOSS*) because firms with higher leverage and firms with reported negative earnings are more likely to receive a modified opinion (Reynolds and Francis 2000; DeFond et al. 2002). We also include controls related to a client's ability to fund future operations. Ownership of investment securities (*INVEST*), higher operating cash flows (*OCF*), and the issuance of debt or equity in the subsequent year (*FINANCE*) indicate that the client may have the capital to avoid failure (Mutchler et al. 1997; Geiger and Rama 2003). We also control for report lag (*REPLAG*) because audits of financially distressed clients are more time consuming, and auditors tend to delay issuance of reports modified with GC opinions (Chen and Church 1992; Geiger et al. 2005). Finally, we control for the ratio of nonaudit service (NAS) fees to audit fees (*FEERATIO*) because prior research has hypothesized a link between the payment of NAS fees and lower levels of GC reporting (DeFond et al. 2002; Blay and Geiger 2013).

We also include variables capturing firm and auditor attributes that potentially correlate with location. We control for the *DISTANCE* between the auditor and the client to account for the possibility that auditor-client bases in certain states are less geographically concentrated. Prior research argues that larger auditors are more conservative (DeAngelo 1981), therefore we control for the log of total auditor office-level fees (*LNOFEES*), as well as the number of clients in the auditor's office (*COUNT*).

In addition to auditor office characteristics, we also include several state-level characteristics that likely influence GC reporting. Since auditor liability for negligence varies by state and auditors are influenced by the state's level of litigation risk (Gaver, Paterson, and Pacini 2012), we control for each state's common law status to eliminate auditor's negligence to third parties as an alternative explanation for our results. *AUDLIAB* measures the state-specific tort litigation environment to control for potential increases or decreases in location-based auditor conservatism (Pacini, Hillison, and Sinason 2000; Gaver et al. 2012). We control for the natural log of the state's population (*LNPOP*) since more productive, or less distressed, states likely have larger workforces. We also include a series of macroeconomic controls that capture the overall level of distress in the auditor's home state. We control for overall productivity of firms in the state using capital expenditures by manufacturers (*CAPEX*), the gross domestic product (*GDP*), and personal income (*PERSINC*), all measured on a per-capita basis. We also measure state-level financial distress using the unemployment rate in the auditor's state (*URATE*), average employee wages (*WAGES*), and the percentage of households receiving government support (*FOODSTAMPS*).[13]

The previously described variables do not require market-level data, which allows for a larger sample. However, consistent with prior research, we also expand our models to include financial market measures that increase the likelihood of GC opinions. Specifically, we include the log of client age (*LNAGE*) because younger firms are more likely to fail (Dopuch, Holthausen, and Leftwich 1987). We also include return variance (*VOL*) because it is positively related to GC opinions (DeFond et al. 2002). We control for litigation risk using *PROBLIT* (Rogers and Stocken 2005), which measures the firm-

[13] We also considered a summary measure of state economics, the State Coincident Index from the Federal Reserve Bank of Philadelphia, both in addition to and in lieu of our other state-level economic controls. This variable fails to exhibit a significant relation with GC reporting in all specifications and does not alter any reported results.

TABLE 1

Sample Attrition Details

Nonfinancial, nonutility firms in Compustat and Audit Analytics with opinions dated between 2001 and 2011	65,211
Less: missing operating cash flows or earnings	(1,038)
Less: missing auditor-state	(195)
Less: duplicate GVKEY-year combinations	(1,838)
Less: non-U.S. offices	(8,412)
Less: non-distressed observations	(25,686)
Less: repeat GC	(5,180)
Data used to compute prior-year first-time GC rates	22,862
Less: observations from 2001	(3,328)
Less: observations in states without two consecutive years	(30)
Sample used to generate Table 2	19,504
Less: Big N observations	(10,849)
Less: observations with missing data for regression models	(2,089)
Sample used in hypothesis testing[a]	6,566

[a] Control variables requiring CRSP data and inclusion of *VIOL* further reduce this sample, as shown in Table 4.

specific litigation risk and may be correlated with industries clustered by location. We include stock market returns (*RET*) and systematic risk (*BETA*) because GC opinions have been shown to be related to these market measures (DeFond et al. 2002; Blay and Geiger 2013). Prior research has documented a strong link between technical default on debt, which may vary with lending terms clustered by state, and auditor GC reporting (Chen and Church 1992; Menon and Williams 2010). Therefore, we control for debt covenant violation (*VIOL*) in some specifications.

SAMPLE AND DESCRIPTIVE STATISTICS

Data

To construct our sample, we begin with auditor opinion data filed between 2001 and 2011 from the Audit Analytics database. We use Compustat for operating cash flows (data item OANCF) and earnings (data item IB), which we use to identify financial distress. We remove financial and utilities firms, leaving us with a sample of 65,211 observations. Table 1 details attrition from this sample, which we discuss next.

We first remove 1,038 observations with missing values for earnings or operating cash flows. We then delete 195 observations with missing values for auditor-state. We drop 1,838 duplicate GVKEY-year combinations, retaining the observation with the largest value for audit fees. We drop an additional 8,412 observations audited by non-U.S. offices. As in prior research examining going-concern decisions, we restrict our sample to those observations identified as distressed; a firm is considered distressed if either operating cash flows or income before extraordinary items is negative in year *t* (DeFond et al. 2002). Removing non-distressed firms reduces our sample by 25,686 observations. Furthermore, since we are interested in the effect of geography on first-time going-concern decisions, we remove 5,180 repeat going-concern firms from our sample used in our primary analyses.[14] These basic screens leave us with a sample of 22,862 observations, which we use to compute our first-time GC rate by state (*STATEGC*).[15] After computing these rates, we delete 3,328 observations from 2001 and 30 observations with missing values for *STATEGC*, leaving us with a sample of 19,504 observations with opinions filed between 2002 and 2011, which comprises the overall sample of distressed firms presented in Table 2.[16]

For hypothesis testing, we lose an additional 10,849 observations audited by the Big 4, and an additional 2,089 observations after imposing the data requirements necessary to estimate Equation (2). These final deletions result in a sample of 6,566 observations.

[14] Thus, if a firm receives a clean opinion in year *t* and a going-concern modification in years *t*+1 and *t*+2, then the firm remains in the sample in year *t* and *t*+1 but is removed in *t*+2.

[15] We calculate *STATEGC* using the full sample of distressed public firms because even though we analyze non-Big 4 auditors, all public firms have prior-year publicly available data available to auditors.

[16] These missing values relate to states that do not have two consecutive years of distressed observations.

TABLE 2

Going-Concern Rates and Related Metrics by State

Panel A: GC Related Statistics by State

State	n	FT GC	Overall GC	BR	Type I	Type II	Number BRs
WY	3	33.33%	16.67%	33.33%	0.00%	0.00%	1
HI	22	18.18%	35.14%	0.00%	100.00%	†	0
UT	380	17.89%	62.77%	1.84%	92.65%	28.57%	9
SC	54	16.67%	29.87%	5.56%	66.67%	0.00%	4
NV	158	15.19%	56.61%	1.27%	95.83%	50.00%	2
NM	7	14.29%	29.41%	0.00%	100.00%	†	0
FL	949	14.23%	44.31%	2.21%	89.63%	33.33%	25
MO	268	11.94%	29.69%	2.61%	87.50%	42.86%	8
NJ	895	11.84%	37.10%	1.23%	94.34%	45.45%	13
CO	803	11.33%	35.34%	1.49%	95.60%	66.67%	14
NY	2,135	11.24%	31.80%	1.50%	91.25%	34.38%	38
AR	27	11.11%	41.86%	7.41%	66.67%	50.00%	2
DC	9	11.11%	38.10%	11.11%	0.00%	0.00%	2
KY	45	11.11%	18.87%	2.22%	80.00%	0.00%	1
MI	276	10.87%	23.55%	2.90%	90.00%	62.50%	9
AZ	230	10.43%	35.54%	1.30%	95.83%	66.67%	3
TX	1,695	10.27%	30.30%	2.30%	86.21%	38.46%	45
VA	471	9.98%	19.77%	2.55%	87.23%	50.00%	14
NC	305	9.51%	19.18%	3.61%	82.76%	54.55%	13
WA	492	9.15%	34.19%	0.81%	97.78%	75.00%	5
CA	4,509	8.12%	22.80%	1.20%	93.17%	53.70%	63
LA	76	7.89%	16.00%	3.95%	66.67%	33.33%	4
MD	229	7.86%	19.31%	0.44%	94.44%	0.00%	1
PA	732	7.65%	19.10%	2.60%	87.50%	63.16%	22
OH	479	7.52%	14.70%	2.30%	83.33%	45.45%	13
CT	304	7.24%	16.87%	2.63%	81.82%	50.00%	10
MA	1,299	7.24%	17.19%	1.62%	87.23%	42.86%	25
IL	639	7.20%	17.16%	2.82%	84.78%	61.11%	21
OK	126	7.14%	28.57%	1.59%	100.00%	100.00%	2
ID	15	6.67%	17.24%	0.00%	100.00%	†	0
OR	180	6.67%	16.67%	2.22%	83.33%	50.00%	5
GA	454	6.17%	14.09%	2.64%	67.86%	25.00%	14
MN	603	6.14%	15.87%	1.49%	91.89%	66.67%	11
TN	135	5.93%	17.51%	2.22%	87.50%	66.67%	4
WI	155	5.81%	11.35%	1.29%	88.89%	50.00%	2
IN	156	5.77%	10.00%	2.56%	77.78%	50.00%	4
RI	35	5.71%	28.30%	2.86%	50.00%	0.00%	1
AL	49	4.08%	10.77%	0.00%	100.00%	†	0
NE	34	2.94%	9.09%	0.00%	100.00%	†	0
IA	48	2.08%	10.17%	2.08%	100.00%	100.00%	1
AK	2	0.00%	0.00%	0.00%	†	†	0
KS	3	0.00%	0.00%	0.00%	†	†	0
ME	3	0.00%	0.00%	0.00%	†	†	0
MS	2	0.00%	28.57%	0.00%	†	†	0
MT	6	0.00%	0.00%	0.00%	†	†	0
NH	3	0.00%	16.67%	0.00%	†	†	0
SD	1	0.00%	42.86%	0.00%	†	†	0
VT	3	0.00%	0.00%	0.00%	†	†	0
Total	19,504	9.39%	27.73%	1.79%	89.90%	47.14%	410

(continued on next page)

TABLE 2 (continued)

Panel B: Sample Industry Distribution by State

	1	2	3	4	5	6	7	9	10	12	Total
AK	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	2 (0%)	0 (NA)	0 (NA)	0 (NA)	2 (0%)
AL	4 (0%)	1 (0%)	5 (0%)	0 (NA)	0 (NA)	4 (0%)	0 (NA)	5 (0%)	17 (6%)	13 (8%)	49 (4%)
AR	11 (0%)	3 (0%)	1 (0%)	0 (NA)	0 (NA)	2 (50%)	0 (NA)	0 (NA)	2 (0%)	8 (25%)	27 (11%)
AZ	1 (0%)	7 (14%)	26 (8%)	11 (0%)	4 (50%)	72 (10%)	0 (NA)	21 (0%)	28 (7%)	60 (17%)	230 (10%)
CA	147 (4%)	98 (7%)	228 (11%)	47 (17%)	65 (22%)	1,891 (7%)	123 (7%)	249 (7%)	1,206 (9%)	455 (11%)	4,509 (8%)
CO	40 (10%)	12 (0%)	48 (10%)	136 (10%)	29 (10%)	167 (11%)	64 (9%)	44 (16%)	109 (12%)	154 (14%)	803 (11%)
CT	17 (6%)	16 (6%)	33 (3%)	4 (25%)	24 (21%)	77 (5%)	4 (0%)	26 (8%)	58 (5%)	45 (9%)	304 (7%)
DC	2 (0%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	3 (33%)	0 (NA)	0 (NA)	3 (0%)	9 (11%)
FL	55 (7%)	31 (13%)	61 (8%)	4 (25%)	26 (15%)	201 (16%)	45 (13%)	125 (15%)	140 (19%)	261 (13%)	949 (14%)
GA	24 (17%)	3 (0%)	48 (4%)	3 (33%)	4 (0%)	157 (4%)	46 (9%)	29 (3%)	59 (5%)	81 (9%)	454 (6%)
HI	3 (0%)	0 (NA)	0 (NA)	2 (0%)	0 (NA)	5 (20%)	0 (NA)	0 (NA)	4 (25%)	8 (25%)	22 (18%)
IA	6 (0%)	0 (NA)	5 (0%)	2 (0%)	0 (NA)	1 (0%)	4 (0%)	2 (0%)	19 (5%)	9 (0%)	48 (2%)
ID	0 (NA)	1 (0%)	0 (NA)	0 (NA)	0 (NA)	1 (100%)	0 (NA)	4 (0%)	3 (0%)	6 (0%)	15 (7%)
IL	39 (15%)	22 (5%)	116 (5%)	12 (33%)	20 (0%)	117 (2%)	20 (10%)	60 (5%)	100 (14%)	133 (6%)	639 (7%)
IN	2 (0%)	16 (6%)	45 (11%)	1 (0%)	2 (0%)	29 (3%)	8 (0%)	15 (0%)	9 (0%)	29 (7%)	156 (6%)
KS	1 (0%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	3 (0%)
KY	2 (50%)	6 (0%)	8 (13%)	6 (17%)	0 (NA)	2 (50%)	0 (NA)	6 (0%)	2 (0%)	13 (8%)	45 (11%)
LA	11 (0%)	0 (NA)	9 (33%)	29 (7%)	0 (NA)	0 (NA)	0 (NA)	5 (20%)	0 (NA)	22 (0%)	76 (8%)
MA	22 (5%)	12 (8%)	115 (6%)	0 (NA)	14 (7%)	445 (6%)	29 (7%)	47 (6%)	523 (9%)	92 (8%)	1,299 (7%)
MD	23 (13%)	0 (NA)	6 (17%)	0 (NA)	1 (0%)	56 (0%)	17 (0%)	1 (0%)	79 (10%)	46 (13%)	229 (8%)
ME	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	2 (0%)	0 (NA)	3 (0%)
MI	0 (NA)	63 (11%)	60 (20%)	2 (0%)	8 (13%)	49 (6%)	4 (25%)	15 (13%)	30 (7%)	45 (4%)	276 (11%)
MN	16 (0%)	18 (11%)	65 (8%)	2 (50%)	3 (0%)	183 (7%)	26 (0%)	88 (5%)	138 (7%)	64 (5%)	603 (6%)
MO	13 (8%)	22 (18%)	49 (10%)	9 (11%)	19 (11%)	44 (9%)	14 (7%)	27 (4%)	26 (19%)	45 (18%)	268 (12%)
MS	1 (0%)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	2 (0%)
MT	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	0 (NA)	5 (0%)	6 (0%)
NC	41 (12%)	22 (0%)	44 (7%)	0 (NA)	5 (20%)	43 (14%)	16 (6%)	32 (6%)	75 (11%)	27 (11%)	305 (10%)
NE	0 (NA)	0 (NA)	6 (0%)	0 (NA)	5 (0%)	11 (0%)	3 (0%)	7 (14%)	0 (NA)	2 (0%)	34 (3%)
NH	0 (NA)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	2 (0%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	3 (0%)
NJ	16 (19%)	16 (25%)	63 (6%)	4 (25%)	42 (14%)	195 (11%)	70 (11%)	74 (11%)	258 (12%)	157 (13%)	895 (12%)
NM	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	4 (0%)	0 (NA)	0 (NA)	3 (33%)	0 (NA)	7 (14%)
NV	11 (27%)	10 (0%)	2 (50%)	3 (67%)	5 (0%)	11 (9%)	7 (14%)	12 (25%)	12 (25%)	85 (12%)	158 (15%)
NY	119 (9%)	37 (14%)	160 (12%)	27 (26%)	66 (9%)	559 (10%)	172 (9%)	294 (6%)	332 (15%)	369 (14%)	2,135 (11%)
OH	28 (7%)	28 (18%)	146 (8%)	21 (10%)	34 (0%)	44 (7%)	21 (10%)	57 (5%)	34 (3%)	66 (11%)	479 (8%)
OK	6 (0%)	0 (NA)	6 (17%)	39 (0%)	7 (14%)	13 (0%)	10 (20%)	7 (14%)	6 (33%)	32 (6%)	126 (7%)
OR	6 (0%)	6 (17%)	26 (4%)	0 (NA)	5 (20%)	85 (4%)	7 (14%)	13 (8%)	13 (8%)	19 (16%)	180 (7%)
PA	18 (17%)	2 (0%)	99 (13%)	9 (0%)	14 (14%)	207 (6%)	27 (0%)	66 (3%)	189 (8%)	101 (8%)	732 (8%)
RI	0 (NA)	0 (NA)	9 (11%)	0 (NA)	0 (NA)	15 (7%)	0 (NA)	0 (NA)	4 (0%)	7 (0%)	35 (6%)
SC	14 (14%)	1 (0%)	9 (11%)	0 (NA)	3 (33%)	9 (22%)	1 (0%)	9 (11%)	5 (20%)	3 (33%)	54 (17%)
SD	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)
TN	10 (10%)	4 (25%)	23 (4%)	7 (14%)	1 (0%)	10 (0%)	0 (NA)	19 (0%)	29 (0%)	32 (13%)	135 (6%)
TX	50 (4%)	7 (0%)	135 (7%)	435 (8%)	66 (12%)	295 (9%)	62 (26%)	198 (11%)	147 (15%)	300 (11%)	1,695 (10%)
UT	14 (21%)	4 (50%)	28 (25%)	38 (26%)	16 (13%)	87 (20%)	15 (13%)	35 (9%)	71 (7%)	72 (24%)	380 (18%)
VA	18 (6%)	4 (25%)	25 (16%)	11 (0%)	1 (0%)	135 (7%)	73 (12%)	29 (10%)	94 (10%)	81 (14%)	471 (10%)
VT	0 (NA)	0 (NA)	1 (0%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	2 (0%)	0 (NA)	3 (0%)
WA	20 (10%)	5 (20%)	17 (12%)	5 (0%)	15 (7%)	161 (7%)	32 (3%)	30 (10%)	134 (13%)	73 (8%)	492 (9%)
WI	5 (20%)	12 (0%)	55 (7%)	0 (NA)	0 (NA)	30 (7%)	1 (0%)	2 (0%)	30 (3%)	20 (5%)	155 (6%)
WY	0 (NA)	0 (NA)	0 (NA)	2 (50%)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	1 (0%)	3 (33%)
Total	816 (9%)	489 (10%)	1,783 (9%)	871 (11%)	506 (12%)	5,423 (8%)	926 (10%)	1,654 (8%)	3,992 (10%)	3,044 (11%)	19,504 (9%)

(continued on next page)

TABLE 2 (continued)

Panel C: *STATEGC* Distributional Statistics by State

State	State-Years	Mean	Std. Dev.	Min.	Max.	Times in *STATEGC* Quartile			
						1 (Low)	2	3	4 (High)
AK	2	0.00%	0.00%	0.00%	0.00%	2	0	0	0
AL	10	4.45%	7.61%	0.00%	20.00%	9	0	0	1
AR	10	15.83%	27.34%	0.00%	75.00%	7	0	0	3
AZ	10	10.74%	8.50%	0.00%	26.47%	3	0	2	5
CA	10	9.21%	3.93%	4.70%	18.49%	0	5	5	0
CO	10	12.48%	7.27%	2.90%	27.78%	1	1	2	6
CT	10	8.76%	6.22%	3.23%	20.83%	5	2	1	2
DC	3	23.61%	20.55%	0.00%	37.50%	1	0	0	2
FL	10	15.46%	9.35%	5.31%	34.34%	0	0	3	7
GA	10	6.75%	3.36%	0.00%	11.90%	8	1	1	0
HI	8	27.92%	35.81%	0.00%	100.00%	4	0	0	4
IA	10	4.76%	11.00%	0.00%	33.33%	8	0	0	2
ID	6	7.50%	11.73%	0.00%	25.00%	4	0	1	1
IL	10	8.11%	5.31%	2.94%	18.75%	5	0	4	1
IN	10	6.24%	2.57%	0.00%	9.52%	7	1	2	0
KS	3	0.00%	0.00%	0.00%	0.00%	3	0	0	0
KY	10	11.25%	12.43%	0.00%	25.00%	5	0	2	3
LA	10	6.79%	10.37%	0.00%	27.27%	8	0	0	2
MA	10	7.88%	2.99%	4.23%	13.51%	5	3	1	1
MD	10	9.85%	6.34%	0.00%	20.69%	4	0	3	3
ME	3	0.00%	0.00%	0.00%	0.00%	3	0	0	0
MI	10	11.79%	7.23%	3.45%	25.00%	3	0	3	4
MN	10	6.97%	4.84%	1.82%	15.69%	8	0	1	1
MO	10	12.95%	5.57%	4.00%	20.69%	3	0	1	6
MS	1	0.00%	†	0.00%	0.00%	1	0	0	0
MT	5	0.00%	0.00%	0.00%	0.00%	5	0	0	0
NC	10	9.15%	4.01%	3.23%	15.00%	5	1	2	2
NE	10	2.22%	7.03%	0.00%	22.22%	9	0	1	0
NH	3	0.00%	0.00%	0.00%	0.00%	3	0	0	0
NJ	10	13.67%	4.71%	10.10%	24.63%	0	1	3	6
NM	2	8.33%	11.79%	0.00%	16.67%	2	0	0	0
NV	10	17.07%	15.15%	0.00%	46.88%	3	0	0	7
NY	10	12.56%	5.53%	5.33%	24.87%	0	2	3	5
OH	10	8.67%	4.04%	4.76%	19.48%	5	2	2	1
OK	10	8.13%	8.03%	0.00%	20.00%	5	2	2	1
OR	10	8.25%	11.51%	0.00%	33.33%	6	0	3	1
PA	10	8.20%	4.93%	0.00%	16.67%	5	3	1	1
RI	10	11.44%	19.90%	0.00%	50.00%	7	0	0	3
SC	9	24.92%	29.65%	0.00%	100.00%	3	0	1	5
SD	1	0.00%	†	0.00%	0.00%	1	0	0	0
TN	10	8.18%	10.14%	0.00%	26.92%	6	0	2	2
TX	10	12.10%	6.80%	5.21%	27.76%	0	2	4	4
UT	10	22.49%	16.89%	5.13%	63.64%	0	1	1	8
VA	10	11.45%	5.86%	3.64%	20.21%	3	1	3	3
VT	3	0.00%	0.00%	0.00%	0.00%	3	0	0	0
WA	10	10.40%	7.78%	2.13%	28.57%	4	0	2	4
WI	10	8.10%	7.64%	0.00%	25.00%	5	1	3	1
WY	1	0.00%	†	0.00%	0.00%	1	0	0	0

(continued on next page)

TABLE 2 (continued)

† Missing values denote observations where the denominator of the rate variable equals 0.
Panel A presents state frequency rates of first-time going-concerns, overall going-concerns including repeat modifications, bankruptcy, Type I errors, and Type II errors for 47 states and Washington, DC. Rates are computed using 22,862 distressed firm-year observations with audit opinions filed between 2001 and 2011. Distressed firms are defined as those reporting either negative net income or negative operating cash flows. The three missing states, ND, DE, and WV, have no valid distressed-firm observations in the sample period.
Panel B presents the number of observations (GC percentage) by state and industry, defined using the Fama-French 12 industry classification. These classifications are as follows: 1 = Consumer Nondurables; 2 = Consumer Durables; 3 = Manufacturing; 4 = Oil and Gas; 5 = Chemicals; 6 = Business Equipment; 7 = Telephone, 9 = Wholesale and Retail; 10 = Healthcare and Medical Equipment; and 12 = Other. Note that the sample excludes Utilities (Industry 8) and Financial Firms (Industry 11).
Panel C presents the number of years each state appears in our sample, as well as the mean, standard deviation, minimum, and maximum of *STATEGC* for each state. The final four columns report the number of years the state appears in each of the *STATEGC* quartiles, where 1 (4) corresponds to the lowest (highest) rate of GC reporting.

Financial statement information is obtained from Compustat, and returns information is obtained from CRSP. We obtain disclosure of a technical default due to debt covenant violation (*VIOL*) from the website of Professor Amir Sufi.[17] Bankruptcy data are obtained from BankruptcyData.com. We designate bankrupt firms (*BR* = 1) as those that go bankrupt within 12 months of the audit opinion date. We obtain our state-level variables from a variety of sources. In every non-census year, the U.S. Census Bureau conducts the American Community Survey (ACS), which collects a variety of economic information.[18] Using these ACS responses, made available in machine-readable form by the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2010), we construct measures of unemployment (*URATE*), average wages (*WAGES*) for employed workers, economic hardship (*FOODSTAMPS*), and total population (*LNPOP*). We also control for overall productivity, on a per-capita basis, using GDP (*GDP*), personal income (*PERSINC*), and capital expenditures (*CAPEX*). We obtain GDP and personal income information from the Bureau of Economic Analysis and capital expenditures from the Census Bureau.[19] We obtain state-level auditor liability data (*AUDLIAB*) from Gaver et al. (2012).

State First-Time GC Percentages

Table 2 presents statistics related to GC reporting and related measures by state. Table 2, Panel A displays all 19,504 financially distressed observations. This larger number of observations exceeds the 6,566 used in our tests because it includes Big N observations and observations with insufficient data for the going-concern prediction models. Three states with no financially distressed observations during our analysis period are excluded from the table.[20] Table 2, Panel A highlights the variability in overall and first-time GC rates for the overall sample period. For the overall sample, 9.39 percent of all distressed observations received a first-time GC opinion in the observation year. Among larger states, the rate ranged from Florida (14.23 percent) down to Georgia and Minnesota, each below 7 percent. California was near the median at 8.12 percent. To obtain a clearer picture of our quantile distributions over time, Figure 1 graphically presents states by frequency of appearance in the annually created top quartile. An examination of Figure 1 shows no strong regional or size clustering. For example, Florida, Texas, and NY appear in the highest quartile four or more times each, yet California never appears in the top quartile.[21] Further, with the exception of Michigan, areas often thought of as economically depressed, such as the Midwest (see, e.g., High 2003), do not appear in the top quartile a significant portion of the time. An analysis of Panel A of Table 2 also shows that many of these economically depressed states fall in the bottom half of the distribution of overall first-time GC percentage. There are no clear economic or geographic similarities among the states most commonly or least commonly in the top or bottom quartile.

Table 2, Panel B tabulates the 19,504 distressed firms by Fama-French 12 industry classification, and by GC status. There are no clear clusters of observations within specific states, either by industry or by GC status. This suggests that *STATEGC* is

[17] Available at: http://www.faculty.chicagobooth.edu/amir.sufi/data.html
[18] In census years this information is collected through the diennial census, and these data are harmonized with ACS data by the IPUMS.
[19] See http://www.bea.gov for the Bureau of Economic Analysis and http://www.census.gov for the Census Bureau. Capital Expenditures data are collected through the Annual Survey of Manufacturers and the Economic Census, depending on the year.
[20] The overall GC percent includes observations receiving repeat GC opinions. These observations are excluded from all other calculations in the study.
[21] Neither large nor small states are driving our results. By design, we prevent small states from driving our results by calculating frequencies on a number of observations basis instead of using each state as an observation. Similarly, excluding California or New York, for example, does not materially change our results. Note that California did not enter the top or bottom quartile in any of our analyses.

FIGURE 1
Map of First-Time GC Quartiles from 2001–2011

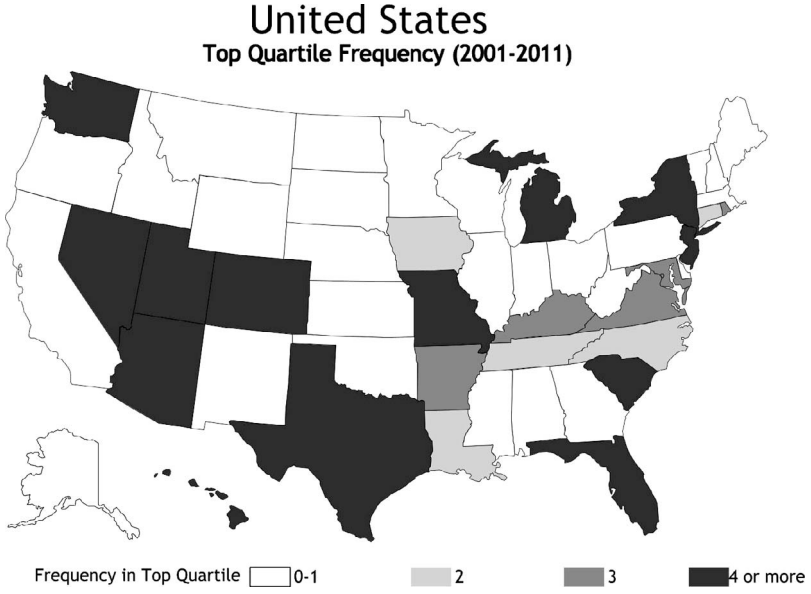

Figure 1 illustrates quartiles of first-time GC percentages by state from 2001 to 2011. Quartiles are recalculated each year. This table charts the number of times a state was in the top quartile during the ten-year period. States with no usable observations (ND, DE, and WV) are coded as Q1.

not merely capturing characteristics of a limited number of industries in select states. Nonetheless, we control for industry fixed effects in all multivariate models.

Panel C of Table 2 presents distributional characteristics of *STATEGC* for each state. We include the number of years the state is present in the sample ("State-Years"), and the mean, standard deviation, minimum, and maximum value of *STATEGC* for each state. We also report the number of times the state appears in each *STATEGC* quartile, which is used in our tests of H2a and H2b. We observe significant variation in both small and large states. For instance, *STATEGC* for Michigan, a state with roughly 300 observations in our Table 2 sample, varies between 3.45 and 25 percent. This variation is very similar to that of New York (minimum and maximum of 5.33 and 24.87 percent, respectively). The quartile distribution of *STATEGC* reveals a similar pattern. Only six states appear in the top quartile of *STATEGC* more than half the time (CO, FL, MO, NJ, NV, and UT) and only 14 states fail to appear in the top quartile at least once.

To examine whether autocorrelation in economics appears to drive autocorrelation in GC rates, we examine correlations between several state-level macroeconomic variables and *STATEGC*. In untabulated analysis, we find that only *PERSINC* and *CAPEX* exhibit significant Pearson correlations with *STATEGC*. We also examine the mean level of each of the six macroeconomic factors used in our study by *STATEGC* quartile. In untabulated analysis, we observe significantly lower values of *CAPEX* in the top *STATEGC* quartile, consistent with those states experiencing less economic growth. We also observe slightly higher values for *URATE* in high GC states, again consistent with higher-quartile states being more economically distressed. Conversely, *WAGES* is higher in the top quartile of *STATEGC*. Similarly, *GDP* and *PERSINC* are also higher in the top quartile, although the differences are, at best, marginally significant. In sum, there does not appear to be strong evidence that geographic characteristics correlate strongly with *STATEGC*. We control for all of these variables in our regressions.

Descriptive Statistics

Table 3 presents descriptive statistics for our final sample of 6,566 financially distressed firm-years audited by non-Big 4 auditors. Panel A presents full sample means, as well as means for GC firms and non-GC firms, and overall means for firms from the bottom and top quartiles. Reported t-tests show that GC firms are more distressed (*ZSCORE, LOSS, OCF;* $p < 0.01$), smaller (*LNASSETS;* $p < 0.01$), younger (*LNAGE;* $p < 0.01$), and generally conform to prior research. Comparing observations from the highest quartile observations to lowest quartile observations, states in the highest quartile have greater leverage (*LEV;* $p < 0.01$), distress (*ZSCORE;* $p < 0.01$), lower cash flows (*OCF;* $p < 0.01$), and longer reporting lags (*REPLAG;* $p < 0.01$). However, there is not a strong overall indication of greater financial distress as *LOSS, CHLEV,*

TABLE 3

Descriptive Statistics

Panel A: Means of Full Sample, GC/Non-GC, and Top and Bottom State Quartiles

	Full Sample		GC = 1		GC = 0		Test of	Bottom Quartile		Top Quartile		Test of
Variable	n	Mean	n	Mean	n	Mean	Differences	n	Mean	n	Mean	Differences
GC	6,566	0.122	803	1	5,763	0	NA	1,129	0.097	2,202	0.139	NA
STATEGC	6,566	0.104	803	0.116	5,763	0.103	5.867***	1,129	0.049	2,202	0	49.67***
ZSCORE	6,566	0.448	803	0.827	5,763	0.395	29.261***	1,129	0.412	2,202	0.472	3.96***
LNASSETS	6,566	3.011	803	1.94	5,763	3.16	18.836***	1,129	3.207	2,202	2.783	6.52***
LEV	6,566	0.667	803	1.226	5,763	0.589	21.010***	1,129	0.597	2,202	0.705	3.50***
CHLEV	6,566	0.027	803	0.317	5,763	−0.013	16.877***	1,129	0.034	2,202	0.019	0.74
LOSS	6,566	0.886	803	0.96	5,763	0.876	7.088***	1,129	0.888	2,202	0.877	0.97
INVEST	6,566	0.33	803	0.253	5,763	0.34	6.069***	1,129	0.297	2,202	0.321	1.79*
FINANCE	6,566	0.657	803	0.537	5,763	0.674	7.687***	1,129	0.667	2,202	0.646	1.22
OCF	6,566	−0.242	803	−0.678	5,763	−0.181	24.791***	1,129	−0.196	2,202	−0.263	3.28***
REPLAG	6,566	82.721	803	100.501	5,763	80.243	12.944***	1,129	78.625	2,202	85.63	4.47***
FEERATIO	6,566	0.155	803	0.141	5,763	0.157	2.658***	1,129	0.165	2,202	0.151	2.36**
DISTANCE	6,566	3.875	803	4.441	5,763	3.797	7.687***	1,129	3.55	2,202	4.091	6.57***
COUNT	6,566	8.7	803	8.128	5,763	8.78	2.429**	1,129	7.243	2,202	9.252	7.42***
LNOFEES	6,566	13.968	803	13.524	5,763	14.03	8.502***	1,129	13.821	2,202	13.829	0.15
AUDLIAB	6,566	0.388	803	0.39	5,763	0.367	1.256	1,129	0.572	2,202	0.445	7.02***
LNPOP	6,566	16.371	803	16.383	5,763	16.369	0.459	1,129	15.657	2,202	16.165	21.78***
WAGES	6,566	46.623	803	46.145	5,763	46.689	1.994**	1,129	43.261	2,202	47.104	12.69***
FOODSTAMPS	6,566	0.069	803	0.067	5,763	0.069	1.634	1,129	0.072	2,202	0.072	0.44
CAPEX	6,566	0.385	803	0.365	5,763	0.388	3.891***	1,129	0.465	2,202	0.32	25.93***
PERSINC	6,566	40.489	803	39.923	5,763	40.568	2.898***	1,129	39.202	2,202	41.339	8.41***
GDP	6,566	45.009	803	44.736	5,763	45.047	1.502	1,129	43.046	2,202	45.233	9.16***
URATE	6,566	6.476	803	6.409	5,763	6.485	0.905	1,129	6.244	2,202	6.176	0.90
VIOL	4,061	0.155	506	0.178	3,555	0.152	1.527	685	0.19	1,382	0.13	3.58***
LNAGE	3,224	2.254	251	1.909	2,973	2.284	6.414***	629	2.429	942	2.224	4.33***
VOL	3,224	0.052	251	0.069	2,973	0.051	10.802***	629	0.05	942	0.054	2.51**
PROBLIT	3,224	0.107	251	0.104	2,973	0.107	0.202	629	0.076	942	0.108	2.50**
BETA	3,224	0.668	251	0.558	2,973	0.677	2.975***	629	0.617	942	0.616	0.04
RET	3,224	0.023	251	−0.42	2,973	0.061	8.927***	629	−0.015	942	−0.012	0.06

(continued on next page)

FINANCE, BETA, and *RET* are not significantly different. Thus, there do not appear to be clear economic indicators that the highest GC quartile states are composed of firms that appear significantly more likely to receive GC opinions.

Table 3, Panel B contrasts GC and non-GC firms between the top and bottom GC quartiles. There is some indication that GC firms in the top quartile experience a higher incidence of loss (*LOSS*) and pay lower ratios of nonaudit to audit fees (*FEERATIO*) than those in the bottom quartile, and these patterns are not apparent for non-GC firms. Other differences across high and low *STATEGC* quartiles in GC firms also appear in non-GC firms.

RESULTS

GC Prediction Models

Table 4 reports results for H1. Recall that H1 predicts that auditors operating in states with higher rates of GC reporting in the prior year are more likely to issue GC opinions in the current year. Column (1) of Table 4 presents results from estimating Equation (2) using only basic control variables requiring Compustat or Audit Analytics data. Consistent with H1, we find a significantly positive coefficient on *STATEGC* ($p < 0.05$). Most control variables exhibit predicted relations with GC opinions. That is, firms experiencing greater financial distress, evidenced by greater values for *ZSCORE* and *CHLEV* and lower values for *INVEST, FINANCE,* and *OCF* are more likely receive GC opinions. Similar to Blay and Geiger (2013), a higher ratio of NAS

TABLE 3 (continued)

Panel B: Means of GC and Non-GC Observations in Top and Bottom State Quartiles

	GC = 1					GC = 0				
	Bottom Quartile		Top Quartile		Test of	Bottom Quartile		Top Quartile		Test of
Variable	n	Mean	n	Mean	Differences	n	Mean	n	Mean	Differences
GC	110	1	306	1	NA	1,019	0.000	1,896	0.000	NA
STATEGC	110	0.05	306	0.159	14.689***	1,019	0.049	1,896	0.145	47.908***
ZSCORE	110	0.827	306	0.81	0.484	1,019	0.368	1,896	0.418	3.234***
LNASSETS	110	1.887	306	1.809	0.333	1,019	3.349	1,896	2.940	6.295***
LEV	110	1.108	306	1.236	0.836	1,019	0.541	1,896	0.620	2.824***
CHLEV	110	0.283	306	0.286	0.035	1,019	0.007	1,896	−0.024	1.658*
LOSS	110	0.991	306	0.935	2.321**	1,019	0.877	1,896	0.868	0.746
INVEST	110	0.232	306	0.271	0.899	1,019	0.304	1,896	0.330	1.780*
FINANCE	110	0.564	306	0.503	1.086	1,019	0.678	1,896	0.669	0.512
OCF	110	−0.738	306	−0.652	0.802	1,019	−0.138	1,896	−0.200	3.700***
REPLAG	110	99.291	306	102.069	0.440	1,019	76.395	1,896	82.977	4.255***
FEERATIO	110	0.163	306	0.123	2.256**	1,019	0.166	1,896	0.156	1.529
DISTANCE	110	4.114	306	4.658	2.048**	1,019	3.489	1,896	3.999	5.921***
COUNT	110	5.764	306	8.967	3.867***	1,019	7.402	1,896	9.297	6.611***
LNOFEES	110	13.226	306	13.488	1.448	1,019	13.885	1,896	13.885	0.002
AUDLIAB	110	0.555	306	0.441	2.048**	1,019	0.574	1,896	0.445	6.689***
LNPOP	110	15.711	306	16.135	5.555***	1,019	15.652	1,896	16.169	21.197***
WAGES	110	43.505	306	46.162	2.639***	1,019	43.234	1,896	47.256	12.695***
FOODSTAMPS	110	0.074	306	0.07	1.112	1,019	0.072	1,896	0.073	0.909
CAPEX	110	0.431	306	0.304	8.576***	1,019	0.468	1,896	0.322	24.241***
PERSINC	110	39.233	306	40.448	1.456	1,019	39.199	1,896	41.483	8.577***
GDP	110	43.112	306	44.428	1.866*	1,019	43.039	1,896	45.363	9.145***
URATE	110	6.278	306	6.316	0.173	1,019	6.240	1,896	6.153	1.076
VIOL	68	0.25	191	0.178	1.281	617	0.183	1,191	0.123	3.495***
LNAGE	28	2.2	98	1.765	2.032**	601	2.439	844	2.278	3.364***
VOL	28	0.069	98	0.066	0.423	601	0.050	844	0.052	2.107**
PROBLIT	28	0.102	98	0.083	0.353	601	0.075	844	0.111	2.706***
BETA	28	0.458	98	0.459	0.007	601	0.625	844	0.635	0.309
RET	28	−0.535	98	−0.398	1.623	601	0.010	844	0.033	0.556

***, **, * Denotes a significant difference in means at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ level, respectively.

This table contains variable means and tests of differences for non-Big 4 firm-year observations used in the GC prediction models. Panel A reports statistics for the full sample, GC versus non-GC, and top versus bottom state GC rate quartiles. Panel B reports statistics for GC and non-GC observations within the top and bottom quartile. Reported tests of differences are based on t-tests of the difference between means of GC and non-GC observations, and observations in the top and bottom quartile of state GC rate distributions.

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fees to audit fees (*FEERATIO*) is negatively related to the issuance of a GC opinion.[22] Smaller firms (*LNASSETS*) and firms located further away from their auditor (*DISTANCE*) also are more likely to receive GC opinions. Surprisingly, greater leverage (*LEV*) lowers the likelihood of GC reporting in this sample.

Column (2) of Table 4 introduces state-level variables to determine whether the effect of social, legal, or economic characteristics of the state largely explain the significance of *STATEGC* in Column (1). Introducing these variables has no significant impact on *STATEGC,* although none of these additional variables exhibit a significant association with GC reporting.[23]

Column (3) introduces the remaining market-based control variables. Note that these variables reduce the sample size considerably (from 6,566 to 3,224), so results are not directly comparable across the columns. However, we again find strong support for H1, as *STATEGC* is significantly positive in this smaller subsample ($p < 0.01$). Further, the magnitude of the

[22] In untabulated analysis, we find similar inferences when replacing *FEERATIO* with the log of audit and nonaudit fees.

[23] Additional analyses (untabulated) provide evidence that religiosity lacks a significant association with GC reporting.

TABLE 3 (continued)

Variable Definitions:
GC = a dummy variable equal to 1 for observations receiving a first-time going-concern opinion in fiscal year *t;*
STATEGC = the mean first-time GC rate for the auditor state in period *t*−1;
ZSCORE = a financial distress measure based on Altman (1968);
LNASSETS = the natural log of total assets;
LEV = the ratio of long-term debt to total assets;
CHLEV = the change in financial leverage from year *t*−1 to *t;*
LOSS = an indicator equal to 1 if the firm reports negative earnings, and 0 otherwise;
INVEST = the sum of short- and long-term investments, including cash and cash equivalents, deflated by total assets;
FINANCE = a dummy variable equal to 1 if the company obtains external financing in year *t*+1;
OCF = operating cash flows in year *t* scaled by total assets;
REPLAG = the number of days between the fiscal year-end and audit opinion issuance;
FEERATIO = the ratio of nonaudit fees to audit fees;
DISTANCE = the natural log of the straight-line distance between auditor city and client zip code;
COUNT = the number of clients audited by an audit office in a given year;
LNOFEES = the natural log of total fees paid by all clients in an auditor's office;
AUDLIAB = a dummy variable equal to 1 for states with high third-party litigation risk (i.e., states with an auditor liability index greater than 4.5 on the 0 to 9 scale defined by Gaver et al. [2012]), and 0 otherwise;
LNPOP = the natural log of the auditor's home state population, estimated using American Community Survey (ACS) responses;
WAGES = the mean wages of the workforce in the auditor's home state, computed using ACS data;
FOODSTAMPS = the percentage of the population in the auditor's home state receiving food subsidies, estimated using ACS responses;
CAPEX = the per-capita capital expenditures for manufacturing firms in the auditor's home state;
PERSINC = the state's per-capita personal income;
GDP = the gross domestic product in the auditor's home state;
URATE = the unemployment rate in the auditor's state;
VIOL = 1 if the firm reports a debt covenant violation during the fiscal year (data obtained from Professor Amir Sufi's personal website: http://www.faculty.chicagobooth.edu/amir.sufi/data.html);
LNAGE = the natural log of firm age;
VOL = standard deviation of residuals from the market model;
PROBLIT = the probability of litigation, as defined by Rogers and Stocken (2005);
BETA = estimated using the market model over the fiscal year; and
RET = the 12-month return over the fiscal year.

coefficient increases by nearly threefold. We find that younger firms (*LNAGE*) operating in more volatile environments (*VOL*) are more likely to receive GC opinions. Further, higher stock returns (*RET*) during the year reduces the likelihood of a GC. Column (4) introduces one additional control variable, *VIOL,* which further reduces the sample due to limited data availability. Nonetheless, we continue to find a strong, positive coefficient on *STATEGC* ($p < 0.05$).

Columns (5) through (7) replicate Columns (2) through (4), but replace the level of state economic factors (i.e., *CAPEX, WAGES, FOODSTAMPS, PERSINC, GDP,* and *URATE*) with the change in that factor over the year (i.e., Δ*CAPEX,* Δ*WAGES,* etc.). Note that our *CAPEX* data begin in 2002, so using Δ*CAPEX* rather than *CAPEX* limits our sample period to 2003 to 2011. As shown, we continue to find significantly positive coefficients on *STATEGC* in all regressions. We observe some evidence that increases in *CAPEX, WAGES,* and *GDP* reduce the likelihood of GC reporting, although these results are not consistent across all columns. Surprisingly, increases in *URATE* correspond to a reduced likelihood of GC reporting in one specification.[24]

To summarize, our results strongly suggest that *STATEGC* significantly contributes to auditors' GC reporting decisions. To provide a sense of the economic significance of this effect, we compute the average marginal effect of *STATEGC* across all columns. We find that a one standard deviation (0.06 percent, untabulated) increase in *STATEGC* corresponds to a 0.7 percent increase in the likelihood of a GC. While this may not seem significant, it represents 5.8 percent of the sample GC reporting rate of 12.2 percent (reported in Table 4). Further, we compare the magnitude of this effect to the magnitude of the average marginal effect of a one standard deviation increase in three well-known determinants of GCs: *LNASSETS, OCF,* and *ZSCORE*. The magnitude of the *STATEGC* marginal effect is 79 (51, 27) percent of the magnitude of the effect of *LNASSETS* (*OCF, ZSCORE*). Thus, compared to other GC determinants, *STATEGC* appears to play an economically

[24] Note that in some specifications, collinearity among state-level variables leads to variance inflation factors exceeding 10. We repeat our analyses with virtually all combinations of state-level factors and find that *STATEGC* relates positively to GC reporting in all specifications. We also perform a basic regression including only *STATEGC,* state economic factors, and year and industry fixed effects and continue to find a significantly positive coefficient on *STATEGC*.

TABLE 4

GC Prediction Models

Variables	Pred. Sign	(1)	Levels of State Economic Factors (2)	(3)	(4)	Δ in State Economic Factors (5)	(6)	(7)
STATEGC	(+)	0.912**	0.838*	2.488***	2.528**	0.764*	2.912***	3.357**
		(1.88)	(1.59)	(2.76)	(2.02)	(1.34)	(2.94)	(2.22)
AUDLIAB	(+)		−0.108	−0.093	0.094	−0.096	−0.091	−0.083
			(−1.45)	(−0.63)	(0.55)	(−1.63)	(−0.85)	(−0.60)
LNPOP	(±)		0.053	0.134*	−0.001	0.068**	0.122**	0.081
			(1.29)	(1.76)	(−0.01)	(2.15)	(2.00)	(0.92)
CAPEX (or Δ)	(−)		−0.197	−0.365	−0.284	−0.591*	−0.627	−0.220
			(−1.02)	(−1.08)	(−0.65)	(−1.60)	(−0.91)	(−0.25)
WAGES (or Δ)	(−)		−0.001	−0.007	0.043	−0.000*	−0.000	−0.000
			(−0.05)	(−0.21)	(1.07)	(−1.29)	(−1.22)	(−0.46)
FOODSTAMPS (or Δ)	(+)		0.616	−2.066	−6.587	−6.292	−6.137	−3.586
			(0.39)	(−0.65)	(−1.47)	(−1.10)	(−0.58)	(−0.25)
PERSINC (or Δ)	(−)		−0.006	0.001	−0.034	0.000	−0.000	0.000
			(−0.41)	(0.05)	(−0.86)	(0.46)	(−0.09)	(0.33)
GDP (or Δ)	(−)		0.001	−0.002	−0.016	−0.000	−0.000*	−0.000
			(0.16)	(−0.08)	(−0.60)	(−0.95)	(−1.42)	(−1.11)
URATE (or Δ)	(+)		−0.012	−0.043	−0.035	−0.131#	−0.097	−0.074
			(−0.45)	(−0.81)	(−0.35)	(−1.98)	(−0.86)	(−0.41)
ZSCORE	(+)	1.227***	1.221***	0.960***	0.921***	1.231***	0.980***	0.956***
		(16.59)	(16.51)	(7.19)	(5.19)	(15.84)	(6.78)	(4.85)
LNASSETS	(−)	−0.039**	−0.040**	−0.082**	−0.142***	−0.040**	−0.090**	−0.160***
		(−1.92)	(−1.97)	(−1.72)	(−2.35)	(−1.91)	(−1.83)	(−2.52)
LEV	(+)	−0.125#	−0.125#	−0.050	−0.026	−0.123#	−0.035	0.008
		(−3.76)	(−3.77)	(−0.39)	(−0.16)	(−3.63)	(−0.28)	(0.06)
CHLEV	(+)	0.230***	0.229***	0.120	0.052	0.216***	0.159	0.100
		(4.44)	(4.44)	(0.65)	(0.24)	(4.14)	(0.93)	(0.50)
LOSS	(+)	0.086	0.093	−0.091	−0.004	0.070	−0.120	−0.050
		(0.84)	(0.91)	(−0.57)	(−0.02)	(0.68)	(−0.74)	(−0.24)
INVEST	(−)	−0.468***	−0.484***	−0.303**	−0.421**	−0.481***	−0.282*	−0.371*
		(−4.47)	(−4.61)	(−1.73)	(−1.66)	(−4.56)	(−1.63)	(−1.47)
FINANCE	(−)	−0.414***	−0.410***	−0.521***	−0.445***	−0.429***	−0.544***	−0.482***
		(−7.94)	(−7.86)	(−5.85)	(−3.70)	(−7.91)	(−5.68)	(−3.73)
OCF	(−)	−0.328***	−0.326***	−0.451***	−0.516***	−0.319***	−0.389***	−0.387**
		(−7.41)	(−7.34)	(−4.48)	(−3.35)	(−6.79)	(−3.63)	(−2.28)
REPLAG	(+)	0.003***	0.003***	0.004***	0.003***	0.003***	0.005***	0.002**
		(6.00)	(5.85)	(4.86)	(2.49)	(5.53)	(4.67)	(1.81)
FEERATIO	(−)	−0.275**	−0.273**	−0.606**	−0.634**	−0.282**	−0.575**	−0.555*
		(−1.77)	(−1.76)	(−2.32)	(−1.94)	(−1.72)	(−1.98)	(−1.50)
DISTANCE	(±)	0.040***	0.039***	0.061***	0.086***	0.041***	0.057***	0.079***
		(3.69)	(3.57)	(3.14)	(3.45)	(3.59)	(2.74)	(2.97)
COUNT	(±)	0.002	0.003	−0.006	−0.010	0.004	−0.003	−0.006
		(0.44)	(0.60)	(−0.61)	(−0.89)	(0.68)	(−0.29)	(−0.53)
LNOFEES	(±)	−0.022	−0.032	0.007	0.009	−0.034	−0.016	−0.018
		(−0.83)	(−1.16)	(0.13)	(0.13)	(−1.17)	(−0.31)	(−0.27)
LNAGE	(−)			−0.112***	−0.149**		−0.127***	−0.172***
				(−2.54)	(−2.23)		(−2.81)	(−2.53)
VOL	(+)			4.185**	4.557**		4.799***	4.966**
				(2.32)	(1.89)		(2.43)	(1.73)
PROBLIT	(+)			0.046	0.138		0.061	0.177
				(0.28)	(0.64)		(0.38)	(0.78)
BETA	(+)			−0.124	−0.019		−0.105	0.008
				(−1.50)	(−0.19)		(−1.21)	(0.07)

(continued on next page)

TABLE 4 (continued)

Variables	Pred. Sign	(1)	Levels of State Economic Factors (2)	(3)	(4)	Δ in State Economic Factors (5)	(6)	(7)
RET	(−)			−0.397***	−0.388***		−0.399***	−0.393***
				(−3.52)	(−2.68)		(−3.46)	(−2.59)
VIOL	(+)				0.238**			0.195*
					(1.83)			(1.32)
Constant	(±)	−5.791***	−6.209***	−8.285***	−4.654**	−6.734***	−8.456***	−5.995***
		(−13.69)	(−7.40)	(−5.17)	(−2.31)	(−9.93)	(−6.81)	(−3.67)
Observations		6,566	6,566	3,224	1,883	6,179	3,027	1,691
Area under ROC Curve		0.849	0.849	0.893	0.892	0.850	0.895	0.896
Pseudo R^2		0.252	0.253	0.325	0.321	0.253	0.329	0.323

***, **, * Denote significance at the $p < 0.01$, 0.05, and 0.10 level, respectively, statistical significance reflects one-tailed tests where predictions are made.

# Denotes a two-tailed significance at the $p < 0.05$ level in the direction opposite of that predicted.

This table reports probit-derived coefficient estimates (z-statistics) from several specifications of Equation (2). z-statistics are derived from standard errors that are heteroscedasticity robust and clustered by firm to correct for serial correlation in residuals.

Variable Definitions:

STATEGC = the mean GC rate for the auditor state in period *t*−1;
AUDLIAB = a dummy variable equal to 1 for states with high third-party litigation risk (i.e., states with an auditor liability index greater than 4.5 on the 0 to 9 scale defined by Gaver et al. [2012]), and 0 otherwise;
LNPOP = the natural log of the auditor's home state population, estimated using American Community Survey (ACS) responses;
WAGES = the mean wages of the workforce in the auditor's home state, computed using ACS data;
FOODSTAMPS = the percentage of the population in the auditor's home state receiving food subsidies, estimated using ACS responses;
CAPEX = the per-capita capital expenditures for manufacturing firms in the auditor's home state;
PERSINC = the state's per-capita personal income;
GDP = the gross domestic product in the auditor's home state;
URATE = the unemployment rate in the auditor's state;
ZSCORE = a financial distress measure based on Altman (1968);
LNASSETS = the natural log of total assets;
LEV = the ratio of long-term debt to total assets;
CHLEV = the change in financial leverage from year *t*−1 to *t;*
LOSS = an indicator equal to 1 if the firm reports negative earnings, and 0 otherwise;
INVEST = the sum of short- and long-term investments, including cash and cash equivalents, deflated by total assets;
FINANCE = a dummy variable equal to 1 if the company obtains external financing in year *t*+1;
OCF = operating cash flows in year *t* scaled by total assets;
REPLAG = the number of days between the fiscal year-end and audit opinion issuance;
FEERATIO = the ratio of nonaudit fees to audit fees;
DISTANCE = the natural log of the straight-line distance between auditor city and client zip code;
COUNT = the number of clients audited by an audit office in a given year;
LNOFEES = the natural log of total fees paid by all clients in an auditor's office;
LNAGE = the natural log of firm age;
VOL = standard deviation of residuals from the market model;
PROBLIT = the probability of litigation, as defined by Rogers and Stocken (2005);
BETA = estimated using the market model over the fiscal year;
RET = the 12-month return over the fiscal year; and
VIOL = 1 if the firm reports a debt covenant violation during the fiscal year (data obtained from Professor Amir Sufi's personal website: http://www.faculty.chicagobooth.edu/amir.sufi/data.html).

relevant role in GC reporting. We next examine whether the effect of *STATEGC* on GC reporting leads to differences in GC reporting accuracy.

Reporting Accuracy

To provide evidence on the effects of increased propensity to issue a GC opinion, we investigate whether auditor accuracy rates are different in higher-propensity states. We examine auditor accuracy in year *t* for states with a high GC percentage (i.e., *STATEGC*) in year *t*−1. Panel A of Table 5 presents the results of our analysis. Note that we report accuracy for both the full sample, which corresponds to the 6,566 observations, as well as the smaller sample of observations with sufficient data for CRSP-based control variables. Overall, Type I errors (between 90.6 and 93.0 percent) and Type II errors (between 43.4 and

TABLE 5
Type I and Type II Rate Comparisons

Panel A: Univariate Tests

	Type I Errors				Type II Errors			
	All Observations		CRSP Observations		All Observations		CRSP Observations	
STATEGC Quartile	n	Mean	n	Mean	n	Mean	n	Mean
1	110	0.909	23	0.783	20	0.500	15	0.667
2	144	0.924	46	0.913	14	0.214	5	0.200
3	243	0.914	67	0.881	37	0.432	18	0.556
4	306	0.954	88	0.955	28	0.500	11	0.636
Total	803	0.930	224	0.906	99	0.434	49	0.571
Hi-Lo		0.045		0.172		0.000		−0.030
t-stat		1.74		2.76		0.000		0.154
p-value		0.08		0.001		1.000		0.88

Panel B: Multivariate Tests

Variables	(1) Δ Type I	(2) Δ Type I	(3) Δ Type I	(4) Δ Type II	(5) Δ Type II	(6) Δ Type II
$\Delta STATEGC_{t-1}$	0.463**	0.427**	0.440**	6.895***	6.533*	7.255***
	(2.28)	(2.10)	(2.17)	(2.98)	(2.10)	(2.89)
$\Delta WAGES_t$		0.000			−0.000	
		(1.27)			(−1.10)	
$\Delta FOODSTAMPS_t$		−0.501			−0.227	
		(−0.20)			(−0.01)	
$\Delta CAPEX_t$		0.178			0.708	
		(1.14)			(1.43)	
$\Delta PERSINC_t$		−0.000***	−0.000		−0.000	−0.000
		(−2.90)	(−1.57)		(−0.31)	(−0.64)
ΔGDP_t		0.000			0.000	
		(1.33)			(1.02)	
$\Delta URATE_t$		−0.016			0.299	
		(−0.46)			(1.03)	
$\Delta LNPOP_t$		−2.375			−0.346	
		(−1.51)			(−0.02)	
Constant	0.082	0.135	0.110	0.689***	0.735*	0.822**
	(1.27)	(1.57)	(1.63)	(2.98)	(1.86)	(2.54)
Year Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131	131	131	31	31	31
Adjusted R^2	0.107	0.162	0.122	0.452	0.536	0.462

***, **, * Denote two-tailed significance at the $p < 0.01$, $p < 0.05$, and $p < 0.10$ levels, respectively.

Panel A presents Type I and Type II error rates for non-Big 4 observations within quartiles defined by prior-year first-time GC rates by state. Specifically, state GC ranks are ranked into quartiles in period $t-1$ based on the number of observations in each state. Error rates are then computed within each quartile. Type I errors are defined as those firms receiving a GC opinion for fiscal year t but not entering into bankruptcy in the year following the opinion date. Type II errors are defined as those firms receiving a clean opinion in fiscal year t but then entering into bankruptcy proceedings within one year following the opinion date. Note that Type I (II) errors are only computed for GC (bankrupt) firms. "All Observations" ("CRSP Observations") refers to the full sample of 6,566 observations (the subsample of 3,224 observations with CRSP data).

Panel B presents multivariate tests of the relation between changes in Type I and Type II error rates and lagged changes in *STATEGC* after controlling for changes in other macroeconomic factors. Δ is the change operator.

(continued on next page)

TABLE 5 (continued)

Variable Definitions:
WAGES = the mean wages of the workforce in the auditor's home state, computed using American Community Survey (ACS) data;
FOODSTAMPS = the percentage of the population in the auditor's home state receiving food subsidies, estimated using ACS responses;
CAPEX = the per-capita capital expenditures for manufacturing firms in the auditor's home state;
PERSINC = the state's per-capita personal income;
GDP = the gross domestic product in the auditor's home state;
URATE = the unemployment rate in the auditor's state; and
LNPOP = the natural log of the auditor's home state population, estimated using ACS responses.

57.1 percent) are similar to rates reported in prior research. However, we find significant differences in accuracy across GC quartiles, thus rejecting H2a. For the full sample, the top quartile Type I error rate of 95.4 percent is significantly greater than the 90.9 percent for the bottom quartile ($p = 0.08$). For the CRSP sample, we observe an even starker difference. The top quartile Type I error rate of 95.5 percent far surpasses the 78.3 percent for the bottom quartile ($p < 0.01$). These results provide evidence that Type I errors increase in states with higher prior rates of GC opinions.

Next, we investigate H2b. As shown in Panel A of Table 5, Type II error rates are neither monotonically changing across quartiles nor significantly different among quartiles. In fact, for the full sample we observe identical Type II error rates in the bottom and top *STATEGC* quartiles. In the observations with sufficient data for CRSP variables we observe fewer Type II errors in the top quartile, but this difference is far from significant ($p = 0.88$).[25] Thus, we fail to reject H2b, although lack of power may hinder this analysis of Type II errors given the small number of observations in each *STATEGC* quartile.

While prior research generally uses univariate tests such as those in Panel A of Table 5 to examine differences in reporting accuracy, this approach fails to control for other possible determinants of Type I and Type II errors. To mitigate concerns associated with correlated, omitted variables, we present a multivariate test of H2a and H2b in Panel B of Table 5.[26] Specifically, we regress the state-level change in accuracy rates from $t-1$ to t on changes in *STATEGC* from $t-2$ to $t-1$. This approach provides two advantages relative to the univariate tests. First, it allows us to examine how lagged changes in our variable of interest correspond to changes in accuracy, which is a more powerful, causal test. Second, it allows us to control for changes in economic conditions, which could potentially impact GC accuracy through changes in perceived litigation risk. This approach limits our tests to states with consecutive years of firms receiving GC opinions, which yields only 131 state-year combinations.

In Column (1), we report results of a univariate regression of the change in a state's Type I error rate on the lagged change in *STATEGC*. As shown, we find a significantly positive coefficient ($p < 0.05$) on Δ*STATEGC,* suggesting that increases in prior-period GC reporting rates precede increases in Type I errors. In Column (2), we introduce concurrent changes in state-level economic variables (i.e., *WAGES, FOODSTAMPS,* etc.). The significance of the change in *STATEGC* is unaffected by these control variables. We also observe some evidence that improving economics decreases Type I errors, as the coefficient on Δ*PERSINC* is highly significant ($p < 0.01$). Variance Inflation Factors in Column (2) are high, so we repeat the estimation retaining only Δ*PERSINC* and Δ*STATEGC*. Δ*STATEGC* remains significantly related to the change in Type I errors, although Δ*PERSINC* is no longer significant. In sum, our multivariate evidence also supports rejection of H2a.

Columns (4) through (6) repeat the same analyses using the change in Type II errors. Recall that measurement of Type II errors requires the firm to experience a bankruptcy. Thus, our analysis requires a state to have two consecutive years with at least one firm declaring bankruptcy, leaving a small sample of state-years ($n = 31$). Despite this small sample, we find a significantly positive coefficient on Δ*STATEGC* in all three columns, suggesting increases in state-level GC reporting precede increases in Type II errors for current-year reporting. Thus, in contrast to our univariate tests related to Type II errors, we find evidence rejecting H2b using a multivariate changes approach. Further, this evidence is inconsistent with increasing auditor conservatism (i.e., increase Type I errors to reduce Type II errors) but is consistent with auditors' overweighting less relevant, proximate information at the expense of more relevant information.[27]

Overall, our evidence provides strong support for the notion that higher proximate GC rates impair GC reporting accuracy measured using Type I errors. We view this evidence as consistent with information availability playing a role in auditors'

[25] We repeat our analyses using a two-year bankruptcy window and find statistically similar results.
[26] We thank our anonymous referees for this suggestion.
[27] We caution that while the estimated coefficient on Δ*STATEGC* is significantly positive in all three tests, these results are based on small samples and may be limited in terms of their generalizability. This caution also stems from the lack of statistically significant results for Type II errors reported in Panel A of Table 5.

decision making. That is, auditors overweight proximate information in making the GC decision. This leads to higher Type I error rates, which can be costly to the auditor. We also observe some limited evidence that perhaps this salient information takes precedence over more relevant information, as increases in state-level GC rates precede increases in Type II errors.

ADDITIONAL ANALYSES AND ROBUSTNESS TESTS

In this section we perform several robustness analyses related to our hypothesis tests. For brevity, we focus on regressions including all control variables (except for *VIOL,* which limits our sample period) since those models are most similar to prior research.

Big 4 Firms

As discussed in our motivation, our interviews with practitioners lead us to believe the influence of proximate information likely affects decisions by auditors affiliated with smaller firms than those employed by the Big 4. Nonetheless, we repeat our analyses on observations audited by the Big 4. We fail to find a significant coefficient on *STATEGC* in any empirical model. Not surprisingly, we also fail to find a difference in Type I or Type II error rates across *STATEGC* quartiles. We believe this provides further evidence that information biases, rather than economics, explain the relation between prior-year GC modifications and current-year decisions, as economics-based explanations should apply equally to both large and small audit firms.

Alternatives to *STATEGC*

Sample size prevents us from assessing the effect of prior period GC reporting at the city or office level on current-year GC decisions. Requiring only ten observations per city in a given year reduces our sample by over 60 percent. Alternatively, we consider "areas" defined by the proximity between auditor cities in our sample. Specifically, we proxy for the auditor's proximate area using a 60-mile radius and compute the rate of GC reporting for any offices within this radius. One benefit of this approach is that it considers GC reporting from cities in multiple states when those states are close together, such as in New England, while also distinguishing between cities that, while in the same state, are not in close geographic proximity (e.g., San Francisco and Los Angeles, Houston and Dallas). Using this "area GC" measure, we repeat our analyses in Table 5. We find results similar to those using *STATEGC* ($p = 0.02$).

To alleviate concerns that our results are primarily driven by offices in smaller cities, we also consider GC reporting in the five largest Metropolitan Statistical Areas (MSAs) in the U.S. (New York; Los Angeles; Chicago; Washington, DC; and San Francisco). Specifically, we compute the MSA's GC reporting rate using audit offices headquartered in or within 60 miles of each of these MSA's city center. Approximately 41 percent of our sample falls within one of these major MSAs. Using these alternative rates and a smaller sample, we find some evidence in support of H1 (prior proximate GC reporting affects current-year GC), although the significance of this result is weaker ($p = 0.09$).

In sum, these alternative approaches provide results consistent with primary findings—prior-year GC reporting in areas surrounding the auditor appears to influence current-year GC decisions.[28]

Time Period Analysis

To assess whether our results are driven by recessionary periods, we conduct three additional analyses. First, we remove observations from fiscal year 2008 to verify that our documented effect is not solely (or largely) driven by the Great Recession. Our variable of interest, *STATEGC,* remains significantly positive in this subsample. Some argue that the Great Recession actually began in 2007. Accordingly, we repeat this analysis after dropping 2007 as well and find similar results.

Second, we partition the sample into two subperiods: observations from fiscal years prior to and including 2007, and observations from 2008 and later. We continue to find a significantly positive coefficient on *STATEGC* in the pre-2008 period. However, in the post-2007 period, we fail to find a significantly positive coefficient on *STATEGC* ($p > 0.10$). While this suggests that perhaps the local GC rate does not relate to GC decision making in post-recession periods, we observe similar changes in other variables. For instance, we fail to find significant coefficients on *LNASSETS* or *CHLEV,* two determinants

[28] We repeat our prior-year rate-calculation procedures using U.S. Census Bureau-defined "divisions." There are nine geographic divisions within the U.S.: New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. We fail to find a significant relation between prior-year rates computed at this level and current-year GC decisions. This further supports the notion that proximity to the auditor rather than geographic clustering explains our results.

generally found to be highly related to the issuance of GC opinions. Thus, we are unable to rule out the possibility that loss of power (especially given our high number of control variables) and/or other differences in this period play a role in this difference.

Finally, we estimate Equation (2) for each year in our sample. While the samples are small, we observe positive coefficients on *STATEGC* in most years. Further, we find significantly positive coefficients ($p < 0.10$ or better) in 2002 and 2009, implying the effect of *STATEGC* is not clustered at the beginning or end of our sample period.

Same versus Different Auditor and Client State

We use the GC rate of each auditor's home state in the prior year as our variable of interest because we believe that the news related to the auditor's home state is likely more salient than news from the client's state. However, it is possible that auditors who audit out-of-state clients are also aware, and may more heavily weigh, information pertaining to the client's geographical area. Therefore, we assess whether the relation between *STATEGC* and *GC* varies depending on whether the auditor and client reside in the same state. In our sample, approximately 36 percent of observations pertain to clients headquartered in different states than their auditors. We estimate Equation (2) for each of these two subsamples and find that *STATEGC* loads significantly in both regressions. Thus, whether the auditor and client are located in the same state does not appear to affect our primary results.

DISCUSSION AND CONCLUSION

Prior research has demonstrated that financial statement users rely on the auditor's first-time GC opinion in assessing the financial strength of firms. The issuance of a first-time GC opinion has also been used by researchers as a measure of auditor independence and high audit quality. Despite the importance of audit opinions and the attention paid especially to first-time GC opinions, Type I and Type II errors rates for audit opinions remain high. We investigate first-time GC opinions with a focus on auditor characteristics and circumstances surrounding them. Specifically, we find evidence that first-time GC reporting for non-Big 4 firms is correlated with lagged first-time GC reporting within a state, even after controlling for other factors known to influence auditor reporting for clients facing extreme financial distress. In addition, we demonstrate that higher lagged frequencies of GC audit reports are correlated with lower current-year accuracy when compared with subsequent client bankruptcy. Finally, we document that current-year economic conditions, based on a wide range of economic data, are no worse, and in many cases better, in states with higher overall GC rates on distressed firms.

A plausible explanation for our findings is overweighting of more readily available information. Responses to our interviews provide some evidence that auditors are more aware of GC opinions within their home state and that auditors consider this information in making their decisions. This qualitative evidence is supported by research in multiple fields that documents overweighing of proximate information and state boundaries to relevant information flows (e.g., Singh and Marx 2013; Brown et al. 2015). Joe (2003) documented a similar effect with experimental evidence of auditors overweighting client-related distress information that was made more readily available. In contrast, our study documents a potential bias in an archival setting and provides insight into the extent to which proximate geographic location matters. Specifically, we document that first-time GC opinions appear to be influenced by GC opinions from within the home states. Further, this higher propensity to issue GC opinions increases Type I error rates without a corresponding decrease in Type II error rates. Although we are not able to determine with certainty the causation of our findings, we demonstrate that this state-level effect is not explained by economic factors identified by prior research. Rather, the cause appears to be psychological in nature, but experimental research is needed to corroborate our findings. We call for future research, particularly experimental research, to investigate whether information availability drives auditors to overweigh salient information and events at the expense of both Type I and Type II error rates.

Our study provides evidence that proximity to information may not always lead to informational advantages, and can lead to less accurate decisions in certain circumstances. This result is in contrast to prior research on geographic proximity and location that finds informational advantages to geographic proximity (Choi et al. 2012; Kedia and Rajgopal 2011; Malloy 2005). One possible explanation is that while more proximate information is more available, it may not always be more relevant to decisions. Our study also differs in that these prior studies examine proximity between economic agents and ours examines proximity to information. Further research, both experimental and archival, should examine other situations where geographic proximity influences the accuracy of auditor decision making.

Finally, our study's results show that limits exist with respect to the use of the auditor's GC opinion as a measure of audit quality. If a higher propensity to issue a GC opinion is correlated with lower accuracy, then this makes the link between GC reporting and higher audit quality tenuous and circumstantial. We do find that even after controlling for lagged state GC rates, NAS fees continue to be negatively related to auditor GC reporting during the time period of our study. This provides some indication that the results from the most recent auditor independence research continue to hold after controlling for GC

propensity. However, our accuracy results indicate that while this correlation may be related to independence, it is not necessarily an indication of higher quality. Future research should investigate whether controlling for GC propensity influences the interpretation of prior research results. If greater disclosure of financial distress leads to potential overweighting or overreaction to the information, then standard setters may want to consider the implications of increased emphasis on GC disclosures and whether they are beneficial to financial statement users. Further, our results suggest that non-Big 4 auditors may benefit from developing and maintaining a greater awareness of nationwide GC rates as a practical way of mitigating overweighting of local rates.

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APPENDIX A
Interviews with Practicing Auditors

We conducted semi-structured interviews with eight auditors from three Big 4 firms, two mid-tier firms, and three small firms, each registered with the PCAOB. Auditors were either senior managers or partners and came from practice offices in California, Colorado, Connecticut, Florida, Georgia, Michigan, New York, and Tennessee. Auditors were asked the first question on the list, followed up by other questions as relevant.

1. Are you aware when other businesses in your area receive going-concern opinions?
2. Does this include clients of your firm and other firms?
3. Are you more aware of local GCOs than GCOs in other states?
4. If yes, how do you get this information?
5. Does this ever come from local press?
6. Do you use the local press for other information about local businesses?
7. Do you take knowledge of local GC opinions into account in determining a GC opinion for your client?
8. Does this increase your bargaining power with the client?
9. Do you consider non-firm-specific factors when assessing whether to issue a GCO (like unemployment rates, etc.)?
10. If so, what local or state economic issues/statistics do you consider in making a GCO?
11. Do you specifically consider the GC status of local suppliers or customers, etc.?
12. If so, do you consider national and local suppliers/customers, or just local?
13. How much interaction do you have with auditors from (1) other offices of your firm in state, (2) other offices of your firm out of state, (3) other firms in state, and (4) other firms out of state?
14. Do you believe that you have potential risk of either litigation or losing the client when you modify an opinion for GC uncertainty? Does this concern you?
15. Do you believe that you have potential risk of litigation or losing the client when you do not modify an opinion for a financially distressed client?

In this section of the appendix, we report the coding of the responses to the three questions most relevant to our research question and representative responses. Responses are noted by auditor level (senior manager [SM] or partner [P]), and firm size (Big 4 [B4], mid-tier [MT], and small [S]).

Q1: Are auditors aware when other businesses in their area receive going-concern opinions? (Yes = 87.5 percent)

- Yes. Particularly clients in my industry. (SM, B4)
- Everybody knows about issuers, but not non-issuers. (P, S)

- When we are considering issuing a GC opinion, yes. I talk with risk management and they give me feedback on the public space. (SM, B4)
- We use prior financials to identify prospective clients. We definitely know financial conditions and GC outcome of public companies. (P, B4)
- That wasn't overly relevant for me personally. Most of my clients weren't in the local area. (SM, MT).
- Yes. (SM, S)
- I know the financial condition of all issuers in our market. (P, S)
- I for sure know clients in our area. I may or may not know others. What I read in the paper. (P, MT)

Q2: If yes, are auditors more aware of GC opinions in their local area and state than other states and how do they learn about them? (Yes = 87.5 percent)

- I interact with people from my firm anywhere in the world within my industry group. (SM, B4)
- My area is a pretty closed network. (P, S)
- Our risk management department considers both local and national. General trends in the public space. No formal process, but I read the newspaper every day (*Wall Street Journal, National Business Journal,* local papers). I'd notice if the press brought it up. (SM, B4)
- In my geography [Michigan], I learn about it through the press. I don't usually know about, say, California. (P, B4)
- I focus on our market. I only talk within our network. (SM, S)
- In my role, I am more involved with local accountants. But ten years ago [with a Big 4 firm], I would have said national. (P, S)
- I definitely know more about what's going on with clients in my office. I know most about local companies doing very well and doing very poorly than middle of the road. Draw a circle around my office and I know more about companies within that circle than outside. (P, MT)

Q3: Do auditors take knowledge of other GC opinions into account in determining a GC opinion for clients? (Yes = 50 percent)

- We would consider state economics, but not local. Unless it was a retailer. (SM, B4)
- From a client perspective, no one wants to be the first. "Your airline sucks too." (P, S)
- I don't view it as a bargaining effort, so I don't consider other company opinions. (SM, B4)
- It isn't something I think about specifically. (P, B4)
- Yes, absolutely. We also consider personal finances. (SM, S)
- That is a very important part of it. What else might lead them to fail? (P, S)
- Not at all, but kind of sort of maybe? (P, MT)

APPENDIX B

Variable Definitions

Variable	Definition
$AUDLIAB_{i,t}$	Indicator equal to 1 for states with high auditor liability (liability rating of 4.5 or higher), and 0 otherwise. Pacini et al. (2000) assess auditor liability for each state and develop a nine-point liability scale ranging from lowest auditor liability (Privity) to greatest liability (Reasonable Foreseeability). Gaver et al. (2012, Appendix B) more fully describes this rating procedure.
$BETA_{i,t}$	The firm's beta estimated using a value-weighted index market model estimated over the 12 months corresponding to the fiscal year.
$CAPEX_{i,t}$	Total capital expenditures by manufacturers, per capita, obtained from the Annual Survey of Manufacturers (2003–2006, 2008–2010) or the Economic Census (2002, 2007). Both datasets are available through the United States Census Bureau (http://www.census.gov).
$CHLEV_{i,t}$	The change in *LEV* from fiscal year $t-1$ to year t.
$COUNT_{i,t}$	The number of clients audited by auditor-office in year t. Note that *COUNT* is computed using the full sample of observations in Audit Analytics.
$DISTANCE_{i,t}$	Log of the straight-line distance between the client's zip code and the auditor's city.
$FEERATIO_{i,t}$	The ratio of nonaudit fees to audit fees paid to current auditor in year t.
$FINANCE_{i,t}$	Indicator variable equaling 1 if the firm issues equity or debt in year $t+1$, and 0 otherwise.
$FOODSTAMPS_{i,t}$	Percentage of households receiving food stamps in auditor's home state during year of opinion. Percentage computed using American Community Survey (ACS) responses obtained from the Institute of Public Use Microdata Series (IPUMS, Ruggles et al. 2010).
$GDP_{i,t}$	Per-capita gross domestic product for the auditor's home state, obtained from the Bureau of Economic Analysis (http://www.bea.gov).
$INVEST_{i,t}$	The firm's total investments (short and long term, as well as cash or cash equivalents) scaled by total assets at time t.
$LEV_{i,t}$	The firm's financial leverage ratio at the end of fiscal year t (computed as total liabilities divided by total assets).
$LNAGE_{i,t}$	Natural log of firm age, computed as the number of years appearing in CRSP, as of year t.
$LNASSETS_{i,t}$	Natural log of the firm's total assets in year t.
$LNOFEES_{i,t}$	Log of the total fees in year t in auditor's office. Note that *LNOFEES* is computed using the full sample of observations in Audit Analytics.
$LNPOP_{i,t}$	Natural log of the total state population, estimated using ACS data obtained through IPUMS.
$LOSS_{i,t}$	Indicator variable equaling 1 if the firm's earnings in fiscal year t are negative, and 0 otherwise.
$OCF_{i,t}$	The firm's operating cash flows scaled by total assets in year t.
$PERSINC_{i,t}$	Per-capita personal income, obtained from the Bureau of Economic Analysis (http://www.bea.gov).
$PROBLIT_{i,t}$	The probability of litigation as defined by Rogers and Stocken (2005) measured over the fourth quarter of the fiscal year. Specifically, $PROBLIT = \Phi(-5.738 + 0.141 * SIZE + 0.284 * TURN + 0.012 * BETA - 0.237 * QRET - 1.34 * STDRET + 0.011 * SKEWRET - 3.161 * MINRET - 0.025 * BIO + 0.378 * HW + 0.075 * ELEC - 0.034 * RETAIL + 0.211 * SOFT)$ where $\Phi(\cdot)$ is the standard normal cumulative distribution function; $SIZE$ = log(average daily MVE); $TURN$ = average daily volume/average shares outstanding; $BETA$ = beta from regressing daily returns on CRSP equal-weighted index; $QRET$ = buy and hold return over quarter; $STDRET$ = standard deviation of daily returns; $SKEWRET$ = skewness of daily returns; and $MINRET$ = minimum of daily returns. Other variables are indicators for high-litigation industries (BIO = SIC codes 2833–2836; HW = SIC codes 3570–3577; $ELEC$ = SIC codes 3600–3674; $RETAIL$ = SIC codes 5200–5961; $SOFT$ = SIC codes 7371–7379).
$REPLAG_{i,t}$	Report lag, measured as the number of days between the fiscal year-end and audit report date.
$RET_{i,t}$	The firm's 12-month stock return over the fiscal year.
$URATE_{i,t}$	Unemployment rate computed using ACS responses, obtained from the IPUMS in the auditor's home state.
$VIOL_{i,t}$	Indicator variable equaling 1 if firm discloses a violation of a debt covenant in the annual report, and 0 otherwise. Violation data obtained from Professor Amir Sufi's personal website (http://www.faculty.chicagobooth.edu/amir.sufi/data.html).
$VOL_{i,t}$	The variance in firm residuals from the market model over the fiscal year.
$WAGES_{i,t}$	Average workforce wages for the auditor's home-state workforce during the year of the opinion, computed using ACS responses obtained from the IPUMS.
$ZSCORE_{i,t}$	The firm's probability of bankruptcy score based on Altman (1968).