Does Auditor Industry Specialization Improve Audit Quality? Evidence from Comparable Clients

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ABSTRACT: The objective of this study is to examine the relation between auditor industry specialization and audit quality using an alternative research design to mitigate the influence of client characteristics. After matching clients of specialist and non-specialist auditors according to industry, size and performance, I find no significant differences in audit quality between these two groups of auditors. My findings are robust to using alternative matching approaches, to using various proxies for auditor industry specialization and audit quality, and to controlling for the effect of imperfectly matched characteristics. In addition, I perform two analyses that do not rely primarily on matched samples. First, in examining a sample of Arthur Andersen clients that switched auditors in 2002, I find no evidence of industry-specialization effects following the auditor change. Second, I observe that the industry-specialization effects are simulated by randomly assigning clients to auditors. Overall, these findings do not imply that industry knowledge is not important for auditors, but that the extant methodology may not fully parse out the effects of auditor industry expertise from client characteristics.

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I. INTRODUCTION

Accounting firms recognize the importance of industry expertise in providing high-quality audits and organize their assurance practices along industry lines. In large firms, individual auditors specialize by auditing clients in the same industry. For example, PwC highlights that "our audit approach, at the leading edge of best practice, is tailored to suit the size and nature of your organisation and draws upon our extensive industry knowledge (PwC 2010)." A report on the U.S. audit market issued by the U.S. General Accounting Office (GAO) in 2008 also acknowledges the importance of industry expertise, noting that "a firm with industry expertise may exploit its specialization by developing and marketing audit-related services which are specific to clients in the industry and provide a higher level of assurance (GAO 2008; p. 111)." Asserting the benefits of auditor industry specialization is relevant for public companies choosing among auditors, to regulators concerned with high concentration on the U.S. audit market, and to audit firms aiming to perform high-quality audits while maintaining their competitive position in each industry.[1]

Auditing researchers have extensively studied the consequences of auditor expertise. Experimental auditing research confirms the importance of auditor expertise by providing evidence that knowledge of the industry may increase audit quality, improving the accuracy of error detection (Owhoso et al. 2002; Solomon et al. 1999), enhancing the quality of the auditor's risk assessment (Low 2004; Taylor 2000), and influencing the choice of audit tests and the

[1] Since four audit firms hold the majority of the U.S. audit market for public companies, specialization may lead to dominance of a single audit firm within an industry. Dominance by a single audit firm in an industry may have undesirable consequences such as high audit fees and low audit quality. Extant research shows that auditors may be able to obtain a specialization fee premium by improving efficiency and creating barriers to entry. Francis et al., (2005) find an association between fee premiums and joint national and city specialist auditors in the U.S. audit market; DeFond et al. (2000) find a specialization premium in addition to audit quality effects the Hong Kong audit market; however, Carson and Fargher (2007), focusing on the Australian audit market, find that the association between the specialist fee premium and auditor specialization is concentrated in audit fees paid by the largest clients in each industry.

allocation of audit hours (Low 2004). Empirical auditing research has also examined the effects of auditor industry expertise; however, empirical researchers cannot directly observe expertise at the firm, office, or auditor level, and this area of the literature has used each audit firm's within-industry market share, or auditor industry specialization, as an indirect proxy for auditor industry expertise. A specialist is a firm that has "differentiated itself from its competitors in terms of market share within a particular industry" (Neal and Riley 2004; p. 170). Previous studies that use within-industry market share proxies for industry specialization have shown that the clients of specialist auditors have better financial reporting quality, exhibiting on average from 0.3 to 2.0 percent lower absolute discretionary accruals, compared to clients of non-specialist auditors (Balsam et al. 2003; Krishnan 2003; Reichelt and Wang 2010).

Measuring the effects of auditor industry expertise on audit quality is problematic because the proxies for industry specialization and audit quality are associated with underlying client characteristics. For example, large clients have lower absolute discretionary accruals and large clients are often audited by industry specialists. For determining causal inference in observational studies, empirical researchers should aim to compare treated and control groups that have similar client characteristics, ideally approximating experimental conditions. A potential way to achieve this objective is by matching treatment and control observations on all relevant observable dimensions except for the treatment and outcome variables. This study proposes a methodology to find economically comparable clients and applies it to mitigate the effect differences in client characteristics between specialists and non-specialist auditors.

Controlling for confounding factors is particularly important in studying the effects on industry specialization for two main reasons. First, an audit firm may have extensive industry knowledge even when its within-industry market share is small relative to other audit firms.

Industry knowledge could be gained through other means; for instance, by the number of years an audit team has audited clients in the industry, by providing training to individual auditors, by auditing private clients in the same industry, by providing consulting services, and by hiring experts from within the industry or from other audit firms.[2] Thus, it is not obvious that auditors with larger market share will have higher quality. Second, the evidence in Boone et al. (2010) and Lawrence et al. (2010) shows that the previously documented association between auditor size and audit quality could be attributed to differences in client characteristics, particularly to differences in client size. The separation of specialist and non-specialist auditors by within-industry market share also creates two groups of auditors with different client characteristics. For example, specialist auditors have larger and more profitable clients compared to non-specialist auditors.

Prior studies of auditor industry specialization control for the impact of client characteristics by including client size, performance, growth, and other linear control variables in multivariate regression analyses. There are two problems with the linear control approach: important variables such as client size and performance are nonlinear to both the auditor choice decision and the proxies for audit quality (Kothari et al. 2005; Hribar et al. 2009; Lawrence et al. 2010), and differences in client characteristics are partially a result of endogenous self-selection. Furthermore, previous research by Rubin (1979), Heckman et al. (1998), Rubin and Thomas (2000), and Rubin (2001), shows that linear regression may increase bias in the estimation of treatment effects when there are even moderately nonlinear relationships between the dependent and independent variables, and this problem is exacerbated when there are significant differences

[2] For example, a recent article in Bloomberg's *BusinessWeek* notes that "Deloitte recruiters say they're doing better head-to-head against such old-shoe firms as McKinsey and BCG Consulting, both in recruiting and getting new business" and that this firm "typically gets more than 85 percent of the experienced hires it makes an offer to" (Byrnes 2010).

in means and variances in the independent variables between treated and control groups. To overcome the endogeneity problem, some studies use econometric designs that explicitly model the mechanism that results on differences in client characteristics between auditors, such as the Heckman (1979) self-selection model or two-stage models. A limitation of these research designs is that they require identifying appropriate exogenous instrumental variables or exclusion restrictions in the first stage, which is a difficult condition to meet in models predicting auditor choice (Francis et al. 2010). Moreover, two-stage models may perform poorly when there is insufficient overlap between treatment and control observations (Glazerman et al. 2003; Dehejia and Wahba 2002). The matching models used in this study constitute an alternative to determine the auditor treatment effects. [3]

Consistent with previous studies, I first document the relation between audit quality and auditor industry specialization at the U.S. national and city level in my full sample analyses. Throughout my analyses, I use three audit-quality proxies: discretionary accruals, a revenue manipulation proxy from Stubben (2009), and the auditor's propensity to issue a going-concern opinion. The main matching approach used in this study is based on three fundamental economic dimensions: industry, size, and performance. After matching clients of specialist and non-specialist auditors, I find no significant differences in audit quality between the two groups of auditors. My findings are robust to using alternative matching approaches, to using various proxies for auditor industry specialization and audit quality, and to controlling for the effect of imperfectly matched characteristics.

[3] Heckman (2005) discusses extensively the advantages and disadvantages of matching versus explicit modelling of the selection process. Both approaches are acceptable for estimating treatment effects; however, the matching approach does not require identification of exclusion restrictions. Conversely, matching relies on the assumption that selection is strictly based on observables or that treatment assignment is "strongly ignorable," and also requires some degree of overlap or "common support" between treatment and control observations. I discuss the implications of this assumption for my research design in Section II.

I also document confirmatory evidence from two additional analyses. First, I find statistically insignificant pre-post differences in discretionary accruals or revenue manipulation for Arthur Andersen's clients that exogenously switched to auditors with a different degree of specialization in 2002. Second, using a simulation procedure, I assign clients to five simulated auditors at random and designate specialist and non-specialist auditors based on within-industry market share. I observe that the auditor that is assigned the largest clients of the industry is often designated as specialist, and that specialist auditors appear to have higher audit quality compared to non-specialist auditors, highlighting the confounding effect of client size on tests of auditor industry specialization.

In sum, the combined evidence provided in this study suggests that the extant empirical methodology may not fully parse out the confounding effects of client characteristics in tests of auditor industry specialization and audit quality. I caution that my findings do not imply that industry knowledge is not important for auditors. Furthermore, my results are subject to the intrinsic limitations of matching for estimating causal effects, resulting from a trade-off between internal and external validity, and to the proxies for audit quality and auditor industry specialization used in this study. Finally, beyond the audit literature, this study contributes to the broad accounting literature on matching and economic comparability. The methodology used here could be adapted to other studies in accounting research comparing treated and control groups, particularly where it is difficult to specify a correct model or to find exogenous predictors of treatment choice.[4]

[4] For example, a study using discretionary accruals as a dependent variable and a treatment variable correlated with firm size and performance (e.g., management compensation, corporate governance, or financial analyst following) may benefit from using the methodology applied in this study.

II. AUDIT QUALITY AND ECONOMIC COMPARABILITY

Peer-Matching and economic comparability

Using peer-firms as a benchmark is common among practitioners and researchers. Peer-firms are used by financial analysts to support their price-earnings ratios, earnings forecasts, and overall stock recommendations (Bradshaw et al. 2009; De Franco et al. 2009), by investment managers in structuring their portfolios (Chan et al. 2007), by compensation committees in setting executive compensation (Albuquerque 2009), by business valuators in determining valuation multiples (Bhojraj et al. 2002), and by auditors in applying analytical procedures (Hoitash et al. 2006). In using peer-firms as benchmarks, practitioners rely on comparability or uniformity of financial information and on the overall quality of the mapping of economic events into financial reporting. Several prior studies in accounting research have used peer-matching "as a research design device for isolating a variable of particular interest" (Bhojraj et al. 2002; p. 410), to simplify data collection (Geiger and Rama 2003), to provide more reliable inferences in market-based research (Barber and Lyon 1997), and to mitigate the effect of nonlinearities (Kothari et al. 2005).[5] A primary objective of this study is to use fundamental economic characteristics to match peer-firms in order to obtain inferences about relative accounting quality between two groups of auditors.

Peer-matched test of audit quality

To investigate the difference in audit quality between two auditors, researchers must ascertain that the observed differences between the auditors' clients are the result of the auditors'

[5] Furthermore, other disciplines have done extensive research on the benefits and drawbacks of matching to identify causal effects; for example, applied statistics (Stuart 2009; Rubin 2006; Rosenbaum 2002), epidemiology (Brookhart et al. 2006), sociology (Morgan and Harding 2006), applied econometrics (Imbens 2004), and political science (Ho et al. 2007). Zhao (2004, p.100) notes that "Selection bias due only to observables is a strong assumption. But with a proper data set and if the selection-on-observables assumption is justifiable, matching methods are useful tools to estimate treatment effects."

effect. A peer-based approach could be useful in identifying the auditor treatment effects under two general scenarios.

In the first scenario, assume that (1) clients do not engage routinely in earnings management, (2) low-quality auditors allow random noise in accounting accruals as a result of inconsistent enforcement of accounting principles, and (3) two clients are economically comparable and have the same drivers of accounting accruals, but one client has a low-quality auditor and the other client has a high-quality auditor. Under these ideal conditions, the only difference between these two clients' accruals is the random noise introduced by the low-quality auditor.

In the second scenario, assume that (1) clients engage routinely in earnings management, (2) low-quality auditors are not able to fully uncover earnings management, and (3) two clients are economically comparable and have the same drivers of accounting accruals, but one client has a low-quality auditor and the other client has a high-quality auditor. Under these conditions, the effect of earnings management should be the only difference between these two clients' accruals.

Along these lines, researchers may identify differences between the accruals of clients of specialist and non-specialist auditors if specialist auditors are better at enforcing the right accounting policies and at constraining earnings management. In a general setting where the true accrual function is unknown, the overall difference in accrual quality between two clients can be approximated by employing a combination of a discretionary accruals model and matching on economic comparability. Similarly, a test of the differences in propensity to issue a going-concern opinion between specialist and non-specialist auditors could be well specified if the matching process mitigates differences in client characteristics that could influence the probability of bankruptcy.

Matched-sample estimators of the effects of specialization

A univariate t-test of the differences in means between perfectly matched clients constitutes a direct estimator of the specialist auditor treatment effects (Zhao 2004). However, if the matching process is not perfect, it is still important to control for unmatched client characteristics using multivariate analyses. I conduct multivariate analyses in all matched samples of specialist and non-specialist auditors' clients using two approaches. Under the first approach, the same model estimated on the full sample is estimated in the pooled matched sample of clients, while under the second approach, the pair-wise differences in the dependent variables between peer-matched clients of specialists are regressed on the pair-wise differences of the independent variables in the original model (Rubin 1973; Imbens 2004; Cram et al. 2009). The intercept of this pair-wise differences model is interpreted as the average difference resulting from the specialist's treatment effects. For the matched sample analyses of the propensity to issue a going-concern opinion, I estimate a conditional fixed effect logistic regression based on matched pairs of clients of specialist and non-specialist auditors with variation in going-concern opinions (Cram et al. 2009).

Advantages and disadvantages of peer-matching approaches

An advantage of the peer-matched approach is that it imposes weak stationarity or linearity conditions on the relation between the matched firm characteristics and the proxies for audit quality. Although the peer-based approach reflects the relative quality between peer-firms, idiosyncratic differences should be mitigated in large samples, allowing researchers to assess the average treatment effects of specialist auditors. This argument is similar to that in Kothari et al. (2005); however, this approach aims to isolate a wider set of client characteristics, beyond *ROA*, from the proxies for audit quality. Another advantage of the peer-based approach is that it does not require identification of exclusion restrictions. Finally, this approach is suitable for a differences-in-differences test of the effect of auditor specialization for clients that switch auditors as a result of an exogenous shock.

Using matched samples comes at a cost, thus three underlying threats to matching approaches are (1) firms deemed to be economically similar may not be truly comparable, (2) the results from matched samples may not be immediately extended to the entire population, and (3) matching reduces sample sizes. These threats result from a trade-off between internal and external validity. The first threat can be mitigated by verifying that matched firms have homogenous characteristics across matched groups, by triangulating evidence from different matching approaches, and by controlling for the effect of imperfectly matched variables. The second threat may be mitigated by a combination of analyses including calculating bootstrap standard errors and verifying that the matched sample results hold separately for industries where specialization matters the most. The third threat may be mitigated by verifying that the result in non-matched samples could be found even in random samples of equal or smaller size than the matched samples, and aiming to get the largest possible matched samples. I document the results of additional analyses to mitigate these threats in Section VIII.

Selection of matching variables and matching approach

There are two primary research-design choices applicable to matched samples. The first choice is the set of variables or dimensions used for matching; the second is the mechanism to aggregate across dimensions and to find comparable observations. The choice of matching variables is important because in a strict sense, matching assumes that bias is only due to observables. The source of bias is the difference between observables in the treatment and control groups. The bias due to non-matched characteristics decreases as the number of matching variables increases. On the other hand, the complexity and structure of the methods needed to aggregate across dimensions increases as the number of matching variables increases.

When the number of matching variables is small, the researcher can directly match on the variables of interest or within a specified distance from each variable of interest without requiring a weighting approach to aggregate across dimensions. This type of matching is known as attributes-based or covariate matching. The main approach used in this study is a form of covariate matching. I propose that the three most important fundamental variables that affect the audit-quality proxies and also influence the differences between auditor groups are the client's industry, size, and performance. The literature on discretionary accruals has repeatedly highlighted the importance of these three dimensions and recommends estimating discretionary accruals by industry, scaling by total assets and controlling for *ROA*.

To match on these dimensions, for a given fiscal year-end, industry (defined by two-digit SIC code), and size distance (firms that are within a size distance of 50 percent), firm *i* is matched to firm *j* with the most comparable performance, measuring performance as stock returns' covariance over the preceding 48 months, where higher covariance indicates higher comparability.[6] As per the De Franco et al. (2009) methodology, I measure returns covariance using the adjusted R^2 of the following regression of firm *i's* monthly returns on firm *j's* monthly returns[7]:

$$RETURNS_{i,t} = \Phi_{i,j} + \Phi_{i,j} RETURNS_{j,t} + \varepsilon_{j,t} \tag{1}$$

[6] As noted by Chan et al. (2007, p. 57), "if equity market participants consider a set of companies closely related, then shocks in the group of stocks should experience coincident movements in their stock returns."
[7] I also estimate Kendall's (1938) Tau or rank correlation coefficient for my matched peer-firms. This non-parametric statistic measures co-movement or serial dependence and can be directly interpreted as the probability of observing concordant or discordant pairs of observations. Both correlation measures produce similar matched pairs.

In addition, I require matched firms to have their fiscal year-end on the same month to reduce differences from timing in financial reporting. Allowing for 50 percent distance in total assets results in more than one potential control for every treatment observation, and the final selection among all possible controls is based on returns' covariance. This procedure is likely to closely match peer-firms deemed economically comparable by the market. Compared to other matching approaches, it does not rely on a specific functional form to predict comparability, beyond a returns covariance structure, and can be used not only in case-control research settings, but also in situations where a company needs to be matched with its economic peers; for example, to form benchmark groups for valuation or to perform analytical audit procedures.

In order to mitigate any bias resulting from imperfect matching, the pair-wise differences analyses control for differences in size, performance and other variables between matched observations. Furthermore, as robustness test, I also use propensity-score matching, including several additional variables in the matching. Using propensity score, control observations are matched to treatment observations based on a specified distance between their overall probabilities of undergoing treatment. These probabilities are estimated using a number of covariates that predict choice, effectively aggregating multiple dimensions into a single matching variable. This alternative matching requires specifying a functional form for the choice model and an acceptable distance between observations in terms of probability. I obtain similar results either matching on the three proposed covariates or using propensity-score matching. These two approaches are complementary in examining my main research question, and confirm that the specialization effect may be attributable to differences in client characteristics. I describe the propensity-score matching result in Section VIII.[8]

III. RELATED EMPIRICAL STUDIES AND MEASURES OF SPECIALIZATION

Prior studies primarily measure auditor industry specialization using the auditor's within-industry market share. Each auditor's industry market share is calculated as:

$$MARKETSHARE_{ki} = \frac{\sum_{j=1}^{J_{ik}} S_{kij}}{\sum_{i=1}^{I}\sum_{j=1}^{J} S_{kij}} \tag{2}$$

where $MARKETSHARE_{ki}$ is the market share of auditor i in industry k, S_{kij} represents the total assets of client firm j in industry k audited by auditor i, J represents the number of clients that are served by audit firm i in industry k, and I is the number of audit firms in industry k.[9] The two main proxies for auditor industry specialization in this study are:

NLEAD1	=	"1" for auditors that have the largest market share in a given industry and year at the U.S. national level and have more than 10 percent greater market share than the closest competitor, and "0" otherwise;
CLEAD1	=	"1" for auditors that have the largest market share in a given industry and year at the U.S. city level, where city is defined as a Metropolitan Statistical Area following the 2003 U.S. Census Bureau MSA definitions, and have more than 10 percent greater market share than

[8] Zhao (2004) concludes that there is no clear winner between covariates and propensity-score matching methods. When the correlation between covariates and treatment choice are high, propensity-score matching is a good choice; however, when the sample size is small, covariate matching performs better. Hahn (1998) shows that covariate matching is asymptotically efficient because it attains the efficiency bound, and Angrist and Hahn (2004) show that covariate matching may be more efficient in finite samples than propensity-score matching.

[9] Prior studies have also used total sales or auditor fees to compute within-industry market shares. I use total assets to calculate my specialization measures at city and national level because total assets are available for most firms in my sample period.

the closest competitor, and "0" otherwise. [10]

The main analyses presented in all tables use these two proxies, and I describe similar results using an alternative cut-off for market share and combined national and city-level specialization proxies in Section VIII.

Balsam et al. (2003) find a negative relationship between auditor specialization and the client's absolute discretionary accruals. Discretionary accruals are calculated using the industry cross-sectional Jones (1991) model and auditor industry specialization is measured using six proxies: *LEADER* that equals one for auditors with the top three market shares in a given industry, and zero otherwise; *DOMINANCE* that equals one for auditors that have the largest market share in a given industry and have more than 10 percent greater market share than the closest competitor, and zero otherwise; *MOSTCL* that equals one for auditors that have the most number of clients in a given industry, and zero otherwise; *SHARE* that is a continuous auditor market share variable (measured in client sales) in a given industry; *SHARECL* that is a continuous auditor market share variable (measured in number of clients) in a given industry; and *NCLIENTS* that is the number of clients of an auditor in a given industry.

Krishnan (2003) documents a negative relationship between auditor specialization and the client's absolute discretionary accruals. Discretionary accruals are calculated using the industry cross-sectional Jones (1991) model and auditor industry specialization is measured using two proxies: *IMS1* that equals one for auditors with market share greater or equal to 15 percent in a given industry, and zero otherwise; and *IMS2* that is a continuous auditor market share variable (measured in client sales) in a given industry.

[10] Francis et al. (2005) and Reichelt and Wang (2010) also use MSA definitions to identify city-level specialists. I delete cases when there are only two observations in a given city. MSA definitions are available at the U.S. Census Bureau's website: http://www.census.gov/population/www/metroareas/metrodef.html.

Reichelt and Wang (2010) show a negative relationship between auditor specialization and the client's absolute discretionary accruals. Discretionary accruals are calculated using the industry cross-sectional Jones (1991) model, including *ROA* as per Kothari et al. (2005), and auditor industry specialization is measured using two proxies at the national level, city level, and both levels combined: *SPECIALIST1* that equals one for auditors that have the largest market share in a given industry and have more than 10 percent greater market share than the closest competitor, and zero otherwise; and *SPECIALIST2* that equals one for auditors that have over 30 percent market share in a given industry and year, and zero otherwise. In addition, this study documents a positive association between the city-level and combined national and city-level measures and the auditor's propensity to issue a going-concern opinion.

Lim and Tan (2008) test the moderating effect of auditor specialization on the relationship between non-audit fees and absolute discretionary accruals and find no statistically significant association between absolute discretionary accruals and auditor specialization in a model without non-audit-fee measures. At the same time, they find an interaction effect between auditor specialization and non-audit fees, suggesting that clients audited by specialists are associated with higher absolute levels of discretionary current accruals as non-audit fees increase. Lim and Tan (2008) calculate discretionary accruals using the industry cross-sectional Jones (1991) model, including *ROA* as per Kothari et al. (2005), and their measure of specialization equals one if the auditor has the largest market share in the client's industry, and zero otherwise. Furthermore, this study documents a positive association between auditor industry specialization and the auditor's propensity to issue a going-concern opinion; however, the association is negative once the specialization proxy is interacted with audit fees.

The studies summarized above consistently document a relationship between auditor industry specialization and audit quality. Consistent with prior studies, I use the client's absolute discretionary accruals and the auditor's propensity to issue a going-concern opinion as audit-quality proxies. Additionally, I use a proxy for discretionary revenue, proposed by Stubben (2010), which considers a number of cross-sectional characteristics in the estimation process. This measure is arguably better specified at detecting revenue manipulation than the previously used discretionary accruals measures.[11]

IV. AUDIT-QUALITY PROXIES AND SAMPLE SELECTION

Discretionary Accruals

As a first audit-quality proxy, I use absolute discretionary accruals, estimated using an annual cross-sectional model for each industry. I employ two different approaches to calculate discretionary accruals: *ADA* is based on a model including *ROA* (Kothari et al. 2005) as an additional predictor (Equation (3) below), and *ADA_FULL* is based on a more comprehensive model (Equation (4) below) including *ROA* (Kothari et al. 2005), cash flows in periods t and $t-1$ scaled by total assets (McNichols 2002), and a non-linear interaction term based on the sign of cash flows in period t (Ball and Shivakumar 2006). In the main analyses, I use the absolute value of discretionary accruals from the Kothari et al. (2005) model (*ADA*). All results are similar using *ADA_FULL*, or estimating the Kothari et al. (2005) model using prior year's *ROA* instead of current year's *ROA*.[12]

$$AC_{i,t} = \alpha + \beta_1 \Delta R_{i,t} + \beta_2 PPE_{i,t} + \beta_3 ROA_{i,t} + \varepsilon_{i,t} \qquad (3)$$

[11] Table 3 in Stubben (2010, p.707) shows that this discretionary measure detects a combination of 1 percent simulated manipulation in both revenue and expenses in 23.6 percent of the samples with manipulation, compared to 11.6 percent using the Jones model or 11.2 percent using the performance-matched modified Jones model.
[12] I winsorize all variables at the 1 and 99 percent levels before estimating the discretionary accruals and discretionary revenue models.

$$AC_{i,t} = \alpha + \beta_1 \Delta R_{i,t} + \beta_2 PPE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 CFO_{i,t-1} + \beta_5 CFO_{i,t} + \beta_6 CFO_{i,t+1} + \beta_7 D_{i,t} + \beta_8 D \times CFO_{i,t} + \varepsilon_{jt} \quad (4)$$

Discretionary Revenue

As a second audit-quality proxy, I use *ADREV,* the absolute value of discretionary revenue, as proposed by Stubben (2010). The revenue manipulation or discretionary revenue model (Equation (5) below) is similar to the discretionary accruals model in that it uses the relation between changes in accounts receivable and changes in revenue to predict earnings management. Moreover, the estimation of this measure allows for variation in the model coefficients across client characteristics and also considers nonlinear terms, compared to discretionary accruals models that assume the same coefficient for all clients in the same industry.

$$\Delta AR_{i,t} = \alpha + \beta_1 \Delta R_{i,t} + \beta_2 \Delta R_{i,t} \times SIZE_{i,t} + \beta_3 \Delta R_{i,t} \times AGE_{i,t} + \beta_4 \Delta R_{i,t} \times AGE\_SQ_{i,t} + \beta_5 \Delta R_{i,t} \times GRR\_P_{i,t} + \beta_6 \Delta R_{i,t} \times GRR\_N_{i,t} + \beta_7 \Delta R_{i,t} \times GRM_{i,t} + \beta_8 \Delta R_{i,t} \times GRM\_SQ_{i,t} + \varepsilon_{jt} \quad (5)$$

Appendix A describes the main variables of Equations (3) to (5) and the calculation of the discretionary accruals and revenue manipulation audit-quality proxies that I use in this study.

Going-Concern Opinions

As a third audit-quality proxy, I use the auditor’s propensity to issue a going-concern opinion. The variable for going-concern opinion (*GCONCERN*) is directly taken from Audit Analytics and is coded as “1” if the auditor gave a going-concern opinion to a client in the fiscal year, and “0” otherwise.

Multivariate regression models

I first replicate the findings of prior studies that test the relation between auditor specialization and each audit-quality proxy using the following model[13]:

$$\begin{aligned} QUALITY\_PROXY_{i.t} = {} & \omega_0 + \omega_1 LEAD_{i,t} + \omega_2 BIG4_{i,t} + \omega_3 LOGMKT_{i,t} + \omega_4 LEV_{i,t} \\ & + \omega_5 ROA_{i,t} + \omega_6 ROAL_{i,t} + \omega_7 LOSS_{i,t} + \omega_8 CFO_{i,t} + \omega_9 BTM_{i,t} \\ & + \omega_{10} ABS(ACCRL)_{i,t} + \omega_{11} GROWTH_{i,t} + \omega_{12} ALTMAN_{i,t} \\ & + \omega_{13} STDEARN_{i,t} + \omega_{14} TENURE_{i,t} + \omega_{15} YEAR\ F.E. + v_{i,t} \end{aligned} \qquad (6)$$

where for client *i* and fiscal year-end *t*:

QUALITY_PROXY	=	audit quality proxies as defined above;
LEAD	=	indicator variable for each measure of auditor industry specialization as defined above (*NLEAD1* or *CLEAD1*);
BIG4	=	"1" if the client has a Big 4 auditor and "0" otherwise;
LOG_MKT	=	natural logarithm of market value;
LEV	=	(total liabilities) / average total assets;
ROA	=	(net income) / average total assets;
ROAL	=	(net $income_{t-1}$) / average total assets $_{t-1}$;
LOSS	=	indicator variable equal one if net income is negative, and "0" otherwise;
CFO	=	(cash flow from operations)/average total assets;
BTM	=	(book value of equity) / market value of equity;
ABS(ACCRL)	=	(absolute value of total $accruals_{t-1}$)/average total $assets_{t-1}$;
GROWTH	=	sales growth calculated as (sales – $sales_{t-1}$)/$sales_{t-1}$;
ALTMAN	=	Altman's (1983) scores;

[13] I winsorize all variables at the 1 and 99 percent levels before estimating my main models in the full samples of each audit-quality proxy.

STDEARN = standard deviation of income before extraordinary items in the past four years;

YEAR F.E. = year fixed effects.

Prior literature documents that auditor industry specialization increases audit quality and reduces the absolute value of discretionary accruals and discretionary revenue, and it increases the auditor's propensity to issue a going-concern opinion. Consistent with Balsam et al. (2003) and Reichelt and Wang (2010), lower discretionary accruals are expected for larger firms (*LOG_MKT*), firms with higher operating cash flow (*CFO*), firms with higher leverage (*LEV*), firms audited by a Big 4 auditor (*BIG4*), and firms with longer tenure (*TENURE*). Higher absolute discretionary accruals are expected for growth firms (*GROWTH* and *BTM*), firms with losses (*LOSS*), firms with extreme performance (*ROA* and *ROAL*), firms with high-income volatility (*STDEARN*), firms with high probability of bankruptcy (*ALTMAN*), and for firms with higher prior total accruals (*ABS(ACCRL)*). I expect the signs of all controls variables to be similar in the discretionary revenue model as both proxies are influenced similarly by incentives and opportunities for earnings management.

In the going-concern model, I expect that the probability of going concern will be lower for larger and more stable clients (*LOG_MKT, BIG4, TENURE*), and decrease as liquidity (*CFO, ALTMAN*) and profitability increases (*ROAL, ROA*). On the other hand, the probability of going concern will increase as risk (*STDREARN*, *ABS(ACCRL)*, *LOSS*) and leverage increases (*LEV*).[14]

[14] Consistent with prior studies, the discretionary accruals and discretionary revenue models do not include industry fixed effects because these measures are estimated by industry. My going-concern model, estimated using logistic regression, includes both year and industry fixed effects.

Analysis of matched samples: pooled and pair-wise differences models

For each specialization measure, *NLEAD1* and *CLEAD1*, I pair-match clients of specialist and non-specialist auditors by fiscal year-end month and industry, within a 50 percent size distance, selecting the peer with the highest stock return covariance from all the possible matches. I estimate two alternative models using the matched samples. First, I estimate Equation (6) in the pooled matched sample of clients of specialist and non-specialist auditors. Second, for the discretionary accruals and discretionary revenue proxies, I estimate the following pair-wise differences model as per Cram et al. (2009):

$$\begin{aligned} QUALITY\_MEASUREij_t = \; & \gamma_0 + \gamma_1 BIG4ij_t + \gamma_2 LOGMKTij_t + \gamma_3 LEVij_t + \gamma_4 ROAij_t \\ & + \gamma_5 ROALij_t + \gamma_6 LOSSij_t + \gamma_7 CFOij_t + \gamma_8 BTMij_t \\ & + \gamma_9 ABS(ACCRLij)_t + \gamma_{10} GROWTHij_t + \gamma_{11} ALTMANij_t \\ & + \gamma_{12} STDEARNij_t + \gamma_{13} TENUREij_t + \gamma_{14} YEAR\ F.E. + u_t \end{aligned} \tag{7}$$

where for fiscal year-end *t*, *ij* denotes the pair-wise difference between the value of each variable (as previously defined) for the client of the specialist auditor minus the value of the same variable for the matched client of a non-specialist auditor, and the intercept γ_0 represents the average pair-wise difference between matched observations, controlling for the effect of differences resulting from imperfectly matched variables. For the going-concern audit-quality proxy, I estimate a conditional fixed effects logistic regression, using the pair matched observations with intra-pair variation in going concern.

Data and sample selection

For the discretionary accruals analyses, I use U.S. public company data for the years 1988 to 2008 from COMPUSTAT and data for the years 2000 to 2008 from Audit Analytics.[15] I delete firms in the financial services industries (SIC codes 6000–6999), firms with negative assets, market price, or sales, and firms without the necessary data to calculate the control variables in the main regression model. This results in a full sample consisting of 75,188 firm-year observations with the national-level measure. The sample size is reduced to 23,307 firm-year observations with the city-level measure. This measure is calculated for the years 2000 to 2008 with auditor city data in Audit Analytics and a corresponding city in the U.S. Census Bureau MSA classification.

For the discretionary revenue analyses, I start with the national and city-level samples that I use in the discretionary accruals analyses. I delete firms without the additional variables required to calculate the discretionary revenue proxy as per Stubben (2010), in particular the changes in accounts receivables from the statement of cash flows. This results in a full sample consisting of 69,512 firm-year observations with the national-level measure and 21,914 firm-year observations with the city-level measure.

For the propensity to issue going-concern analyses, I use U.S. public company data for the years 2000 to 2008 from COMPUSTAT and auditor opinion data from Audit Analytics. I delete firms in the financial services industries, firms with negative assets, market price, or sales, and firms without the necessary data to calculate the control variables in the main regression

[15] I restrict my analyses to this time period because reported operating cash flows, needed to calculate discretionary accruals, are only available starting from 1988 as per SFAS No. 95 (FASB 1987).

model. This results in a full sample consisting of 35,406 firm-year observations with the national-level measure and 23,349 firm-year observations with the city-level measure.[16]

V. RESULTS

Discretionary accruals –full-sample analyses

Table 1 presents the descriptive statistics of the full sample. Panel A shows how client size, performance, and total accruals vary across the top eight auditors ranked by within-industry market share at U.S. national level. I calculate the ranks by industry and year. For example, for two-digit SIC 49, in year 2007, the auditor with the highest market share for that two-digit SIC will be in the first rank, the auditor with the second highest will be in the second rank, and so on. Clients of auditors with high market share are larger, have better performance, lower absolute total accruals and lower absolute discretionary accruals and discretionary revenue. This pattern is persistent regardless of the cut-off value used to divide specialist and non-specialist auditors.

Table 1, Panel B shows the descriptive statistics of the national-level full sample and for a partition using *NLEAD1* as measure of auditor industry specialization. Clients of national-level specialist auditors represent 10.84 percent of the total sample, similar to the 11.6 percent reported in Reichelt and Wang (2010, p.658). Clients of national-level specialists have on average approximately 2 percent lower absolute discretionary accruals, are more than two times larger, have more leverage, have lower total accruals and exhibit better performance in terms of profitability, losses, cash flow from operations, and growth, compared to clients of non-specialist auditors. Table 1, Panel C shows the descriptive statistics of the city-level full sample and for a

[16] Some prior studies, such as Balsam et al. (2003) and Krishnan (2003), eliminate clients of the Big 4 firms from their sample in order to get a cleaner test of specialization separate from the Big 4 effect. In order to get the largest possible sample size, I keep clients of all firms in my main analyses, controlling for the Big 4 effect using an indicator variable for clients of these auditors. This is consistent with Reichelt and Wang (2010).

partition using *CLEAD1* as measure of auditor industry specialization. Clients of city-level specialist auditors represent 33.8 percent of the total sample, similar to 35 percent in Reichelt and Wang (2010, p.658), and the city-level partition has similar differences in characteristics compared to the national-level partition; however, the size difference is more pronounced using the city-level partition.

Table 2 presents the results of the full-sample analyses using *NLEAD1* and *CLEAD1* as measures of auditor specialization. In line with previous studies, the coefficient on both variables in the first two columns show that clients of specialist auditors have on average from 0.26 to 0.37 percent lower absolute discretionary accruals compared to clients of non-specialists auditors.

Discretionary accruals –matched sample analyses

Table 1, Panel B presents the descriptive statistics for the national-level matched sample of clients of specialist and non-specialist auditors. Using *NLEAD1* as measure of auditor industry specialization, I was able to find a match for 5,479 clients of the specialist auditors within the specified criteria. In this matched sample, clients of the specialist auditors have statistically insignificant differences (at 1 percent level) in absolute discretionary accruals, are on average approximately 1.2 times larger, have more leverage, and exhibit statistically weak differences (at 5 percent level) in performance in terms of profitability, losses, cash flow from operations, and growth, compared to clients of non-specialist auditors. Other variables still exhibit statistically significant differences, but the magnitude of the differences is considerably smaller than in the full sample. These results show that the matching procedure balances performance and growth, and mitigates size differences, but it does not fully mitigate differences in all variables across the two auditor groups. Table 1, Panel C presents the descriptive statistics for the city-level matched sample of clients of industry specialist and non-specialist auditors. Using *CLEAD1* as measure of auditor industry specialization, I was able to find a match for 4,979 clients of the specialist auditors within the specified criteria. At the city level, the matching procedure is not as effective in mitigating size and performance differences, primarily due to a different percentage of potential control observation for each treatment observation in the full sample. In this matched sample, there is a weakly significant difference (at 10 percent level) in mean absolute discretionary accruals between specialist and non-specialist auditor clients; however, the magnitude of the difference is roughly 7 percent (-0.002 compared to -0.028) of the difference in means for the full sample.

Table 2 presents the results of the pooled matched sample analyses using *NLEAD1* and *CLEAD1* as measures of auditor specialization. The coefficient on both variables, in the last two columns, is statistically insignificant (at 1 percent level). Similarly, in Table 3, the statistically insignificant coefficients on the intercept of the pair-wise differences regression indicate that, controlling for unmatched characteristics between observations, there are no differences in absolute discretionary accruals between specialist and non-specialist auditors. The combined evidence from the univariate difference in means, pooled multivariate regressions, and pair-wise differences regressions suggests that after controlling for differences in client characteristics between the two auditor groups by matching, the extant research design is unable to detect differences in absolute discretionary accruals as a result of auditor industry specialization.

Discretionary revenue –full-sample analyses

Table 4 presents the descriptive statistics of the full sample. Panel A shows the descriptive statistics of the national-level full sample and for a partition using *NLEAD1* as measure of auditor industry specialization. Clients of national-level specialist auditors have similar proportions as those in the discretionary accruals sample and exhibit approximately 0.8 percent lower absolute discretionary revenue on average, compared to clients of non-specialist auditors. The separation of client characteristics is very similar to those in the discretionary accruals samples. Table 4, Panel B shows the descriptive statistics of the city-level full sample and for a partition using *CLEAD1* as measure of auditor industry specialization. Clients of city-level specialist auditors exhibit similar characteristics as the clients of national-level specialist auditors, compared to the clients of non-specialist auditors; however, the size difference is more pronounced in the city-level partition than in the national-level partition.

Table 5 presents the results of the full-sample analyses using *NLEAD1* and *CLEAD1* as measures of auditor specialization, the coefficient on both variables in the first two columns show that clients of specialist auditors have on average from 0.13 to 0.2 percent lower absolute discretionary revenue compared to clients of non-specialists auditors. These full-sample results are consistent with the discretionary accruals full-sample results.

Discretionary revenue –matched sample analyses

Table 4, Panel A presents the descriptive statistics for the national-level matched sample of clients of industry specialist and non-specialist auditors. Using *NLEAD1* as measure of auditor industry specialization, I find a match for 5,053 clients of the specialist auditors within the specified criteria. In this matched sample, clients of the specialist auditors have statistically insignificant differences (at 1 percent level) in absolute discretionary revenue. The matching procedure balances performance and growth, mitigates size differences, but it does not fully mitigate differences in all variables across the two auditor groups. Table 4, Panel B presents the descriptive statistics for the city-level matched sample of clients of industry specialist and non-specialist auditors. Using *CLEAD1* as measure of auditor industry specialization, I was able to find a match for 4,695 clients of the specialist auditors within the specified criteria. At the city level, the matching procedure is not as effective at mitigating size and performance differences; nevertheless, in this matched sample, there is a statistically insignificant difference (at 10 percent level) in mean absolute discretionary revenue between specialist and non-specialist auditor clients.

Table 5 presents the results of the pooled matched sample analyses using *NLEAD1* and *CLEAD1* as measures of auditor specialization. The coefficient on both variables, in the last two columns, is statistically insignificant (at 1 percent level). Similarly, in Table 6, the statistically insignificant coefficients on the intercept of the pair-wise differences regression indicate that, controlling for unmatched characteristics between observations, there are no differences in absolute discretionary revenue between specialist and non-specialist auditors. These matched sample results are in line with the discretionary accruals matched sample results.

Propensity to issue a going-concern opinion –full-sample analyses

Table 7 presents the descriptive statistics of the full sample. This sample is smaller than the previous two samples because auditor opinion data in Audit Analytics is only available since 2000. Panel A shows the descriptive statistics of the national level full sample and for a partition using *NLEAD1* as measure of auditor industry specialization. Clients of national-level specialist auditors have a slightly higher proportion than those in the previous two full samples and exhibit approximately 4.3 percent incidence of going concern, compared to 10.2 percent for clients of non-specialist auditors. This is consistent with auditor specialists having larger and more profitable clients, which are generally less likely to go bankrupt. Table 7, Panel B shows the descriptive statistics of the city level full sample and for a partition using *CLEAD1* as measure of auditor industry specialization.

Table 8 presents the results of the full-sample analyses using *NLEAD1* and *CLEAD1* as measures of auditor specialization. In these analyses, only the coefficient on the city-level measure of specialization is significant (at 1 percent level) and in the right direction, indicating that clients of city-level specialist auditors are more likely to issue going-concern opinions.

Propensity to issue a going-concern opinion –matched sample analyses

Table 7, Panel A, presents the descriptive statistics for the national-level matched sample of clients of industry specialist and non-specialist auditors. Using *NLEAD1* as measure of auditor industry specialization, I was able to find a match for 2,539 clients of the specialist auditors within the specified criteria. In this matched sample, clients of the specialist auditors have statistically insignificant differences (at 1 percent level) in incidence of going-concern opinion. Panel B shows the city-level matched sample. Using *CLEAD1* as measure of auditor industry specialization, I was able to find a match for 4,951 clients of the specialist auditors within the specified criteria. In this matched sample, there is a statistically insignificant difference (at 10 percent level) in incidence of going-concern opinion between clients of specialist and non-specialist auditor clients.

Table 8 presents the results of the pooled matched sample analyses using *NLEAD1* and *CLEAD1* as measures of auditor specialization. The coefficient on both variables, in the last two columns, is statistically insignificant (at 1 percent level). In Table 9, the statistically insignificant coefficients on the *NLEAD1* and *CLEAD1* conditional logistic regression indicate that, controlling for unmatched characteristics between observations, there are no differences in propensity to issue a going-concern opinion between specialist and non-specialist auditors. The results of this procedure should be interpreted with caution because they are based on a small sample of matched pairs with intra-pair variation in going-concern opinions; however, they confirm the more general results from the overall difference in means between specialist and non-specialist auditors and from the pooled logistic regression.[17]

After matching economically comparable clients between specialist and non-specialist auditors, in all the matched samples, I find that the treatment effects of specialist auditors are insignificantly different from those of non-specialist auditors with respect to absolute discretionary accruals, absolute discretionary revenue, and auditor's propensity to issue a going-concern opinion.

VI. ANALYSES OF AUDITOR SWITCHES

I take advantage of the setting created by the demise of Arthur Andersen (AA), after the firm's indictment for obstruction of justice in 2002, to examine the changes in absolute discretionary accruals and absolute discretionary revenue in former AA clients as a result of a switch to a specialist auditor. Previous studies examining the result of this unique exogenous shock find that there was a negative market reaction for AA clients during the key dates in the AA trial (Chaney and Philipich 2002; Callen and Morel 2003), although there were some confounding market events around the same dates (Nelson et al. 2008); that successor auditors required more conservative accounting for former AA clients (Nagy 2005; Cahan and Zhang 2006); and that the differences pre-post switch were related to whether former AA employees continued auditing the client after they were hired by the successor auditor in 2002 (Blouin et al. 2007). A more general study by Knechel et al. (2007) examines 318 non-AA clients that switched auditors between 2000 and 2003, and documents that those clients who switched from non-specialist to specialist auditors experienced statistically significant positive abnormal returns of 2.5 percent surrounding the date of the auditor change, providing additional evidence of a

[17] I estimate these regressions using the Stata command clogit. Tenure, year, and industry-specific intercepts are not included because there is insufficient intra-pair variation in these variables.

perceived specialist auditor effect.

In order to test whether there was a pre-post effect of a switch to a specialist auditor for AA former clients, using each client as its own control, first I estimate the following regression for AA clients:

$$\Delta QUALITY\_MEASURE_i = \delta_0 + \delta_1 \Delta LEAD_i + \delta_2 \Delta BIG4_i + \delta_3 \Delta LOGMKT_i + \delta_4 \Delta LEV_i + \delta_5 \Delta ROA_i + \delta_6 \Delta ROAL_i + \delta_7 \Delta LOSS_i + \delta_8 \Delta CFO_i + \delta_9 \Delta BTM_i + \delta_{10} \Delta ABS(ACCRL)_i + \delta_{11} \Delta GROWTH_i + \delta_{12} \Delta ALTMAN_i + \delta_{13} \Delta STDEARN_i + v_i \quad (8)$$

where Δ denotes the difference between the level of each variable (as previously defined) in 2002 and the level of that variable in 2001. In this model, the intercept δ_0 represents the average change in dependent variable controlling for changes in other characteristics, and the coefficient δ_1 on $\Delta LEAD$ represents the incremental change as a result of switching between specialist and non-specialist auditors ($\Delta NLEAD$ and $\Delta CLEAD$ at national and city-level respectively).

To test whether there was an effect of a switch to a specialist auditor for AA former clients, compared to a control group of economically comparable clients, for each specialization measure, I pair-match AA and non-AA clients in 2001 by fiscal year-end month and industry, within a 50 percent size distance, keeping the pairs with the highest stock return covariance from all the possible matches. Using the matched sample of AA and non-AA clients, I estimate the following pre-post regression:

$$\Delta QUALITY\_MEASURE_i = \rho_0 + \rho_1 AA_i + \rho_2 \Delta LEAD1_i + \rho_3 AA\_\Delta LEAD_i + \rho_4 \Delta BIG4_i + \rho_5 \Delta LOG\_MKT + \rho_6 \Delta ROA_i + \rho_7 \Delta ROAL_i + \rho_8 \Delta LOSS_i + \rho_9 \Delta CFO_i + \rho_{10} \Delta BTM_i + \rho_{11} \Delta ABS(ACCRL)_i + \rho_{12} \Delta GROWTH_i + \rho_{13} \Delta ALTMAN_i + \rho_{14} \Delta STDEARN_i + z_i \quad (9)$$

where Δ denotes the level of each variable (as previously defined) in 2002 minus the level of that variable in 2001 for all clients in the sample, and for client *i*

AA	=	"1" for AA clients and "0" otherwise; and,
AA_ΔLEAD	=	interaction term between AA and changes between specialist auditors, where *ΔLEAD*= "-1" for clients that switched in industries where AA was a specialist and the successor is not a specialist auditor, *ΔLEAD*= "1" for clients that switched in industries where AA was not a specialist and the successor is a specialist auditor, and *ΔLEAD*= "0" for all other cases.

An advantage of this research design is that it uses an exogenous shock to test whether specialist auditors have a direct and immediate impact on the client's financial reporting quality. Nevertheless, there are limitations inherent to these analyses. First, as noted by Blouin et al. (2007), in several instances, former AA employees were hired by the successor auditors and continued to audit the same clients. Second, there were changes in the environment that may have motivated all auditors, specialist and non-specialist, to be more conservative in 2002. Third, the effect of auditor specialization may not be immediately reflected in the two proxies for financial reporting quality used in these analyses. I expect these results to be incremental to the matched sample analyses, providing additional evidence on the shortcomings of the extant methodology to test the association between auditor industry expertise and audit quality.

To analyze auditor switches, I use 393 AA clients that switched to a different auditor during 2002, and for which I can estimate the discretionary accruals, discretionary revenue, and auditor specialization proxies.[18] Next, I identify clients of other auditors in 2001 that did not switch auditors in 2002. After matching AA clients to an economically comparable group of non-

[18] I do not use going-concern opinions in this analysis due to the low incidence of this variable within the clients in my AA sample.

AA clients in 2001, the differences-in-differences sample has 287 AA clients and 287 non-AA clients.

Panel A of Table 10 shows the results of the multivariate pre-post analyses for AA clients. I do not find evidence of a pre-post change in discretionary accruals or discretionary revenue as a result from switching between specialist and non-specialist auditors. Panel B, the differences-in-differences results, comparing changes between 2002 and 2001 for AA and non-AA clients, shows a weakly statistically significant coefficient (at 10 percent level) in the wrong direction for the interaction variable *AA_CLEAD1* in column three, and statistically insignificant coefficients for this interaction term in all other columns, suggesting that there was no effect in absolute discretionary accruals or absolute discretionary revenue from a switch between specialist and non-specialist auditors for former AA clients. The results in Table 8 are robust to excluding clients in industries where AA was a specialist, and switching to a non-specialist auditor ($\Delta LEAD1 = -1$), or clients in industries where AA was a specialist, and switching to a specialist auditor ($\Delta LEAD1 = 0$ and $LEAD1 = 1$). The results of the switches analyses are robust to standard errors calculated using 1,000 bootstrap replications, mitigating the concerns that the low statistical significance could be a result of small sample size.

VII. SIMULATION ANALYSES

Using a simulation procedure, I investigate whether the observed association between audit quality and auditor industry specialization could be observed when clients are assigned to five auditors at random. This simulation approach aims to examine the effectiveness of the extant methodology to isolate the effects of client characteristics from the effects of auditor industry specialization.[19] The simulation is conducted in four steps; first, each year I randomly assign all clients in the full discretionary accruals sample, as defined in previous analyses, to five auditors using a draw from a uniform distribution; second, I identify industry specialists using industry market share at national level, calling this simulated variable *LEAD1*, based on the randomly assigned clients; third, I estimate the main regression model (Equation 6) using this simulated sample; and finally, I repeat the first three steps 1,000 times.

Figure 1 shows the coefficients for 1,000 iterations of the simulation procedure, employing *ADA* as dependent variable and *LEAD1* as measure of auditor industry specialization. The coefficient estimate for *LEAD1* is negative in 97.4 percent of the iterations and has a mean statistically different from zero (at 1 percent level) of -0.0025. In these simulations, the auditors that are randomly assigned a sufficient number of the largest clients in each industry are often designated as specialists, and these auditors appear to be of higher quality compared to non-designated specialists. Overall, the results from the simulations are suggestive that client characteristics, particularly client size, influence the observed association between audit quality and auditor industry specialization, and that the hypothesized causal effect can be partially replicated by random assignment of clients to auditors. Nonetheless, there is a limitation inherent to these analyses, the randomly assigned clients from the original full sample were actually audited by specialist or non-specialist auditors, and the actual proportion of clients audited by specialists is increasing as client size increases, thus the designated specialists in the simulation have clients from both specialist and non-specialist groups.

[19] This approach is similar to the one used by Carson and Fargher (2007) to assess the importance of client size to determine audit fee premiums.

VIII. ADDITIONAL MATCHING ANALYSES AND SENSITIVITY TESTS

Propensity score matching

Another approach that can be used to find comparable firms is the propensity score methodology proposed by Rosenbaum and Rubin (1983). Propensity score matching is a widely used methodology to find a group of comparable cases and control observations to mitigate the effect of self-selection in observational causal studies. In general, propensity score matching can be used to pair match observations that belong to two different regimes, in the context of this study, to find comparable clients audited by specialist and non-specialist auditors. A potential drawback of this approach is that it depends on the specification of the choice model, known as the "strongly ignorable treatment assignment assumption." The main advantage of propensity-score matching is that it's usually effective at selecting observations that are closely matched in the predefined covariates.

For each audit-quality proxy and specialization measure, I match clients of specialist and non-specialist auditors using propensity scores. I predict the propensity of choosing specialist auditors at national or city level using a logistic regression where the dependent variable is the specialist indicator variable and the independent variables are all the control variables in the main model, including industry and year-indicator variables (Equation (6)). I match observations by propensity score, within common support, without replacement, using a caliper distance of 0.03, and estimate the main model in the matched sample of clients of industry specialist and non-specialist auditors. [20] Using this methodology, I again find that clients of the industry specialist

[20] These propensity score settings are consistent with Lawrence at al. (2010) and generally result in balanced covariates between auditor groups. I obtain similar results by reducing the caliper distance, although this reduces the sample size further. I also use the logarithm of total assets in the propensity score calculation as a size variable, instead of the logarithm of market value, and find the same results in my matched samples as those documented in my main analyses. In general, the logarithm of total assets in the model results in more balanced client characteristics

auditors have statistically insignificant differences in absolute discretionary accruals, absolute discretionary revenue, and incidence of going-concern opinions, compared to clients of non-specialist auditors.

Size and industry matching

I match clients of specialist and non-specialist auditors by year, industry, and total assets only. I match observations using propensity score, estimated using the logarithm of total assets and industry and year indicator variables as predictors in the logistic regression, within common support, without replacement, and using a caliper distance of 0.03. In the industry and size matched samples, clients of the specialist auditors have statistically insignificant differences in absolute discretionary accruals, absolute discretionary revenue, and incidence of going-concern opinions, compared to clients of non-specialist auditors, estimated using the main model on each matched sample.

In general, I find that the industry and size matching are successful at balancing size, performance, and leverage between auditor groups, but are not successful at mitigating differences in cash flow from operations and absolute accruals between auditor groups. These results suggest that, within an industry, a close match on client size is an alternative to a close match on returns covariance or to a match on several covariates. These alternatives might not be equivalent in small samples where idiosyncratic differences need to be more closely matched between the case and control groups, and for those samples researchers should aim to use the comparability measures that produce the best possible balance between matched observations.

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between auditor groups. I only observe a difference in the city-level going-concern analysis, where I observe a statistically significant coefficient on the variable *CLEAD1* (at 5 percent level) in the matched sample regression model, using the logarithm of market value in addition to the other covariates of the propensity score model, but a statistically insignificant coefficient (at 10 percent level) using the logarithm of total assets in addition to the other covariates of the propensity score model.

Overall, companies of similar size within an industry have correlated stock returns and exhibit similar performance, and matching clients on these criteria using alternative specifications shows that the extant research design cannot distinguish between the clients of specialist and non-specialist auditors.

Bootstrap, random sub-samples, and stratified samples

To mitigate concerns that the lack of significance in the matched samples analyses is not a result of smaller sample sizes, I perform three types of sensitivity analyses. First, I estimate bootstrap standard errors for all the matched sample models using 1,000 replications and find similar results as those documented in the main tables. Second, for the national and city-level full samples of the three audit-quality proxies, I draw a random sub-sample of the same size as the matched sample and estimate the main models with bootstrap standard errors using 500 replications. I find that sample size does not affect the results for the discretionary accruals and discretionary revenue models. For the going-concern samples, I find that the results are sensitive to sample size due to the low incidence of going-concern opinions, equal to 9.5 percent in the full sample. Third, I examine whether the matched sample results hold separately for industries where auditor specialization could matter incrementally to detect earnings management or to determine the probability of going concern. Managers could have more opportunities for manipulation in industries with high total accruals and high volatility of earnings, and may also face higher incentives to meet expectations in competitive or high-growth industries. Similarly, determining the probability of going concern is difficult for low-growth industries, where competition is intense and there is high-earnings volatility. For each industry and year in the matched samples, I calculate the median total accruals using the variable *ABS(ACCRL)*, median sales growth using the variable *GROWTH*, median industry concentration using the Herfindahl index based on total assets, and median earnings volatility using the variable *STDEARN*. Next, each year I rank industries using the industry median for each of these variables and estimate the main models separately for observations in the top and bottom quartiles. I find similar results to those documented in the main tables using the full matched samples.

Alternative measures of auditor industry specialization

I perform all of the full and matched sample analyses using an alternative market share cut-off for the national and city-level specialist measures, equal to “1” for auditors that have over 30 percent market share in a given industry and year, and “0” otherwise. This measure results in a greater number of clients deemed to be audited by a specialist, and larger matched samples than in the results shown in the main tables. Using this alternative measure, the effects of auditor industry specialization are also statistically insignificant in the matched samples for all three audit-quality proxies and in the pre-post switch analysis for Arthur Andersen clients. Moreover, using this alternative measure, the coefficient on the city-level specialist variable (*CLEAD1*=0.0042) for the discretionary accruals matched sample is significant (at 1 percent level) in opposite direction, mitigating the concerns that the lack of statistical significance in the match samples is a result of smaller sample size.

I addition, I repeat all the full and matched sample analyses using a combined measure of city-level and national-level auditor industry specialization, equal to “1” for auditors that are specialists at both levels in a given industry and year, and “0” otherwise. I match clients of combined city-level and national-level experts with clients of other auditors. The effect of combined national and city-level auditor industry specialization is statistically insignificant in the matched samples for all three audit-quality proxies.

IX. CONCLUSION

To determine causal inference in observational studies, empirical researchers should aim to compare treated and control groups that have similar client characteristics, ideally approximating experimental conditions. A potential way to achieve this objective is by matching treatment and control observations on all relevant observable dimensions except for the treatment variable. This study proposes a methodology to find economically comparable clients in tests of audit quality and applies it to mitigate the effect differences in client characteristics between specialists and non-specialist auditors in tests of auditor industry specialization and audit quality.

I use discretionary accruals, discretionary revenue, and propensity to issue a going-concern opinion as proxies for audit quality, and within-industry market share proxies for auditor industry specialization at the U.S. national and city level, and after matching clients of specialist and non-specialist auditors, I document that the previously documented association between auditor industry specialization and audit quality may be attributable to client characteristics. I match clients based on economic comparability, by year, industry, size, and returns covariance. Alternatively, I also match clients using different specifications of a propensity score model.

Furthermore, I do not find evidence of a pre-post change in discretionary accruals or discretionary revenue resulting from an exogenous switch between specialist and non-specialist auditors for a sample of Arthur Andersen clients that changed auditors in 2002. Finally, using a simulation approach, I find that client characteristics, particularly client size, influence the observed association between audit quality and auditor industry specialization, and that the hypothesized causal effect can be partially replicated by random assignation of clients to auditors.

The results of this study do not imply that industry knowledge does not contribute to audit quality, but that the extant methodology does not fully capture the effects of auditor industry expertise.

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APPENDIX A –Variable Definitions

ADA	=	absolute discretionary accruals estimated using the cross-sectional Jones (1991) model, including *ROA* as per Kothari et al. (2005), estimated by industry and year;
ADA_FULL	=	absolute discretionary accruals estimated using the cross-sectional Jones (1991) model, including *ROA* (Kothari et al. 2005), cash flows in periods *t* and *t-1* scaled by total assets (McNichols 2002), and a non-linear interaction term based on the sign of cash flows in period *t* (Ball and Shivakumar, 2006);
ADREV	=	absolute discretionary revenue estimated using the cross-sectional Stubben (2010) model, estimated by industry and year;
NLEAD1	=	"1" for auditors that have the largest market share in a given industry at the U.S. national level and have more than 10 percent greater market share than the closest competitor, and "0" otherwise;
CLEAD1	=	"1" for auditors that have the largest market share in a given industry at the U.S. city level, where city is defined as a Metropolitan Statistical Area following the 2003 U.S. Census Bureau MSA definitions, and have more than 10 percent greater market share than the closest competitor, and "0" otherwise.
BIG4	=	"1" if the client has a Big 4 auditor and "0" otherwise;
LOG_MKT	=	natural logarithm of market value;
LEV	=	(total liabilities)/average total assets;
ROA	=	(net income)/average total assets;
ROAL	=	(net income$_{t-1}$) / average total assets $_{t-1}$;
LOSS	=	indicator variable equal one if net income is negative, and "0" otherwise;
CFO	=	(cash flow from operations)/average total assets;
BTM	=	(book value of equity)/market value of equity;
ABS(ACCRL)	=	absolute value of (total accruals$_{t-1}$)/average total assets$_{t-1}$;
GROWTH	=	sales growth calculated as (sales – sales$_{t-1}$)/sales$_{t-1}$;
ALTMAN	=	Altman's (1983) scores;
STDEARN	=	standard deviation of income before extraordinary items in the past four years;
YEAR	=	year fixed effects;
AA	=	"1" for AA clients and "0" otherwise;
ΔLEAD_AA		interaction term between *AA* and changes between specialist auditors, where *ΔLEAD*= "-1" for clients that switched in industries where AA was a specialist and the successor is not a specialist auditor, *ΔLEAD*= "1" for clients that switched in industries where AA was not a specialist and the successor is a specialist auditor, and *ΔLEAD*= "0" for all other cases;
ij	=	pair-wise difference between matched observations; and,
Δ		one-year change in the level of each variable.

APPENDIX B – Summary of Discretionary Accruals and Discretionary Revenue Estimates

Jones (1991) discretionary accruals model including *ROA:*

$$AC_{i,t} = \alpha + \beta_1 \Delta R_{i,t} + \beta_2 PPE_{i,t} + \beta_3 ROA_{i,t} + \varepsilon_{i,t} \tag{3}$$

Jones (1991) discretionary accruals model including *ROA* and other accrual drivers:

$$\begin{aligned} AC_{i,t} = {} & \alpha + \beta_1 \Delta R_{i,t} + \beta_2 PPE_{i,t} + \beta_3 ROA_{i,t} + \beta_4 CFO_{i,t-1} + \beta_5 CFO_{i,t} \\ & + \beta_6 CFO_{i,t+1} + \beta_7 D_{i,t} + \beta_8 D \times CFO_{i,t} + \varepsilon_{jt} \end{aligned} \tag{4}$$

Stubben (2010) discretionary revenue model:

$$\begin{aligned} \Delta AR_{i,t} = {} & \alpha + \beta_1 \Delta R_{i,t} + \beta_2 \Delta R_{i,t} \times SIZE_{i,t} + \beta_3 \Delta R_{i,t} \times AGE_{i,t} + \beta_4 \Delta R_{i,t} \times AGE\_SQ_{i,t} \\ & + \beta_5 \Delta R_{i,t} \times GRR\_P_{i,t} + \beta_6 \Delta R_{i,t} \times GRR\_N_{i,t} + \beta_7 \Delta R_{i,t} \times GRM_{i,t} \\ & + \beta_8 \Delta R_{i,t} \times GRM\_SQ_{i,t} + \varepsilon_{jt} \end{aligned} \tag{5}$$

where for each firm *i*, and fiscal year-end *t*:

ADA_JROA	=	absolute value of error term $\varepsilon_{i,t}$ in Equation (3) ;
ADA_FULL	=	absolute value of error term $\varepsilon_{i,t}$ in Equation (4);
ADREV	=	absolute value of error term $\varepsilon_{i,t}$ in Equation (5);
AC	=	(cash flow from operations - income before extraordinary items)/average total assets;
ΔR	=	(revenue_t - revenue_{t-1})/average total assets;
PPE	=	gross property, plant and equipment/average total assets;
ROA	=	(net income before extraordinary items)/average total assets;
CFO	=	(cash flow from operations)/average total assets;
D	=	“1” if CFO is negative and “0” otherwise;
ΔAR	=	change in accounts receivable reported in the cash flow statement;
SIZE	=	natural logarithm of total assets;
AGE	=	natural logarithm of the number of years since the firm has data in COMPUSTAT;
GRR_P	=	industry-median-adjusted revenue growth (=0 if negative);
GRR_N	=	industry-median-adjusted revenue growth (=0 if positive);
GRM	=	industry-median-adjusted gross margin; and
_SQ	=	square of variable.

I estimate each model by industry (defined as two-digit SIC code) and year, eliminating observations in industries with less than 20 observations. All variables are winsorized at the 1 and 99 percent levels before estimating each model.

TABLE 1 –Discretionary Accruals Analyses
Descriptive Statistics
PANEL A: Ranking Auditors by Industry Market Share at National Level

Market share rank	***Total Number of clients***	***Total assets*** *Mean Median*	***Market value*** *Mean Median*	***ROA*** *Mean Median*	***GROWTH*** *Mean Median*	***ABS(ACCRL)*** *Mean Median*	***ADA*** *Mean Median*
1	14,759	3,444	3,671	-0.006	0.077	0.136	0.055
		467	434	0.037	0.061	0.062	0.036
2	12,947	2,552	2,697	-0.005	0.082	0.133	0.057
		366	316	0.037	0.066	0.062	0.037
3	11,659	1,941	2,151	-0.018	0.079	0.143	0.061
		252	222	0.035	0.066	0.067	0.041
4	10,519	1,433	1,660	-0.036	0.070	0.160	0.065
		198	177	0.029	0.063	0.068	0.043
5	7,254	676	886	-0.045	0.074	0.189	0.070
		99	82	0.028	0.066	0.070	0.046
6	5,543	394	454	-0.059	0.066	0.202	0.076
		61	46	0.022	0.060	0.074	0.049
7	3,234	177	171	-0.075	0.054	0.343	0.081
		24	18	0.013	0.048	0.083	0.055
8	1,921	75	82	-0.080	0.074	0.417	0.087
		19	15	0.009	0.049	0.090	0.057

PANEL B: Full Sample Partition by Industry Specialization at National Level (*NLEAD1)*

	Full sample				*NLEAD1 Matched sample matching clients on economic comparability*		
	All Obs. *Mean* *Std Dev*	*NLEAD1=1* *Mean* *Std Dev*	*NLEAD1=0* *Mean* *Std Dev*	*Univariate* *Estimate* *(t-statistic)*	*NLEAD1=1* *Mean* *Std Dev*	*NLEAD1=0* *Mean* *Std Dev*	*Univariate* *Estimate* *(t-statistic)*
ADA	**0.068**	**0.053**	**0.070**	**-0.017*****	**0.054**	**0.054**	**-0.001**
	0.077	**0.060**	**0.079**	**(-19.22)**	**0.063**	**0.065**	**(-0.74)**
Total assets	1,723	3,676	1,486	2,190***	3,790	3,253	537***
	4,873	7,280	4,435	(-38.68)	8,950	7,714	(3.36)
Market value	1,823	3,851	1,644	2,207***	4,879	4,101	778**
	6,202	9,066	5,711	(-30.53)	18,857	16,180	(2.32)
BIG4	0.793	0.981	0.771	0.210***	0.975	0.894	0.081***
	0.405	0.137	0.421	(44.86)	0.156	0.308	(17.37)
LOG_MKT	4.870	5.990	4.734	1.256***	6.038	5.890	0.148***
	2.535	2.510	2.505	(42.70)	2.330	2.291	(3.36)
LEV	0.256	0.282	0.253	0.029***	0.278	0.269	0.009**
	0.251	0.238	0.253	(9.84)	0.236	0.226	(2.06)
ROAL	-0.035	0.005	-0.040	0.045***	0.005	-0.004	0.009*
	0.263	0.195	0.270	(14.52)	0.223	0.293	(1.82)
ROA	-0.046	-0.004	-0.051	0.046***	-0.002	-0.010	0.008*
	0.254	0.187	0.260	(15.63)	0.199	0.247	(1.78)
LOSS	0.364	0.285	0.373	-0.088***	0.288	0.297	-0.009
	0.481	0.451	0.484	(-15.66)	0.453	0.457	(-1.03)
CFO	0.029	0.061	0.025	0.036***	0.061	0.054	0.007*
	0.201	0.158	0.205	(15.17)	0.163	0.229	(1.88)
BTM	0.444	0.419	0.447	-0.028***	0.410	0.445	-0.035***
	0.429	0.369	0.435	(-5.59)	0.742	0.435	(-3.04)
ABS(ACCRL)	0.145	0.102	0.151	-0.049***	0.122	0.126	-0.004
	0.308	0.212	0.318	(-13.43)	0.793	0.799	(-0.24)
GROWTH	0.071	0.078	0.070	0.008**	0.084	0.085	-0.002
	0.318	0.266	0.323	(2.13)	0.378	0.282	(-0.25)
ALTMAN	3.452	3.889	3.398	0.491***	4.263	3.914	0.349**
	8.279	6.341	8.483	(5.05)	10.250	7.783	(2.01)
STDEARN	37.24	62.17	34.22	27.95***	63.14	55.03	8.11***
	94.23	122.20	89.78	(25.39)	153.40	134.60	(2.94)
TENURE	0.993	0.992	0.993	-0.001	0.994	0.994	0.001
	0.084	0.090	0.083	(1.15)	0.076	0.076	(0.00)
N. Obs.	75,188	8,147	67,041	75,188	5,479	5,479	10,958
% Obs.	100.00%	10.84%	89.16%		50.00%	50.00%	

PANEL C: Full Sample Partition by Industry Specialization at City Level (*CLEAD1)*

		Full sample			***CLEAD1 Matched sample matching clients on economic comparability***		
	All Obs. *Mean* *Std Dev*	*CLEAD1=1* *Mean* *Std Dev*	*CLEAD1=0* *Mean* *Std Dev*	*Univariate Estimate (t-statistic)*	*CLEAD1=1* *Mean* *Std Dev*	*CLEAD1=0* *Mean* *Std Dev*	*Univariate Estimate (t-statistic)*
ADA	**0.075**	**0.057**	**0.085**	**-0.028*****	**0.056**	**0.059**	**-0.002***
	0.089	**0.070**	**0.097**	**(-22.68)**	**0.070**	**0.072**	**(-1.74)**
Total assets	1,979	4,128	877	3,251***	3,380	2,673	707***
	5,621	8,238	3,072	(33.44)	8,108	6,203	(4.89)
Market value	2,175	4,399	1,035	3,364***	3,799	2,892	907***
	7,127	10,450	4,129	(35.01)	15,671	12,132	(3.23)
BIG4	0.718	0.940	0.605	0.335***	0.963	0.855	0.108***
	0.450	0.239	0.489	(57.43)	0.189	0.352	(19.09)
LOG_MKT	5.164	6.367	4.548	1.819***	6.407	6.228	0.179***
	2.522	2.382	2.365	(55.43)	1.969	1.922	(4.58)
LEV	0.242	0.259	0.233	0.025***	0.249	0.238	0.011**
	0.284	0.247	0.300	(6.45)	0.245	0.249	(2.17)
ROAL	-0.079	-0.014	-0.112	0.098***	-0.014	-0.038	0.024***
	0.342	0.239	0.380	(20.98)	0.237	0.279	(4.65)
ROA	-0.088	-0.022	-0.123	0.101***	-0.022	-0.042	0.020***
	0.321	0.223	0.356	(23.04)	0.221	0.244	(4.25)
LOSS	0.425	0.318	0.480	-0.162***	0.319	0.364	-0.044***
	0.494	0.466	0.500	(-23.98)	0.466	0.481	(4.67)
CFO	0.003	0.053	-0.022	0.075***	0.051	0.033	0.017***
	0.255	0.182	0.282	(21.58)	0.191	0.204	(4.40)
BTM	0.417	0.388	0.432	-0.044***	0.409	0.425	-0.016**
	0.461	0.380	0.498	(-7.01)	0.394	0.383	(2.06)
ABS(ACCRL)	0.125	0.092	0.142	-0.050***	0.086	0.089	-0.003
	0.171	0.118	0.191	(-21.21)	0.102	0.109	(1.34)
GROWTH	0.052	0.067	0.045	0.022***	0.070	0.063	0.008
	0.310	0.245	0.338	(5.04)	0.351	0.307	(1.19)
ALTMAN	2.306	3.630	1.627	2.003***	4.433	3.968	0.465*
	11.550	7.623	13.060	(12.57)	15.260	9.347	(1.83)
STDEARN	51.42	88.53	32.40	56.13***	71.68	64.13	7.55***
	123.10	165.20	88.66	(33.75)	165.40	140.30	(2.46)
TENURE	0.997	0.996	0.998	-0.002***	0.997	0.999	-0.002*
	0.055	0.064	0.050	(-2.09)	0.053	0.035	(1.79)
N. Obs.[a]	23,307	7,897	15,410	23,307	4,979	4,979	9,958
% Obs.	100.00%	33.88%	66.12%		50.00%	50.00%	

This table presents the descriptive statistics of the data used in the discretionary accruals analyses: Panel A shows descriptive statistics ranking the top eight auditors by market share at industry-national level; Panel B shows descriptive statistics for the full sample and for a partition by industry specialization at national level (*NLEAD1)*; and Panel C shows descriptive statistics for the full sample and for a partition by industry specialization at city level (*CLEAD1*). Matching on economic comparability refers to a pair-wise match of specialist and non-specialist auditors' clients, based on industry, size, and returns covariance. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. [a] The sample size is reduced to those years with auditor city data in audit analytics matched to the U.S. Census Bureau 2003 list of Metropolitan Statistical Areas.

TABLE 2 – Discretionary Accruals Analyses: Pooled Multivariate Tests
Full and Matched Samples

		Dependent variable = ADA			
		Full samples		*Matched samples*	
	Predicted sign	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*
NLEAD1	**(-)**	**-0.0037***** **(-4.39)**		**0.0006** **(0.40)**	
CLEAD1	**(-)**		**-0.0026**** **(-2.18)**		**0.0009** **(0.56)**
BIG4		-0.0082*** (-7.59)	-0.0104*** (-5.87)	-0.0029 (-0.73)	-0.0050 (-1.42)
LOG_MKT		-0.0060*** (-29.02)	-0.0062*** (-15.30)	-0.0050*** (-9.21)	-0.0053*** (-8.71)
LEV		-0.0357*** (-17.30)	-0.0306*** (-8.80)	-0.0288*** (-5.20)	-0.0237*** (-4.66)
ROAL		0.0343*** (6.40)	0.0178** (2.35)	0.0199 (1.25)	0.0034 (0.16)
ROA		-0.1116*** (-16.17)	-0.0985*** (-9.08)	-0.1003*** (-3.91)	-0.1264*** (-4.04)
LOSS		-0.0031*** (-3.54)	-0.0044*** (-2.89)	0.0061** (2.40)	-0.0010 (-0.34)
CFO		-0.0133** (-2.39)	0.0076 (0.77)	0.0054 (0.22)	0.0411 (1.59)
BTM		-0.0242*** (-21.40)	-0.0194*** (-9.99)	-0.0077 (-1.52)	-0.0152*** (-5.26)
ABS(ACCRL)		0.0269*** (16.74)	0.0764*** (11.97)	0.0013 (0.92)	0.0893*** (6.45)
GROWTH		0.0106*** (7.95)	0.0086*** (3.16)	0.0104*** (2.68)	0.0051 (1.59)
ALTMAN		-0.0003*** (-3.76)	-0.0004*** (-3.73)	0.0001 (0.98)	-0.0001* (-1.83)
STDEARN		0.0001*** (6.51)	0.0001*** (3.89)	0.0001** (2.14)	0.0001** (2.48)
TENURE		-0.0046 (-1.44)	0.0006 (0.09)	0.0057 (1.02)	0.0148** (2.44)
Intercept		0.0979*** (23.88)	0.1215*** (16.22)	0.0842*** (8.46)	0.0839*** (9.95)
Year F.E.		*Included*	*Included*	*Included*	*Included*
N. Obs.		75,188	23,307	10,958	9,958
Adj-R^2		0.21	0.25	0.16	0.20

This table presents the pooled discretionary accruals analyses for the full sample and matched samples, using *NLEAD1*and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm. For brevity, the year-specific intercepts are not reported.

TABLE 3 – Discretionary Accruals Analyses: Multivariate Pair-Wise Differences Tests Matched Samples

		Dependent variable = ADAij	
		NLEAD1	*CLEAD1*
	Predicted	*Estimate*	*Estimate*
	sign	*(t-statistic)*	*(t-statistic)*
BIG4ij		-0.0008	-0.0001
		(-0.19)	(-0.03)
LOG_MKTij		0.0052***	0.0008
		(3.68)	(0.51)
LEVij		0.0003	-0.0021
		(0.07)	(-0.28)
ROALij		0.0148	0.0094
		(1.12)	(0.51)
ROAij		-0.0901***	-0.1189***
		(-3.92)	(-3.84)
LOSSij		0.0033	-0.0021
		(1.23)	(-0.64)
CFOij		0.0210	0.0506*
		(1.03)	(1.75)
BTMij		-0.0034	-0.0082*
		(-1.34)	(-1.90)
ABS(ACCRL)ij		0.0009	0.0659***
		(0.19)	(3.92)
GROWTHij		0.0075**	-0.0011
		(2.24)	(-0.32)
ALTMANij		-0.0003**	-0.0003*
		(-2.14)	(-1.87)
STDEARNij		0.0001*	0.0001***
		(1.73)	(3.07)
TENUREij		0.0068	0.0199*
		(0.77)	(1.81)
Intercept	**(-)**	**-0.0013**	**-0.0014**
		(-1.12)	**(-1.02)**
Year F.E.		*Included*	*Included*
N. Obs.		5,479	4,979
Adj-R^2		0.05	0.08

This table presents the pair-wise differences in discretionary accruals for the matched samples, using *NLEAD1* and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A and *ij* denotes the pair-wise difference between matched observations. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm. For brevity, the year-specific intercepts are not reported.

TABLE 4 – Analyses of Discretionary Revenue – Panel A: Full Sample Partition by Industry Specialization at National Level (*NLEAD1)*

	Full Sample				*NLEAD1 Matched sample matching clients on economic comparability*		
	All Obs. Mean Std Dev	*NLEAD1=1 Mean Std Dev*	*NLEAD1=0 Mean Std Dev*	*Univariate Estimate (t-statistic)*	*NLEAD1=1 Mean Std Dev*	*NLEAD1=0 Mean Std Dev*	*Univariate Estimate (t-statistic)*
ADREV	**0.031**	**0.024**	**0.032**	**-0.008*****	**0.024**	**0.023**	**0.001**
	0.038	**0.031**	**0.039**	**(-17.45)**	**0.031**	**0.031**	**(0.84)**
Total assets	1,667	3,594	1,432	2,162***	3,714	3,174	540***
	4,721	7,121	4,280	(38.01)	8,774	7,501	(3.32)
Market value	1,798	3,695	1,566	2,129***	4,697	3,836	861***
	5,855	8,572	5,385	(30.05)	18,141	15,028	(2.60)
BIG4	0.797	0.980	0.775	0.205***	0.973	0.893	0.081***
	0.402	0.141	0.418	(42.33)	0.161	0.310	(16.41)
LOG_MKT	4.878	5.979	4.744	1.235***	6.024	5.870	0.154***
	2.505	2.501	2.472	(40.97)	2.321	2.284	(3.35)
LEV	0.256	0.285	0.253	0.032***	0.281	0.268	0.013***
	0.247	0.238	0.248	(10.74)	0.239	0.224	(2.76)
ROAL	-0.025	0.011	-0.029	0.040***	0.012	0.003	0.009*
	0.241	0.179	0.247	(13.81)	0.210	0.255	(1.91)
ROA	-0.036	0.002	-0.040	0.043***	0.004	- 0.003	0.007*
	0.234	0.170	0.240	(15.04)	0.187	0.192	(1.87)
LOSS	0.353	0.277	0.362	-0.086***	0.280	0.292	- 0.012
	0.478	0.447	0.481	(-14.72)	0.449	0.455	(-1.32)
CFO	0.038	0.067	0.034	0.033***	0.066	0.061	0.006*
	0.183	0.142	0.187	(14.80)	0.149	0.164	(1.85)
BTM	0.446	0.419	0.450	-0.031***	0.409	0.449	- 0.040***
	0.419	0.362	0.425	(-6.13)	0.762	0.432	(-3.25)
ABS(ACCRL)	0.141	0.101	0.146	-0.045***	0.123	0.121	0.003
	0.293	0.205	0.302	(-12.51)	0.823	0.688	(0.18)
GROWTH	0.074	0.081	0.074	0.007*	0.084	0.086	- 0.003
	0.314	0.265	0.320	(1.84)	0.382	0.283	(-0.37)
ALTMAN	3.461	3.770	3.424	0.346***	4.183	3.872	0.311*
	6.884	5.418	7.042	(4.13)	9.530	6.660	(1.91)
STDEARN	36.09	60.83	33.08	27.75***	62.68	53.50	9.18***
	90.68	118.80	86.14	(25.24)	153.70	130.20	(3.24)
TENURE	0.994	0.993	0.995	-0.001	0.994	0.997	- 0.003*
	0.075	0.082	0.074	(-1.40)	0.076	0.056	(-1.94)
N. Obs.	69,512	7,558	61,954	69,512	5,053	5,053	10,106
% Obs.	100.00%	10.87%	89.13%		50.00%	50.00%	

Panel B: Full Sample Partition by Industry Specialization at City Level (*CLEAD1)*

	Full sample				*CLEAD1 Matched sample matching clients on economic comparability*		
	All Obs. *Mean* *Std Dev*	*CLEAD1=1* *Mean* *Std Dev*	*CLEAD1=0* *Mean* *Std Dev*	*Univariate* *Estimate* *(t-statistic)*	*CLEAD1=1* *Mean* *Std Dev*	*CLEAD1=0* *Mean* *Std Dev*	*Univariate* *Estimate* *(t-statistic)*
ADREV	**0.030**	**0.022**	**0.034**	**-0.012*****	**0.023**	**0.023**	**- 0.001**
	0.038	**0.029**	**0.041**	**(-21.91)**	**0.029**	**0.030**	**(-0.70)**
Total assets	2,000	4,152	887	3,265***	3,370	2,664	706***
	5,646	8,254	3,082	(42.19)	8,148	6,205	(4.72)
Market value	2,186	4,378	1,052	3,326***	3,735	2,910	825***
	7,108	10,359	4,171	(33.67)	15,773	12,397	(2.82)
BIG4	0.726	0.943	0.613	0.330***	0.963	0.850	0.112***
	0.446	0.231	0.487	(55.46)	0.190	0.357	(19.05)
LOG_MKT	5.210	6.398	4.596	1.802***	6.398	6.215	0.183***
	2.495	2.355	2.339	(53.93)	1.966	1.933	(4.56)
LEV	0.241	0.260	0.231	0.029***	0.249	0.239	0.010*
	0.274	0.243	0.289	(7.51)	0.245	0.249	(1.87)
ROAL	-0.062	-0.004	-0.092	0.088***	- 0.006	- 0.029	0.023***
	0.308	0.215	0.342	(20.24)	0.221	0.258	(4.58)
ROA	-0.072	-0.013	-0.103	0.091***	- 0.015	- 0.034	0.020***
	0.290	0.201	0.323	(22.16)	0.202	0.227	(4.39)
LOSS	0.413	0.309	0.467	-0.158***	0.314	0.356	- 0.042***
	0.492	0.462	0.499	(-22.70)	0.464	0.479	(-4.33)
CFO	0.017	0.061	-0.006	0.068***	0.057	0.039	0.018***
	0.229	0.162	0.253	(20.95)	0.172	0.187	(4.80)
BTM	0.421	0.389	0.438	-0.050***	0.413	0.429	- 0.017**
	0.451	0.372	0.487	(-7.71)	0.395	0.387	(-2.05)
ABS(ACCRL)	0.120	0.090	0.135	-0.045***	0.086	0.089	- 0.003
	0.157	0.109	0.175	(-20.50)	0.101	0.107	(-1.49)
GROWTH	0.056	0.068	0.050	0.018***	0.071	0.064	0.006
	0.301	0.241	0.328	(4.24)	0.358	0.305	(0.95)
ALTMAN	2.502	3.559	1.956	1.603***	4.142	3.832	0.310*
	9.449	6.434	10.640	(11.94)	9.529	8.560	(1.66)
STDEARN	52.45	89.94	33.05	56.89***	72.30	64.15	8.15**
	124.90	167.10	90.00	(32.74)	166.50	141.60	(2.55)
TENURE	0.997	0.996	0.998	-0.001*	0.997	0.999	- 0.002***
	0.052	0.060	0.047	(-1.89)	0.055	0.025	(-2.67)
N. Obs.[a]	21,914	7,471	14,443	21,914	4,695	4,695	9,390
% Obs.	100.00%	34.09%	65.91%		50.00%	50.00%	

This table presents the descriptive statistics of the data used in the discretionary revenue analyses: Panel A shows descriptive statistics for the full sample and for a partition by industry specialization at national level (*NLEAD1)*; and, Panel B shows descriptive statistics for the full sample and for a partition by industry specialization at city level (*CLEAD1*). Matching on economic comparability refers to a pair-wise match of specialist and non-specialist auditors' clients, based on industry, size, and returns covariance. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. [a] The sample size is reduced to those years with auditor city data in audit analytics matched to the U.S. Census Bureau 2003 list of Metropolitan Statistical Areas.

TABLE 5 – Discretionary Revenue Analyses: Pooled Multivariate Tests
Full and Matched Samples

		Dependent Variable = ADREV			
		Full samples		*Matched samples*	
	Predicted sign	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*
NLEAD1	**(-)**	**-0.0013****		**0.0011**	
		(-2.41)		**(1.32)**	
CLEAD1	**(-)**		**-0.0020*****		**0.0004**
			(-3.23)		**(0.50)**
BIG4		-0.0041***	-0.0062***	-0.0001	-0.0023
		(-5.92)	(-6.23)	(-0.05)	(-1.32)
LOG_MKT		-0.0042***	-0.0036***	-0.0036***	-0.0039***
		(-32.07)	(-16.42)	(-12.43)	(-11.52)
LEV		-0.0208***	-0.0138***	-0.0153***	-0.0131***
		(-17.91)	(-7.51)	(-6.57)	(-5.83)
ROAL		0.0115***	0.0073**	0.0089*	0.0171***
		(4.12)	(2.16)	(1.93)	(3.79)
ROA		-0.0058*	-0.0040	-0.0085	-0.0138**
		(-1.86)	(-0.97)	(-1.37)	(-2.28)
LOSS		0.0024***	0.0005	0.0020*	-0.0001
		(5.07)	(0.62)	(1.77)	(-0.06)
CFO		-0.0116***	-0.0032	-0.0091*	0.0004
		(-5.84)	(-1.08)	(-1.71)	(0.08)
BTM		-0.0113***	-0.0071***	-0.0027	-0.0037**
		(-16.78)	(-6.83)	(-1.30)	(-2.24)
ABS(ACCRL)		0.0098***	0.0212***	0.0009	0.0125***
		(12.08)	(7.70)	(1.27)	(2.92)
GROWTH		0.0105***	0.0086***	0.0087***	0.0027
		(14.04)	(5.92)	(3.67)	(1.17)
ALTMAN		-0.0002***	-0.0002***	0.0010	0.0010
		(-5.26)	(-4.25)	(0.93)	(0.86)
STDEARN		0.0001***	0.0001*	0.0001***	0.0001***
		(6.13)	(1.75)	(4.82)	(4.06)
TENURE		-0.0038**	0.0093***	-0.0002	0.0075**
		(-2.24)	(4.93)	(-0.06)	(2.39)
Intercept		0.0590***	0.0537***	0.0478***	0.0517***
		(26.39)	(20.19)	(10.33)	(11.40)
Year F.E.		*Included*	*Included*	*Included*	*Included*
N. Obs.		69,512	21,914	10,106	9,390
Adj-R^2		0.12	0.13	0.13	0.09

This table presents the pooled discretionary revenue analyses of the full sample and matched samples, using *NLEAD1*and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm. For brevity, the year-specific intercepts are not reported.

TABLE 6 – Discretionary Revenue Analyses: Multivariate Pair-Wise Differences Tests Matched Samples

		Dependent variable = ADREVij	
		NLEAD1	*CLEAD1*
	Predicted Sign	*Estimate (t-statistic)*	*Estimate (t-statistic)*
BIG4ij		0.0011	-0.0010
		(0.59)	(-0.56)
LOG_MKTij		-0.0001	-0.0022***
		(-0.14)	(-3.00)
LEVij		-0.0060**	-0.0005
		(-2.20)	(-0.19)
ROALij		-0.0024	0.0207***
		(-0.55)	(4.06)
ROAij		-0.0002	-0.0141*
		(-0.03)	(-1.85)
LOSSij		0.0029**	0.0003
		(2.26)	(0.25)
CFOij		0.0074	0.0043
		(1.15)	(0.62)
BTMij		-0.0020	-0.0023
		(-1.05)	(-1.23)
ABS(ACCRL)ij		0.0027*	0.0150***
		(1.75)	(2.88)
GROWTHij		0.0082***	0.0025
		(2.79)	(0.90)
ALTMANij		-0.0002**	-0.0001
		(-2.30)	(-1.38)
STDEARNij		0.0010	0.0010
		(1.11)	(1.43)
TENUREij		-0.0014	-0.0025
		(-0.44)	(-0.60)
Intercept	**(-)**	**0.0005**	**-0.0002**
		(0.67)	**(-0.26)**
Year F.E.		*Included*	*Included*
N. Obs.		5,053	4,695
Adj-R^2		0.02	0.02

This table presents the pair-wise differences in discretionary revenue for the matched samples, using *NLEAD1* and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A and *ij* denotes the pair-wise difference between matched observations. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm. For brevity, the year-specific intercepts are not reported.

TABLE 7 – Going-Concern Analyses – Panel A: Full Sample Partition by Industry Specialization at National-Level (*NLEAD1)*

	Full sample				*NLEAD1 Matched sample matching clients on economic comparability*		
	All Obs. *Mean* *Std Dev*	*NLEAD1=1* *Mean* *Std Dev*	*NLEAD1=0* *Mean* *Std Dev*	*Univariate* *Estimate* *(t-statistic)*	*NLEAD1=1* *Mean* *Std Dev*	*NLEAD1=0* *Mean* *Std Dev*	*Univariate* *Estimate* *(t-statistic)*
GCONCERN	**0.095**	**0.043**	**0.102**	**-0.059*****	**0.029**	**0.026**	**0.003**
	0.293	**0.202**	**0.302**	**(-12.55)**	**0.167**	**0.159**	**(0.60)**
Total assets	2,608	5,957	2,138	3,819***	6,143	5,294	849*
	7,773	11,814	6,896	(30.75)	17,042	15,291	(1.87)
Market value	2,785	6,071	2,324	3,747***	7,077	5,803	1,274**
	9,159	13,777	8,206	(25.50)	24,418	19,232	(2.07)
BIG4	0.725	1.000	0.687	0.313***	1.000	0.894	0.106***
	0.446	0.000	0.464	(44.54)	0.000	0.307	(17.31)
LOG_MKT	5.211	6.638	5.011	1.627***	6.699	6.552	0.147**
	2.634	2.412	2.602	(39.01)	2.178	2.167	(2.41)
LEV	0.246	0.257	0.244	0.013***	0.251	0.243	0.007
	0.279	0.228	0.285	(2.95)	0.230	0.215	(1.20)
ROAL	-0.069	-0.005	-0.078	0.072***	0.002	- 0.010	0.013
	0.335	0.223	0.347	(13.37)	0.591	0.273	(0.97)
ROA	-0.077	-0.012	-0.086	0.074***	- 0.006	- 0.016	0.010
	0.310	0.209	0.321	(14.76)	0.481	0.224	(0.99)
LOSS	0.405	0.297	0.420	-0.122***	0.302	0.312	- 0.010
	0.491	0.457	0.494	(-15.43)	0.459	0.463	(-0.79)
CFO	0.010	0.056	0.004	0.052***	0.053	0.047	0.005
	0.248	0.178	0.255	(12.99)	0.183	0.201	(0.99)
BTM	0.432	0.407	0.436	-0.029***	0.384	0.414	- 0.029***
	0.470	0.377	0.482	(-3.84)	0.348	0.351	(-2.99)
ABS(ACCRL)	0.123	0.083	0.128	-0.045***	0.091	0.082	0.010
	0.173	0.106	0.180	(-16.01)	0.559	0.096	(0.86)
GROWTH	0.055	0.063	0.054	0.009*	0.063	0.076	- 0.013
	0.307	0.232	0.317	(1.89)	0.353	0.265	(-1.52)
ALTMAN	2.472	3.916	2.270	1.646***	4.764	4.167	0.597**
	11.530	7.556	11.970	(8.83)	12.720	8.230	(1.98)
STDEARN	78.75	137.40	70.53	66.87***	138.20	122.20	16.00
	238.80	307.40	226.30	(17.36)	440.00	387.20	(1.37)
TENURE	0.985	0.984	0.985	-0.001	0.987	0.987	- 0.001
	0.122	0.126	0.121	(-0.63)	0.113	0.112	(0.12)
N. Obs.	35,406	4,351	31,055	35,406	2,539	2,539	5,078
% Obs.	100.00%	12.29%	87.71%		50.00%	50.00%	

Panel B: Full-Sample Partition by Industry Specialization at City Level (*CLEAD1)*

		Full sample			*CLEAD1 Matched sample matching clients on economic comparability*		
	All Obs. *Mean* *Std Dev*	*CLEAD1=1* *Mean* *Std Dev*	*CLEAD1=0* *Mean* *Std Dev*	*Univariate Estimate (t-statistic)*	*CLEAD1=1* *Mean* *Std Dev*	*CLEAD1=0* *Mean* *Std Dev*	*Univariate Estimate (t-statistic)*
GCONCERN	**0.097**	**0.051**	**0.120**	**-0.069*****	**0.027**	**0.031**	**- 0.004**
	0.295	**0.220**	**0.325**	**(-17.02)**	**0.161**	**0.173**	**(-1.26)**
Total assets	1,998	4,172	880	3,292***	3,236	2,577	659***
	5,728	8,406	3,107	(43.23)	8,499	6,539	(4.32)
Market value	2,193	4,440	1,037	3,403***	3,123	2,672	451**
	7,227	10,605	4,159	(34.97)	9,236	11,035	(2.21)
BIG4	0.719	0.940	0.605	0.335***	0.963	0.854	0.109***
	0.450	0.238	0.489	(57.54)	0.189	0.353	(19.09)
LOG_MKT	5.168	6.368	4.550	1.818***	6.380	6.208	0.172***
	2.521	2.383	2.361	(55.55)	1.940	1.904	(4.45)
LEV	0.241	0.256	0.233	0.023***	0.246	0.237	0.009*
	0.282	0.244	0.300	(5.92)	0.242	0.247	(1.90)
ROAL	-0.080	-0.015	-0.113	0.098***	- 0.016	- 0.039	0.023***
	0.345	0.243	0.383	(20.67)	0.240	0.282	(4.43)
ROA	-0.089	-0.023	-0.123	0.100***	- 0.024	- 0.043	0.019***
	0.322	0.226	0.357	(22.73)	0.223	0.246	(4.09)
LOSS	0.425	0.317	0.480	-0.162***	0.320	0.365	- 0.044***
	0.494	0.466	0.500	(-24.05)	0.467	0.481	(-4.64)
CFO	0.003	0.052	-0.022	0.074***	0.049	0.032	0.017***
	0.255	0.184	0.281	(21.34)	0.194	0.205	(4.16)
BTM	0.419	0.390	0.434	-0.044***	0.409	0.425	- 0.016**
	0.461	0.379	0.497	(-6.90)	0.395	0.384	(-2.02)
ABS(ACCRL)	0.125	0.093	0.142	-0.049***	0.087	0.091	- 0.004*
	0.173	0.121	0.193	(-20.65)	0.105	0.130	(-1.86)
GROWTH	0.053	0.067	0.045	0.021***	0.071	0.063	0.008
	0.311	0.248	0.338	(5.01)	0.353	0.313	(1.22)
ALTMAN	2.360	3.647	1.698	1.949***	4.451	3.981	0.470*
	11.330	7.569	12.790	(12.49)	15.290	9.369	(1.84)
STDEARN	64.53	113.30	39.41	73.89***	101.10	76.72	24.38**
	189.30	255.80	136.80	(28.75)	718.60	271.00	(2.24)
TENURE	0.997	0.996	0.998	-0.002**	0.997	0.999	- 0.002*
	0.054	0.063	0.049	(-2.18)	0.053	0.035	(-1.79)
N. Obs.[a]	23,349	7,934	15,415	23,349	4,951	4,951	9,902
% Obs.	100.00%	33.98%	66.02%		50.00%	50.00%	

This table presents the descriptive statistics of the data used in the analysis of propensity to issue a going-concern opinion: Panel A shows descriptive statistics for the full sample and for a partition by industry specialization at national level (*NLEAD1)*; and Panel B shows descriptive statistics for the full sample and for a partition by industry specialization at city level (*CLEAD1*). Matching on economic comparability refers to a pair-wise match of specialist and non-specialist auditors' clients, based on industry, size, and returns covariance. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. [a] The sample size is reduced to those years with auditor city data in audit analytics matched to the U.S. Census Bureau 2003 list of Metropolitan Statistical Areas.

TABLE 8 – Going-Concern Analyses: Pooled Multivariate Tests
Full and Matched Samples

		Dependent variable = GCONCERN			
		Full samples		*Matched samples*	
	Predicted sign	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*
NLEAD1	**(+)**	**0.0932**		**0.0384**	
		(0.66)		**(0.15)**	
CLEAD1	**(+)**		**0.2722*****		**0.0563**
			(2.58)		**(0.27)**
BIG4		-0.1295	-0.2110**	0.5010	0.0300
		(-1.58)	(-2.14)	(1.04)	(0.11)
LOG_MKT		-0.5703***	-0.6265***	-0.6554***	-0.8479***
		(-24.75)	(-21.70)	(-7.12)	(-10.25)
LEV		0.3023**	0.2278	-0.3286	-0.3550
		(2.36)	(1.53)	(-0.36)	(-0.86)
ROAL		-0.2932**	-0.2698	1.0041	0.5848
		(-1.99)	(-1.54)	(1.40)	(1.17)
ROA		-0.9298***	-0.8906***	-2.2854*	-2.1210***
		(-4.83)	(-3.90)	(-1.94)	(-2.85)
LOSS		1.0772***	1.0299***	1.8303***	1.7608***
		(12.53)	(9.64)	(3.30)	(5.53)
CFO		-0.5781***	-0.8187***	-0.0617	-0.3220
		(-3.74)	(-4.63)	(-0.07)	(-0.58)
BTM		-0.8838***	-0.8464***	-1.4887**	-1.3189***
		(-10.69)	(-8.89)	(-2.00)	(-4.22)
ABS(ACCRL)		0.9087***	0.8791***	-0.2848	0.2768
		(7.13)	(5.71)	(-0.41)	(0.75)
GROWTH		-0.2110***	-0.1917**	-0.2216	-0.2634*
		(-2.73)	(-2.07)	(-1.32)	(-1.68)
ALTMAN		-0.0183***	-0.0204***	-0.0851***	-0.0240
		(-5.90)	(-5.64)	(-2.89)	(-1.47)
STDEARN		0.0012***	0.0015***	0.0008	0.0001*
		(6.91)	(5.66)	(1.24)	(1.87)
TENURE		-0.0962	-0.8863	0.0001	0.0001
		(-0.33)	(-1.27)	(0.01)	(0.01)
Intercept		-0.2901	-15.0146***	3.6700	2.6239**
		(-0.53)	(-12.69)	(0.79)	(2.52)
Year F.E.		*Included*	*Included*	*Included*	*Included*
Industry F.E.		*Included*	*Included*	*Included*	*Included*
N. Obs.		35,406	22,961	5,078	9,902
Pseudo-R^2		0.48	0.49	0.40	0.46

This table presents the pooled analyses of propensity to issue a going-concern opinion for the full sample and matched samples, using *NLEAD1*and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm. For brevity, the year and industry-specific intercepts are not reported.

TABLE 9 – Going-Concern Analyses: Conditional Logistic Regression Tests Matched Samples

		Dependent variable = GCONCERN	
	Predicted sign	*NLEAD1* *Estimate* *(t-statistic)*	*CLEAD1* *Estimate* *(t-statistic)*
BIG4		0.4226	0.2801
		(0.57)	(0.45)
LOG_MKT		-0.7570***	-0.7444***
		(-2.77)	(-3.62)
LEV		-1.5445	0.0954
		(-1.30)	(0.11)
ROAL		-1.4976	-0.0618
		(-0.96)	(-0.06)
ROA		-0.5987	-1.6951
		(-0.29)	(-1.32)
LOSS		1.7702***	1.7337***
		(2.87)	(2.74)
CFO		-0.4037	-1.2199
		(-0.17)	(-0.91)
BTM		-0.9670	-1.0829***
		(-1.44)	(-2.85)
ABS(ACCRL)		-2.5354	-0.8835
		(-1.20)	(-0.83)
GROWTH		0.1051	-0.7950
		(0.13)	(-1.50)
ALTMAN		-0.1130	-0.0970**
		(-1.29)	(-2.29)
STDEARN		0.0019	0.0028
		(0.74)	(1.57)
Intercept	**(+)**	**0.1758**	**-0.3481**
		(0.48)	**(-1.26)**
N. Obs.		264	466
Pseudo-R^2		0.58	0.64

This table presents the conditional logistic regression analyses of propensity to issue a going-concern opinion for the matched pairs with intra-pair variation in going concern opinions, using *NLEAD1* and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm. Tenure, year, and industry-specific intercepts are not included because there is insufficient intra-pair variation in these variables.

TABLE 10 – Clients that Switched from Arthur Andersen 2001–2002
PANEL A: Pre-Post Switch Analyses for Arthur-Andersen Clients

		Dependent variable = ΔADA		*Dependent variable = ΔADREV*	
	Predicted sign	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*
ΔNLEAD1	**(-)**	**-0.0081**		**-0.0057**	
		(-0.79)		**(-1.16)**	
ΔCLEAD1	**(-)**		**0.0115**		**-0.0011**
			(1.48)		**(-0.29)**
ΔBIG4		0.0280*	0.0219	0.0055	0.0051
		(1.77)	(1.37)	(0.73)	(0.66)
ΔLOG_MKT		-0.0020	-0.0012	0.0037	0.0044
		(-0.33)	(-0.20)	(1.27)	(1.50)
ΔLEV		-0.1179***	-0.1194***	-0.0446***	-0.0435***
		(-3.90)	(-3.96)	(-3.06)	(-2.98)
ΔROAL		-0.0343	-0.0361	0.0013	-0.0011
		(-1.07)	(-1.14)	(0.08)	(-0.07)
ΔROA		-0.0520	-0.0511	-0.0385**	-0.0366*
		(-1.30)	(-1.28)	(-1.99)	(-1.90)
ΔLOSS		-0.0060	-0.0058	-0.0076*	-0.0080*
		(-0.63)	(-0.61)	(-1.66)	(-1.73)
ΔCFO		0.0297	0.0294	-0.0127	-0.0134
		(0.88)	(0.87)	(-0.78)	(-0.82)
ΔBTM		0.0042	0.0044	0.0025*	0.0023
		(1.37)	(1.44)	(1.73)	(1.59)
ΔABS(ACCRL)		-0.0661***	-0.0660***	-0.0481***	-0.0484***
		(-3.13)	(-3.14)	(-4.73)	(-4.75)
ΔGROWTH		0.0141	0.0139	0.0034	0.0034
		(1.45)	(1.43)	(0.73)	(0.72)
ΔALTMAN		0.0010	0.0010	0.0005	0.0004
		(1.26)	(1.30)	(1.27)	(1.14)
ΔSTDEARN		0.0001	0.0001	0.0001	0.0001
		(0.30)	(0.12)	(0.94)	(1.03)
Intercept		-0.0036	-0.0053	-0.0055**	-0.0056**
		(-0.77)	(-1.12)	(-2.41)	(-2.47)
N. Obs.		393	393	393	393
R^2		0.11	0.12	0.13	0.12

This table presents the pre-post switch discretionary accruals and revenue manipulation analyses for the sample of Arthur Andersen Clients, using *NLEAD1* and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A and Δ denotes the difference between 2002 and 2001 for each observation. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm.

PANEL B: Pre-Post Switch Analyses for Arthur-Andersen Clients and Matched Control Group

		Dependent variable = ΔADA		*Dependent variable = ΔADREV*	
	Predicted sign	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*	*Estimate (t-statistic)*
AA		0.0076	0.0051	0.0008	-0.0001
		(0.95)	(0.65)	(0.25)	(-0.03)
ΔNLEAD1		0.0105		0.0039	
		(0.63)		(0.59)	
AA_ΔNLEAD1	**(-)**	**-0.0131**		**-0.0119**	
		(-0.59)		**(-1.34)**	
ΔCLEAD1			-0.0235		0.0050
			(-1.52)		(0.81)
AA_ΔCLEAD1	**(-)**		**0.0324***		**-0.0028**
			(1.76)		**(-0.38)**
ΔBIG4		0.0160	0.0114	0.0106	0.0091
		(0.75)	(0.53)	(1.24)	(1.05)
ΔLOG_MKT		-0.0083	-0.0080	0.0042*	0.0048*
		(-1.32)	(-1.30)	(1.68)	(1.94)
ΔLEV		-0.0838**	-0.0850**	-0.0253*	-0.0255*
		(-2.45)	(-2.49)	(-1.86)	(-1.87)
ΔROAL		-0.0123	-0.0120	0.0097	0.0086
		(-0.32)	(-0.31)	(0.63)	(0.56)
ΔROA		-0.0599	-0.0573	-0.0193	-0.0189
		(-1.43)	(-1.37)	(-1.16)	(-1.13)
ΔLOSS		-0.0187**	-0.0177**	-0.0046	-0.0043
		(-2.12)	(-2.03)	(-1.30)	(-1.22)
ΔCFO		0.0252	0.0243	0.0144	0.0135
		(0.79)	(0.76)	(1.13)	(1.05)
ΔBTM		0.0047	0.0051	0.0002	0.0002
		(1.10)	(1.20)	(0.12)	(0.13)
ΔABS(ACCRL)		-0.1841***	-0.1886***	-0.0157	-0.0152
		(-5.83)	(-5.96)	(-1.25)	(-1.20)
ΔGROWTH		-0.0006	-0.0007	0.0009	0.0010
		(-0.12)	(-0.16)	(0.51)	(0.53)
ΔALTMAN		0.0007	0.0007	-0.0001	-0.0001
		(1.05)	(1.12)	(-0.28)	(-0.37)
ΔSTDEARN		-0.0001	0.0001	0.0001	0.0001
		(-1.12)	(0.96)	(0.33)	(0.58)
Intercept		-0.0073	-0.0059	-0.0065***	-0.0065***
		(-1.24)	(-1.00)	(-2.78)	(-2.78)
N. Obs.		574	574	574	574
R^2		0.11	0.11	0.04	0.03

This table presents the pre-post switch discretionary accruals and revenue manipulation analyses for the sample of Arthur-Andersen Clients and a control group of comparable clients, using *NLEAD1* and *CLEAD1* as definitions of auditor industry specialization. Variable definitions are included in Appendix A and Δ denotes the difference between 2002 and 2001 for each observation. *, **, *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, using two-tailed tests. T-statistics and p-values are calculated using clustered standard errors by firm.

FIGURE 1- *LEAD1* Simulation Results from 1,000 replications
Assigning Clients to Five Auditors at Random