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Auditor Industry Specialization and Earnings Quality

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SUMMARY: This study examines the association between measures of earnings quality and auditor industry specialization. Prior work has examined the association between auditor brand name and earnings quality, using auditor brand name to proxy for audit quality. Recent work has hypothesized that auditor industry specialization also contributes to audit quality. Extending this literature, we compare the absolute level of discretionary accruals (DAC) and earnings response coefficients (ERC) of firms audited by industry specialists with those of firms not audited by industry specialists. We restrict our study to clients of Big 6 (and later Big 5) auditors to control for brand name. Because industry specialization is unobservable, we use multiple proxies for it. After controlling for variables established in prior work to be related to DAC and the ERC, we find clients of industry specialist auditors have lower DAC and higher ERC than clients of nonspecialist auditors. This finding is consistent with clients of industry specialists having higher earnings quality than clients of nonspecialists.

Keywords: industry specialization; discretionary accruals; earnings response coefficient; audit quality.

Data Availability: Data are publicly available from sources identified in the paper.

INTRODUCTION

The role of auditing in ensuring the quality of corporate earnings has come under considerable scrutiny due to recent earnings restatements and the collapse of Enron (Browning and Weil 2002). Audit quality differences result in variation in credibility offered by auditors, and in the earnings quality of their clients. Because auditor quality is multidimensional and inherently unobservable, there is no single auditor characteristic that can be used to proxy for it. Most prior work has used auditor brand name to proxy for audit quality and examined the association between brand name and earnings quality (Becker et al. 1998; Reynolds and Francis 2000). Other researchers (Craswell et al. 1995; Beasley and Petroni 2001) have hypothesized that, in addition to brand name,

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an auditor's industry specialization contributes positively to the credibility offered by the auditor. Some evidence of industry specialists producing more effective audits is provided by Owhoso et al. (2002). Recent structural shifts by audit firms in the direction of greater industry focus also suggest that industry specialization may play an increasingly important role in audit quality (Hogan and Jeter 1999; Solomon et al. 1999).

We extend this literature by comparing the earnings quality of clients of industry specialist and nonspecialist auditors. Earnings quality is a concept that does not have a common definition in the literature. Rather, the extant literature uses various measures to capture different manifestations of quality of earnings. Following this literature, we examine the effect of auditor specialization on: (1) the absolute level of discretionary accruals (DAC) and (2) earnings response coefficients (ERC). We expect that, if auditors' industry specialization results in greater audit quality, industry specialization would be negatively associated with clients' DAC and positively associated with clients' ERC. We restrict our study to clients of Big 6 (and later Big 5) auditors to control for brand name.

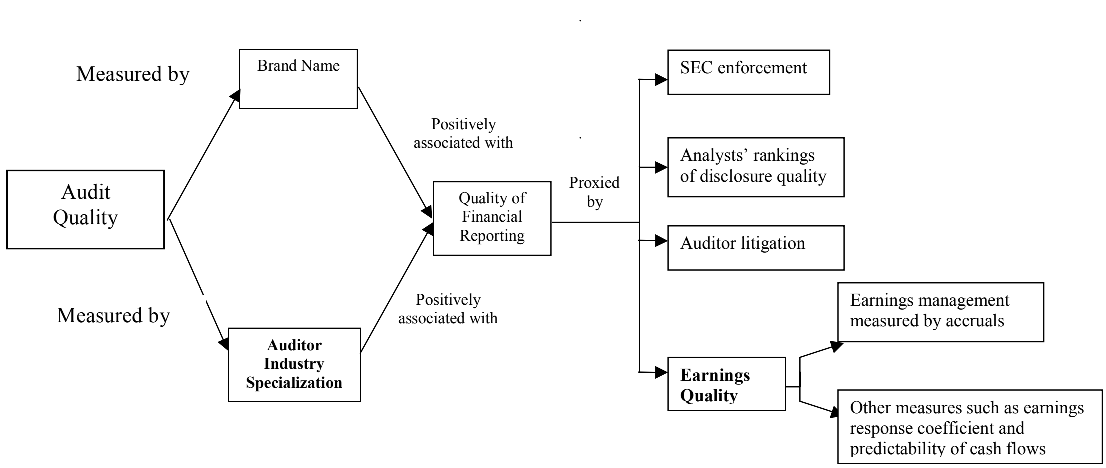
Because industry specialization is unobservable, we use multiple proxies for it. Multivariate models suggest that, after controlling for previously established correlates of DAC and the ERC, clients of industry specialist auditors have lower levels of DAC (for five out of our six proxies for industry specialization) and higher ERC (for all six proxies) than clients of nonspecialist auditors, consistent with industry specialists providing a higher quality audit. One interesting finding is that the effect of specialization on DAC is nonlinear: absolute discretionary accruals actually increase slightly at lower levels of market share, but decline rapidly thereafter.

The rest of the paper is organized as follows. The next section describes the motivation and hypotheses for the study. This is followed by sections that describe the models and data. The fifth and sixth sections present the empirical results and sensitivity analysis. The last section contains conclusions.

HYPOTHESES DEVELOPMENT

Figure 1 presents a framework for placing the current study within the existing research. This line of research examines whether audit quality is positively associated with financial reporting

FIGURE 1
Overview of Research



quality. Audit quality is measured typically by one of two variables, auditor brand name, and auditor industry specialization. Similarly, "financial reporting quality" is measured in different ways, for example, auditor litigation, analyst rankings, SEC enforcement actions, and earnings quality.[1]

The initial studies in this area focused on the association between auditor brand name and financial reporting quality measured by one of the facets listed at the right of Figure 1. The findings are broadly consistent with the conjecture that auditor brand name is positively associated with financial reporting quality, including earnings quality.

A recent stream of literature argues that, in addition to brand name, an industry specialist offers a higher level of assurance than does a nonspecialist (e.g., Craswell et al. 1995; Beasley and Petroni 2001). For example, Owhoso et al. (2002) show that industry-experienced auditors are better able to detect errors within their industry specialization than outside their specialization. O'Keefe et al. (1994) report significantly greater compliance with auditing standards for industry specialists than nonspecialists.

There is a growing literature that links industry specialization with financial reporting quality.[2] Carcello and Nagy (2002) provide evidence that clients of specialists are less likely to be associated with SEC enforcement actions. Dunn et al. (2000) find that clients of industry-specialist audit firms are ranked higher in terms disclosure quality by financial analysts than clients of nonspecialists. Gramling et al. (2001) show that earnings of clients of specialist auditors predict future cash flows more accurately than those of nonspecialist auditors. In contrast Lys and Watts (1994) fail to find significantly different levels of auditor litigation between industry specialists and nonspecialists.

In terms of Figure 1, we focus on whether audit quality, as measured by industry specialization, is associated with earnings quality. A large literature has documented that managers have incentives to manage earnings. These incentives arise out of explicit and implicit contracts that link outcomes of interest to management (e.g., managerial compensation to reported earnings). The quality of the firm's auditor is one factor that restricts the extent to which managers can manage earnings.

A number of studies have examined whether audit quality, measured by *auditor brand name*, is associated with earnings quality. Becker et al. (1998) and Reynolds and Francis (2000) argue that high-quality auditors (in their case Big 6 auditors) are able to detect earnings management because of their superior knowledge, and act to curb opportunistic earnings management to protect their reputation. Becker et al. (1998), Francis, Maydew, and Sparks (1999), and Reynolds and Francis (2000) all find that clients of Big 6 auditors have lower discretionary accruals than clients of non-Big 6 auditors. Teoh and Wong (1993) show a positive association between auditor brand name and the earnings response coefficient. In sum, this literature supports the hypothesis that auditor brand name is associated with greater earnings quality.

Whether *auditor industry expertise* is similarly positively associated with earnings quality is an empirical question. However, it seems likely that a specialist's knowledge of the industry and its accounting will yield a greater ability to detect and curb earnings management and minimize unintentional errors. Thus, we expect the auditor's industry specialization to be positively associated with earnings quality.

[1] We recognize that these different constructs may be related. In particular, auditor litigation, analyst rankings and SEC enforcement actions may also impact or be correlated with earnings quality, our measure of financial reporting quality.

[2] Other studies have examined the effect of industry specialization on audit fees. Research on audit fees has yielded mixed findings. While Craswell et al. (1995) and Elder (1994) report that there are audit fee premiums associated with industry specialization, Palmrose (1986) and Pearson and Trompeter (1994) do not find an association between industry specialization and audit fee. DeFond et al. (2000), using Hong Kong data, report a fee premium for Big 6 industry specialists and a fee discount for non-Big 6 industry specialists.

Earnings quality is a concept that is not observable, and therefore a variety of proxies are used in the literature. Most auditing studies use the level of discretionary accruals, arguing that it is a "direct" measure of earnings management (Becker et al. 1998), which is one factor contributing to earnings quality (Frankel et al. 2002). Others use measures that can reflect differential earnings management and general error generation (intentional or otherwise), such as the earnings response coefficient and the ability of earnings to predict cash flows (Gramling et al. 2001).

Following the literature in this area, we measure earnings quality using two measures, discretionary accruals and the earnings response coefficient.[3] First, we argue that an industry specialist should be able to control the level of discretionary accruals (DAC) generated by the client's accounting system. Hence we test the hypothesis (stated in the alternative form):

H1: The discretionary accruals of a company whose auditor is an industry specialist are lower than the discretionary accruals of a company whose auditor is not a specialist.

Second, we examine whether an auditor's industry specialist status is associated with earnings response coefficients (ERC), which measures the extent of stock market responsiveness to earnings surprises. Researchers have argued that higher audit quality can reduce the perceived uncertainty and noise in reported earnings resulting in higher ERC. Teoh and Wong (1993) found higher ERC for clients of Big 6 auditors than for clients of non-Big 6 auditors. Using Securities and Exchange Commission (SEC) sanctions against auditors as a measure of audit quality, Moreland (1995) reports client ERC declined after their (Big 8) auditors were subject to SEC sanctions. Last, Hackenbrack and Hogan (2002) argue that disclosures about reasons for auditor changes signal information about earnings precision, leading to changes in ERC following auditor changes. Extending these arguments, we expect that a specialist auditor signals greater credibility, and therefore greater earnings precision.[4] Therefore, we expect that unexpected earnings for clients of specialist auditors should be associated with a larger stock market response (higher ERC) than those of clients of nonspecialists. This leads to the following hypothesis (stated in the alternative form):

H2: The earnings response coefficient of a company whose auditor is an industry specialist is greater than the earnings response coefficient of a company whose auditor is not a specialist.

MODEL SPECIFICATION

We estimate two sets of multivariate models for DAC and ERC. The independent variables include a measure of auditor industry specialization and control variables based on prior work.

Measure of Auditor Industry Specialization

Because the auditor's specialist status is not directly observed, prior work has used several proxies to measure industry specialization. These measures are mostly variants of market share, based on the assumption that industry expertise is built by repetition in similar settings and therefore

[3] Gramling et al. (2001) is the closest study to ours in that they too examine the association between earnings quality and auditor industry specialization. Because "earnings quality" and "industry specialization" are unobserved and measured only by plausible proxies, the two studies complement each other by providing similar evidence using different approaches. The two studies differ in the measure of earnings quality. Their measure, the predictability of future cash flows, like our ERC measure, captures the overall effect of intentional earnings management and unintentional errors. In addition, we use a direct measure of earnings management, DAC, which is one component of earnings quality. Thus we provide evidence that the improved earnings quality may be resulting, at least partly, from reduced earnings management.

[4] Teoh and Wong (1993) use a simplified model to demonstrate that the ERC will, *ceteris paribus,* increase with: (1) increases in prior uncertainty about underlying cash flows and (2) increases in the quality of the earnings signal. The studies cited here generally argue that audit-related factors affect the ERC through increasing (or decreasing in the case of SEC sanctions against auditors or some auditor changes) the quality of the earnings signal.

a large volume of business in an industry indicates expertise. However, market share is subject to several limitations as a measure of specialization (Gramling et al. 2001; Krishnan 2001). For example, it is not clear whether the advantages to specializing in an industry accrue from auditing a large number of clients or a few large clients.[5] To address these shortcomings, we use several proxies from the literature. These measures include continuous market share and dummy variables representing a substantial market share/industry dominance.

First, industry specialists are identified following Palmrose (1986) as "the largest supplier in each industry, as well as the second- and third-largest suppliers in industries in which readily observable differences existed between the second and the third or between the third and the remaining suppliers." The auditor's industry share (using client sales as the base) in each two-digit SIC code is computed using the population of available observations (comprising Big 6 (5) and non-Big 6 (5) clients) from Compustat for each year.[6] Second, we define an auditor's industry specialization in terms of industry dominance, which is more restrictive than the Palmrose (1986) measure. Following Mayhew and Wilkins (2002), we define an auditor as specialist in an industry if they are the largest supplier in the industry and the difference between the first and second supplier in the industry is at least 10 percent. Third, we proxy for industry specialization using continuous market share based upon client sales.

Our next three measures use the number of clients as the base. Such a base avoids the bias toward large clients that is implied by using sales as the base. Thus, situations where an auditor has a number of small clients in an industry and has developed the knowledge base to be a specialist may be captured by a number-of-clients-based measure and not by the sales-based measures.[7] Our fourth measure identifies an industry specialist as the auditor with the greatest number of clients in the industry. Our fifth measure uses market share, this time defined in terms of the number of clients, not client sales. Our sixth measure is the number of clients audited by the auditor.

One largely unexplored issue in the literature is whether there are nonlinearities in the relation between the auditor's industry specialization and the outcome of interest (earnings quality, in our case). Although knowledge about an industry is determined by repetition, it is possible that threshold levels of industry knowledge must be reached before benefits accrue. Diminishing returns to accumulation of industry expertise may arise at some high level of specialization. To investigate this possibility, we estimate nonlinear specifications of our DAC and ERC models. For the three models involving the continuous measures (i.e., market share defined in terms of client sales, market share defined in terms of number of clients, and the number of clients) we include both the variable and its square as independent variables.

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[5] A shortcoming, which we are unable to address in this paper, is that specialization may actually occur at the city rather than national level (Francis, Stokes, and Anderson 1999).

[6] To construct this measure, we ranked auditors in each industry by their market shares. We then identified the top four suppliers, and applied Palmrose's (1986) criterion to identify specialists based on the differences between the shares of these suppliers. We minimized potential problems with the somewhat subjective nature of this definition by having two of the coauthors independently identify the specialist for each industry. We then compared the two sets of classifications, and reconciled the differences, which were relatively few in number. For industry-year combinations for which more than one auditor was classified as specialist, the mean (median) difference in market share between the lowest ranked auditor classified as specialist and the next auditor classified as nonspecialist was 11.9 percent (9.7 percent).

[7] Some behavioral research also suggests that "task-specific experience and training often provided the best explanations of [auditor] expertise" (Bonner and Lewis 1990, 18). To the extent that such experience is industry-specific, having a large number of clients in an industry rather than having a few large clients may achieve industry specialization.

Discretionary Accruals Model

We estimate discretionary accruals using the cross-sectional version of the Jones (1991) model as in DeFond and Jiambalvo (1994).[8] We use the Jones model because prior research examining the relative performance of alternative DAC models has shown that the cross-sectional version of the Jones model is the best measure of the discretionary portion of total accruals (see Bartov et al. 2000). Total accruals are regressed on the change in sales and the level of property, plant, and equipment for each year using all firm-years with the same 2-digit SIC code. The model is as follows:

$$TACC_{it}/A_{it-1} = \alpha_1(1/A_{it-1}) + \alpha_2\,(\Delta REV_t/A_{it-1}) + \alpha_3\,(PPE_{it}/A_{it-1}) + \varepsilon_{it} \quad (1)$$

where $TACC$ is total accruals,[9] ΔREV is revenues in year t less revenues in year t–1, PPE is gross property, plant, and equipment, A is total assets, ε is the residual, and the subscripts i and t denote firm and year. The residual (ε) represents DAC for firm i in year t.

Our multivariate model then regresses the absolute value of DAC on our industry specialization variable and control variables based on prior work (e.g., Reynolds and Francis 2000; Becker et al. 1998; Warfield et al. 1995):

$$Abs(\mathrm{DAC}_{it}) = \alpha_0 + \alpha_1{*}SP_{it} + \alpha_2{*}LTA_{it} + \alpha_3{*}CFO_{it} + \alpha_4{*}LEV_{it} + \alpha_5{*}Abs(TACC)_{it} + \varepsilon_{it} \quad (2)$$

where SP is our industry specialization measure, LTA is the log of total assets and is used as a proxy for firm size, CFO is cash flow from operations scaled by assets, LEV is the ratio of long-term debt to total assets, and $Abs(TACC)$ is the absolute value of total accruals, and the subscripts i and t denote firm and year, respectively. Six versions of this model are estimated to correspond to the six measures that represent SP.

Becker et al. (1998) and Reynolds and Francis (2000) include firm size and cash flow from operations as variables that influence discretionary accruals. Leverage is included, as in Reynolds and Francis (2000), because prior research has documented that firms with high levels of debt have an incentive to engage in earnings management to increase earnings (see Watts and Zimmerman 1986). Finally, we include total absolute accruals as a control for the firm's "accruals-generating potential" (Becker et al. 1998). After controlling for the other specified factors, the difference in the absolute value of DAC between clients of specialist and nonspecialist auditors is captured by α_1 in Equation (2). If the reports issued by clients of specialist auditors are of higher quality, we would expect the absolute value of DAC to be lower, which implies that the coefficient α_1 will be negative. While we are not testing the effect of our control variables (LTA, CFO, LEV, and $abs(TACC)$) on the absolute value of discretionary accruals, based upon our intuition and the research referred to above we expect the coefficient on LTA, CFO, and LEV to be negative, and that on $abs(TACC)$ to be positive.[10]

Earnings Response Coefficient Model

To examine the effect of specialization on the ERC we estimate the following regression using ordinary least squares (OLS):

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 UE_{it} + \lambda_2 UE_{it}{*}NEG_{it} + \lambda_3 UE_{it}{*}SP_{it} + \lambda_4 UE_{it}{*}MB_{it} + \lambda_5 UE_{it}{*}LTA_{it} \\ & + \lambda_6 UE_{it}{*}BETA_{it} + \lambda_7 UE_{it}{*}NO_{it} + \lambda_8 UE_{it}{*}YIELD_t + \lambda_9 RET_{it} + \Sigma\delta_i YR + \Sigma\gamma_i UE_{it}{*}IND + \varepsilon_{it} \quad (3) \end{aligned}$$

where CAR is cumulative abnormal return; UE, unexpected earnings; NEG, an indicator variable that takes the value of 1 if unexpected earnings are negative; SP, the industry specialization variable; MB,

[8] Our results are slightly stronger when we use the modified version of the cross-sectional Jones model (see Dechow et al. 1995 for a discussion of the modification).

[9] We use the cash flow approach (see Hribar and Collins 2002) to compute $TACC_{it}$ as follows: $TACC_{it} = EXBI_{it} - CFO_{it}$ where $EXBI_{it}$ is earnings before extraordinary items for firm i in year t, and CFO_{it} is cash flow from operations for firm i in year t.

[10] For example, Reynolds and Francis (2000) find a negative association between absolute DAC and size and absolute DAC and cash flow from operations; Becker et al. (1998) find a negative association between signed DAC and cash flow from operations and signed DAC and leverage; Frankel et al. (2002) find a negative association between absolute DAC and leverage.

the market to book ratio; *LTA,* the log of total assets; *BETA,* the market model beta; *NO*, the number of analyst forecasts available on I/B/E/S; *YIELD,* the yield on long-term government bonds; *RET*, the return from the day after the analyst forecast till the day before the earnings announcement date; and *YR* and *IND,* indicator variables for year and industry. The subscripts i and t denote company and year, respectively.

The dependent variable *CAR,* the abnormal return, is computed for the two-day window consisting of the day before and the day of the firm's earnings announcement. We estimate the market model parameters over the 200-day window ending 21 days before the earnings announcement, requiring a minimum of 100 daily stock returns required for a company to be included in the sample.[11]

Unexpected earnings, *UE,* is measured as the earnings per share excluding extraordinary items minus forecasted earnings (the mean of I/B/E/S analysts' forecasts of firm's EPS immediately prior to the earnings announcement),[12] scaled by the stock price two days prior to the earnings announcement.

Based on prior work, Equation (3) includes controls to allow for variation in ERC due to other factors. Because these variables are expected to affect the ERC (a slope coefficient), they are entered in the regression as interactions with the earnings surprise variable, *UE*. After controlling for the other specified factors, the difference in the ERC of specialist auditors and nonspecialist auditors is captured by λ_3. If the earnings of clients of specialist auditors are perceived as more credible, the ERC will be larger for those firms, which implies that the coefficient λ_3 will be positive.[13]

An indicator variable, *NEG,* is used to denote firms with negative unexpected earnings because recent research (e.g., Basu 1997; Hayn 1995) indicates that the market views negative earnings and negative unexpected earnings differently. Systematic risk, measured by *BETA,* is expected to have a negative effect on the ERC, through its effect on the firm's expected rate of return (Collins and Kothari 1989; Lipe 1990). Following prior work, we include additional controls for firm size, measured by logarithm of total assets, *LTA* (Bowen et al. 1992); growth, measured by ratio of market to book value of equity, *MB* (Collins and Kothari 1989; Hackenbrack and Hogan 2002); and number of analysts, *NO* (Teoh and Wong 1993; Atiase 1985).

Prior work has also noted temporal variation in ERC (Collins and Kothari 1989; Easton and Harris 1991; Moreland 1995). Following Collins and Kothari (1989), yields on long-term government bonds (*YIELD*) for each sample year are included to control for such temporal variations. We also include indicator variables for year (*YR*), to control for temporal variations not picked up by *YIELD*, and for industry (*IND*). While the industry dummies are interacted with *UE* because we believe the ERC may change with industry characteristics, *a priori* we do not expect *ERC* to be systematically related to year. Hence, we include indicator variables for eight of the nine years but do not interact them with *UE*. A final control variable, *RET*, is included to mitigate problems arising from measurement errors in *UE* (Easton and Zmijewski 1989).

As with the discretionary accruals model, we are not testing the effect of our control variables on the earnings response coefficient. However, based upon our intuition and the prior research described above, we expect the coefficients on the interactions between *UE* and *NEG*, *LTA*, *BETA*, *NO*, and *RET* to be negative, and that on the interaction between *UE* and *MB* to be positive.[14]

[11] Our results are robust to other estimation periods.

[12] Our results are similar when we use the median instead of the mean forecasts.

[13] For completeness we also ran the model with an additional independent variable, *SP*. The coefficient on the specialization variable was never significant and its inclusion did not affect the significance of the variables of interest.

[14] For example, Easton and Zmijewski (1989), Lipe (1990), and Hackenbrack and Hogan (2002) show that the ERC is negatively related to systematic risk. Hackenbrack and Hogan (2002) also find a negative association between *CAR* and the interactions between *UE* and *LOSS*, and *UE* and firm size, and a positive association between *CAR* and the interaction between *UE* and *MB*.

DATA

An initial sample of 62,847 observations with Big 6 (5) auditors was identified from the primary, secondary, tertiary, and full coverage files of the 2001 Compustat annual industrial tape for year-ends from 1991 to 1999. For both our tests we required that sample firms belong to industries with at least 90 observations over the nine-year period. For the DAC sample, the requirement that firms have sufficient data on Compustat to compute DAC and other variables reduced the sample to 50,116 firm year observations. For the ERC sample we required firms have earnings announcement dates on quarterly Compustat, I/B/E/S earnings forecasts, and stock returns on CRSP. These additional requirements resulted in a final sample of 19,091 firm year observations for the ERC model.

Table 1 contains the variable definitions. Descriptive statistics for our specialization variables are reported in Table 2. Despite the difference in the size of the two samples, the means for the variables are similar. However, note that the different measures of specialization classify the observations very differently. In particular, the percentage of firms classified as specialists under the three discrete measures, *LEADER, DOMINANCE,* and *MOSTCL* are about 33 percent, 6 percent, and 28 percent, respectively, in both samples. It therefore matters whether we characterize "specialization"

TABLE 1
Variable Definitions

LEADER	=	is coded 1 for industry specialists, 0 otherwise. Industry specialists are identified, following Palmrose (1986), as "the largest supplier in each industry, as well as the second- and third-largest suppliers in industries in which readily observable differences existed between the second and the third or between the third and the remaining suppliers;"
DOMINANCE	=	is coded 1 if the auditor is the largest supplier and its market share is at least 10 percent greater than that of the second supplier (following Mayhew and Wilkins 2002), 0 otherwise;
SHARE	=	the actual market share (measured in client sales) in a two-digit industry;
MOSTCL	=	is coded 1 if the audit firm has the most clients in the industry, 0 otherwise;
SHARECL	=	the actual market share (measured in number of clients) in a two-digit industry;
NCLIENTS	=	the number of clients in a two-digit industry;
Abs(DAC)	=	absolute value of discretionary accruals scaled by lagged total assets;
LTA	=	natural logarithm of total assets;
CFO	=	operating cash flows scaled by lagged total assets;
LEV	=	ratio of total debt to total assets;
Abs(*TACC*)	=	absolute value of total accruals scaled by lagged total assets;
CAR	=	cumulative abnormal return from the market model over two days, one day before and the day of the earnings announcement;
UE	=	earnings surprise for firm *i* calculated as actual earnings disclosed minus I/B/E/S/ mean forecasts scaled by the stock price on the day prior to the cumulation period for *CAR*;
NEG	=	variable taking value of 1 if unexpected earnings are negative, 0 otherwise;
MB	=	market value of equity divided by book value of equity;
BETA	=	market model slope coefficient estimated over the 200-day window ending 21 days prior to the cumulation period for *CAR*;
NO	=	number of analysts' forecasts included in the consensus forecast;
YIELD	=	yields on long-term U.S. Government bonds for years 1991 through 1999;
RET	=	stock returns from the day after the I/B/E/S report date through two days prior to earnings announcement date;
YR	=	year dummies indicating years 1991 through 1998; and
IND	=	industry dummies indicating SIC codes between 10 and 87. There are 43 two-digit industries in the ERC sample.

TABLE 2
Specialization Measures

Panel A: Descriptive Statistics for the Specialization Variables

	Mean	Standard Deviation	First Quartile	Median	Third Quartile
DAC Sample					
LEADER	0.327	0.469	0	0	1
DOMINANCE	0.064	0.244	0	0	0
SHARE	0.185	0.127	0.093	0.157	0.234
MOSTCL	0.283	0.450	0	0	1
SHARECL	0.164	0.058	0.122	0.155	0.194
NCLIENTS	57.271	55.070	17	39	82
n	50,116				
ERC Sample					
LEADER	0.334	0.472	0	0	1
DOMINANCE	0.064	0.245	0	0	0
SHARE	0.188	0.121	0.098	0.161	0.237
MOSTCL	0.285	0.452	0	0	1
SHARECL	0.165	0.057	0.125	0.157	0.197
NCLIENTS	60.431	55.440	19	46	85
n	19,091				

Panel B: Correlations between Specialization Variables

	LEADER	*DOMINANCE*	*SHARE*	*MOSTCL*	*SHARECL*	*NCLIENTS*
DAC Sample						
LEADER	1.000	0.357***	0.777***	0.222***	0.322***	–0.002
DOMINANCE		1.000	0.512***	0.318***	0.434***	–0.020***
SHARE			1.000	0.258***	0.433***	0.023***
MOSTCL				1.000	0.699***	0.175***
SHARECL					1.000	0.182***
NCLIENTS						1.000
ERC Sample						
LEADER	1.000	0.361***	0.778***	0.199***	0.308***	–0.023***
DOMINANCE		1.000	0.517***	0.318***	0.429***	–0.014*
SHARE			1.000	0.255***	0.425***	0.010
MOSTCL				1.000	0.703***	0.197***
SHARECL					1.000	0.197***
NCLIENTS						1.000

***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, two-tailed.
See Table 1 for variable definitions.

as market leadership, dominance, or the greatest number of clients audited. On the other hand, two of the continuous measures, *SHARE* and *SHARECL,* yield fairly similar descriptive statistics. The average industry share in terms of sales (*SHARE*) is about 19 percent, and in terms of the number of clients (*SHARECL*) is about 16.5 percent. Finally, the mean number of clients (*NCLIENTS*) in an industry is 57 (60) in the DAC (ERC) samples.

Table 2, Panel B, presents correlations among the specialization variables. Again, because the measures capture different aspects of the auditor's industry activity, the correlations differ. In both samples, the correlations between *LEADER*, *DOMINANCE*, *SHARE*, *MOSTCL*, and *SHARECL* are positive and significant, with the correlations ranging from 0.199 to 0.778. However, *NCLIENTS* is different. Its correlations with *SHARE*, *MOSTCL*, and *SHARECL* are positive and significant (except for its correlation with *SHARE* in the ERC sample, which is not significant) but lower than the other correlations (0.010–0.197 range). The correlation between *NCLIENTS* and *LEADER* and *NCLIENTS* and *DOMINANCE* is negative in both samples.

There are 63 (43) two-digit SIC codes in the DAC (ERC) sample. Based upon number of firms in a two-digit SIC code, the specialists (where specialists are determined based on the Palmrose (1986) definition) audit between 13 (15) and 79 (77) percent of the firms in an industry in the DAC (ERC) sample. Specialists audit over 50 percent of the firms in 11 (10) industries, between 25 and 50 percent of the firms in 42 (26) industries, and less than 25 percent of the firms in 10 (7) industries in the DAC (ERC) sample. Looking at market share, as a percentage of sales, the extent of specialization in each industry (again based on the Palmrose (1986) definition) varies between 28 (28) and 93 (85) percent, and in 45 (28) of the 63 (43) industries in the DAC (ERC) sample, specialists have a market share in excess of 50 percent.

EMPIRICAL RESULTS

Discretionary Accruals Model

Descriptive statistics for the independent variables in the discretionary accruals models are reported in Table 3, Panel A. The mean absolute value of discretionary accruals is slightly less than 10 percent of total assets, indicating that the amounts involved are significant, both economically and statistically. By comparison, mean cash flows from operations are only 2.7 percent of total assets. The mean value of total assets ($1,248 million) indicates that the firms are large, which would be expected given our sample selection criteria.

Univariate tests using *LEADER* to partition the sample are presented in Table 3, Panel B. Consistent with H1, absolute DAC are lower, on average, for clients of specialists than those of nonspecialists. In addition, clients of specialist auditors are larger (*LTA*), have higher cash flows from operations (*CFO*), and higher leverage (*LEV*) than clients of nonspecialist auditors. There is also some evidence (t-statistic is significant, but Wilcoxon Z is insignificant) that clients of specialist auditors have lower absolute total accruals (*TACC*).

In Table 3, Panel C, the correlations between DAC and five of the measures of auditor specialization are negative and significant, again showing, consistent with H1, that clients of specialist auditors have lower levels of absolute DAC. However, the correlation between DAC and *NCLIENTS* is positive and significant. This inconsistent result is repeated in the multivariate results for DAC, at which point we discuss possible reasons for the inconsistency. The correlations among the independent variables used in the model are reasonable, with the highest correlation being 0.357. Similarly, the highest variance inflation factor (VIF) is less than 1.3, suggesting that multicollinearity is not a problem.

TABLE 3
Descriptive Statistics and Correlation Matrix for the Variables in DAC Models

Panel A: Descriptive Statistics for Pooled Sample

Variable	n	Mean	Standard Deviation	First Quartile	Median	Third Quartile
Abs(DAC)	50,116	0.099	0.126	0.023	0.056	0.121
Total Assets ($ Millions)	50,116	1,248.029	3,706.492	35.602	133.490	626.639
LTA	50,116	5.062	2.057	3.572	4.894	6.440
CFO	50,116	0.027	0.177	–0.007	0.062	0.119
LEV	50,116	0.189	0.202	0.009	0.130	0.306
Abs(*TACC*)	50,116	0.111	0.134	0.035	0.071	0.133

Panel B: Descriptive Statistics for Specialists (*LEADER* = 1) and Nonspecialists (*LEADER* = 0) Subsamples

	LEADER = 1					*LEADER* = 0					
Variable	n	Mean	First Quartile	Median	Third Quartile	n	Mean	First Quartile	Median	Third Quartile	t-statistic[a] (Wilcoxon Z)[b]
Abs(DAC)	16,381	0.091	0.022	0.051	0.113	33,735	0.102	0.024	0.058	0.125	–9.035*** (–9.375)***
Total Assets ($ Millions)	16,381	1,756.20	46.430	196.905	989.896	33,735	1,001.27	31.772	113.047	501.276	21.456*** (24.786)***
LTA	16,381	5.404	3.838	5.283	6.898	33,735	4.896	3.459	4.728	6.217	26.136*** (24.786)
CFO	16,381	0.044	0.009	0.071	0.124	33,735	0.019	–0.015	0.058	0.116	14.479*** (14.888)***
LEV	16,381	0.199	0.014	0.154	0.317	33,735	0.184	0.007	0.119	0.299	7.946*** (10.430)***
Abs(*TACC*)	16,381	0.109	0.036	0.071	0.131	33,735	0.112	0.034	0.071	0.134	–2.333** (–0.134)

***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, two-tailed.
[a] Tests the hypothesis that the means for the groups are significantly different from each other.
[b] Tests the hypothesis that the medians for the groups are significantly different from each other.
See Table 1 for variable definitions.

(continued on next page)

Table 3 (continued)

Panel C: Correlation Matrix

	***Abs* (DAC)**	***LEADER***	***DOMINANCE***	***SHARE***	***MOSTCL***	***SHARECL***	***NCLIENTS***	***LTA***	***CFO***	***LEV***	***Abs*(*TACC*)**
Abs(DAC)	1.000	–0.040***	–0.044***	–0.038***	–0.021***	–0.044***	0.264***	–0.255***	–0.238***	–0.111***	0.715***
LEADER		1.000	0.357***	0.777***	0.222***	0.322***	–0.002	0.116***	0.064***	0.035***	–0.010**
DOMINANCE			1.000	0.512***	0.318***	0.434***	–0.020***	0.103***	0.027***	0.077***	–0.025***
SHARE				1.000	0.258***	0.433***	0.023***	0.137***	0.052***	0.049***	–0.021***
MOSTCL					1.000	0.699***	0.175***	0.034***	–0.010**	0.014***	0.001
SHARECL						1.000	0.182***	0.118***	0.004	0.057***	–0.025***
NCLIENTS							1.000	–0.154***	–0.175***	–0.201***	0.143***
LTA								1.000	0.357***	0.287***	–0.236***
CFO									1.000	0.069***	–0.207***
LEV										1.000	–0.058***
Abs(*TACC*)											1.000

***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, two-tailed.

The results for the multivariate models with DAC as the dependent variable are reported in Table 4, Panel A. To test H1, the six alternative measures of industry specialization are used. The adjusted R^2 for each model exceeds 50 percent. Consistent with previous work, *LTA*, *CFO*, and *LEV* are significantly negatively associated with the absolute value of DAC, and the absolute value of *TACC* is positively and significantly associated with the absolute value of DAC.

The coefficients of *LEADER*, *DOMINANCE*, *SHARE*, *MOSTCL*, and *SHARECL* in columns (A) through (E) are all significantly negative, suggesting that the absolute value of DAC for clients of specialist auditors are lower than that of the nonspecialist auditors. This is consistent with specialist

TABLE 4
Multivariate Models Explaining (Absolute Value of) Discretionary Accruals

Panel A: Models Using Different Measures of Industry Specialization

		Coefficient Estimate (t-statistic) [a]					
		(A)	(B)	(C)	(D)	(E)	(F)
	Predicted	Specialization Variable					
Variable	Sign	*LEADER*	*DOMINANCE*	*SHARE*	*MOSTCL*	*SHARECL*	*NCLIENTS*
Intercept		0.052*** (33.627)	0.051*** (33.253)	0.052*** (32.883)	0.052*** (33.579)	0.056*** (32.350)	0.028*** (15.803)
LEADER	–	–0.006*** (–6.924)					
DOMINANCE	–		–0.008*** (–6.913)				
SHARE	–			–0.010*** (–3.579)			
MOSTCL	–				–0.006*** (–6.535)		
SHARECL	–					–0.039*** (–6.856)	
NCLIENTS	–						0.003*** (22.605)
LTA	–	–0.003*** (–14.498)	–0.003*** (–14.697)	–0.003*** (–14.744)	–0.003*** (–14.928)	–0.003*** (–14.405)	–0.003*** (–13.786)
CFO	–	–0.052*** (–16.750)	–0.053*** (–16.939)	–0.053*** (–16.891)	–0.053*** (–17.024)	–0.053*** (–17.088)	–0.039*** (–12.306)
LEV	–	–0.032*** (–15.823)	–0.031*** (–15.553)	–0.032*** (–15.796)	–0.032*** (–15.831)	–0.032*** (–15.702)	–0.016*** (–7.812)
Abs(*TACC*)	+	0.645*** (86.848)	0.665*** (86.662)	0.645*** (86.721)	0.645*** (86.760)	0.645*** (86.729)	0.631*** (83.497)
F-value		11,162.847	11,154.894	11,147.886	11,161.112	11,157.863	12,060.187
Adjusted R^2		0.527	0.527	0.527	0.527	0.527	0.546
n		50,116	50,116	50,116	50,116	50,116	50,116

***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively; one-tailed where signs are predicted, two-tailed otherwise.
See Table 1 for variable definitions.

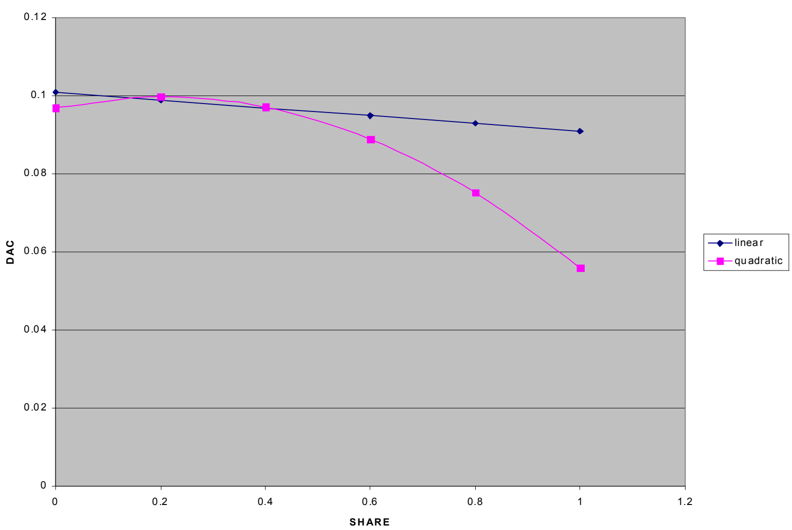
(continued on next page)

Table 4 (continued)

Panel B: Nonlinear DAC Models

	Coefficient Estimate (t-statistic)[a]		
	(A)	(B)	(C)
	Specialization Measure		
Variable[b]	*SHARE*	*SHARECL*	*NCLIENTS*
SHARE	0.028*** (3.405)		
SHARE Squared	–0.069*** (–5.123)		
SHARECL		0.201*** (6.230)	
SHARECL Squared		–0.642*** (–7.587)	
NCLIENTS			0.0002 (0.768)
NCLIENTS Squared			0.000001*** (8.759)
F-value	9,296.656	9,327.170	10,196.461
Adjusted R^2	0.527	0.528	0.550
n	50,116	50,116	50,116

Panel C: Graph of Predicted DAC against *SHARE* for the Linear and Quadratic Models[c]



***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively; one-tailed where signs are predicted, two-tailed otherwise.

[a] The t-statistic is based on White's (1980) heteroscedasticity adjusted standard errors.

[b] Only coefficients of specialization variables are reported; other variables included in the model are the same as in Panel A.

[c] Predicted values for the linear model are computed using the coefficients reported for the *SHARE* model in Panel A. Predicted values for the quadratic model are computed using coefficients from the quadratic model shown in Panel B. The values for all variables other than *SHARE* were set equal to their mean sample values.

auditors providing a higher quality audit. However, the coefficient of *NCLIENTS* in column (F) is positive and significant. Although we do not observe a similar inconsistent result in the ERC estimates (reported later), we find that *NCLIENTS* yields inconsistent results in many sensitivity exercises that we conduct. The reason for these inconsistencies is not clear. One possibility is that aggregation at national levels, which has been identified as a shortcoming of most specialization measures, is particularly problematic for this variable (O'Keefe et al. 1994).[15] Another potential explanation is that the number of clients an auditor has in a particular industry increases with the size of that industry.[16] As the size of the industry increases, so does the heterogeneity of the firms in the industry, and hence the number of clients an auditor must have to develop the required expertise to be a specialist. *NCLIENTS* does not control for this variation across industry.

We also investigated nonlinearities in the effects of industry specialization by including the squared terms for the continuous specialization variables as regressors. The results are shown in Table 4, Panel B. Columns (A) and (B) indicate that, for *SHARE* and *SHARECL,* the variable and its squared term both have significant coefficients. The sign of these coefficients indicates that the effect of the specialization variables have an inverse U-shaped form. That is, absolute DAC increases initially as *SHARE* (or *SHARECL*) increases, and then decreases. We graphically show this effect for *SHARE* in Panel C. The figure also shows the predicted absolute DAC derived from the linear model in Panel A. For the quadratic model, as *SHARE* increases from 0 through about 20 percent, absolute DAC increases from 9.7 percent to 9.99 percent. Thereafter, as *SHARE* increases, absolute DAC declines sharply reaching 5.59 percent when *SHARE* = 100 percent.[17] Results for *SHARECL* show a similar pattern.

However, the nonlinear *NCLIENT*S model in column (C) of Table 4, Panel B, continues to show inconsistent results. *NCLIENTS* is insignificant but the squared term is significant and positive, indicating that absolute DAC increases at an increasing rate as *NCLIENTS* increases.

In sum, we find that, with the exception of *NCLIENTS,* our measures indicate a negative association between the level of absolute discretionary accruals and industry specialization measures. However, the results for our nonlinear models, while confirming the results from our linear models, suggest that the benefit to specialization begins only after the auditor achieves a threshold level of industry knowledge. Before this threshold level is reached, there is even a slight increase in DAC.

Earnings Response Coefficient Model

Descriptive statistics for the independent variables in the ERC model are reported in Table 5, Panel A. Cumulative abnormal returns (*CAR*) and returns (*RET*) are both close to zero, with means of 0.1 and 0.8 percent respectively over the two-day accumulation period. Mean (median) unexpected earnings are slightly less (greater) than zero, with unexpected earnings being negative 44.5 percent of the time. The mean (median) market-to-book ratio is 3.137 (2.214) and the mean (median) beta is 1.215 (1.069). The firms in question are widely followed with a mean (median) of 7.156 (5) analysts following each firm.

Univariate tests using *LEADER* to partition the sample are presented in Table 5, Panel B. There is no difference in *CAR* or *RET* between the specialist and nonspecialist groups. Mean *UE,* although

[15] Unfortunately, prior literature does not provide us with insight on the matter. Three studies (O'Keefe et al. 1994; Cullinan 1998; Deis and Giroux 1992), use a measure based on number of clients (Gramling and Stone 2001). However these studies all examine not-for-profit situations, have samples with mostly local CPA firms as auditors, and use the number of clients audited by the *local* audit office as the measure of specialization. None of these characteristics correspond to the characteristics of our study.

[16] As might be expected the correlation between number of clients and number of firms in an industry is highly positive and statistically significant.

[17] We compared the predicted values in Panel C with actual sample mean DAC for ranges of *SHARE*. The actual DAC also shows a declining nonlinear trend, although it declines more rapidly than the predicted DAC.

TABLE 5
Descriptive Statistics and Correlation Matrix for the Variables in ERC Models

Panel A: Descriptive Statistics for Pooled Sample

Variable	n	Mean	Standard Deviation	First Quartile	Median	Third Quartile
CAR	19,091	0.001	0.068	–0.026	0.001	0.030
UE	19,091	–0.021	0.101	–0.013	0.0003	0.010
NEG	19,091	0.445	0.497	0	0	1
MB	19,091	3.137	3.443	1.430	2.214	3.669
Total Assets ($ Millions)	19,091	2,952.202	16,013.500	86.017	292.303	1,184.194
LTA	19,091	5.841	1.855	4.455	5.678	7.077
BETA	19,091	1.215	0.802	0.641	1.069	1.666
NO	19,091	7.156	6.936	2	5	10
RET	19,091	0.008	0.098	–0.038	0.000	0.047

See Table 1 for variable definitions.

(continued on next page)

Table 5 (continued)

Panel B: Descriptive Statistics for the Specialists (*LEADER* = 1) and Nonspecialists (*LEADER* = 0) Subsamples

	LEADER = 1					*LEADER* = 0					
Variable	**n**	**Mean**	**First Quartile**	**Median**	**Third Quartile**	**n**	**Mean**	**First Quartile**	**Median**	**Third Quartile**	**t-statistic[a] (Wilcoxon Z)[b]**
CAR	6,379	0.0001	–0.025	0.0002	0.028	12,712	0.001	–0.027	0.001	0.031	–1.312
											(–0.965)
UE	6,379	–0.018	–0.011	0.001	0.012	12,712	–0.022	–0.014	0.0001	0.009	2.559**
											(4.879)***
NEG	6,379	0.428	0	0	1	12,712	0.454	0	0	1	–3.523***
											—
MB	6,379	3.005	1.409	2.098	3.468	12,712	3.204	1.446	2.279	3.767	–3.754***
											(–5.517)***
Total Assets	6,379	4,733.68	113.552	400.946	1,777.16	12,712	2,058.24	76.807	248.083	955.104	10.922***
($ Millions)											(16.302)***
LTA	6,379	6.171	4.732	5.994	7.483	12,712	5.675	4.341	5.514	6.862	17.551***
											(16.304)***
BETA	6,379	1.150	0.595	1.014	1.564	12,712	1.248	0.665	1.099	1.708	–7.940***
											(–7.979)***
NO	6,379	8.219	3	5	11	12,712	6.622	2	4	9	15.097***
											(13.849)***
RET	6,379	0.007	–0.033	0.000	0.041	12,712	0.008	–0.040	0.000	0.050	–0.494
											(–0.291)

**, **, and *indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, two-tailed.

[a] Tests the hypothesis that the means for the groups are significantly different from each other.

[b] Tests the hypothesis that the medians for the groups are significantly different from each other.

(continued on next page)

Table 5 (continued)

Panel C: Correlation Matrix

	CAR	*LEAD-ER*	*DOMIN-ANCE*	*SHARE*	*MOST-CL*	*SHARE-CL*	*NCLIENTS*	*UE*	*NEG*	*MB*	*LTA*	*BETA*	*NO*	*RET*
CAR	1.000	–0.010	–0.002	–0.007	0.014*	0.005	–0.004	0.040***	–0.090***	–0.014**	0.005	–0.020***	0.003	–0.070***
LEADER		1.000	0.361***	0.778***	0.199***	0.308***	–0.023***	0.019**	–0.025***	–0.028***	0.126***	–0.057***	0.109***	–0.004
DOMINANCE		1.000	0.517***	0.318***	0.429***	–0.014*	–0.010	–0.001	–0.008	0.068***	–0.051***	0.026***	–0.012*	
SHARE				1.000	0.255***	0.425***	0.010	–0.005	–0.012	–0.012*	0.147***	–0.041***	0.106***	–0.010
MOSTCL					1.000	0.703***	0.197***	–0.001	–0.004	–0.005	0.017**	–0.003	0.023***	–0.007
SHARECL						1.000	0.197***	–0.013*	–0.003	–0.027***	0.084***	–0.051***	0.028***	–0.020***
NCLIENTS							1.000	–0.027***	0.051***	0.206***	–0.197***	0.253***	–0.054***	0.007
UE								1.000	–0.416***	0.051***	0.100***	–0.019***	0.121***	0.099***
NEG									1.000	–0.009	–0.088***	0.008	–0.086***	–0.081***
MB										1.000	–0.075***	0.229***	0.114***	0.009
LTA											1.000	–0.160***	0.686***	–0.015**
BETA												1.000	0.012	0.047***
NO													1.000	0.009
RET														1.000

***, **, and *indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively; two-tailed.

negative, is significantly higher for the specialist group. As might be expected, firms hiring specialist auditors are larger (*LTA*) and, hence, have a greater analyst following (*NO*), lower expected growth (*MB*), and lower risk (*BETA*). They are also less likely to have negative unexpected earnings (*NEG*).

Correlations among variables are reported in Table 5, Panel C. The correlations among the independent variables used in the model are reasonable, with the exception of the correlation between *LTA* and *NO,* which is 0.686. Sensitivity analysis in which we exclude either *LTA* or *NO* does not change the results reported later. We also examined the variance inflation factor (VIF). For the model presented in Table 6, the VIFs indicate that multicollinearity could be a problem, as the VIF for *UE* exceeds the acceptable level of 10. However, when we remove some of the control-interaction variables, i.e., *UE*MB, UE*BETA, UE*LTA, UE*NO,* and *UE*YIELD,* the maximum VIF is 1.17. Given the difference between the model presented and this reduced model is the inclusion of control variables, in particular control variables interacted with *UE,* and that our primary results are the same in both models, we conclude that multicollinearity is not driving our results.

Table 6, Panel A, presents regression results using the six measures of auditor specialization. Consistent with previous work, across all six regressions we find a positive association between abnormal returns and unexpected earnings.[18] As hypothesized, in all six regressions, we also find the interaction between *UE* and each of the specialist variables is positive and significant, indicating that clients with specialist auditors have higher ERC. As with the DAC models, we also checked for nonlinearity in the effects of specialization by including quadratic forms of the continuous variables as interactions with *UE.* The results, shown in Table 6, Panel B, indicate however, that the nonlinear effects observed with DAC do not seem to hold for ERC. The coefficients on each variable (*SHARE*, *SHARECL*, and NCLIENTS in columns (A), (B), and (C), respectively) as well as its squared value (*SHARE* squared, *SHARECL* squared, and *NCLIENTS* squared in columns (A), (B), and (C), respectively) are either insignificant or marginally significant. Thus, while specialization appears to have an effect on the ERC, that effect appears to be linear, rather than nonlinear.

As with the DAC model, we computed the effect of specialization on ERC. These computations use the linear models reported in Table 6, Panel A, because (as discussed above) the models in Panel B do not indicate the presence of nonlinearities. For *UE*LEADER,* the coefficient is 0.024, meaning that on average, the association between *CAR* and *UE* almost doubles, from 0.026 to 0.050 (0.026 plus 0.024), by switching from a nonspecialist to a specialist auditor. For *UE*MOSTCL,* the coefficient is 0.019, meaning that on average, the association between *CAR* and *UE* increases by more than 70 percent, from 0.026 to 0.045 (0.026 plus 0.019), if the client switches from a nonspecialist to a specialist auditor. Similarly, for the continuous measures, the increase in ERC is substantial. For example, ERC increases from 0.030 to 0.084 as *SHARE* goes from 0 to 100 percent. We demonstrate this effect in Table 6, Panel C. Results for *SHARECL* and *NCLIENTS* show a similar upward trend.

Consistent with the previous literature, in all six regressions, we find a negative and significant association between *CAR* and *RET.* In addition, in all six regressions, the interaction between *UE* and the indicator variable, (*NEG*), (which takes the value of 1 if unexpected earnings are negative and 0 otherwise) is negative and significant, and that between *CAR* and the interaction between *UE* and *MB* is positive and significant. The interactions of *UE* with *LTA*, *BETA*, *NO*, and *YIELD* (with the exception of *UE*BETA* in column (E)) are never significant.[19] The adjusted R^2s for the models presented are modest, but in line with previous work in this area (see summary in Lev 1989), with the adjusted R^2 for the models ranging from 1.3 to 1.4 percent.

[18] In much of the earlier literature (e.g., Teoh and Wong 1993), the coefficients on *UE* are much higher in magnitude (the sample period in Teoh and Wong was 1980–1989 and the coefficient was 0.42). In the more recent literature, the coefficients have decreased. For example, the sample period in Hackenbrack and Hogan (2002) was 1991–1997 and the coefficient was 0.12. While our coefficient is smaller than in both of these studies, our sample period is different, and the coefficients across studies seem to vary across time and sample composition.

[19] Prior work has reported conflicting results for some of these variables, with some studies finding them significant and others not. For example, systematic risk (*BETA*) is significantly related to ERC in Hackenbrack and Hogan (2002), but not in Teoh and Wong (1993).

TABLE 6
Multivariate Models of Earnings Response Coefficient

Panel A: Models Using Different Measures of Industry Specialization

		Coefficient Estimate (t-statistic)[a]					
		(A)	(B)	(C)	(D)	(E)	(F)
		Specialization Measure					
Variable	Predicted Sign	*LEADER*	*DOMINANCE*	*SHARE*	*MOSTCL*	*SHARECL*	*NCLIENTS*
Intercept		0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
		(3.358)	(3.443)	(3.341)	(3.448)	(3.389)	(3.429)
UE	+	0.026***	0.027***	0.030***	0.026***	0.030***	0.030***
		(2.455)	(2.511)	(2.800)	(2.418)	(2.758)	(2.807)
*UE*NEG*	–	–0.028***	–0.023**	–0.028***	–0.023**	–0.028***	–0.024**
		(–2.606)	(–2.088)	(–2.460)	(–2.188)	(–2.445)	(–2.189)
*UE*LEADER*	+	0.024***					
		(3.472)					
*UE*DOMINANCE*	+		0.018**				
			(2.040)				
*UE*SHARE*	+			0.054***			
				(3.015)			
*UE*MOSTCL*	+				0.019***		
					(2.884)		
*UE*SHARECL*	+					0.140***	
						(3.176)	
*UE*NCLIENT*S	+						0.0003**
							(1.827)
*UE*MB*	+	0.0003**	0.0003**	0.0003**	0.0003**	0.0002**	0.0003**
		(1.951)	(1.907)	(1.912)	(1.792)	(1.666)	(1.862)
*UE*LTA*	–	0.003	0.002	0.003	0.002	0.001	0.002
		(1.021)	(0.848)	(1.111)	(0.796)	(0.365)	(0.575)
*UE*BETA*	–	–0.004	–0.003	–0.005	–0.004	–0.005*	–0.005
		(–0.931)	(–0.729)	(–1.128)	(–0.893)	(–1.333)	(–1.058)
*UE*NO*	–	0.0003	0.001	–0.0001	0.001	0.001	0.001
		(0.219)	(0.827)	(–0.045)	(0.899)	(0.577)	(0.730)
*UE*YIELD*	?	0.065	0.123	0.083	0.134	0.164	0.158
		(0.463)	(0.871)	(0.601)	(0.972)	(1.212)	(1.150)
RET	–	–0.058***	–0.057***	–0.057***	–0.058***	–0.058***	–0.058***
		(–9.944)	(–9.914)	(–9.918)	(–9.951)	(–9.958)	(–9.933)
YR	?	Not Reported	Not Reported	Not Reported	Not Reported	Not Reported	Not Reported
IND	?	Not Reported	Not Reported	Not Reported	Not Reported	Not Reported	Not Reported
F-value		5.452	5.140	5.324	5.318	5.333	5.232
Adjusted R^2		0.014	0.013	0.013	0.013	0.013	0.013
n		19,091	19,091	19,091	19,091	19,091	19,091

***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively; one-tailed where signs are predicted, two-tailed otherwise.
[a] The t-statistic is based on White's (1980) heteroscedasticity adjusted standard errors.
See Table 1 for variable definitions.

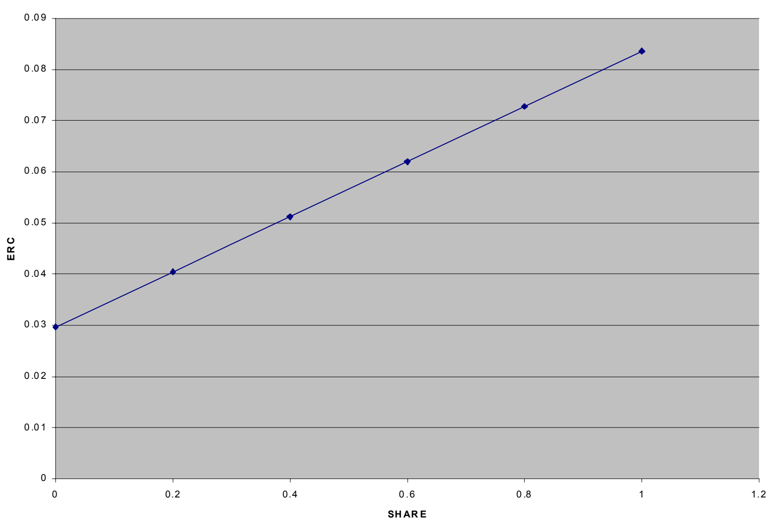
(continued on next page)

TABLE 6 (continued)

Panel B: Nonlinear ERC Models

	Coefficient Estimate (t-statistic)[a]		
	(A)	(B)	(C)
	Specialization Measure		
Variable[b]	*SHARE*	*SHARECL*	*NCLIENTS*
*UE**SHARE	0.120* (1.686)		
*UE*SHARE* Squared	–0.121 (–0.984)		
*UE*SHARECL*		–0.217 (–0.969)	
*UE*SHARECL* Squared		1.101 (1.675)	
*UE*NCLIENTS*			0.0002 (0.589)
*UE*NCLIENTS* Squared			0.0000 (0.335)
F-value	5.262	5.321	5.152
Adjusted R^2	0.013	0.013	0.013
n	19,091	19,091	19,091

Panel C: Graph of Estimated ERC against *SHARE*[c]



***, **, and *indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively; one-tailed where signs are predicted, two-tailed otherwise.

[a] The t-statistic is based on White's (1980) heteroscedasticity adjusted standard errors.

[b] Only coefficients of specialization variables are reported; other variables included in the model are the same as in Panel A.

[c] Estimated *ERC* are computed using the coefficients reported for the *SHARE* model in Panel A. The values for all variables other than *SHARE* were set equal to their mean sample values.

ADDITIONAL ANALYSES

Sensitivity Tests

We conducted several sensitivity tests.[20] First, as in Reynolds and Francis (2000), we partition the DAC sample into those with positive (income-increasing) discretionary accruals and those with negative (income-decreasing) discretionary accruals, as the incentives to manage accruals could be different for the two situations. We expect that auditor industry specialization will be negatively associated with the level of positive discretionary accruals and positively associated with the level of negative discretionary accruals. As expected, the coefficients on *LEADER* (p = 0.00), *DOMINANCE* (p = 0.00), *SHARE* (p = 0.00), *MOSTCL* (p = 0.00), and *SHARECL* (p = 0.02) are negative and significant in the regression with positive DAC as the dependent variable. However, *NCLIENTS* has an unexpected positive sign. In the regression with negative DAC as the dependent variable, the coefficients on *LEADER* (p = 0.00), *DOMINANCE* (p = 0.03), *SHARE* (p = 0.07), *MOSTCL* (p = 0.02), *SHARECL* (p = 0.00), and *NCLIENTS* (p = 0.00) are all positive and significant.

Second, the possibility exists that we are picking up an auditor, rather than a specialist, effect. To control for that possibility we augment our DAC regression by adding indicator variables for five of the Big 6 audit firms. The results (not presented) show that inclusion of auditor controls increases the R^2 slightly, and that the coefficients *LEADER* (p = 0.00), *DOMINANCE* (p = 0.00), *SHARE* (p = 0.00), *MOSTCL* (p = 0.00), and *SHARECL* (p = 0.00), are still negative and significant. *NCLIENTS* remains positive and significant (p = 0.00). For the ERC models, we augment our regression by adding indicator variables representing 5 of the 6 audit firms, interacted with unexpected earnings as control variables (e.g., *UE*AA*). The results (not presented) show that inclusion of auditor controls increases the R^2 slightly and more importantly, that the coefficients on *UE*LEADER* (p = 0.00), *UE*DOMINANCE* (p = 0.02), *UE*SHARE* (p = 0.00), *UE*MOSTCL* (p = 0.00), and *UE*SHARECL* (p = 0.00) are still positive and significant. *UE*NCLIENTS* has a significant negative sign.

Third, the sample used in this study is pooled across nine years. This could be problematic if there are shifts in the cross-sectional parameters over time or if the error terms are autocorrelated. To address this potential problem, we estimated our models for each year and computed the Fama and MacBeth (1973) t-statistic.[21] The p-values of the Fama MacBeth t-statistic for the *LEADER, DOMINANCE, SHARE, MOSTCL,* and *SHARECL* variables in the DAC models reported in Table 3 are still negative and significant at 0.01, 0.00, 0.02, 0.00, and 0.00, respectively, and *NCLIENTS* is still positive and significant at the 0.01 level. For the ERC models reported in Table 6, the Fama and MacBeth (1973) t-statistic indicates that the coefficient of interest continues to be positive and significant with p-values of 0.00, 0.02, 0.00, 0.00, 0.01, and 0.06 for *UE*LEADER, UE*DOMINANCE, UE*SHARE, UE*MOSTCL, UE*SHARECL,* and *UE*NCLIENTS,* respectively, suggesting that our results are not influenced by pooling the observations across years.

Our final sensitivity test is for the ERC models. Easton and Zmijewski (1989) point out that the use of analysts' forecasts to construct *UE* creates a trade-off in that a longer holding period increases the number of confounding events, while a two-day holding period increases the measurement error in *UE.* Furthermore, Cho and Jung (1991) note that results in prior work differ depending on the length of the window used. To examine this possibility, we define an alternative event window as starting on the date of the most recent I/B/E/S forecast and ending on the day of earnings announcement. In contrast to the two-day window used in our primary analysis, the regression utilizing long window returns has slightly higher explanatory power (R^2 is 2.2 percent, 2.1 percent, 2.1 percent, 2.1 percent, 2.1 percent, and 2.1 percent for the models using *LEADER, DOMINANCE, SHARE, MOSTCL SHARECL,* and *NCLIENTS,* respectively). More importantly, the coefficients on *UE*LEADER* (p = 0.00), *UE*DOMINANCE* (p = 0.07), *UE*SHARE* (p = 0.01), *UE*MOSTCL* (p = 0.04), *UE*SHARECL* (p = 0.01), and *UE*NCLIENTS* (p = 0.04) are positive and statistically significant, confirming that our results are robust to choice of event window.

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[20] For brevity, in our sensitivity analyses we discuss only the results for the specialization variables. Results for the control variables are, in general, similar to those reported in our main analyses.

[21] The t-statistic, $t(a_i)$, = $\overline{a}_i$ / ($\sigma(a_i)/\sqrt{N}$) (Kerstein and Kim 1995, 519) where a_i is the regression coefficient for variable i, $\overline{a}_i$ is the average of the regression coefficients a_i over the 9 years, $\sigma(a_i)$ is the standard deviation of the coefficients a_i over the 9 years, and n = 9.

Industry Level Results

Both the demand for, and supply of, specialization can differ by industry (Craswell et al. 1995). Specialized contracts and industry specific accounting can lead to a greater demand for, and greater returns from investment in, auditor industry specialization. We reran our regressions for major industry groups. The results for the specialization measures for the DAC model are shown in Table 7, Panel A, and those for ERC are shown in Table 7, Panel B.

The results vary by specialization measure, industry, and across the two panels. Focusing on the results for DAC in Panel A, we see that for each of the specialization measures there are between one and three industries with a negative and statistically significant coefficient. Looking at the industries, except for construction and mining, which is never statistically significant, the other industries have negative and statistically significant coefficients for between two and four of our specialization measures.

TABLE 7
Industry Estimates

Panel A: Coefficient Estimates (t-statistics) for the Specialization Measures for the DAC Models, by Major Industry Groups

Industry	*LEADER*	*DOMINANCE*	*SHARE*	*MOSTCL*	*SHARECL*	*NCLIENTS*
Construction and Mining	–0.0001	0.005	0.012	–0.001	0.011	0.0000
	(–0.058)	(0.766)	(1.225)	(–0.396)	(0.493)	(0.166)
Manufacturing	–0.004	0.0002	0.001	–0.0031***	–0.021**	0.0002***
	(–0.402)	(0.055)	(0.177)	(–3.246)	(–2.285)	(12.028)
Transportation	–0.003**	–0.014***	–0.021***	0.002	–0.024***	0.0003***
	(–1.748)	(–8.103)	(–3.283)	(1.063)	(–2.714)	(8.200)
Trade	–0.004**	–0.005*	–0.006	–0.002	–0.012	0.001***
	(–2.208)	(–1.643)	(–1.212)	(–0.783)	(–0.787)	(6.738)
Finance and Insurance	–0.002	0.003	0.002	–0.007***	–0.052***	–0.0001***
	(–0.933)	(0.464)	(0.132)	(–3.085)	(–2.991)	(–2.807)
Services	–0.027***	–0.039***	–0.058***	–0.017***	–0.010	0.0005***
	(–7.170)	(–12.086)	(–6.691)	(–5.210)	(–0.441)	(20.144)

Panel B: Coefficient Estimates (t-statistics) for the Specialization Measures for the ERC Models, by Major Industry Groups

Industry	*LEADER*	*DOMINANCE*	*SHARE*	*MOSTCL*	*SHARECL*	*NCLIENTS*
Construction and Mining	0.047***	–0.027	0.126***	0.022**	0.395***	0.002***
	(3.628)	(–0.812)	(4.501)	(1.817)	(3.383)	(5.683)
Manufacturing	–0.004	–0.028**	–0.005	–0.015*	–0.084	–0.0002**
	(0.358)	(–1.700)	(–0.163)	(–1.468)	(–0.956)	(–1.685)
Transportation	0.028	0.042	0.055	0.035*	0.197	0.0004
	(1.126)	(1.118)	(0.478)	(1.438)	(1.071)	(1.104)
Trade	0.019*	0.061*	0.065	0.022**	0.258**	–0.0002
	(1.337)	(1.386)	(1.193)	(1.651)	(2.081)	(–0.267)
Finance and Insurance	0.052*	0.135	–0.040	0.022	–0.230	–0.001**
	(1.320)	(0.977)	(–0.181)	(0.615)	(–0.782)	(–1.860)
Services	0.036**	0.023*	0.125**	0.038***	0.053	–0.000
	(2.147)	(1.341)	(2.288)	(2.352)	(0.432)	(–0.699)

***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively, one-tailed.

Turning to the results for ERC in Panel B, we see that for each of the specialization measures there are between one and four industries with a positive and statistically significant coefficient (for three of the measures there are also either one or two industries with a statistically significant negative coefficient). Looking at the industries, the number of positive and statistically significant coefficients ranges from zero for Manufacturing to five for Construction and Mining.

Because of the complex interaction of the factors that drive benefits of specialization, it is not surprising that the results differ across industries. However, we also find that the results differ by earnings quality measures. We conjecture that this may be because of differences in the measures. Previous work has reported differences across industries in both absolute discretionary accruals Francis, Maydew, and Sparks (1999), and in ERC (Biddle and Seow 1991).[22] DAC is a focused measure that directly attempts to measure earnings management, whereas ERC is a broader measure that includes the market's perception of that earnings management, but also includes the market's perception of the nonearnings driven noise and expectations of growth and firm risk, among other factors. These factors vary systematically across industry and may explain the lack of results for some industries. In general, research in this area (DAC and ERC) has focused on broad groups of firms and not individual industries. *A priori* there is no reason to expect that their effects will be similar in all situations. In industries where accruals are more amenable to manipulation, specialist auditors may play a role. In others, specialists may not play a role in curbing accruals management, but may nevertheless reduce the perceived noise in earnings, e.g., by reducing unintentional errors.

Still, to assess the importance of specialization within an industry, we combine the results in Panels A and B. Taken together, these results suggest that the impact of specialization varies by industry. The service industry appears to have the strongest and most consistent results across the two measures of earnings quality. The service industry may include firms with complex contracting or revenue recognition issues, and thus may benefit from auditor industry specialization. Owhoso et al. (2002) report beneficial effects of industry specialization in two industries, one of which—health care—belongs to the services sector. However, the second industry that they examine, banking, is part of the financial services industry for which we find weaker results. To the extent that the financial services industry is largely regulated, our finding is consistent with the conjecture that regulated industries have less to gain from auditor industry specialization (Dunn et al. 2000).[23] Other industries in which auditor industry specialization has a beneficial effect on earnings quality, i.e., significant coefficients in the predicted direction, are trade (six significant coefficients), transportation (five significant coefficients), and construction and mining (five significant coefficients).

CONCLUSIONS

Previous studies have documented that discretionary accruals are lower (Becker et al. 1998; Reynolds and Francis 2000) and earnings response coefficients are higher (Teoh and Wong 1993) for clients of Big 6 (now Big 4) auditors compared to non-Big 6 auditors, possibly due to higher

[22] Francis, Maydew, and Sparks (1999, Table 3) report higher absolute DAC in mining (SIC 1000-1499), followed by services (SIC 7000-9999) and financial services (SIC 6000-6999). Agriculture (SIC 0000-0999) has the lowest DAC in their sample. Biddle and Seow (1991, Table 5) using SIC more disaggregated industry categories, report high ERC for some transportation and utility industries (SIC 4511-4700; 4911-4953), some nondurable manufacturing industries (e.g., SIC 2600-2643; 2800-2821; 2834; 2840-2891), and for financial (SIC 6120-6281) and personal services (SIC 7011-8062). By contrast, many durable manufacturing industries (e.g., SIC 3310-3312; 3550-3590; 3330-3350) have lower ERC. Further, Biddle and Seow show that differences across industries in ERC can be explained by differences in their operating and structural characteristics. Although differences in industry definitions make comparison difficult, the two studies suggest DAC and ERC may not be correlated across industries.

[23] We also estimated our models for two-digit SIC industries. The results differed across industries, specialization measures and for the DAC and ERC models. For services, 4 of 6 two-digit industries included in both DAC and ERC estimations showed some significant results in the predicted direction. For the other industry groups, the frequencies were as follows: construction and mining, 2 out of 2; manufacturing, 15 out of 18; transportation, 4 out of 5; trade, 5 out of 9; financial services, 4 out of 5.

audit quality provided by the Big 6 firms. We extend this literature by examining the effect of another dimension of audit quality, auditor industry specialization, on discretionary accruals and earnings response coefficients of clients. It is argued that industry specialization is associated with greater audit assurance, and therefore, better earnings quality.

Because both auditor industry specialization and earnings quality are unobserved, we use multiple proxies for them. Prior work has measured auditors' industry specialization in different ways: market leadership, dominance, and market shares. We use six different measures that capture these different aspects of auditors' industry activities. We proxy for earnings quality using absolute discretionary accruals (DAC) and the earnings response coefficients (ERC). The results indicate a significant negative association between five of the six measures of auditor industry specialization and clients' absolute discretionary accruals. Moreover, we find evidence of nonlinearities in the effect of specialization on accruals: as market shares increase, absolute discretionary accruals increase initially, but decline thereafter at an increasing rate. We also find a significant positive association between the six measures of auditor industry specialization and client earnings response coefficients. The negative association observed between auditor industry specialization and client absolute discretionary accruals indicates that on average, specialist auditors reduce earnings management by their clients. The positive association observed between auditor industry specialization and the earnings response coefficient indicates that on average, specialist auditors increase the market's perception about the quality of these earnings. These results hold after controlling for a number of variables shown in prior work to be related to DAC and ERC.

The beneficial effects of auditor industry specialization are most marked in the services industry, and in varying degrees, in the mining and construction, trade, and transportation industries. The findings suggest that industry specialist auditors may contribute positively to the earnings quality of their clients and to the perception of that quality in the financial markets. This in turn suggests that recent structural shifts by the Big 6 (now Big 4) firms in the direction of greater industry focus is likely to have a favorable impact on financial reporting.

The use of proxies to measure auditor industry specialization is a limitation of this study. As prior work has noted, specialization measures based on national market shares may not capture specializations in situations where the auditor has a concentrated local clientele. Because this criticism is probably more relevant for analysis of non-Big 6 auditors, we restricted our analysis to the Big 6 auditors.

Future studies should focus on refinements of the specialization measures, with a view to being able to incorporate smaller auditors in their analyses. Similarly, our measures of earnings quality and the market's perception of that quality are imperfect. Discretionary accrual models measure discretionary accruals with error. (See Bernard and Skinner 1996 for a discussion.) Also, the low explanatory power associated with the earnings response coefficient models indicates there is a significant omitted variable problem. However, these problems are endemic to the respective literatures and we are using the best currently available models.

REFERENCES

Atiase, R. 1985. Predisclosure information, firm capitalization and security price behavior around earnings announcements. *Journal of Accounting Research* 23 (Spring): 21–36.

Bartov, E., F. A. Gul, and J. S. L. Tsui. 2000. Discretionary accruals models and audit qualifications. *Journal of Accounting and Economics* 30 (December): 421–452.

Basu, S. 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24 (December): 3–37.

Beasley, M. S., and K. Petroni. 2001. Board independence and audit firm type. *Auditing: A Journal of Practice & Theory* 20 (March): 97–114.

Becker, C. L., M. L. DeFond, J. Jiambalvo, and K. R. Subramanyam. 1998. The effect of audit quality on earnings management. *Contemporary Accounting Research* 15 (Spring): 1–24.

Bernard, V. L., and D. J. Skinner. 1996. What motivates managers' choice of discretionary accruals? *Journal of Accounting and Economics* 22 (August–December): 313–326.

Biddle, G. C., and G. S. Seow. 1991. The estimation and determinants of associations between returns and earnings: Evidence from cross-industry comparisons. *Journal of Accounting, Auditing, and Finance* 6 (Spring): 183–232.

Bonner, S. E., and B. L. Lewis. 1990. Determinants of auditor expertise. *Journal of Accounting Research* 28 (Supplement): 1–20.

Bowen, R. M., M. F. Johnson, T. Shevlin, and D. Shores. 1992. Determinants of the timing of quarterly earnings announcements. *Journal of Accounting, Auditing, and Finance* 7 (Fall): 395–422.

Browning, E. S., and J. Weil. 2002. Accounting woes roil stock markets as nervous investors stampede exits. *Wall Street Journal* (January 29).

Carcello, J. V., and A. L. Nagy. 2002. Auditor industry specialization and fraudulent financial reporting. Working paper, University of Tennessee and John Carroll University, Cleveland, Ohio.

Cho, J. Y., and K. Jung. 1991. Earnings response coefficients: A synthesis of theory and empirical evidence. *Journal of Accounting Literature* 10: 85–116.

Collins, D. W., and S. P. Kothari. 1989. An analysis of intertemporal and cross-sectional determinants of earnings response coefficient. *Journal of Accounting and Economics* 11 (July): 143–181.

Craswell, A. T., J. R. Francis, and S. L. Taylor. 1995. Auditor brand name reputations and industry specializations. *Journal of Accounting and Economics* 20 (December): 297–322.

Cullinan, C.P. 1998. Evidence of non-Big 6 market specialization and pricing power in a niche assurance service market. *Auditing: A Journal of Practice & Theory* 17 (Supplement): 47–57.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney. 1995. Detecting earnings management. *The Accounting Review* 70 (April): 193–226.

DeFond, M. L., and J. Jiambalvo. 1994. Debt covenant violation and manipulation of accruals. *Journal of Accounting and Economics* 17 (January): 145–176.

———, J. R. Francis, and T. J. Wong. 2000. Auditor industry specialization and market segmentation: Evidence from Hong Kong. *Auditing: A Journal of Practice & Theory* 19 (Spring): 49–66.

Deis, D. R., and G. A. Giroux. 1992. Determinants of audit quality in the public sector. *The Accounting Review* 67 (July): 462–479.

Dunn, K. A., B. W. Mayhew, and S. G. Morsfield. 2000. Auditor industry specialization and client disclosure quality, Working paper, Baruch College of City University of New York, University of Wisconsin, and The Capital Markets Company.

Easton, P. D., and M. E. Zmijewski. 1989. Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting and Economics* 11 (July): 117–142.

———, and T. S. Harris. 1991. Earnings as an explanatory variable for returns. *Journal of Accounting Research* 29 (Spring): 19–36.

Elder, R. J. 1994. The relation of audit firm size and industry specialization with auditor compensation and underpricing of initial public offerings. Working paper, Syracuse University.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 18 (May/June): 607–636.

Francis, J. R., E. L. Maydew, and H. C. Sparks. 1999. The role of Big 6 auditors in the credible reporting of accruals. *Auditing: A Journal of Practice & Theory* 18 (Fall): 17–34.

———, D. J. Stokes, and D. Anderson. 1999. City markets as a unit of analysis in audit research and the re-examination of Big 6 market shares. *Abacus* 35 (June): 185–206.

Frankel, R. M., M. F. Johnson, and K. K. Nelson. 2002. The relation between auditors' fees for nonaudit services and earnings quality. *The Accounting Review* 77 (Supplement): 71–105.

Gramling, A. A., and D. N. Stone. 2001. Audit firm industry expertise: A review and synthesis of the archival literature. *Journal of Accounting Literature* (20): 1–29.

———, V. E. Johnson, and I. K Khurana. 2001. Audit firm industry specialization and financial reporting quality. Working paper, Georgia State University and University of Missouri–Columbia.

Hackenbrack, K. E., and C. E. Hogan. 2002. Market response to earnings surprises conditional on reasons for an auditor change. *Contemporary Accounting Research* 19 (Summer): 195–223.

Hayn, C. 1995. The information content of losses. *Journal of Accounting and Economics* 20 (September): 125–153.

Hogan, C. E., and D. C. Jeter. 1999. Industry specialization by auditors. *Auditing: A Journal of Practice & Theory* 18 (Spring): 1–17.

Hribar, P., and D. W. Collins. 2002. Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research* 40 (March): 105–134.

Jones, J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29 (Fall): 193–228.

Kerstein, J., and S. Kim. 1995. The incremental information content of capital expenditures. *The Accounting Review* 70 (July): 513–526.

Krishnan, J. 2001. A comparison of auditors' self-reported industry expertise and alternative measures of industry specialization. *Asia-Pacific Journal of Accounting & Economics* 8 (December): 127–142.

Lev, B. 1989. On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research. *Journal of Accounting Research* 27 (Supplement): 153–192.

Lipe, R. 1990. The relation between stock returns and accounting earnings given alternative information. *The Accounting Review* 65 (January): 49–71.

Lys, T., and R. L. Watts. 1994. Lawsuits against auditors. *Journal of Accounting Research* 32 (Supplement): 65–93.

Mayhew, B., and M. S. Wilkins. 2002. Audit firm industry specialization as a differentiation strategy: Evidence from fees charged to firms going public. Working paper, University of Wisconsin–Madison and Texas A&M University.

Moreland, K. A. 1995. Criticisms of auditors and the association between earnings and returns of client firms. *Auditing: A Journal of Practice & Theory* 14 (Spring): 94–104.

O'Keefe, T. B., R. D. King, and K. M. Gaver. 1994. Audit fees, industry specialization, and compliance with GAAS reporting standards. *Auditing: A Journal of Practice & Theory* 13 (Fall): 41–55.

Owhoso, V. E., W. F. Messier, Jr., and J. G. Lynch, Jr. 2002. Error detection by industry-specialized teams during sequential audit review. *Journal of Accounting Research* 40 (June): 883–900.

Palmrose, Z-V. 1986. Audit fees and auditor size: Further evidence. *Journal of Accounting Research* 24 (Spring): 97–110.

Pearson, T., and G. Trompeter. 1994. Competition in the market for audit services: The effect of supplier concentration on audit fees. *Contemporary Accounting Research* 11 (Summer): 115–135.

Reynolds, J. K., and J. R. Francis. 2000. Does size matter? The influence of large clients on office-level auditor reporting decisions. *Journal of Accounting and Economics* 30 (December) 375–400.

Solomon, I., M. D. Shields, and O. R. Whittington. 1999. What do industry-specialist auditors know? *Journal of Accounting Research* 37 (Spring): 191–208.

Teoh, S. H., and T. J. Wong. 1993. Perceived auditor quality and the earnings response coefficient. *The Accounting Review* 68 (April): 346–366.

Warfield, T. D., J. J. Wild, and K. L. Wild. 1995. Managerial ownership, accounting choices, and informativeness of earnings. *Journal of Accounting and Economics* 20 (July): 61–91.

Watts, R. L., and J. L. Zimmerman. 1986. *Positive Accounting Theory*. Upper Saddle River, NJ: Prentice Hall.

White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48: 817–838.