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Does Auditor Industry Specialization Improve Audit Quality?

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ABSTRACT

This study examines whether auditor industry specialization, measured using the auditor's within-industry market share, improves audit quality and results in a fee premium. After matching clients of specialist and nonspecialist auditors on a number of dimensions, as well as only on industry and size, there is no evidence of differences in commonly used audit-quality proxies between these two groups of auditors. Moreover, there is no consistent evidence of a specialist fee premium. The matched sample results are confirmed by including client fixed effects in the main models, examining a sample of clients that switched auditors, and using an alternative proxy that aims to capture the auditor's industry knowledge. The combined evidence in this study suggests that

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the auditor's within-industry market share is not a reliable indicator of audit quality. Nevertheless, these findings do not imply that industry knowledge is not important for auditors, but that the methodology used in extant archival studies to examine this issue does not fully parse out the effects of auditor industry specialization from client characteristics.

1. *Introduction*

Accounting firms recognize the importance of industry expertise in providing high-quality audits and they strategically organize their assurance practices along industry lines. A report on the U.S. audit market issued by the U.S. Government Accountability 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]). For example, PricewaterhouseCoopers 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]). Understanding the benefits of auditor industry expertise is relevant for public companies choosing among auditors, to regulators concerned with competition in the U.S. audit market, and to audit firms aiming to perform high-quality audits while maintaining their competitive position in each industry.

The importance of industry expertise has led auditing researchers to extensively study its impact on audit quality. Experimental auditing research provides evidence that industry expertise generally enhances auditor judgment. Specifically, the findings of prior studies suggest that the auditor's knowledge of the industry increases audit quality, improving the accuracy of error detection (Solomon, Shields, and Whittington [1999], Owhoso, Messier, and Lynch [2002]), enhancing the quality of the auditor's risk assessment (Taylor [2000], Low [2004]), and influencing the choice of audit tests and the allocation of audit hours (Low [2004]). Archival auditing research has also examined the effects of auditor industry expertise; however, archival researchers cannot directly observe expertise at the firm, office, or auditor level. Consequently, this area of the literature has used each audit firm's within-industry market share as an indirect proxy for industry specialization, which in turn is assumed to be associated with industry expertise. A specialist auditor is defined as a firm that has "differentiated itself from its competitors in terms of market share within a particular industry" (Neal and Riley [2004, p. 170]). A number of previous studies employing market share proxies have shown that the clients of specialist auditors have better financial reporting quality than the clients of nonspecialist auditors do and that specialist auditors charge a fee premium.

There are conceptual and econometric problems associated with using a market share proxy for auditor industry specialization. Conceptually, an audit firm may have extensive industry knowledge even when its within-industry market share is small relative to other audit firms. In addition, using a market share proxy causes important econometric issues. Defining specialization based on within-industry market share results in differences in client characteristics between auditor types. By construction, auditors with large market share are more likely to have larger clients compared to nonspecialist auditors. This definition of expertise constitutes a problem because a number of size-related client characteristics are simultaneously correlated with the specialist variable and with commonly used audit-quality proxies and audit fees. The confounding effect of these differences may not be properly addressed by cross-sectional regression models.[1]

A fundamental issue in this literature is determining causal inference. Empirical researchers should aim to compare treatment and control groups that have similar client characteristics, ideally approximating experimental conditions where treatment is assigned at random. One way to achieve this objective is by matching clients of specialist and nonspecialist auditors on all relevant observable dimensions except for the treatment and outcome variables. Furthermore, matching mitigates model misspecification problems by reducing or even eliminating the correlation between the treatment variable and the matching variables.

Following the prior literature on industry specialization, this study employs three main audit-quality proxies: discretionary accruals, the auditor's propensity to issue a going-concern opinion, and the client's propensity to meet or beat analysts' earnings forecasts. Consistent with prior studies, this study first shows a relation between the audit-quality proxies and auditor industry specialization, and also between audit fees and auditor industry specialization. However, after matching clients of specialist and nonspecialist auditors on a number of dimensions, as well as only on industry and size, there are no statistically significant differences in any of the audit-quality proxies between the two groups of auditors. Moreover, there is no consistent evidence supporting the existence of a specialist fee premium. These findings are robust to employing a number of alternative matching approaches, additional market share cutoffs for auditor industry specialization, additional audit-quality proxies, and controlling for the effect of imperfectly matched characteristics by considering the pairwise structure of the matched sample data.

This study also documents confirmatory evidence from three additional analyses that do not rely on matched samples. First, including client fixed

[1] These issues also impact the Big 4 audit-quality proxy. Boone, Khurana, and Raman [2010] and Lawrence, Minutti-Meza, and Zhang [2011] show that the previously documented association between auditor size and audit quality can be attributed to differences in client characteristics, particularly to differences in client size. Similarly, the separation of specialist and nonspecialist auditors by within-industry market share creates two groups of auditors with different client characteristics.

effects in the audit quality and fee models makes the coefficient on the specialist variable statistically insignificant. Second, there are insignificant pre-/postdifferences in discretionary accruals, propensity to meet or beat analysts' forecasts, and audit fees for Arthur Andersen's (AA's) clients that switched to auditors with a different degree of specialization in 2002. Third, employing a measure of specialization based on the auditor's portfolio of clients provides a pattern of evidence inconsistent with a specialist effect on audit quality and audit fees.

Overall, the combined evidence provided in this study suggests that the auditor industry specialization, measured using the auditor's within-industry market share, is not a reliable indicator of audit quality. Moreover, the extant empirical methodology does not fully parse out the confounding effects of client characteristics in determining the effect of industry specialization on audit quality and audit fees. Finally, this study contributes to the broad accounting literature on matching and comparability in estimating treatment effects.[2] Nevertheless, the reader should be cautioned that, although this study suggests that using the market share proxies for industry specialization leads to biased inferences, it does not imply that industry knowledge is not important for auditors.

2. *Related Empirical Studies and Measures of Auditor Industry Specialization*

The literature on auditor industry specialization has examined the impact of the auditor's within-industry market share on audit quality and audit fees. Using various proxies based on market share, extant studies have documented a positive relation between auditor industry specialization and the quality of reported earnings, suggesting that industry specialists provide higher quality audits than nonindustry specialists. Balsam, Krishnan, and Yang [2003] and Krishnan [2003] find a negative relation between auditor industry specialization and the client's absolute discretionary accruals. Balsam, Krishnan, and Yang [2003] also find a positive interaction effect between auditor specialization and earnings surprise in an Earnings Response Coefficient (ERC) model. Reichelt and Wang [2010] document a negative relation between auditor specialization, measured at the city, national, and a combination of both levels, and the client's absolute discretionary accruals. In addition, Reichelt and Wang [2010] show a negative association between auditor

[2] The methodology used here could be adapted to other studies in accounting research comparing treatment and control groups, particularly where it is difficult to specify a correct model. 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.

industry specialization and the likelihood of meeting or beating analysts' earnings forecasts and a positive association between auditor industry specialization and the auditor's propensity to issue a going-concern opinion.

It follows that if specialists differentiate themselves by providing higher quality audits, they may be able to charge a fee premium. Although the literature has extensively examined this question, studies in this area have shown mixed evidence. Several studies find a positive association between auditor industry specialization and audit fees, for example, Craswell, Francis, and Taylor [1995], Defond, Francis, and Wong [2000], Ferguson, Francis, and Stokes [2003], Mayhew and Wilkins [2003], Casterella et al. [2004], Francis, Reichelt, and Wang [2005], Carson [2009], and Cahan, Jeter, and Naiker [2011]. 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. In contrast, some studies do not find evidence of a fee premium, for example, Palmrose [1986], Ettredge and Greenberg [1990], Pearson and Trompeter [1994], Ferguson and Stokes [2002], and Mayhew and Wilkins [2003]. Moreover, the GAO's 2008 report examining competition among audit firms in the United States finds no evidence that large firms use market power to extract rents.[3]

Prior studies primarily measure auditor industry specialization using the auditor's within-industry market share. In this study, for each auditor and year, industry market share is calculated as follows:

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

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. The two main proxies for auditor industry specialization used in this study are:

[3] Audit fees may be considered an audit-quality proxy; however, high fees alone do not necessarily imply high quality. Fees are related to the level of service provided (e.g., Whisenant, Sankaraguruswamy, and Raghunandan [2003]) and are negatively associated with levels of earnings management (e.g., Ashbaugh, Lafond, and Mayhew [2003]). On the other side, specialists may charge higher fees if they have oligopoly-type power in certain industries, without necessarily providing higher quality audits (Cahan, Jeter, and Naiker [2011]). Since four audit firms currently 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. Furthermore, O'Keefe, Simunic, and Stein [1994, p. 242] caution that "inferences about prices in such studies can be erroneous if the cross-sectional variations in auditor effort caused by differences in client characteristics are not adequately controlled."

NLEAD = "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% market share than their closest competitor, and "0" otherwise, and

CLEAD = "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 (MSA) following the 2003 U.S. Census Bureau MSA definitions, and have more than 10% market share than their closest competitor, and "0" otherwise.[4]

In the main analyses this study examines the impact of auditor industry specialization on the client's absolute discretionary accruals, the auditor's propensity to issue a going-concern opinion, the client's propensity to meet or beat analysts' consensus estimates, and audit fees. In section 7, this study reports additional analyses using ERCs and a discretionary revenue measure from Stubben [2010] as audit-quality proxies, in addition to alternative measures of auditor industry specialization.

3. *Mitigating the Bias Resulting from Using the Auditor's Within-Industry Market Share as a Proxy for Auditor Industry Expertise*

3.1 BIAS RESULTING FROM USING A MARKET SHARE PROXY

There are conceptual and econometric issues associated with using the auditor's within-industry market share as a proxy for industry expertise. Conceptually, an audit firm may have extensive industry expertise 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 an industry, by providing training to individual auditors, by auditing private clients in the same industry, by providing consulting services, or by hiring experts from within the industry or from other audit firms.[5] Thus, it is not clear-cut that auditors with large within-industry market share have comparatively higher levers of industry expertise.

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[4] Francis, Reichelt, and Wang [2005] and Reichelt and Wang [2010] also use MSA definitions to identify city-level specialists. Cities with less than three observations are deleted from the sample. MSA definitions are available at the U.S. Census Bureau's Web site: http://www.census.gov/population/www/metroareas/metrodef.html.

[5] The market share for private clients is excluded from industry specialization studies due to lack of data availability. Audit firms can also acquire expertise by hiring individuals with industry expertise. 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]).

Moreover, using a market share proxy causes important econometric issues. Using the auditor's market share as a proxy causes differences in client characteristics between auditor types. By construction, auditors with large market share are more likely to have larger clients compared to nonspecialist auditors. These differences in clientele constitute a problem because a number of size-related client characteristics are simultaneously correlated with the specialist variable and with commonly used audit-quality proxies and audit fees. A simple numerical example, focusing on differences in client size, can illustrate this problem.[6] Suppose that a given industry has four clients and three auditors, as follows:

Client	Assets	Auditor	Market Share	Specialist	Expected Quality
1	\$100 M	A	0.63	Yes	High
2	\$ 40 M	B	0.25	No	Low
3	\$ 10 M	C	0.12	No	Low
4	\$ 10 M	C	0.12	No	Low

In the above example, Auditor A has a single large client and is designated as industry specialist because Auditor A has the largest market share based on the sum of all clients' assets. In addition, earnings quality and fees will be different for Client 1 for reasons different from Auditor A's industry specialization, given that Client 1 is much larger than the other three clients in the industry.

Extant studies in the auditing literature employ cross-sectional regression models with linear control variables to estimate the effects of auditor specialization. However, cross-sectional regressions may result in inappropriate causal inferences due to model misspecification resulting from including correct independent variables but assuming an incorrect functional form and from excluding unobservable variables in the analysis.

Prior research suggests that important variables such as client size and performance are nonlinearly related to the proxies for audit quality (Kothari, Leone, and Wasley [2005], Francis [2011], Lawrence, Minutti-Meza, and Zhang [2011]). Furthermore, studies by Rubin [1979], Heckman, Ichimura, and Todd [1998], Rubin and Thomas [2000], Rubin [2001], and Ho et al. [2007] indicate that linear regression may increase bias in the estimation of treatment effects when there are even moderately nonlinear relations between the dependent and independent variables.

Given that client size has a nonlinear relationship with the audit-quality proxies and audit fees, and client size is correlated with the auditor's within-industry market share, the coefficient on the specialist variable may be

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[6] Differences in client characteristics are persistent regardless of the market-share cutoff value used to divide specialist and nonspecialist auditors. Using the *NLEAD* definition, the specialist audits the largest client in 49% of the industry–year combinations. Using the *CLEAD* definition, the specialist audits the largest client in 78% of the city–industry–year combinations. I thank an anonymous reviewer for suggesting this example.

capturing the effect of nonlinearity. The matching approach proposed by this study aims to balance client characteristics between specialists and nonspecialist auditor and provides a viable alternative to estimate the auditor treatment effects.

3.2 EVIDENCE ON THE ASSOCIATION BETWEEN THE SPECIALIST VARIABLE AND CLIENT CHARACTERISTICS

In order to determine which observable characteristics are more strongly associated with the specialist variable, I estimate a multivariate logistic regression model where the dependent variable is an indicator variable, equal to "1" for the clients of the specialist auditor, and "0" otherwise, and where the independent variables are the natural logarithm of total assets (*LOGASSETS*), return on assets (*ROA*), leverage (*LEV*), book-to-market ratio (*BTM*), the Altman score (*ALTMAN*), and industry and year indicator variables. The model is estimated using a sample of 10,000 observations selected at random from the years 2000 to 2008 with available data.[7] Next, reduced forms of the model are estimated excluding industry and year indicator variables and including only one characteristic at a time. The results of the estimated models for the national and city-level specialists are shown in table 1, panels A and B.

A comprehensive way to evaluate the relative performance of these models in predicting the probability that a client will be audited by a designated specialist is by examining the receiver operating characteristic (ROC) curve for each model. This curve represents the performance of a binary classifier as its discrimination threshold is varied.[8] The area under the ROC curve is a useful indicator of the predictive power of a choice model. As this area approaches one, the true positive rate increases and the false negative rate decreases. An additional approach to assess the relative predictive power of each model is the pseudo R^2.

Table 1 shows evidence indicating that the most important variable associated with the auditor specialist variable is client size, both in terms of the area under the ROC curve and pseudo R^2. For example, in panel A, the area under the ROC curve for a multivariate model without industry and year indicator variables is 0.670 (column II), compared to 0.670 for a univariate model with size as the only predictor (column III).[9] Furthermore, among the predictors in this table, client size is by far the most important,

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[7] Selecting a subsample at random helps to prevent overfitting the model and also to generalize the selection model across the different samples used in this study. The ranking of the models is the same using all observations with available data. The sample selection is described in more detail in section 4.

[8] The ROC curve is created by plotting the fraction of true positives out of the positives (TPR) versus the fraction of false positives out of the negatives (FPR) at various probability cutoffs. TPR is also known as sensitivity and FPR is one minus the specificity or true negative rate. The best possible classifier is one with TPR equal to one and FPR equal to zero.

[9] Including other variables used as controls in cross-sectional audit-quality regressions, such as ROA in a lag period, cash flows scaled by total assets, absolute total accruals scaled by total

TABLE 1

Determinants of the Choice of Industry Specialist Auditor

Panel A: National-Level Specialist

	Dependent Variable = Specialist at National-Level *NLEAD*								
Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
LOGASSETS	0.329***	0.297***	0.299***						
	(10.97)	(11.73)	(12.33)						
ROA	−0.224	−0.535**		1.061***					
	(−0.74)	(−1.96)		(4.87)					
LOSS	−0.132	−0.273**			−0.632***				
	(−1.11)	(−2.53)			(−6.71)				
LEV	−0.531*	0.250				0.247*			
	(−1.80)	(1.10)				(1.86)			
BTM	−0.048	0.005					−0.174**		
	(−0.39)	(0.04)					(−2.30)		
GROWTH	−0.378**	−0.249*						0.083	
	(−2.39)	(−1.74)						(0.93)	
ALTMAN	0.002	0.015**							0.015***
	(0.31)	(2.08)							(4.56)
Intercept	−15.001***	−3.897***	−3.878***	−2.065***	−1.886***	−2.182***	−2.049***	−2.124***	−2.165***
	(−14.92)	(−19.49)	(−24.07)	(−38.44)	(−30.40)	(−34.49)	(−32.91)	(−39.65)	(−39.56)
Industry and Year F.E.	*Included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*
Observations	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Pseudo R^2	0.164	0.068	0.065	0.010	0.013	0.001	0.001	0.000	0.004
ROC Area	0.779	0.670	0.670	0.567	0.562	0.518	0.511	0.499	0.539

(*Continued*)

TABLE 1—*Continued*

Panel B: City-Level Specialist

	Dependent Variable = Specialist at City-Level *CLEAD*								
Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
LOGASSETS	0.404***	0.380***	0.380***						
	(19.29)	(20.29)	(22.56)						
ROA	−0.287*	−0.349**		1.271***					
	(−1.74)	(−2.27)		(10.83)					
LOSS	−0.093	−0.128*			−0.667***				
	(−1.23)	(−1.76)			(−11.83)				
LEV	−0.165	0.059				0.234**			
	(−1.07)	(0.42)				(2.41)			
BTM	−0.138*	−0.131*					−0.232***		
	(−1.70)	(−1.70)					(−4.20)		
GROWTH	−0.040	−0.085						0.225***	
	(−0.42)	(−0.91)						(3.27)	
ALTMAN	0.005	0.009**							0.019***
	(1.11)	(2.25)							(8.03)
Intercept	9.536***	−2.748***	−2.793***	−0.596***	−0.408***	−0.733***	−0.581***	−0.688***	−0.727***
	(7.49)	(−20.76)	(−27.80)	(−16.97)	(−9.78)	(−17.57)	(−13.98)	(−20.12)	(−21.11)
Industry and Year F.E.	*Included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*	*Not included*
Observations	9,994	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Pseudo R^2	0.151	0.118	0.116	0.020	0.018	0.001	0.002	0.001	0.007
ROC Area	0.754	0.727	0.725	0.583	0.580	0.558	0.519	0.524	0.539

This table presents the analyses of the determinants of the choice of industry specialist auditor. All models were estimated using logistic regression and a random subsample of 10,000 observations from the years 2000 to 2008 with available data. In panel A the dependent variable is national-level specialist *NLEAD*. In panel B the dependent variable is city-level specialist *CLEAD*. Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All *Z*-statistics (in parentheses) and *p*-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. Only the model in column (I) includes year- and industry-specific intercepts, but for brevity these are not reported.

explaining the choice of specialist auditor almost as well as the multivariate model in panels A and B. The strong association between size and the market share proxy for specialization indicates that the clients of specialist auditors are often larger than the clients of nonspecialist auditors.

3.3 EVIDENCE ON THE ASSOCIATION BETWEEN CLIENT SIZE AND AUDIT-QUALITY PROXIES AND AUDIT FEES

Client size is not only a primary observable associated with the specialist variable, but is often an important common determinant of audit-quality proxies and audit fees. The literature on propensity-score matching identifies this type of variable, predicting both the treatment and the outcome, as "confounder." Hill [2008, p. 2056] recommends "rank ordering the confounders based on their importance with respect to the outcome variable."

One way to illustrate the importance of size as a confounder variable is by comparing the adjusted R^2 of a comprehensive multivariate model, including commonly used determinants of each dependent variable, to a univariate model including client size (*LOGASSETS*) as a predictor variable. The adjusted R^2 of a full model of discretionary accruals is 0.210 and the adjusted R^2 of a model with only size is 0.127. The pseudo R^2 of a full model of going-concern opinions is 0.475 and the pseudo R^2 of a model with only size is 0.235. The pseudo R^2 of a full model of meet or beat analysts' earnings forecasts is 0.081 and the pseudo R^2 of a model with only size is 0.001.[10] The adjusted R^2 of a full model of audit fees is 0.834 and the adjusted R^2 of a model with only size is 0.690.

The strong explanatory power of size, both in terms of auditor choice and as a determinant of the audit-quality proxies and audit fees, makes it a primary candidate for matching variable. However, the presence of other variables correlated with specialist and the audit-quality proxies and audit fees makes it necessary to verify that any results based on matching on size are similar to the results based on matching on all known determinants of each dependent variable. The analyses presented in the main tables of this study are based on matching on all determinants and only on industry and size. Section 3.4 discusses the matching approach in detail and section 7.2 discusses sensitivity analyses using alternative matching approaches, primarily using a combination of industry, size, and performance.[11]

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assets, sales growth, the standard deviation of earnings, and auditor tenure, increases the area under the ROC curve and pseudo R^2 by less than 1%.

[10] Among all models, the meet or beat model is the least influenced by client size. The most important determinant of the meet or beat model is the standard deviation of analyst forecasts; the R^2 of a model using only this variable as determinant is 0.047.

[11] In general, performance is the second most important independent variable for all models. In addition, there are other characteristics that are strongly associated with the specialist variable and each dependent variable, for example, lagged absolute total accruals and cash flows in the discretionary accruals model, the Altman *Z*-score in the going-concern model, the standard deviation of analysts' forecasts in the meet or beat model, and total sales and

Size is also nonlinearly related to the audit-quality proxies and audit fees. An F-test comparing nested models with and without squared and cubed terms of *LOGASSETS* in a model of discretionary accruals, going-concern opinions, meet or beat analysts' earnings forecasts, and audit fees indicates that these nonlinear terms improve the fit of all models. Furthermore, a Ramsey [1969] RESET test in these four models suggests that there is potential misspecification.[12]

The problem with using the auditor's within-industry market share as a proxy for auditor expertise can be summarized in the following argument: (1) using this proxy results in differences between the clients of specialist and nonspecialist auditors, and client size stands out as the characteristic most strongly associated with the specialist variable; (2) client size is also a primary driver of the audit-quality proxies and audit fees; (3) having client size and other characteristics as a control variables may not solve this problem because of model misspecification.

3.4 MITIGATING THE BIAS BY MATCHING CLIENTS OF SPECIALIST AND NONSPECIALIST AUDITORS

By reducing or even eliminating the correlation between the specialist variable and the matching variables, matching mitigates misspecification problems caused by nonlinearity.[13] Although the matched sample reflects the relative quality between peer firms, if all relevant observables are properly matched small, idiosyncratic differences should be mitigated in large samples. These features help to identify the average treatment effects of specialist auditors in the matched samples.[14] A key advantage of matching is that it does not require identifying exogenous variables or exclusion

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Big 4 auditor in the audit fee model. The full models are described in section 4. Including more predictor variables in the specification of the propensity score does not decrease the effectiveness of the matching approach. This is a result of the "equal percent bias reducing" property of propensity-score matching. Matching will reduce bias in all the predictor variables by the same amount. Moreover, Ho et al. [2007, p. 216] recommend including all variables in the second stage also in the determination of the propensity score. In order to avoid omitted variable bias, the predictors of the propensity score should include all variables that affect both the treatment assignment and, controlling for the treatment, the dependent variable.

[12] This test determines whether nonlinear combinations of the fitted values of the dependent variable help explain the dependent variable. It is an indicator of misspecification related to omitted variables and nonlinearity.

[13] Ho et al. [2007, p. 211] propose matching as a preprocessing technique before estimating parametric tests as a way to eliminate model misspecification problems. The relation between the treatment variable and the control variables existing in the full samples is eliminated in the matched samples and this reduces model misspecification problems. For example, after matching clients of specialist and nonspecialist auditors on size, the correlation between the specialist variable and size disappears and the nonlinear effect of size is less likely to be captured by the specialist variable.

[14] For identification purposes, matching relies on the assumption that all relevant differences are properly matched, or that treatment assignment is "strongly ignorable," and also requires some degree of overlap or "common support" between treatment and control observations. Other disciplines have investigated the benefits and drawbacks of matching to

restrictions (e.g., variables uncorrelated with the main outcome variable) in predicting treatment choice.

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 matched pairs. The choice of matching variables is important because in a strict sense matching assumes that bias is only due to observables. Matching mitigates the bias resulting from differences between observables in the treatment and control groups. The bias due to non-matched characteristics decreases as the number of matching variables increases. 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. When the number of variables is large, the researcher has to stratify the sample or use a methodology to aggregate across dimensions, such as propensity-score matching as proposed by Rosenbaum and Rubin [1983].

Propensity-score matching is a methodology widely used to find a group of comparable cases and control observations to mitigate the effect of selection bias, or differences in characteristics between treatment and control groups, in observational causal studies. In general, this approach can be used to match observations that belong to two different regimes, and, in the context of this study, to find comparable clients audited by specialist and nonspecialist auditors. 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, aggregating multiple dimensions into the probability of treatment, which is used as a single matching variable. The main advantage of propensity-score matching is that it is usually effective at selecting observations that are closely matched in all the predictors of the propensity score.

In the main analyses of this study, for each audit-quality proxy and specialization measure, clients of specialist and nonspecialist auditors are matched using propensity scores. First, the propensity of choosing specialist auditors at national or city level is predicted using a logistic regression where the dependent variable is the specialist indicator variable and the independent

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identify causal effects, for example, applied statistics (Stuart [2010], Rubin [2006], Rosenbaum [2002]), epidemiology (Brookhart et al. [2006]), medicine (Hill [2008]), sociology (Morgan and Harding [2006]), applied econometrics (Dehejia and Wahba [2002], Imbens [2004]), and political science (Ho et al. [2007]).

variables are all the control variables in the main regression models (equations 4–7 explained in section 4), including industry and year indicator variables.[15] After matching, the main multivariate model is estimated in the matched sample of clients of industry specialist and nonspecialist auditors. Second, following the arguments in section 3.3, this study also investigates whether using client size as the primary matching variable produces similar results to matching on the full propensity score model. Individual observations are matched using a reduced propensity score model, estimated using size, industry, and year indicator variables as predictors in the logistic regression. Finally, section 7.2 documents additional results based on matching on size and performance, as well as other forms of matching. Matching on industry and size or matching on propensity score produces qualitatively similar results.[16] These two approaches are complementary in examining the specialization effects and confirm that the previously documented results may be attributable to differences in client characteristics between auditor types.

3.5 ALTERNATIVE APPROACHES THAT DO NOT RELY ON MATCHED SAMPLES

Despite the advantages of matching methods, using matched samples comes at a cost, partially resulting from a tradeoff between internal and external validity. Five underlying threats to matching approaches are (1) matching cannot control for unobservables driving the choice of treatment, (2) firms deemed to be economically similar may not be truly comparable, (3) the results from matched samples may not be immediately extended to the entire population when there are treatment subjects outside of the range of the control subjects, (4) matching reduces sample size, and (5) it is not possible to match on pretreatment attributes or to control for other treatments.[17]

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[15] Observations are matched by propensity score, within common support, without replacement, using a caliper distance of 0.03. These settings are consistent with those in Lawrence, Minutti-Meza, and Zhang [2011] and generally result in balanced matched samples. Using the logarithm of total assets as a size variable generally results in better balance between treatment and control groups than using the logarithm of market value.

[16] Zhao [2004] concludes that there is no clear alternative between covariates and propensity-score matching methods. When the correlation between covariates and treatment choice is 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.

[17] The fourth threat could result in a bias if the matching variables are affected by the auditor choice. For example, suppose that choosing an industry specialist helps the company to raise external capital. This would mean that companies with industry specialist auditors would grow faster. Then, if we match on company size, we would be throwing out the companies that have become large because they have benefited from high-quality audits. It is not possible to fully rule out concerns that inferences based on matched samples are affected by ex post matching or other treatments.

Although it is impossible to fully eliminate the influence of unobservables, an alternative to matching is including client fixed effects in the main models estimated using the full samples. This approach mitigates the influence of unobservable client characteristics that are stable over time and impact the outcome variable. The fixed effects model isolates the effect of those time-invariant characteristics from the predictor variables in order to assess the predictors' net effect. The coefficient on the industry specialization variable using a fixed effects model i conceptually similar to examining a sample of clients switching between specialist and nonspecialist auditors. This study also examines a one-time switch between specialist and nonspecialist auditors. By focusing on a sample of clients that switched auditors, client characteristics are kept relatively constant. Taking advantage of the setting created by the demise of AA in 2002, this study estimates the pre–post changes in audit-quality proxies and audit fees for a sample of former AA clients that switched to an auditor with a different degree of industry specialization.

Finally, another alternative to matching that may address the effect of unobservables is using the Heckman [1979] approach. This approach frames treatment choice as an omitted variables problem and mitigates the impact of treatment choice through the inclusion of the inverse Mill's ratio in the regression model. Under this approach, the researcher has to identify exogenous independent variables that (1) predict treatment choice reasonably well, and (2) can be excluded from the set of independent variables that drive the outcome variable. Nevertheless, there are significant problems with this approach in the context of this study. In particular, it is very difficult to find compelling exogenous variables. As explained in sections 3.2 and 3.3, the variables that predict specialist choice are also important drivers of the audit-quality proxies and audit fees.[18]

4. Audit-Quality Proxies, Main Regression Models, and Sample Selection

4.1 DISCRETIONARY ACCRUALS

As a first audit-quality proxy, this study uses absolute discretionary accruals, estimated using an annual cross-sectional model for each industry. Absolute discretionary accruals are calculated based on the Jones [1991]

[18] Tucker [2010] and Lennox, Francis, and Wang [2012] discuss the problem of selection based on unobservables. Heckman [2005] provides an extensive discussion of the advantages and disadvantages of matching versus explicitly modeling the selection process and dealing with unobservables. Although both approaches may be acceptable for estimating treatment effects, without valid exclusion restrictions, identification under the Heckman [1979] approach relies only on strict functional form assumptions. Lennox, Francis, and Wang [2012] and Larcker and Rusticus [2010] explain how using ad hoc exclusion restrictions can yield severely biased inferences.

model including ROA (Kothari, Leone, and Wasley [2005]).[19]

$$AC_{i,t} = \alpha + \beta_1 \Delta R_{i,t} + \beta_2 PPE_{i,t} + \beta_3 ROA_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where, for client i and fiscal year-end t: *AC* is (cash flow from operations – income before extraordinary items)/average total assets; ΔR is (revenue$_t$ – revenue$_{t-1}$)/average total assets; *PPE* is gross property, plant, and equipment/average total assets; and, *ROA* is (net income before extraordinary items)/average total assets.

The regression model used to examine the association between discretionary accruals and auditor industry specialization, similar to the one proposed by Reichelt and Wang [2010], is as follows:

$$\begin{aligned} ADA_{i,t} = {} & \omega_0 + \omega_1 LEAD_{i,t} + \omega_2 BIG4_{i,t} + \omega_3 LOGMKT_{i,t} + \omega_4 LEV_{i,t} \\ & + \omega_5 ROA_{i,t} + \omega_6 ROAL_{i,t} + \omega_7 LOSS_{i,t} + \omega_8 CFO_{i,t} + \omega_9 BTM_{i,t} \\ & + \omega_{10} ABS(ACCRL)_{i,t} + \omega_{11} GROWTH_{i,t} + \omega_{12} ALTMAN_{i,t} \\ & + \omega_{13} STDEARN_{i,t} + \omega_{14} TENURE_{i,t} + \omega_{15} YEAR\_FE + v_{i,t}, \end{aligned} \tag{3}$$

where for client i and fiscal year-end t: *ADA* is the absolute value of error term $\varepsilon_{i,t}$ in equation (2); *LEAD* is an indicator variable for each measure of auditor industry specialization as defined above (*NLEAD1* or *CLEAD1*); *BIG4* is "1" if the client has a Big 4 auditor, and "0" otherwise; *LOG_MKT* is the natural logarithm of market value; *LEV* is (total liabilities)/average total assets; *ROA* is (net income)/average total assets; *ROAL* is (net income$_{t-1}$)/average total assets$_{t-1}$; *LOSS* is "1" if net income is negative, and "0" otherwise; *CFO* is (cash flow from operations)/average total assets; *BTM* is (book value of equity)/market value of equity; *ABS(ACCRL)* is (absolute value of total accruals$_{t-1}$)/average total assets$_{t-1}$; *GROWTH* is sales growth calculated as (sales$_t$ – sales$_{t-1}$)/sales$_{t-1}$; *ALTMAN* is the Altman [1983] financial distress score; *STDEARN* is the standard deviation of income before extraordinary items in the past four years; *TENURE* is "1" if the client has kept the same auditor for three or more fiscal years, and "0" otherwise; and, *YEAR_FE* is year fixed effects.[20]

In the discretionary accruals model, lower discretionary accruals are expected for clients of the specialist auditor, larger clients (*LOG_MKT*), clients with higher operating cash flow (*CFO*), clients with higher leverage (*LEV*), clients audited by a Big 4 auditor (*BIG4*), and clients with longer

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[19] All variables are winsorized at the 1% and 99% levels before estimating the discretionary accruals models. All results are qualitatively similar if discretionary accruals are calculated using a more comprehensive model, including ROA (Kothari, Leone, and Wasley [2005]), cash flows in periods t and t–1 scaled by total assets (McNichols [2002]), and a nonlinear interaction term based on the sign of cash flows in period t (Ball and Shivakumar [2006]) as accrual determinants. All results are also qualitatively similar using the lagged ROA in equation (2).

[20] Consistent with prior studies (e.g., Reichelt and Wang [2010]), the discretionary accruals model does not include industry fixed effects because this audit-quality proxy is estimated by industry.

tenure (*TENURE*). Higher absolute discretionary accruals are expected for growth clients (*GROWTH* and *BTM*), clients with losses (*LOSS*), clients with extreme performance (*ROA* and *ROAL*), clients with high-income volatility (*STDEARN*), clients with high probability of bankruptcy (*ALTMAN*), and for clients with higher total accruals in the prior year (*ABS(ACCRL)*).

4.2 GOING-CONCERN OPINIONS

As a second audit-quality proxy, this study uses 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. The logistic regression model used to examine the association between the likelihood of issuing a going-concern opinion and auditor industry specialization, similar to the one proposed by Reichelt and Wang [2010], is as follows:

$$\begin{aligned} GCONDERN_{i,t} = {} & \omega_0 + \omega_1 LEAD_{i,t} + \omega_2 BIG4_{i,t} + \omega_3 LOGMKT_{i,t} + \omega_4 LEV_{i,t} \\ & + \omega_5 ROA_{i,t} + \omega_6 ROAL_{i,t} + \omega_7 LOSS_{i,t} + \omega_8 CFO_{i,t} \\ & + \omega_9 BTM_{i,t} + \omega_{10} ABS(ACCRL)_{i,t} + \omega_{11} GROWTH_{i,t} \\ & + \omega_{12} ALTMAN_{i,t} + \omega_{13} STDEARN_{i,t} + \omega_{14} TENURE_{i,t} \\ & + \omega_{15} YEAR\_FE + \omega_{16} IND\_FE + v_{i,t}, \end{aligned} \tag{4}$$

where for client *i* and fiscal year-end *t*, all variables are as previously defined, and *IND_FE* are industry fixed effects using two-digit SIC codes as industry definitions.

In the going-concern model, the probability of going concern should 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 for clients of the specialist auditor and as risk (*STDREARN*, *ABS(ACCRL)*, *LOSS*) and leverage (*LEV*) increases.

4.3 MEET OR BEAT ANALYSTS' EARNINGS FORECASTS

As a third audit-quality proxy, this study uses the client's propensity to meet or beat analysts' earnings forecasts. The logistic regression model used to examine the likelihood that the client meets or beats analysts' forecasts and auditor industry specialization, similar to the one proposed by Reichelt and Wang [2010], is as follows:

$$\begin{aligned} MEET_{i,t} = {} & \omega_0 + \omega_1 LEAD_{i,t} + \omega_2 BIG4_{i,t} + \omega_3 LOGMKT_{i,t} + \omega_4 LEV_{i,t} \\ & + \omega_5 ROA_{i,t} + \omega_6 ROAL_{i,t} + \omega_7 LOSS_{i,t} + \omega_8 CFO_{i,t} \\ & + \omega_9 BTM_{i,t} + \omega_{10} ABS(ACCR)_{i,t} + \omega_{11} GROWTH_{i,t} \\ & + \omega_{12} ALTMAN_{i,t} + \omega_{13} STDEARN_{i,t} + \omega_{14} TENURE_{i,t} \end{aligned}$$

$$+\,\omega_{15}LOGFOR + \omega_{16}STDFOR + \omega_{17}YEAR\_FE$$
$$+\,\omega_{18}INDUSTRY\_FE + v_{i,t}, \tag{5}$$

where, for client i and fiscal year-end t, *MEET* is "1" if earnings meet or beat the median consensus forecast by one cent, and "0" otherwise; *LOGFOR* is the natural logarithm of the number of analysts following the company; *STDFOR* is the standard deviation of analysts' earnings forecasts; and all other variables are as previously defined.[21]

In the meet or beat model, clients are more likely to meet the analysts' consensus if they are larger (*LOGMKT*, *LOGNUMEST*), have better performance (*ROA*, *ROAL*, *LOSS*, *ALTMAN*), have more growth opportunities (*BTM*, *GROWTH*), and have more opportunity to manipulate earnings (*ABS(ACCR)* and *CFO*). Clients are less likely to meet the analysts' consensus if the specialist auditor constrains earnings management, there is divergence of opinion among analysts (*STDFOR*), the client's earnings are more volatile (*STDEARN*), the client relies more on the debt markets to obtain financing (*LEV*), and other auditor characteristics also constrain earnings management (*BIG4*, *TENURE*).

4.4 AUDIT FEES

The regression model used to examine the association between audit fees and auditor industry specialization, similar to the models proposed by Francis, Reichelt, and Wang [2005] and Ferguson, Francis, and Stokes [2003], is as follows:

$$\begin{aligned} LOGFEES_{i,t} = {} & \omega_0 + \omega_1 LEAD_{i,t} + \omega_2 LOGASSETS_{i,t} + \omega_3 LOGSALES_{i,t} \\ & + \omega_4 LOGNSEG_{i,t} + \omega_5 FOREIGN_{i,t} + \omega_6 CATA_{i,t} \\ & + \omega_7 QUICK_{i,t} + \omega_8 LEV_{i,t} + \omega_9 ROA_{i,t} + \omega_{10} LOSS_{i,t} \\ & + \omega_{11} OPINION_{i,t} + \omega_{12} NONDEC_{i,t} + \omega_{13} BIG_{i,t} \\ & + \omega_{14} YEAR\_FE + \omega_{15} IND\_FE + v_{i,t}, \end{aligned} \tag{6}$$

where, for client i and fiscal year-end t, *LOGFEES* is the natural logarithm of total audit fees; *LOGASSETS* is the natural logarithm of total assets; *LOGSALES* is the natural logarithm of total sales; *LOGNSEG* is the natural logarithm of business and geographic segments; *FOREIGN* is (foreign sales)/total sales; *CATA* is (current assets)/total assets; *QUICK* is (current assets – inventory)/total assets; *OPINION* is "1" if the auditor issued a going-concern opinion, and "0" otherwise; *NONDEC* is "1" if the client's fiscal

[21] Individual analysts' forecasts are obtained from the unadjusted detail I/B/E/S file. The consensus forecast is the median of the most recent forecasts issued by all analysts 60 days prior to the earnings announcement date. The standard deviation of the forecasts is calculated using the most recent forecasts issued by all analysts 60 days prior to the earnings announcement date. Actual earnings are also obtained from I/B/E/S.

year-end is not December 31st, and "0" otherwise; and all other variables are as previously defined.

In the audit fee model, fees increase if there is a specialist premium, and are generally higher depending on the amount of work the auditor has to perform (*LOGASSETS*, *LOGSALES*), the client's complexity (*LOGNSEG*, *FOREIGN*), the client's inherent risk (*CATA*, *QUICK*, *LEV*, *ROA*, *LOSS*, *OPINION*), and the auditor's reputation (*BIG*), while fees are lower if the client has a year-end in an off-peak month (*NONDEC*).

4.5 SAMPLE SELECTION

For the discretionary accruals analyses, this study uses U.S. public company data for the years 1988–2008 from Compustat and data for the years 2000–2008 from Audit Analytics.[22] 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 firm–year observations between 2000 and 2008 with auditor city data in Audit Analytics, a corresponding city in the U.S. Census Bureau MSA classification, and at least two observations in each city–industry combination.[23]

For the going-concern opinion analyses, this study uses U.S. public company data for the years 2000–2008 from Compustat and auditor opinion data from Audit Analytics. This results in a full sample consisting of 35,406 firm–year observations with the national-level measure and 22,961 firm–year observations with the city-level measure.

For the meet or beat analyses, this study uses U.S. public company data for the years 1988–2008 from Compustat, auditor opinion data from Audit Analytics for the years 2000–2008, and analysts' data from I/B/E/S. This results in a full sample consisting of 16,355 firm–year observations with the national-level measure and 8,871 firm–year observations with the city-level measure.

For the audit fee analyses, this study uses U.S. public company data for the years 2000–2008 from Compustat and auditor fees and opinion data from Audit Analytics. This results in a full sample consisting of 24,279 firm–year observations with the national-level measure and 16,388 firm–year observations with the city-level measure.

[22] The main sample is restricted 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]). 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 regression models are deleted from all samples.

[23] Some prior studies, such as Balsam, Krishnan, and Yang [2003] and Krishnan [2003], eliminate clients of the non–Big 4 firms from their sample in order to get a cleaner test of specialization separate from a possible Big 4 effect. In order to get the largest possible sample size, clients of all firms are included in the main analyses, controlling for the Big 4 effect using an indicator variable for clients of the Big 4 auditors. This is consistent with Reichelt and Wang [2010].

5. *Results for Full and Matched Samples*

5.1 DESCRIPTIVE STATISTICS

Table 2, panel A, shows the descriptive statistics for the national and city-level samples used for the discretionary accruals analyses. Clients of national-level specialists *NLEAD* represent 10.8% of the sample, similar to the 11.6% reported in Reichelt and Wang [2010, p. 658]. The national-level sample has 8,147 clients of national-level specialist auditors and 67,041 clients of other auditors. Clients of city-level specialists *CLEAD* represent 33.9% of the sample, similar to the 35% reported in Reichelt and Wang [2010, p. 658]. The city-level sample has 7,897 clients of city-level specialist auditors and 15,409 clients of other auditors.

Table 2, panel B, shows the descriptive statistics for the national- and city-level samples used for the going-concern analyses. Clients of national-level specialists *NLEAD* represent 12.3% of the sample. The national-level sample has 4,351 clients of national-level specialist auditors and 31,055 clients of other auditors. Clients of city-level specialists *CLEAD* represent 34% of the sample. The city-level sample has 7,934 clients of city-level specialist auditors and 15,415 clients of other auditors.

Table 2, panel C, shows the descriptive statistics for the national and city-level samples used for the meet or beat analyses. In general, the clients in this sample are larger and are more likely to have a specialist auditor, because clients that have analyst following are on average larger compared to clients without analyst following. Clients of national-level specialists *NLEAD* represent 16.2% of the sample. The national-level sample has 7,934 clients of national-level specialist auditors and 15,415 clients of other auditors. Clients of city-level specialists *CLEAD* represent 47.5% of the sample. The city-level sample has 2,643 clients of city-level specialist auditors and 13,712 clients of other auditors.

Table 2, panel D, shows the descriptive statistics for the national- and city-level samples used for the audit fee analyses. Clients of national-level specialists *NLEAD* represent 12.4% of the sample. The national-level sample has 3,016 clients of national-level specialist auditors and 21,263 clients of other auditors. Clients of city-level specialists *CLEAD* represent 36.7% of the sample. The city-level sample has 6,016 clients of city-level specialist auditors and 10,372 clients of other auditors.

5.2 DISCRETIONARY ACCRUALS—FULL AND MATCHED SAMPLE ANALYSES

Table 3 presents the results of the full and matched samples regression analyses of discretionary accruals using *NLEAD* and *CLEAD* as measures of auditor specialization. In line with the results in Balsam, Krishnan, and Yang [2003] and Reichelt and Wang [2010]), column (I) shows that the coefficient on *NLEAD1* is –0.004, and column (IV) shows that the coefficient on *CLEAD* is –0.003, and both coefficients are statistically significant (at the 1% and 5% levels, respectively). These coefficients indicate that clients of

TABLE 2
Descriptive Statistics

	National Specialist Sample *NLEAD*			City Specialist Sample *CLEAD*		
Variables	Mean	SD	Median	Mean	SD	Median
Panel A: Analyses of Absolute Discretionary Accruals, Full Samples						
ADA	0.068	0.077	0.044	0.075	0.090	0.046
LEAD	0.108	0.311	0.000	0.339	0.473	0.000
BIG4	0.793	0.405	1.000	0.718	0.450	1.000
LOGMKT	4.870	2.540	4.800	5.160	2.520	5.240
LOGASSETS	5.050	2.390	4.960	5.230	2.420	5.240
LEV	0.256	0.251	0.213	0.242	0.284	0.173
ROAL	– 0.035	0.263	0.031	– 0.079	0.342	0.021
ROA	– 0.046	0.254	0.029	– 0.089	0.321	0.020
LOSS	0.364	0.481	0.000	0.425	0.494	0.000
CFO	0.029	0.201	0.070	0.003	0.255	0.066
BTM	0.444	0.429	0.372	0.417	0.461	0.348
ABS(ACCRl)	0.145	0.308	0.069	0.125	0.171	0.072
GROWTH	0.071	0.318	0.060	0.052	0.310	0.052
ALTMAN	3.450	8.280	2.920	2.310	11.500	2.730
STDNI	37.20	94.20	5.770	51.40	123.00	9.360
TENURE	0.993	0.084	1.000	0.997	0.055	1.000
Observations	75,188			23,306		
Panel B: Analyses of Going-Concern Opinions, Full Samples						
GCONCERN	0.095	0.293	0.000	0.097	0.295	0.000
LEAD	0.123	0.328	0.000	0.340	0.474	0.000
BIG4	0.725	0.446	1.000	0.719	0.450	1.000
LOGMKT	5.210	2.630	5.270	5.170	2.520	5.250
LOGASSETS	5.330	2.540	5.330	5.240	2.430	5.240
LEV	0.246	0.279	0.185	0.241	0.282	0.173
ROAL	– 0.069	0.335	0.024	– 0.080	0.345	0.021
ROA	– 0.077	0.310	0.023	– 0.089	0.322	0.020
LOSS	0.405	0.491	0.000	0.424	0.494	0.000
CFO	0.010	0.248	0.068	0.003	0.255	0.066
BTM	0.432	0.470	0.359	0.419	0.460	0.349
ABS(ACCRl)	0.123	0.173	0.070	0.125	0.173	0.072
GROWTH	0.055	0.307	0.052	0.053	0.311	0.052
ALTMAN	2.470	11.500	2.740	2.360	11.300	2.730
STDNI	78.70	239.00	9.450	64.50	189.00	9.380
TENURE	0.985	0.122	1.000	0.997	0.054	1.000
Observations	35,177			22,961		
Panel C: Analyses of Meet or Beat Analysts' Earnings Forecasts, Full Samples						
MEET	0.216	0.411	0.000	0.240	0.427	0.000
LEAD	0.162	0.368	0.000	0.475	0.499	0.000
BIG4	0.958	0.200	1.000	0.914	0.281	1.000
LOGMKT	7.270	1.760	7.180	7.110	1.750	7.000
LOGASSETS	7.190	1.720	7.150	6.980	1.790	6.910
LEV	0.253	0.202	0.239	0.230	0.215	0.200
ROAL	0.054	0.124	0.060	0.021	0.181	0.050
ROA	0.044	0.103	0.053	0.014	0.156	0.045
LOSS	0.186	0.389	0.000	0.262	0.440	0.000

(*Continued*)

TABLE 2—*Continued*

Variables	National Specialist Sample *NLEAD* Mean	SD	Median	City Specialist Sample *CLEAD* Mean	SD	Median
Panel C: Analyses of Meet or Beat Analysts' Earnings Forecasts, Full Samples						
CFO	0.105	0.094	0.103	0.086	0.135	0.098
BTM	0.360	0.215	0.329	0.366	0.243	0.326
ABS(ACCRl)	0.074	0.065	0.059	0.084	0.078	0.063
GROWTH	0.122	0.205	0.085	0.095	0.191	0.077
ALTMAN	4.750	4.770	3.420	4.790	5.790	3.340
STDNI	93.300	174.000	27.800	102.000	191.000	29.000
TENURE	0.995	0.073	1.000	0.997	0.059	1.000
LOGNFOR	1.660	0.540	1.610	1.350	0.665	1.100
STDFOR	0.079	0.145	0.031	0.042	0.091	0.010
Observations	16,337			8,856		
Panel D: Analyses of Audit Fees, Full Samples						
LOGFEES	13.200	1.420	13.100	13.200	1.360	13.100
LEAD	0.124	0.330	0.000	0.367	0.482	0.000
LOGASSETS	5.850	2.200	5.730	5.700	2.110	5.590
LOGSALES	5.560	2.360	5.560	5.380	2.310	5.430
LOGNSEG	0.728	0.727	0.693	0.701	0.720	0.693
FOREIGN	0.008	0.042	0.000	0.008	0.043	0.000
CATA	0.499	0.248	0.494	0.511	0.251	0.513
QUICK	0.394	0.231	0.350	0.409	0.235	0.368
LEV	0.492	0.263	0.479	0.491	0.273	0.471
ROA	− 0.050	0.257	0.028	− 0.064	0.278	0.025
LOSS	0.361	0.480	0.000	0.385	0.487	0.000
IPINION	0.040	0.196	0.000	0.042	0.200	0.000
NONDEC	0.286	0.452	0.000	0.285	0.451	0.000
BIG	0.795	0.403	1.000	0.782	0.413	1.000
Observations	24,279			16,388		

This table presents the descriptive statistics of the full data used in the main analyses. Variable definitions are included in the appendix. The sample size is smaller for the city-level samples due to availability of auditor data in Audit Analytics matched to the U.S. Census Bureau 2003 list of Metropolitan Statistical Areas.

specialist auditors have between 0.3% and 0.4% lower discretionary accruals compared to clients of nonspecialists auditors.

Columns (II) and (V) in table 3 present the results using matched samples based on a multivariate propensity score, including all control variables in equation (3) as determinants of auditor choice and *LOGASSETS* as a client size variable. Columns (III) and (VI) present the results using matched samples based on a multivariate propensity score, including *LOGASSETS*, industry, and year as determinants of auditor choice. The matched samples in columns (II), (III), (V), and (VI) are of relatively similar size and most of the specialist auditors' clients are included in all samples. For example, the matched sample used in column (II) has 8,111 clients of specialist auditors, compared to 8,147 clients of specialist auditors in the full sample used in column (I). In all models estimated

TABLE 3

Analyses of Absolute Discretionary Accruals, Full and Matched Samples

	Dependent Variable = Absolute Discretionary Accruals (*ADA*)					
		Matched Samples			Matched Samples	
Variables	(I) Full Sample	(II) All Variables	(III) Size	(IV) Full Sample	(V) All Variables	(VI) Size
NLEAD	− 0.004***	0.001	− 0.000			
	(− 4.39)	(0.61)	(− 0.13)			
CLEAD				− 0.003**	0.000	0.001
				(− 2.18)	(0.13)	(0.78)
BIG4	− 0.008***	− 0.015***	− 0.005**	− 0.010***	− 0.015***	− 0.015***
	(− 7.59)	(− 5.23)	(− 2.06)	(− 5.86)	(− 4.32)	(− 5.66)
LOGMKT	− 0.006***	− 0.005***	− 0.005***	− 0.006***	− 0.005***	− 0.005***
	(− 29.02)	(− 15.02)	(− 14.47)	(− 15.30)	(− 9.28)	(− 9.33)
LEV	− 0.036***	− 0.035***	− 0.032***	− 0.031***	− 0.033***	− 0.030***
	(− 17.30)	(− 9.46)	(− 8.72)	(− 8.79)	(− 8.08)	(− 7.16)
ROAL	0.034***	0.035**	0.032**	0.018**	0.026**	0.025**
	(6.40)	(2.09)	(2.06)	(2.35)	(2.11)	(2.09)
ROA	− 0.112***	− 0.125***	− 0.124***	− 0.099***	− 0.137***	− 0.116***
	(− 16.17)	(− 6.26)	(− 6.64)	(− 9.08)	(− 7.87)	(− 6.40)
LOSS	− 0.003***	0.000	0.000	− 0.004***	− 0.003	− 0.001
	(− 3.54)	(0.13)	(0.12)	(− 2.90)	(− 1.43)	(− 0.42)
CFO	− 0.013**	0.004	0.011	0.008	0.026*	0.017
	(− 2.39)	(0.31)	(0.79)	(0.77)	(1.70)	(1.10)
BTM	− 0.024***	− 0.018***	− 0.018***	− 0.019***	− 0.017***	− 0.017***
	(− 21.40)	(− 8.56)	(− 8.43)	(− 9.99)	(− 6.69)	(− 6.33)
ABS(ACCRL)	0.027***	0.020***	0.029***	0.076***	0.084***	0.086***
	(16.74)	(5.30)	(7.13)	(11.97)	(8.34)	(8.81)
GROWTH	0.011***	0.012***	0.015***	0.009***	0.006*	0.007*
	(7.95)	(4.17)	(5.23)	(3.17)	(1.76)	(1.87)
ALTMAN	− 0.000***	0.000	0.000	− 0.000***	− 0.000	− 0.000
	(− 3.76)	(0.21)	(0.22)	(− 3.73)	(− 1.11)	(− 1.08)
STDEARN	0.000***	0.000***	0.000***	0.000***	0.000**	0.000*
	(6.51)	(3.97)	(2.81)	(3.90)	(2.53)	(1.80)
TENURE	− 0.005	− 0.004	− 0.005	0.001	− 0.011	− 0.011
	(− 1.44)	(− 0.86)	(− 0.84)	(0.09)	(− 1.18)	(− 1.17)
Intercept	0.098***	0.075***	0.089***	0.121***	0.121***	0.120***
	(23.88)	(10.05)	(11.53)	(16.22)	(11.24)	(11.42)
Observations	75,188	16,222	16,210	23,306	13,054	13,006
Adjusted R^2	0.210	0.166	0.170	0.248	0.215	0.200

This table presents the analyses of discretionary accruals for the full and matched samples, using the *NLEAD* and *CLEAD* definitions of auditor specialization. Columns (I) and (IV) present the results using the full samples, columns (II) and (V) present the results using matched samples based on a multivariate propensity score, including all control variables in equation (3) as determinants of auditor choice and *LOGASSETS* as a client size variable. Columns (III) and (VI) present the results using matched samples based on a multivariate propensity score, including *LOGASSETS*, industry, and year as determinants of auditor choice. All models were estimated using OLS regression. Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All *t*-statistics (in parentheses) and *p*-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. The models in all columns include year-specific intercepts, but for brevity these are not reported.

using matched samples there is no evidence that specialist auditors at the national or city level reduce absolute discretionary accruals. This evidence 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.

TABLE 4

Analyses of Going-Concern Opinions, Full and Matched Samples

	Dependent Variable = Going-Concern Opinion (*GCONCERN*)					
		Matched Samples			Matched Samples	
Variables	(I) Full Sample	(II) All Variables	(III) Size	(IV) Full Sample	(V) All Variables	(VI) Size
NLEAD	0.093	− 0.053	− 0.221			
	(0.66)	(− 0.31)	(− 1.20)			
CLEAD				0.272***	0.189	0.177
				(2.58)	(1.56)	(1.35)
BIG4	− 0.129	0.01	0.219	− 0.211**	− 0.165	− 0.047
	(− 1.58)	(0.01)	(0.88)	(− 2.14)	(− 0.88)	(− 0.27)
LOGMKT	− 0.570***	− 0.582***	− 0.537***	− 0.627***	− 0.668***	− 0.668***
	(− 24.75)	(− 13.22)	(− 11.83)	(− 21.70)	(− 17.23)	(− 16.97)
LEV	0.302**	0.155	− 0.040	0.228	0.290	0.320
	(2.36)	(0.37)	(− 0.10)	(1.53)	(1.40)	(1.54)
ROAL	− 0.293**	0.270	− 0.424	− 0.270	0.048	− 0.130
	(− 1.99)	(0.49)	(− 0.98)	(− 1.54)	(0.15)	(− 0.41)
ROA	− 0.930***	− 0.788	− 0.875	− 0.891***	− 0.946**	− 0.980**
	(− 4.83)	(− 1.15)	(− 1.38)	(− 3.90)	(− 2.31)	(− 2.38)
LOSS	1.077***	1.041***	1.370***	1.030***	1.229***	1.174***
	(12.53)	(4.27)	(5.23)	(9.64)	(6.73)	(6.64)
CFO	− 0.578***	− 1.044**	− 0.288	− 0.819***	− 0.964***	− 0.759***
	(− 3.74)	(− 2.19)	(− 0.61)	(− 4.63)	(− 3.24)	(− 2.61)
BTM	− 0.884***	− 0.964***	− 1.074***	− 0.846***	− 1.084***	− 1.001***
	(− 10.69)	(− 3.21)	(− 3.42)	(− 8.89)	(− 6.35)	(− 6.05)
ABS(ACCRL)	0.909***	0.001	0.205	0.879***	0.435	0.735***
	(7.13)	(0.00)	(0.48)	(5.71)	(1.50)	(2.70)
GROWTH	− 0.211***	− 0.904***	− 0.715***	− 0.192**	− 0.250	− 0.389**
	(− 2.73)	(− 3.77)	(− 3.26)	(− 2.07)	(− 1.41)	(− 2.20)
ALTMAN	− 0.018***	− 0.043***	− 0.060***	− 0.020***	− 0.021***	− 0.018**
	(− 5.90)	(− 2.85)	(− 3.25)	(− 5.64)	(− 2.99)	(− 2.54)
STDEARN	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***
	(6.91)	(6.23)	(5.80)	(5.66)	(4.85)	(6.21)
TENURE	− 0.096	− 0.285	− 0.422	− 0.886	− 2.144***	
	(− 0.33)	(− 0.37)	(− 0.70)	(− 1.27)	(− 3.42)	
Intercept	− 0.290	− 0.353	− 0.571	− 9.269***	1.477**	− 0.929***
	(− 0.53)	(− 0.40)	(− 0.77)	(− 8.00)	(2.11)	(− 3.43)
Observations	35,177	8,576	8,586	22,961	13,070	13,058
Pseudo R^2	0.475	0.424	0.465	0.486	0.478	0.463

This table presents the analyses of going-concern opinions for the full and matched samples, using the *NLEAD* and *CLEAD* definitions of auditor specialization. Columns (I) and (IV) present the results using the full samples, columns (II) and (V) present the results using matched samples based on a multivariate propensity score, including all control variables in equation (3) as determinants of auditor choice and *LOGASSETS* as a client size variable. Columns (III) and (VI) present the results using matched samples based on a multivariate propensity score, including *LOGASSETS*, industry, and year as determinants of auditor choice. All models were estimated using logistic regression. Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All *t*-statistics (in parentheses) and *p*-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. The models in all columns include industry- and year-specific intercepts, but for brevity these are not reported.

5.3 GOING-CONCERN OPINION—FULL AND MATCHED SAMPLE ANALYSES

Table 4 presents the results of the full and matched samples regression analyses of going-concern opinions using *NLEAD* and *CLEAD* as measures of auditor specialization. In line with the results in Reichelt and Wang

[2010], column (I) shows that the coefficient on *NLEAD* is 0.093 but statistically insignificant and column (IV) shows that the coefficient on *CLEAD* is 0.272 and statistically significant (at the 1% level). These coefficients suggest that, comparatively, city-level specialists issue more going-concern opinions.

Columns (II) and (V) in table 4 present the results using matched samples based on a multivariate propensity score, including all control variables in equation (4) as determinants of auditor choice and *LOGASSETS* as a client size variable. Columns (III) and (VI) present the results using matched samples based on a multivariate propensity score, including *LOGASSETS*, industry, and year as determinants of auditor choice. The matched samples are of relatively similar size and most of the specialist auditors' clients are included in all samples. For example, the matched sample used in column (II) has 4,288 clients of specialist auditors, compared to the 4,351 clients of specialist auditors in the full sample used in column (I). There is no evidence that specialist auditors at the national or city level have a greater propensity to issue a going-concern opinion in the matched samples. This evidence confirms the conclusions of the discretionary accruals analyses presented in table 3.

5.4 MEET OR BEAT—FULL AND MATCHED SAMPLE ANALYSES

Table 5 presents the results of the full and matched samples regression analyses of meet or beat analysts' earnings forecasts using *NLEAD* and *CLEAD* as measures of auditor specialization. In line with the results in Reichelt and Wang [2010], column (I) shows that the coefficient on *NLEAD* is –0.023 but statistically insignificant and column (IV) shows that the coefficient on *CLEAD* is –0.129 and statistically significant (at the 5% level). These coefficients suggest that city-level specialists reduce their clients' propensity to meet or beat analysts' forecasts.

The matched samples in table 5, columns (II), (III), (V), and (VI), are defined in a similar way to those in tables 3 and 4. The matched samples are of relatively similar size and most of the specialist auditors' clients are included in all samples. For example, the matched sample used in column (II) has 2,579 clients of specialist auditors, compared to 2,643 clients of specialist auditors in the full sample used in column (I). Although the results are statistically significant (at the 5% level) only using the city-level definition of specialist in the full sample, there is no evidence that specialist auditors at the national or city levels reduce their clients' propensity to meet or beat analysts' forecasts in the matched samples. This evidence confirms the conclusion of the discretionary accruals and going-concern analyses presented in tables 3 and 4.

5.5 AUDIT FEES—FULL AND MATCHED SAMPLE ANALYSES

Table 6 presents the results of the full and matched samples regression analyses of audit fees using *NLEAD* and *CLEAD* as measures of auditor

TABLE 5

Analyses of Meet or Beat Analysts' Earnings Forecasts, Full and Matched Samples

	Dependent Variable = Meet or Beat Analysts' Forecasts (*MEET*)					
		Matched Samples			Matched Samples	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Variables	Full Sample	All Variables	Size	Full Sample	All Variables	Size
NLEAD	−0.023	−0.065	0.001			
	(−0.39)	(−0.89)	(0.01)			
CLEAD				−0.129**	−0.106	−0.098
				(−2.11)	(−1.58)	(−1.47)
BIG4	−0.019	0.071	0.514*	−0.139	0.156	−0.199
	(−0.18)	(0.28)	(1.96)	(−1.31)	(0.62)	(−1.37)
LOGMKT	0.016	0.035	0.017	0.032	0.069**	0.027
	(0.77)	(0.99)	(0.48)	(1.18)	(2.13)	(0.83)
LEV	−0.458***	−0.410	−0.685**	−0.436**	−0.436*	−0.429*
	(−2.66)	(−1.28)	(−2.20)	(−2.24)	(−1.83)	(−1.83)
ROAL	0.078	−1.036	1.270	−0.688	−0.038	−0.818
	(0.11)	(−0.56)	(0.71)	(−1.17)	(−0.05)	(−1.15)
ROA	1.196	3.032	−0.674	0.650	0.729	1.233
	(1.23)	(1.30)	(−0.30)	(0.79)	(0.70)	(1.25)
LOSS	−0.233***	−0.329*	−0.461***	−0.211**	−0.218*	−0.227*
	(−2.74)	(−1.95)	(−2.69)	(−2.23)	(−1.80)	(−1.94)
CFO	−0.731**	−1.117*	−0.551	0.484	−0.393	−0.072
	(−2.39)	(−1.75)	(−0.85)	(1.06)	(−0.68)	(−0.13)
BTM	−0.634***	−0.455	−0.936***	−0.358**	−0.297	−0.485**
	(−4.40)	(−1.60)	(−3.36)	(−2.31)	(−1.56)	(−2.57)
ABS(ACCR)	−1.212***	−0.873	−0.644	−1.329**	−0.695	−1.040
	(−3.42)	(−1.31)	(−0.93)	(−2.44)	(−1.02)	(−1.56)
GROWTH	−0.147	−0.021	−0.257	−0.152	−0.139	−0.157
	(−1.34)	(−0.09)	(−1.17)	(−1.03)	(−0.74)	(−0.90)
ALTMAN	0.010*	0.020*	0.015	0.006	0.007	0.007
	(1.75)	(1.70)	(1.26)	(1.13)	(0.99)	(0.95)
STDEARN	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(−1.56)	(−1.53)	(−1.61)	(−0.87)	(−0.71)	(−0.32)
TENURE	−0.314	−0.475	−0.795	−0.675*	−1.063**	−0.876
	(−1.10)	(−0.84)	(−1.61)	(−1.87)	(−2.41)	(−1.62)
LOGNFOR	0.148***	0.152**	0.183**	0.310***	0.285***	0.284***
	(3.46)	(2.02)	(2.48)	(5.91)	(4.32)	(4.43)
STDFOR	−5.992***	−5.647***	−5.950***	−6.178***	−6.442***	−6.038***
	(−7.89)	(−4.46)	(−4.17)	(−6.28)	(−5.10)	(−5.05)
Intercept	−2.719**	−14.831***	−11.833***	−0.961	−12.854***	−10.998***
	(−2.54)	(−13.21)	(−8.49)	(−1.14)	(−15.81)	(−9.57)
Observations	16,337	5,147	5,133	8,856	5,955	6,063
Pseudo R^2	0.0811	0.103	0.0994	0.0693	0.0799	0.0726

This table presents the analyses of the client's propensity to meet or beat analysts' earnings forecasts for the full and matched samples, using the *NLEAD* and *CLEAD* definitions of auditor specialization. Columns (I) and (IV) present the results using the full samples, columns (II) and (V) present the results using matched samples based on a multivariate propensity score, including all control variables in equation (3) as determinants of auditor choice and *LOGASSETS* as a client size variable. Columns (III) and (VI) present the results using matched samples based on a multivariate propensity score, including *LOGASSETS*, industry, and year as determinants of auditor choice. All models were estimated using logistic regression. Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All *t*-statistics(in parentheses) and *p*-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. The models in all columns include industry- and year-specific intercepts, but for brevity these are not reported.

TABLE 6

Analyses of Audit Fees, Full and Matched Samples

	Dependent Variable = Natural Logarithm of Audit Fees (*LOGFEES*)					
		Matched Samples			Matched Samples	
Variables	(I) Full Sample	(II) All Variables	(III) Size	(IV) Full Sample	(V) All Variables	(VI) Size
NLEAD	0.048**	0.036	0.044*			
	(2.33)	(1.57)	(1.87)			
CLEAD				− 0.025	− 0.031*	− 0.018
				(− 1.49)	(− 1.77)	(− 1.03)
LOGASSETS	0.378***	0.386***	0.372***	0.393***	0.389***	0.382***
	(33.03)	(17.45)	(16.97)	(32.48)	(25.88)	(24.21)
LOGSALES	0.166***	0.163***	0.182***	0.143***	0.146***	0.156***
	(15.73)	(7.79)	(8.80)	(13.27)	(10.61)	(10.93)
LOGNSEG	0.133***	0.185***	0.190***	0.124***	0.132***	0.138***
	(11.85)	(9.93)	(10.27)	(9.59)	(8.38)	(8.82)
FOREIGN	0.078	0.675**	0.198	− 0.032	0.079	0.035
	(0.55)	(2.30)	(0.79)	(− 0.21)	(0.42)	(0.20)
CATA	0.094	0.045	− 0.063	0.071	0.289**	0.286**
	(1.14)	(0.29)	(− 0.41)	(0.74)	(2.31)	(2.25)
QUICK	0.200**	0.273*	0.384**	0.200**	− 0.021	− 0.002
	(2.46)	(1.75)	(2.42)	(2.10)	(− 0.17)	(− 0.02)
LEV	0.294***	0.400***	0.345***	0.248***	0.280***	0.269***
	(8.61)	(5.44)	(4.90)	(6.44)	(5.76)	(5.53)
ROA	− 0.506***	− 0.563***	− 0.643***	− 0.438***	− 0.492***	− 0.471***
	(− 16.85)	(− 7.20)	(− 8.75)	(− 13.71)	(− 10.99)	(− 10.27)
LOSS	0.100***	0.114***	0.080***	0.094***	0.074***	0.104***
	(7.13)	(4.03)	(2.89)	(5.92)	(3.73)	(5.17)
OPINION	0.152***	0.117	0.148**	0.163***	0.205***	0.157***
	(5.22)	(1.57)	(2.31)	(5.16)	(3.94)	(3.13)
NONDEC	− 0.044**	− 0.094***	− 0.096***	− 0.060***	− 0.087***	− 0.077***
	(− 2.54)	(− 3.17)	(− 3.29)	(− 2.96)	(− 3.56)	(− 3.13)
BIG	0.239***	0.337**	0.246***	0.273***	0.291***	0.277***
	(11.88)	(2.30)	(5.75)	(12.23)	(7.20)	(8.57)
Intercept	8.403***	8.678***	8.656***	8.389***	8.378***	8.379***
	(45.30)	(34.64)	(34.63)	(203.45)	(139.87)	(155.16)
Observations	24,279	5,960	5,906	16,388	9,626	9,710
Adjusted R^2	0.834	0.838	0.842	0.838	0.823	0.819

This table presents the analyses of audit fees for the full and matched samples, using the *NLEAD* and *CLEAD* definitions of auditor specialization. Columns (I) and (IV) present the results using the full samples, columns (II) and (V) present the results using matched samples based on a multivariate propensity score, including all control variables in equation (3) as determinants of auditor choice and *LOGASSETS* as a client size variable. Columns (III) and (VI) present the results using matched samples based on a multivariate propensity score, including *LOGASSETS*, industry, and year as determinants of auditor choice. All models were estimated using OLS regression. Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All *t*-statistics (in parentheses) and *p*-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. The models in all columns include industry- and year-specific intercepts, but for brevity these are not reported.

specialization. In line with the results in Francis, Reichelt, and Wang [2005], column (I) shows that the coefficient on *NLEAD* is 0.048 and statistically significant (at the 5% level); however, there is no evidence of a specialist premium at the city level in the full sample in column (IV).[24]

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[24] The main differences between this study and Francis, Reichelt, and Wang [2005] are: (1) the sample years (restricted to 2000–2001 in Francis et al.), (2) including non–Big 4 clients

The matched samples in table 6, columns (II), (III), (IV), and (VI), are defined in similar way to those in tables 3–5. The matched samples are of relatively similar size and most of the specialist auditors' clients are included in all samples. For example, the matched sample used in column (II) has 2,980 clients of specialist auditors, compared to 3,016 clients of specialist auditors in the full sample used in column (I).

The evidence resulting from the models estimated in the matched samples is mixed. First, matching on all variables results in no evidence of a fee difference in the national-level sample; the coefficient on *NLEAD* is 0.036, not statistically significant (column II). In contrast, matching on all variables results in a fee discount in the city-level sample; the coefficient on *CLEAD* is –0.031, statistically significant at the 10% level (column V). Second, matching on industry and size results in a fee premium in the national-level sample; the coefficient on *NLEAD* is 0.044, statistically significant at the 10% level (column III). Nevertheless, matching on industry and size results in no evidence of a fee difference in the city-level sample; the coefficient on *CLEAD* is –0.018, not statistically significant (column VIII).

The difference between matched samples in the national-level sample can be partially explained because Big 4 is properly matched between specialist and nonspecialist clients in column (II), but not in columns (III) and (VI). In addition, there is a strong correlation between Big 4 and *NLEAD*. If Big 4 is included together with industry and size as a predictor of the propensity score, there is no evidence of a fee premium in national-level matched sample.

The combined evidence presented in tables 3–5 indicates that, after matching comparable clients between specialist and nonspecialist auditors, the treatment effects of specialist auditors are no different from those of nonspecialist auditors with respect to absolute discretionary accruals, the auditor's propensity to issue a going-concern opinion, and the client's likelihood to meet or beat analysts' forecasts. Furthermore, table 6 indicates that there is an inconsistent association between audit fees and auditor industry specialization.

(dropped in Francis et al.), and (3) the calculation of industry market share using client assets (based on audit fees in the main analyses in Francis et al.). In this study, restricting the sample to include only observations from 2000 to 2001 and Big 4 clients produces qualitatively similar results to those in columns (I) and (IV) in table 6. Extant studies in the auditor industry specialization literature have used client audit fees, sales, or assets to calculate the auditor market share. Examples of recent studies using total assets are Cairney and Young [2006], Behn, Choi, and Kang [2008], Cahan et al. [2008], and Gul, Fung, and Jaggi [2009]; however, none of these studies use the same fee model as this study. Using fees to calculate market share may be problematic in cases where the number of companies in a city–industry combination is small. In those cases the dependent variable, company *i* audit fees, is mechanically correlated with the proxy for auditor expertise, based on aggregate fees for the city–industry combination. Furthermore, using assets to calculate market share may be preferable to sales because assets are comparatively more stable over time, possibly reflecting the effect of expertise that is slowly developed and maintained within the audit firm.

TABLE 7
Full Sample Analyses Including Client Fixed Effects in Each Regression Model

Variables	(I) *ADA* Model	(II) *GCONCERN* Model	(III) *MEET* Model	(IV) *LOGFEES* Model	(V) *ADA* Model	(VI) *GCONCERN* Model	(VII) *MEET* Model	(VIII) *LOGFEES* Model
NLEAD	0.000	− 0.037	0.0301	0.006				
	(0.15)	(− 0.16)	(0.35)	(0.36)				
CLEAD					0.000	− 0.038	− 0.098	0.020
					(0.22)	(− 0.21)	(− 0.92)	(1.43)
Observations	75,188	6,077	11,165	24,279	23,306	3,856	5,632	16,388
Adjusted R^2	0.045	0.149	0.026	0.694	0.041	0.155	0.027	0.711

This table presents the analyses of discretionary accruals, going-concern opinions, meet or beat analysts' earnings forecasts, and audit fees, for the full samples, using the *NLEAD* and *CLEAD* definitions of auditor specialization. All columns include client fixed effects. Columns (I) and (V) were estimated using equation (3). Columns (II) and (VI) were estimated using equation (4). Columns (III) and (VII) were estimated using equation (5). Columns (IV) and (VIII) were estimated using equation (6). The going-concern and meet or beat models, estimated using fixed effects logistic regression, drop companies without variation in the dependent variable over time. For example, when either $GCONCERN = 0$ or $GCONCERN = 1$ for all observations for a given client, these observations have no impact on the estimation of the within-company effect of specialization on the propensity to issue a going-concern opinion. Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All t-statistics (in parentheses) and p-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. For brevity, only the coefficients for the city- and national-level variables are reported.

6. *Results of Alternative Approaches That Do Not Rely on Matched Samples*

6.1 FULL SAMPLES INCLUDING CLIENT FIXED EFFECTS

Table 7 shows the coefficients on the specialist variable for the models described in section 4, estimated on the full samples and including client fixed effects. Including client fixed effects makes the coefficient on the specialist variable statistically insignificant in all models. Nevertheless, these results have to be interpreted with caution due to the limitations of fixed effects models, primarily that fixed effects models rely on whether the variation in the independent variables over time determines the variation in the dependent variables for each individual company (Li and Prabhala [2007]).[25]

[25] A relatively small number of clients exhibit variation in the specialist variable over time. For example, in the discretionary accruals *NLEAD* sample consisting of 75,188 observations, only 3,625 clients (4.8%) have variation over time in the *NLEAD* measure; using the discretionary accruals *CLEAD* sample consisting of 23,306 observations, only 1,747 clients (7.5%) have variation over time in the *CLEAD* measure. However, the within-company variation has considerable explanatory power. In general, the differences among within- and between-company adjusted R^2 indicate that, although a comparatively larger portion of the variation in dependent variables is explained by variation between companies, the variation in dependent variables is also explained by variation over time within companies. Using the *NLEAD* proxy models, the within-company adjusted R^2 (last row of table 8) for the discretionary accruals model is 0.045, for the going-concern model is 0.149, for the meet or beat model is 0.026, and for the fee model is 0.694. In contrast, the between-company adjusted R^2 for the discretionary accruals model is 0.368, for the going-concern model is 0.385, for the meet or beat model is

6.2 ANALYSES OF AUDITOR SWITCHES

Taking advantage of the setting created by the demise of AA in 2002, this section examines the pre–post changes in absolute discretionary accruals, meet or beat analysts' earnings forecasts, and audit fees for a sample of former AA clients that switched to an auditor with a different degree of industry specialization.[26] The following regression model is estimated for AA clients that switched auditors in 2002 in order to test whether there was a pre–post effect of a switch to an auditor with a different degree of industry specialization:

$$\Delta QUALITY\_MEASURE_i = \delta_0 + \delta_1 \Delta LEAD_i + \delta_j \Delta CONTROL\ VARIABLES_i + v_i, \qquad (7)$$

where Δ denotes the difference between the level of each variable (as previously defined) in 2002 and the level of that variable in 2001. This model uses each client as its own control. The intercept δ_0 represents the average change in the dependent variable controlling for changes in other client characteristics, and the coefficient δ_1 on $\Delta LEAD$ represents the incremental change as a result of switching between specialist and nonspecialist auditors ($\Delta NLEAD$ and $\Delta CLEAD$ at the national and city level, respectively). If specialist auditors are better at detecting and undoing earnings management, it is expected that a switch to a specialist auditor will decrease absolute discretionary accruals and absolute discretionary revenue.

After estimating equation (7) in the sample of former AA clients with available data, I find no evidence of a pre–post change in discretionary accruals, likelihood to meet or beat, or audit fees from switching between specialist and nonspecialist auditors. These results 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. Nevertheless, there are limitations inherent to these analyses. First,

0.001, and for the fee model is 0.774. The adjusted R^2 comparison is qualitatively similar using the *CLEAD* proxy models. Choosing between fixed and random effects, using a random effects specification confirms the results of the fixed effects specification in most models; however, a Hausman test rejects random effects in favor of fixed effects in all cases. The GAO's [2008, p. 99] analysis of audit fees and market concentration finds similar results for the audit fee model and focuses primarily on the results of a fixed effect model. The going-concern and meet or beat models, estimated using fixed effects logistic regression, drop companies without variation in the dependent variable over time. For example, when either $GCONCERN = 0$ or $GCONCERN = 1$ for all observations for a given client, these observations have no impact on the estimation of the within-company effect of specialization on the propensity to issue a going-concern opinion.

[26] Going-concern opinions are not used in these analyses due to the low incidence of this variable within the clients in the AA sample. The industry leadership variable is calculated using market share of each auditor by industry in each year 2001 and 2002. A number of previous studies have examined the consequences of this unique exogenous shock (e.g., Nagy [2005], Cahan and Zhang [2006], Blouin, Grein, and Roundtree [2007], Knechel, Naiker, and Pacheco [2007], and Nelson, Price, and Roundtree [2008]).

TABLE 8

Full Sample Analyses Using Alternative Definitions of Auditor Industry Specialization Based On Auditor Industry Portfolios

Variables	(I) *ADA* Model	(II) *GCONCERN* Model	(III) *MEET* Model	(IV) *LOGFEES* Model	(V) *ADA* Model	(VI) *GCONCERN* Model	(VII) *MEET* Model	(VIII) *LOGFEES* Model
NFOCUS	− 0.001	0.128	− 0.227**	− 0.081***				
	(− 0.73)	(1.29)	(− 2.44)	(− 3.81)				
CFOCUS					− 0.000	0.150*	0.041	− 0.021
					(− 0.18)	(1.67)	(0.63)	(− 1.19)
Observations	75,188	35,177	16,337	24,279	23,306	22,924	8,856	16,388
Adjusted R^2	0.210	0.475	0.0815	0.834	0.248	0.486	0.0688	0.838

This table presents the analyses of discretionary accruals, going-concern opinions, meet or beat analysts' earnings forecasts, and audit fees, for the full samples using the *NFOCUS* and *CFOCUS* definitions of auditor specialization, based on auditor portfolio shares. Columns (I) and (V) were estimated using equation (3). Columns (II) and (VI) were estimated using equation (4). Columns (III) and (VII) were estimated using equation (5). Columns (IV) and (VIII) were estimated using equation (6). Variable definitions are included in the appendix. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. All *t*-statistics (in parentheses) and *p*-values are calculated using heteroscedasticy-adjusted clustered (HAC) standard errors by company. For brevity, only the coefficients for the city- and national-level variables are reported.

although the shock that caused AA to be dismissed was exogenous, the choice of hiring a new auditor was decided by each client. Second, as noted by Blouin, Grein, and Roundtree [2007], in several instances, former AA employees were hired by the successor auditors and continued to audit the same clients. Third, there were changes in the environment that may have motivated all auditors, specialist and nonspecialist, to be more conservative in 2002. Fourth, the effect of auditor specialization may not be immediately reflected in the two proxies for financial reporting quality used in these analyses.

6.3 ALTERNATIVE MEASURE OF INDUSTRY EXPERTISE

A variation in the measure of auditor expertise confirms the results discussed in the previous sections. This variation is based on a portfolio share approach (Neal and Riley [2004]). An auditor is considered a national- or city-level specialist in those industries, which represent the largest share of the firm's or office's portfolio. Under this approach two new variables *NFOCUS* and *CFOCUS* equal "1" for the top industry in an auditor's portfolio at the national or city level, and "0" otherwise. This measure has a high correlation with the auditors' self-reported industry expertise, as documented by Krishnan [1998], and a weak correlation with client size both in the national- and city-level samples.[27] Table 8 shows that there is no consistent evidence of a specialist effect using the portfolio measure and the

[27] For example, in the discretionary accruals full sample the correlation between *NFOCUS* and *LOGASSETS* is –0.01 and not statistically significant, between *CFOCUS* and *LOGASSETS* is 0.07 and significant at the 1% level, between *NFOCUS* and *NLEAD* is 0.16 and significant at the 1% level, and between *CFOCUS* and *CLEAD* is 0.10 and significant at the 1% level.

audit-quality proxies examined in this study. At the national level there is only a statistically significant association in the predicted direction between *NFOCUS* and meet or beat (column III). At the city level there is only a statistically significant association in the predicted direction between *CFOCUS* and going-concern opinions (column VI). These analyses show an inconsistent pattern of associations between auditor industry specialization and audit quality and audit fees.

7. *Additional Sensitivity Analyses*

7.1 ADDITIONAL AUDIT-QUALITY PROXIES

The results presented in the main analyses are confirmed by using two additional audit-quality proxies. First, following Balsam, Krishnan, and Yang [2003], I examine the incremental effect of the industry specialist on the client's ERCs using an interaction between the earnings surprise variable and the specialist variable. Using an ERC model similar to the one in Balsam, Krishnan, and Yang [2003], only the national-level specialist appears to increase ERCs in the full sample; however, there is no evidence of a specialist effect in the matched samples, the fixed-effects regressions using the full samples, and for the former Andersen clients that switched between specialist and nonspecialist auditors. Second, I use a revenue manipulation measure suggested by Stubben [2010]. The revenue manipulation or discretionary revenue model is related to the discretionary accruals model, relying on the association 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. All results using this alternative measure confirm the results using discretionary accruals.

7.2 ADDITIONAL MATCHING APPROACHES AND PAIRWISE ANALYSES

The second most important client characteristic associated with both the specialist variable and the main dependent variables in this study is performance. Furthermore, the literature has repeatedly highlighted the importance of controlling for industry, size, and performance in tests of earnings management (e.g., Kothari, Leone, and Wasley [2005]). Performance can be captured in different ways. Hence, I perform two complementary approaches to match clients of specialists and nonspecialist auditors on industry, size, and performance. First, observations are matched using a reduced propensity score model, estimated using size, size and ROA, and industry and year indicator variables as predictors in the logistic regression. Second, observations are matched based on three covariates, industry, size, and a measure of comparability based on performance proposed by De Franco, Kothari, and Verdi [2011]. Arguably, the comparability measure in De Franco, Kothari, and Verdi [2011] captures similar economic performance over time between matched companies and might be better than one-period ROA as a performance variable. Using this alternative approach, for a given fiscal year-end, industry, and size distance (firms that are within a size distance of 50%), 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. As per the De Franco, Kothari, and Verdi [2011] methodology, returns covariance is measured using the adjusted R^2 of the regression of firm i's monthly returns on firm j's monthly returns. In addition, matched firms are required to have their fiscal year-end on the same month to reduce differences from timing in financial reporting. Allowing for 50% 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.[28] All results are qualitatively similar to those in the main analyses using these two alternative approaches aiming to match on size and performance.[29]

Furthermore, as an alternative to propensity-score matching on industry and size, clients are matched by year, industry, and size, within a difference in total assets of 20%. All results are qualitatively similar to those presented in the main analyses, except for the national-level meet or beat analyses, where there is a negative and statistically significant association (at the 10% level) between *NLEAD* and meet or beat; and the going-concern city-level analyses, where there is a positive and statistically significant association (at the 10% level) between *CLEAD* and going-concern opinions. Nevertheless, this matching approach results in significantly smaller samples compared to matching on propensity score. For example, after matching using this approach, the discretionary accruals and national-level specialist

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[28] This measure is denoted *CompRet-*R^2 in De Franco, Kothari, and Verdi [2011, p. 923]. Similar results are obtained measuring covariance using Tau or rank correlation. Tau measures comovement or serial dependence and can be directly interpreted as the probability of observing concordant or discordant pairs of observations. Matching on size and returns covariance 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. Under this approach, reducing the size distance more than 50% produces very similar matched pairs to using only industry and size.

[29] In the large samples used in this study, matching on industry, within 50% size, and returns covariance is similar as matching closely only on industry and size. 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. In general, companies of very 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 nonspecialist auditors.

sample has 6,107 clients with *NLEAD* = 1 and the same number of clients with *NLEAD* = 0. In contrast, the sample in table 4, column (III) has 8,105 clients with *NLEAD* = 1 and the same number of clients with *NLEAD* = 0.

Finally, although a univariate *t*-test of the differences in means between perfectly matched clients may constitute a direct estimator of treatment effects (Zhao [2004]), if the matching process is not perfect, it is still important to control for unmatched client characteristics using multivariate analyses with pairwise controls. Adding indicator variables for every matched pair, as suggested by Cram, Karan, and Stuart [2009], produces qualitatively similar results to those presented in the main analyses.

7.3 ALTERNATIVE SPECIALIST CUTOFF AND JOINT NATIONAL- AND CITY-LEVEL SPECIALIZATION

I repeated all the full and matched sample analyses using an alternative market share cutoff for the national- and city-level specialist measures, *LEAD30p* equal to "1" for auditors that have over 30% market share in a given industry and year at the national or city level, 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 analyses; however, it has very similar properties compared to the *LEAD* measure. In addition, I repeated all the full and matched sample analyses using a joint national- and city-level specialist measure, *CNLEAD* equal to "1" for auditors that are both national- (*NLEAD*) and city-level (*CLEAD*) specialists, according to the definitions in section 2, and "0" otherwise. Using these two alternative measures produces qualitatively similar results to those presented in the main analyses.

7.4 BOOTSTRAP, RANDOM SUBSAMPLES, AND STRATIFIED SAMPLES

To mitigate concerns that the lack of significance in the matched samples analyses is a result of smaller sample sizes, this section documents the results of two additional sensitivity analyses. First, bootstrap standard errors are estimated for all the matched sample models using 1,000 replications. These analyses produce qualitatively similar results as those shown in the main tables. Second, 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. Likewise, 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, median total accruals is calculated using the variable *ABS(ACCRL)*, median sales growth is calculated using the variable *GROWTH*, median industry concentration is calculated using the Herfindahl index based on total assets, and median earnings volatility is calculated using the variable

STDEARN. Next, industries are ranked by year using the industry median for each of these variables, and the main models are estimated separately for observations in the top and bottom quartiles. Separating industries by these variables produces similar results to those documented in the main tables using the full matched samples.

8. *Conclusion*

There are conceptual and econometric problems associated with using the auditor's within-industry market share as a proxy for expertise. Defining industry specialization based on market share results in differences in client characteristics between auditor types. By construction, auditors with large market share are more likely to have larger clients compared to nonspecialist auditors. This definition of expertise constitutes a problem because a number of size-related client characteristics are simultaneously correlated with the specialist variable and with commonly used audit-quality proxies and audit fees. The confounding effect of these differences may not be properly addressed by cross-sectional regression models.

Consistent with prior studies, this study first shows a relation between commonly used audit-quality proxies and auditor industry specialization, and between audit fees and auditor industry specialization. However, after matching clients of specialist and nonspecialist auditors in a number of dimensions, as well as only on industry and size, there are no statistically significant differences in the audit-quality proxies between the two groups of auditors. Moreover, there is no clear pattern indicating the presence of a specialist fee premium. This study also documents confirmatory evidence from three additional analyses that do not rely on matched samples. First, including client fixed effects in the audit-quality and fee models makes the coefficient on the specialist variable statistically insignificant. Second, there are insignificant pre–post differences in discretionary accruals, propensity to meet or beat analysts' forecasts, and audit fees for AA's clients that switched to auditors with a different degree of specialization in 2002. Third, employing a measure of specialization based on the auditor's portfolio results in a pattern of evidence inconsistent with a specialist effect on audit quality and audit fees.

Overall, the combined evidence provided in this study suggests that auditor industry specialization, measured using the auditor's within-industry market share, is not a reliable indicator of audit quality. The results of this study do not imply that industry knowledge does not contribute to audit quality, but that the extant methodology does not necessarily capture the effects of auditor industry expertise. The methodology used in this study can be useful to studies of audit quality and may motivate further research on alternative proxies and research designs to investigate the effects of auditor industry specialization.

APPENDIX

Variable Definitions

NLEAD =	"1" for auditors that have the largest market share in a given industry at the U.S. national level and have more than 10% greater market share than the closest competitor, and "0" otherwise
CLEAD =	"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% greater market share than the closest competitor, and "0" otherwise
ADA =	absolute discretionary accruals estimated using the cross-sectional Jones [1991] model, including ROA as per Kothari, Leone, and Wasley [2005], estimated by industry and year
GCONCERN =	"1" if the client received a going-concern opinion in the current fiscal year, and "0" otherwise
MEET =	"1" if the client's earnings meet or beat the median consensus forecast by one cent, and "0" otherwise
LOGFEES =	natural logarithm of total audit fees
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$_{t-1}$
ABS(ACCR) =	absolute value of (total accruals$_t$)/average total assets$_t$
GROWTH =	sales growth calculated as (sales – sales$_{t-1}$)/sales$_{t-1}$
ALTMAN =	Altman's [1983] raw scores
STDEARN =	standard deviation of income before extraordinary items in the past four years
TENURE =	"1" if the client kept the same auditor for three or more years, and "0" otherwise
LOGFOR =	natural logarithm of the number of analysts following the company
STDFOR =	standard deviation of analysts' earnings forecasts
LOGASSETS =	natural logarithm of total assets
LOGSALES =	natural logarithm of total sales
LOGNSEG =	natural logarithm of business and geographic segments
FOREIGN =	(foreign sales)/total sales
CATA =	(current assets)/total assets
QUICK =	(current assets – inventory)/total assets
OPINION =	"1" if the client received a going-concern opinion in the current fiscal year, and "0" otherwise
NONDEC =	"1" if the client's fiscal year-end is not December 31, and "0" otherwise
Δ =	one-year change in the level of each variable
NFOCUS =	"1" for the top industry in an auditor's portfolio at the national level, and "0" otherwise
CFOCUS =	"1" for the top industry in an auditor's portfolio at the city level, and "0" otherwise

REFERENCES

ALTMAN, E. *Corporate Financial Distress: A Complete Guide to Predicting, Avoiding, and Dealing with Bankruptcy.* New York: Wiley, 1983.

ANGRIST, J., AND J. HAHN. "When to Control for Covariates? Panel Asymptotics for Estimates of Treatment Effects." *Review of Economics and Statistics* 86 (2004): 58–72.

ASHBAUGH, H.; R. LAFOND; AND B. MAYHEW. "Do Nonaudit Services Compromise Auditor Independence? Further Evidence." *The Accounting Review* 78 (2003): 611–39.

BALL, R., AND L. SHIVAKUMAR. "The Role of Accruals in Asymmetrically Timely Gain and Loss Recognition." *Journal of Accounting Research* 44 (2006): 207–42.

BALSAM, S.; J. KRISHNAN; AND J. YANG. "Auditor Industry Specialization and Earnings Quality." *Auditing: A Journal of Practice and Theory* 22 (2003): 71–97.

BEHN, B.; J. CHOI; AND T. KANG. "Audit Quality and Properties of Analyst Earnings Forecasts." *The Accounting Review* 83 (2008): 327–49.

BLOUIN, J.; B. MURRAY GREIN; AND B. ROUNDTREE. "An Analysis of Forced Auditor Change: The Case of Former Arthur Andersen Clients." *The Accounting Review* 82 (2007): 621–50.

BOONE, J.; I. KHURANA; AND K. RAMAN. "Do the Big 4 and the Second-Tier Firms Provide Audits of Similar Quality?" *Journal of Accounting and Public Policy* 29 (2010): 330–52.

BROOKHART, M.; S. SCHNEEWEISS; K. ROTHMAN; R. GLYNN; J. AVORN; AND T. STURMER. "Variable Selection for Propensity Score Models." *American Journal of Epidemiology* 163 (2006): 1149–56.

BYRNES, N. "Deloitte Consulting Is Hiring." Bloomberg *BusinessWeek*, February 2010. Available at: http://www.businessweek.com/managing/content/feb2010/ca20100211_911815.htm. Accessed June 18, 2013.

CAHAN, S.; J. GODFREY; J. HAMILTON; AND D. JETER. "Auditor Specialization, Auditor Dominance, and Audit Fees: The Role of Investment Opportunities." *The Accounting Review* 83 (2008): 1393–423.

CAHAN, S.; D. JETER; AND V. NAIKER. "Are All Industry Specialist Auditors the Same?" *Auditing: A Journal of Practice and Theory* 30 (2011): 191–222.

CAHAN, S., AND W. ZHANG. "After Enron: Auditor Conservatism and Ex-Andersen Clients." *The Accounting Review* 81 (2006): 49–82.

CAIRNEY, T., AND G. YOUNG. "Homogenous Industries and Auditor Specialization: An Indication of Production Economies." *Auditing: A Journal of Practice and Theory* 25 (2006): 49–67.

CARSON, E. "Industry Specialization by Global Audit Firm Networks." *The Accounting Review* 84 (2009): 355–82.

CARSON, E., AND N. FARGHER. "Note on Audit Fee Premiums to Client Size and Industry Specialization." *Accounting and Finance* 47 (2007): 423–46.

CASTERELLA, J.; J. FRANCIS; B. LEWIS; AND P. WALKER. "Auditor Industry Specialization, Client Bargaining Power, and Audit Pricing." *Auditing: A Journal of Practice and Theory* 23 (2004): 275–95.

CRAM, D.; V. KARAN; AND I. STUART. "Three Threats to Validity of Choice-Based and Matched Sample Studies in Accounting Research." *Contemporary Accounting Research* 26 (2009): 477–516.

CRASWELL, A.; J. FRANCIS; AND S. TAYLOR. "Auditor Brand Name Reputation and Industry Specialization." *Journal of Accounting and Economics* 20 (1995): 297–322.

DEFOND, M.; J. FRANCIS; AND T. J. WONG. "Auditor Industry Specialization and Market Segmentation: Evidence from Hong Kong." *Auditing: A Journal of Theory and Practice* 19 (2000): 49–66.

DE FRANCO, G.; S. P. KOTHARI; AND R. VERDI. "The Benefits of Financial Statement Comparability." *Journal of Accounting Research* 49 (2011): 895–931.

DEHEJIA, R., AND S. WAHBA. "Propensity Score Matching Methods for Non-Experimental Causal Studies." *Review of Economics and Statistics* 84 (2002): 151–61.

ETTREDGE, M., AND R. GREENBERG. "Determinants of Fee Cutting on Initial Audit Engagements." *Journal of Accounting Research* 28 (1990): 198–210.

FERGUSON, A.; J. FRANCIS; AND D. STOKES. "The Effect of Firm-Wide and Office-Level Industry Expertise on Audit Pricing." *The Accounting Review* 78 (2003): 428–48.

FERGUSON, A., AND D. STOKES. "Brand Name Audit Pricing, Industry Specialization and Industry Leadership Premiums Post Big 8 and Big 6 Mergers." *Contemporary Accounting Research* 19 (2002): 77–110.

FINANCIAL ACCOUNTING STANDARDS BOARD (FASB). *Statement of Cash Flows*. Statement of Financial Accounting Standards No. 95. Norwalk, CT: FASB, 1987.

FRANCIS, J. "A Framework for Understanding and Researching Audit Quality." *Auditing: A Journal of Practice and Theory* 30 (2011): 125–52.

FRANCIS, J.; K. REICHELT; AND D. WANG. "The Pricing of National and City-Specific Reputations for Industry Expertise in the U.S. Audit Market." *The Accounting Review* 80 (2005): 113–36.

GOVERNMENT ACCOUNTABILITY OFFICE (GAO). *Audits of Public Companies. Continued Concentration in Audit Market for Large Public Companies Does Not Call for Immediate Action*. Washington, DC: GAO, 2008.

GUL, F.; S. FUNG; AND B. JAGGI. "Earnings Quality: Some Evidence on the Role of Auditor Tenure and Auditors' Industry Expertise." *Journal of Accounting & Economics* 47 (2009): 265–87.

HAHN, J. "On the Role of the Propensity Score in the Efficient Estimation of Average Treatment Effects." *Econometrica* 66 (1998): 315–32.

HECKMAN, J. "Sample Selection Bias as a Specification Error." *Econometrica* 47 (1979): 153–61.

HECKMAN, J. "The Scientific Model of Causality." *Sociological Methodology* 35 (2005): 1–97.

HECKMAN, J.; H. ICHIMURA; AND P. TODD. "Matching as an Econometric Evaluation Estimator." *The Review of Economic Studies* 65 (1998): 261–94.

HILL, J. "Discussion of Research Using Propensity-Score Matching: Comments on 'A Critical Appraisal of Propensity-Score Matching in the Medical Literature Between 1996 and 2003' by Peter Austin." *Statistics in Medicine* 27 (2008): 2055–61.

HO, D.; K. IMAI; G. KING; AND E. STUART. "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis* 15 (2007): 199–236.

IMBENS, G. W. "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review." *Review of Economics and Statistics* 86 (2004): 4–29.

JONES, J. "Earnings Management During Import Relief Investigation." *Journal of Accounting Research* 29 (1991): 193–228.

KNECHEL, W.; V. NAIKER; AND G. PACHECO. "Does Auditor Industry Specialization Matter? Evidence from Market Reaction to Auditor Switches." *Auditing: A Journal of Practice and Theory* 26 (2007): 19–45.

KOTHARI, S. P.; A. LEONE; AND C. WASLEY. "Performance Matched Discretionary Accrual Measures." *Journal of Accounting & Economics* 39 (2005): 163–97.

KRISHNAN, G. "Does Big 6 Auditor Industry Expertise Constrain Earnings Management?" *Accounting Horizons* 17 (2003): 1–16.

KRISHNAN, J. "A Comparison of Auditor's Self-Reported Industry Expertise and Alternative Measures of Industry Specialization." Working paper, Temple University, 1998. Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=115003

LARCKER, D., AND T. RUSTICUS. "On the Use of Instrumental Variables in Accounting Research." *Journal of Accounting & Economics* 49 (2010): 186–205.

LAWRENCE, A.; M. MINUTTI-MEZA; AND P. ZHANG. "Can Big 4 Versus Non-Big 4 Differences in Audit-Quality Proxies Be Attributed to Client Characteristics?" *The Accounting Review* 86 (2011): 259–86.

LENNOX, C.; J. FRANCIS; AND Z. WANG. "Selection Models in Accounting Research." *The Accounting Review* 87 (2012): 589–616.

LI, K., AND N. PRABHALA. "Self-Selection Models in Corporate Finance," in *Handbook of Corporate Finance: Empirical Corporate Finance*, edited by B. E. Eckso. Amsterdam, The Netherlands: Elsevier Science B.V., 2007: 37–86.

LOW, K. Y. "The Effect of Industry Specialization on Audit Risk Assessments and Audit Planning Decisions." *The Accounting Review* 79 (2004): 201–9.

MAYHEW, B., AND M. WILKINS. "Audit Firm Industry Specialization as a Differentiation Strategy: Evidence from Fees Charged to Firms Going Public." *Auditing: A Journal of Practice and Theory* 22 (2003): 33–52.

MCNICHOLS, M. "Discussion of the Quality of Accruals and Earnings: The Role of Accruals Estimation Errors." *The Accounting Review* 77 (2002): 61–69.

MORGAN, S., AND D. HARDING. "Matching Estimators of Causal Effects: Prospects and Pitfalls in Theory and Practice." *Sociological Methods & Research* 35 (2006): 3–60.

NAGY, A. "Mandatory Audit Firm Turnover, Financial Reporting Quality, and Client Bargaining Power: The Case of Arthur Andersen." *Accounting Horizons* 19 (2005): 51–68.

NEAL, T., AND R. RILEY, JR. "Auditor Industry Specialist Research Design." *Auditing: A Journal of Practice and Theory* 23 (2004): 169–77.

NELSON, K.; R. PRICE; AND B. ROUNDTREE. "The Market Reaction to Arthur Andersen's Role in the Enron Scandal: Loss of Reputation or Confounding Effects?" *Journal of Accounting and Economics* 46 (2008): 279–93.

O'KEEFE, T.; D. SIMUNIC; AND M. STEIN. "The Production of Audit Services: Evidence from a Major Public Accounting Firm." *Journal of Accounting Research* 32 (1994): 241–61.

OWHOSO, V. E.; W. F. MESSIER; AND J. LYNCH. "Error Detection by Industry-Specialized Teams During the Sequential Audit Review." *Journal of Accounting Research* 40 (2002): 883–900.

PALMROSE, Z.-V. "Audit Fees and Auditor Size: Further Evidence." *Journal of Accounting Research* 24 (1986): 97–110.

PEARSON, T., AND G. TROMPETER. "Competition in the Market for Audit Services: The Effect of Supplier Concentration on Audit Fees." *Contemporary Accounting Research* 11 (1994): 115–35.

PRICEWATERHOUSECOOPERS (PwC). 2010. "Audit and Assurance Services," 2010. Available at: http://www.pwc.com/jg/en/audit-and-assurance/index.jhtml. Accessed June 18, 2013.

RAMSEY, J. "Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis." *Journal of the Royal Statistical Society* 31 (1969): 350–71.

REICHELT, K., AND D. WANG. "National and Office-Specific Measures of Auditor Industry Expertise and Effects on Audit Quality." *Journal of Accounting Research* 48 (2010): 647–86.

ROSENBAUM, P. *Observational Studies*, Second edition. New York: Springer Verlag, 2002.

ROSENBAUM, P., AND D. RUBIN. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70 (1983): 41–55.

RUBIN, D. "Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational Studies." *Journal of the American Statistical Association* 74 (1979): 318–28.

RUBIN, D. "Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation." *Health Services & Outcomes Research Methodology* 2 (2001): 169–88.

RUBIN, D. *Matched Sampling for Causal Inference*. Cambridge: Cambridge University Press, 2006.

RUBIN, D., AND N. THOMAS. "Combining Propensity Score Matching with Additional Adjustments for Prognostic Covariates." *Journal of the American Statistical Association* 95 (2000): 573–85.

SOLOMON, I.; M. SHIELDS; AND O. WHITTINGTON. "What Do Industry-Specialist Auditors Know?" *Journal of Accounting Research* 37 (1999): 191–208.

STUART, E. "Matching Methods for Causal Inference: A Review and Look Forward." *Statistical Science* 25 (2010): 1–21.

STUBBEN, S. "Discretionary Revenues as a Measure of Earnings Management." *The Accounting Review* 85 (2010): 695–717.

TAYLOR, M. "The Effects of Industry Specialization on Auditor's Inherent Risk Assessments and Confidence Judgments." *Contemporary Accounting Research* 17 (2000): 693–712.

TUCKER, J. "Selection Bias and Econometric Remedies in Accounting and Finance Research." *Journal of Accounting Literature* 29 (2010): 31–57.

WHISENANT, S.; S. SANKARAGURUSWAMY; AND K. RAGHUNANDAN. "Evidence on the Joint Determination of Audit and Non-Audit Fees." *Journal of Accounting Research* 41 (2003): 721–44.

ZHAO, Z. "Using Matching to Estimate Treatment Effects: Data Requirements, Matching Metrics, and Monte Carlo Evidence." *Review of Economics and Statistics* 86 (2004): 91–107.