

The Investment Opportunity Set and Industry Specialization by Auditors

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ABSTRACT

A report issued by the U.S. General Accounting Office (GAO) in 2003 identified industry specialization as a key driver of consolidation among audit firms and highlighted the extreme levels of auditor concentration in some industries. We investigate an important related issue that is not addressed in the GAO report and that is relatively unexplored in the academic accounting literature: why does auditor specialization differ across industries? Like the GAO, we view auditor concentration as a measure of industry specialization. We posit that the investment opportunity set (IOS) plays an important role in determining whether an industry is an attractive target for auditor specialization and in creating barriers to auditor entry. We argue that when industry-specific IOS is high, auditors will make costly industry-specific investments that allow them to offer a differentiated product and to create entry barriers for other audit firms. However, when a large component of IOS is specific to individual firms within an industry so that IOS is highly variable within the industry, the auditors' knowledge requirements are highly specific to those firms and it is more difficult to transfer knowledge and spread costs across clients in that industry. Using two different measures of IOS and three alternative industry classification schemes, we present evidence that auditor specialization is increasing in industry IOS levels and decreasing in within-industry IOS variability.

I. INTRODUCTION

In July 2003, the U.S. General Accounting Office (GAO) published the results of its Mandated Study on Consolidation and Competition among public accounting firms.² In general, the GAO found no empirical evidence that consolidation had induced impairment of competition in the market for audit services. However, it posed the possibility that future client choices could be further limited and that the changes in the profession may have implications for competition and auditor choice, “especially in certain industries” (GAO 2003, preface).

The report identified auditor industry concentration as one key feature that could affect the choice of an auditor in the future. It recognized that there is a demand for auditors who are industry specialists and reported that 80 percent of the companies responding to a GAO survey said that industry specialization or expertise would be of either “great” or “very great” importance if they had to choose a new auditor. Specialization ranked behind only service quality and auditor reputation as factors influencing auditor choice. The report also noted that the demand for specialists had led to extremely high two-audit firm concentration ratios in some industries.³ The GAO report concluded that one of the factors driving consolidation of the large accounting firms was the need to “build industry-specific expertise” (GAO 2003, 4), and that

² The GAO study was mandated by section 701 of the Sarbanes-Oxley Act 2002. The objectives of the study were to examine (1) factors leading to mergers of the large public accounting firms in the 1980s and 1990s, (2) the effect of consolidation of the accounting firms on competition, (3) the impact of consolidation on auditor independence and the cost and quality of audits, (4) the impact of consolidation on capital markets, and (5) the barriers that smaller audit firms encounter in competing with the largest accounting firms.

³ Comparing 1997 to 2002, the report finds more industries in 2002 where two firms accounted for over 70 percent of the total sales audited. For example, they find that, by 2002, Ernst & Young and PricewaterhouseCoopers audited 90.7 percent of assets of firms in the metal mining industry, while Deloitte & Touche and Ernst & Young audited 80.1 percent in general building contracting (see GAO 2003, 116).

industry specialization is an area that “may warrant ongoing and additional analysis” (GAO 2003, 53).

One issue not addressed in the GAO report is *why* auditor specialization differs across industries. In this study, we examine cross-industry differences in auditor specialization. Consistent with the measures used by the GAO and by other accounting researchers (e.g., Hogan and Jeter 1999, Balsam et al. 2003, Mayhew and Wilkins 2003), we choose auditor concentration based on client size as our measure of industry specialization. As the GAO study points out, an industry specialist could audit a large majority of firm assets in a particular industry even though it audits only a few firms. In contrast, another auditor might audit many smaller companies, but not have the “requisite excess staff capacity or technical expertise necessary to handle the larger clients in that industry, which is implied by the term specialization. Industries conducive to specialization would tend to preclude other firms from easily entering the market and challenging specialist firms’ market share” (GAO 2003, 27, note 18). We recognize that industry specialization and auditor concentration are conceptually different. However, since auditor concentration is used as our measure of specialization, the terms auditor concentration and industry specialization are used interchangeably at times in this paper.

We argue that inter-industry differences in auditor concentration are related to differences in the investment opportunity sets (IOS) facing various industries. IOS is composed of “prospective investment opportunities and associated payoff distributions” (Smith and Watts 1992). Myers (1977) describes IOS as comprising growth options and

assets in place.⁴ While all assets possess some characteristics of each, the relative proportions vary. As growth options increase, so does the dependence of asset valuation on future managerial decisions. Greater certainty surrounding valuation of assets in place means that they require relatively less judgment to audit and are more likely than growth options to form the basis for contractual specifications. Although growth options are less likely to appear on balance sheets, auditing serves an important role in verifying the nature of expenditures and their classification, thus reducing potential agency costs that can arise from firms' failure to invest in positive NPV projects (Smith and Warner 1979; Godfrey and Hamilton 2005). High inherent, control, and detection risks in auditing growth options increase the level of auditor discernment required and the need for a specialist auditor.

Firms with more significant investment opportunities are likely to face greater information disparity between insiders and outsiders, thus increasing the relative importance of the monitoring function and the incremental benefit of industry-specific knowledge and expertise by the firms' auditors. While we do not claim to provide a comprehensive analysis of all the factors that affect decisions related to an auditor's client portfolio, in the spirit of Smith and Watts (1992), we focus on the plausibility of IOS as a measure that distinguishes the degree to which industries might be considered as attractive targets for specialization efforts. Specifically, we argue that the breadth and depth of IOS create requirements for industry-specific knowledge, which in turn create opportunities for product differentiation. The higher costs of obtaining industry-specific

⁴ Consistent with general terminology, we deem increasing IOS to mean increasing growth options (Skinner 1993).

knowledge in high IOS industries, combined with heightened risk issues, also serve to establish barriers to entry by other auditors. Thus, we expect industry specialization to be increasing in the level of industry IOS. At the same time, we argue that auditor concentration will be decreasing in the within-industry variability of IOS. When IOS varies more across firms within an industry, this variability makes it harder for an auditor to transfer industry-specific knowledge from one client to another client, thus mitigating the benefits of investing in industry specific knowledge.

We use industry data from COMPUSTAT for the period 1986-2004 to test our hypotheses. We measure auditor industry specialization using a two-auditor concentration ratio, which captures the portion of total assets audited in a given industry by the top two auditors.⁵ We define industries based on three different classification schemes (3-digit SIC codes, 3-digit NAICS codes, and Fama-French (1997) industries), and we define IOS in two ways using measures from factor analyses based on Baber et al. (1996) and Gaver and Gaver (1993). The median level of IOS within a given industry provides our measure of industry-specific IOS, while the standard deviation of IOS in the industry captures its variability and is our proxy for firm-specific IOS. Consistent with our hypotheses, we find evidence supporting a positive relation between industry-specific IOS and auditor industry specialization and a negative relation between the variability of IOS and auditor industry specialization. Further, these results are insensitive to the industry classification scheme chosen.

⁵ This measure is consistent with that used in the GAO report (2003) and with Hogan and Jeter (1999). Hogan and Jeter use a three-auditor concentration ratio rather than a two-auditor ratio because they focus on the Big 8 and Big 6 periods whereas we also examine the Big 5 and Big 4 periods. In additional analyses presented later in this paper, we also use a three-auditor concentration ratio for the Big 8 and Big 6 periods.

We contribute to the extant literature in several ways, and we address some of the concerns currently facing the profession with regard to the market for audit services. First, in line with the GAO's call for additional analysis of industry specialization (GAO 2003, 53), we provide a deeper understanding of cross-industry differences in auditor concentration. Our theory and results suggest that industry specialization is a rational response by auditors to industry-level knowledge requirements related to IOS. Second, we differ from most prior research by focusing on the cause, rather than the effects, of specialization by auditors. Prior research has addressed changes in specialization over time (e.g., Hogan and Jeter 1999), whether specialist auditors perform "better" audits (e.g., Owoso et al. 2002; Balsam et al. 2003; Low 2004), and whether specialists earn fee premiums (e.g., Mayhew and Wilkins 2003; Ferguson et al. 2003; Francis et al. 2005). Relatively few studies have tried to explain why some industries have a higher level of auditor concentration than others.⁶ Third, we provide the rationale for a linkage between industry specialization and IOS, thus contributing not only to the literature on industry specialization but also to the literature on IOS. Smith and Watts (1992) and Gaver and Gaver (1993) provide evidence that IOS can affect corporate policy decisions (e.g., financing, dividend, and compensation decisions) at the industry and firm levels. We extend this literature by showing that IOS may also affect auditor concentration levels.

The rest of this paper is organized as follows. Section 2 provides background, and section 3 develops our hypotheses, which link auditor specialization to the

⁶ Notable exceptions include Eichenseher and Danos (1981), Danos and Eichenseher (1982), and Cairney and Young (2004).

investment opportunity set. Section 4 describes the sample and method. Section 5 contains results, and section 6 summarizes and concludes.

II. BACKGROUND

Prior academic research supports the GAO's view that auditors seek to specialize in certain industries, but empirical tests of the reasons for specialization are limited. Early research by Eichenseher and Danos (1981) and Danos and Eichenseher (1982) rely on cost reduction arguments as an explanation for industry specialization. They suggest that specialization can reduce auditors' costs either because expertise enables audits to be conducted more efficiently and effectively or because of economies of scale. For example, industry specialists can spread the costs of knowledge acquisition and training across more clients. Further, they argue that knowledge requirements are higher in regulated industries, and they present evidence that regulated industries have higher auditor concentration ratios.

Hogan and Jeter (1999) provide evidence that auditor concentration across all industries has increased over time. They regress the three-firm auditor concentration ratio on measures representing time, regulation, the auditor's self-declared specializations, and at the industry level, measures of client concentration, litigation risk, size, and growth. They also include an interactive variable between regulated status and time. Hogan and Jeter (1999) find significant coefficients for all their variables. The regulation/time interaction and regulation variables indicate that auditor concentration in regulated (nonregulated) industries is unchanged (increasing), in contrast to the findings

of Danos and Eichenseher (1982), who find higher auditor concentration for regulated firms in an earlier period. This latter finding suggests that industry-specific knowledge requirements extend to nonregulated industries as well as regulated industries. Equally important, Hogan and Jeter's (1999) finding that audit leaders' market shares increased over their sample period suggests that industry-related knowledge requirements have been increasing.

More recently, Cairney and Young (2004) find that auditor concentration and specialization are higher in industries where firms are more homogeneous. We suggest that differences in auditor concentration depend not only on intra-industry differences, but also on inter-industry differences, and we identify industry IOS as an important first-order source of differences in intra-industry homogeneity (and inter-industry heterogeneity).

III. HYPOTHESES

Recently, Mayhew and Wilkins (2003) and Casterella et al. (2004) use Porter's (1985) five forces framework to explain why auditors pursue specialization strategies. They argue that firms have incentives to specialize so that they can offer a differentiated product to their clients. There is also evidence that specialization enables the auditor to earn corresponding fee premiums and/or reduce audit costs (Mayhew and Wilkins 2003; Casterella et al. 2004; Ferguson et al. 2003; Francis et al. 2005; Low 2002; Owosho et al. 2002). Auditor specialization provides the audit firms with competitive advantages and

creates barriers to entry.⁷ However, as documented by the GAO, the level of specialization varies across industries. This begs the question: Why do some industries seemingly draw specialization efforts by auditors to a greater degree than others? In other words, what makes an industry an attractive target for specialization?

We hypothesize that the industry's investment opportunities represent an important dimension for identifying potential targets for specialization efforts. We suggest that firms with greater opportunities are viewed as potentially lucrative investments for the future by auditors. However, these firms are also subject to heightened uncertainty and risk, which create natural barriers to prevent other auditors from eroding the specialists' share. Also, firms with high growth potential are likely to present more complex accounting issues to their auditors than firms in more mature industries. Such firms are more likely to be involved in merger activity as a means of growth, in expenditures for which the appropriate accounting is less explicit, and in revenue streams that may raise questions about the timing of revenue recognition.

O'Keefe et al. (1994) suggest that providing audit services to a client requires investments in general knowledge, industry-specific knowledge, and client-specific knowledge. General knowledge (e.g., knowledge of generally accepted accounting principles or generally accepted auditing standards) is important for conducting an audit but is not a dimension on which auditors would differentiate among industries because the costs of acquiring and applying general knowledge are associated with the auditor's

⁷ However, neither Mayhew and Wilkins (2003) nor Casterella et al. (2004) tests this conjecture. Both studies examine whether specialist auditors earn audit fee premiums.

entire client base. Thus, differences in industry specialization by auditors across industries will likely be related to industry-specific or client-specific expertise.

In particular, industry-specific knowledge requirements can be used by auditors to differentiate themselves from other auditors and to create entry barriers. This specialized knowledge will help the auditor in planning and executing the audit (Low 2004). For example, the auditor's assessment of sampling sizes, classification of technology-related expenditures, and revenue recognition timing will depend upon the auditor's assessment of the possible outcomes from managerial discretion, the probabilities of those outcomes, and managers' incentives in reporting related transactions. While Danos and Eichenseher (1982) argue that regulation is one source of industry-specific knowledge, we suggest that industry IOS is another dimension of industry-specific knowledge that is likely to affect levels of auditor specialization. Although IOS is only one of the possible dimensions of industry-specific knowledge that might create specialization opportunities for auditors, we believe that it is a fundamental one that has not been previously explored in this setting. Smith and Watts (1992) and Gaver and Gaver (1993) provide evidence that IOS affects fundamental corporate policy decisions (e.g., financing, dividend, and compensation decisions) at the industry- and firm-level. Since IOS affects the way a firm operates and the business model that it employs, we expect that it will also affect the way it is audited.

The starting point for any audit is for the auditor to have a thorough understanding of the client's business environment and business model (e.g., Bell et al. 1997; ISA 315). One difference between high and low IOS industries is that high IOS industries are likely

to be operating in environments that are more uncertain. Specifically, Myers (1977) contends that a firm's value can be broken into: (1) real assets (assets in place) whose value is independent of the firm's future investment opportunities, and (2) real options (growth options) whose value depends upon the firm's future discretionary investments (i.e., IOS). Examples of growth options include "capacity expansion projects, new product introductions, acquisition of other firms, investments in brand names through advertising, and even maintenance and replacement of existing assets" (Gaver and Gaver 1993, 127). Because growth options depend on the firm's future discretionary spending, and are often intangible, payoffs associated with growth options will be more uncertain than for assets in place.

Investors are likely to demand high levels of assurance where firms have high investments in growth options such as R&D, the outcomes of which are both material to firm value and uncertain (Smith and Watts 1992; Zhang 2006). Given that growth options (e.g., R&D outcomes) are unobservable and that asset impairment due to poor investments can be significant, demand for specialist auditors arises to provide investors with assurance that firms are investing in positive NPV projects, that disclosures of the firm's operations are credible, and that abandonment options are reflected at appropriate values (Godfrey and Hamilton 2005).

Greater uncertainty arising from investment opportunities is likely to increase a client's inherent, control, and detection risk. Inherent risk increases because the uncertain nature of growth options allows for more managerial opportunism and increases the possibility of estimation error. This is true even though many costs related to growth

options are expensed (e.g., R&D, advertising). Skinner and Sloan (2002) find that growth firms have strong incentives to meet earnings forecasts. Thus, firms in high IOS industries are likely to face greater pressure to manage earnings. Control risks increase because growth options are harder to monitor.⁸ As a result, designing and maintaining effective internal controls becomes more difficult. Detection risk increases because of the complexity that growth options add to the audit process. For example, high IOS industries are likely to be characterized by rapid change, and designing appropriate audit procedures can become more complicated in such a setting (e.g., analytical procedures like traditional ratio analysis may be less relevant). These heightened risk issues mean at least two things to prospective auditors: (1) there is an obvious need for specialized knowledge to do an effective and efficient audit, and (2) an auditor who does not currently possess that specialized knowledge must assess the tradeoffs between risk and rewards in deciding whether to attack the barriers to entry.

Evidence in the academic literature suggests that industry specialists are able to conduct audits more effectively and efficiently and provide higher quality audits than non-specialists. Specialist auditors have been found to make better assessments of risk (Low 2004) and to detect more conceptual errors (Owhoso et al. 2002). In addition, firms employing industry specialist auditors appear to have higher earnings quality (Balsam et al. 2003), and higher quality of disclosure (Dunn and Mayhew 2004). Thus, if auditing is more complex in the presence of investment opportunities, and if industry specialist

⁸ In high IOS firms, it is harder to evaluate whether discretionary spending is appropriate not only because of the contingent nature of growth options but also because the payoffs from growth options will not be realized immediately.

auditors are more effective auditors in that environment, there should be a greater demand for specialist auditors in high IOS industries.

Moving beyond the explicit audit function, there is evidence that clients rate their auditors' ability to help the company address its concerns (e.g., helping the company grow, foreseeing problems, understanding the client's business) as being extremely important (Addams and Davis 1994; Addams and Allred 2002; Wooten 2003). For example, Behn et al. (1997) find that industry specialization can lead to higher client satisfaction. Since high IOS industries face more uncertainty than slower growing and more stable industries, firms in high IOS industries may demand and value the auditor's "business knowledge" more highly.

In summary, client demand for specialist auditors is driven by complex accounting and auditing issues associated with IOS levels. Furthermore, auditors have incentives to specialize because of returns derived from less costly audits and/or higher audit fees. The higher costs of obtaining industry-specific knowledge in high IOS industries create barriers to entry by other auditors, thus enabling the specialist to capture a larger portion of the market. We predict that:

H1 Greater industry-specific IOS is associated with greater auditor specialization in an industry.

At the same time, the incidence of industry specialization is also likely to be affected by the level of *client-specific* knowledge that is needed to audit individual clients within a given industry. *Ceteris paribus*, the greater the *client-specific* knowledge requirements, the lower are the barriers to entry to a particular industry because the

auditor is hampered in spreading the costs of acquiring client-specific knowledge across other firms in the industry.

Consider firms in an industry as being located in n -dimensional space, where n represents various client characteristics (e.g., see Chan et al. 2001). Similar firms will be clustered in this n -dimensional space, while dissimilar firms will be separated by more distance. At one extreme, where all firms in an industry are identical, or where firms are located in a single cluster in n -dimensional space, a single specialist auditor could capture the entire industry, *ceteris paribus*. Thus, we expect that where client-specific knowledge is less variable (i.e., industry firms are similar), an audit firm that acquires client-specific knowledge for one firm will be able to transfer that knowledge to other firms in the same industry and will be able to obtain a larger share of the market. In this setting, auditors should also benefit from greater scale economies or from the potential to pass fee reductions to their audit clients as a result of decreasing costs. At the other extreme, where each firm in an industry is unique, or where firms are diffused in n -dimensional space, client specific knowledge is not transferable, and no audit firm can gain a comparative advantage. Thus, in these industries, we expect to find a more even distribution of market share across audit firms.

Overall, in industries where the IOS variability is high and firms' growth options are dissimilar, no auditor will be able to provide a differentiated product that can be offered cost effectively to all firms in an industry, and no auditor (or two auditors) will be able to dominate the industry. Conversely, as the variability of firms' IOS decreases

within an industry, the transfer of industry specific knowledge becomes more feasible, and greater auditor specialization is to be expected. Consequently, we hypothesize:

H2 Greater client-specific IOS (more variable industry IOS) is associated with less auditor specialization in an industry.

We acknowledge that auditor specialization is a two-way street, with client demand and auditor supply interacting in relatively complex ways. While client firms have incentives to use an industry specialist auditor to benefit from specialist advice and assurance and, potentially, lower audit fees, they also have potential incentives to avoid the industry specialist because they do not want proprietary information transferred to their competitors (e.g., Kwon 1996). From the supply side, high client risk levels in an industry may provide opportunities for auditor specialization while also causing some auditors to opt for diversification of their client portfolio (Krishnan and Krishnan 1997). As such, while we provide reasons why auditors might specialize in certain industries, we also recognize that specialization is unlikely to lead either to a single auditor capturing an entire industry or to a given auditor having clients from only one industry.

IV. VARIABLES, METHOD, AND DATA

Variables

We measure industry specialization using a two-auditor concentration ratio, measured in terms of total client assets, as our dependent variable (*ACR2*). This contrasts with Hogan and Jeter (1999), who use a three-audit firm concentration ratio, but their data end in 1993 when there were still six large accounting firms. As our data end in

2004 when there were only four large accounting firms, we believe that the portion of the market captured by the top two auditors (rather than three) captures a more appropriate sector for measuring the extent of specialization. Further, as discussed later, for a subperiod analysis we use the three-auditor concentration ratio instead of the two-auditor ratio for the Big 8 and Big 6 subperiods. Also, we include controls for the number of large audit firms (varying from eight to four) in each year in our principal analysis.

Because there is no single, widely accepted measure for IOS in the literature, we use two measures – one developed by Baber et al. (1996) and the other based on Gaver and Gaver (1993). Both studies rely on a factor analysis to measure firms' IOS, but they include slightly different variables. The Baber et al. (1996) factor score is based on the following four variables: (a) prior investment intensity for years $t-2$ through t , (b) the geometric growth in the market value of assets from years $t-2$ through t , (c) the ratio of the market value to book value of assets at the end of year t , and (d) the ratio of research and development expenditure to book value of assets at the end of year t . The Gaver and Gaver (1993) factor score includes the following variables: (a) the ratio of the market value to book value of total assets at the end of year t , (b) the ratio of research and development expenditure to book value of assets at the end of year t , (c) the ratio of the market value to book value of equity at the end of year t , and (d) the earnings to price ratio (EP).⁹

⁹ Gaver and Gaver (1993) use two other measures in their factor analysis, specifically the variance of total returns on the market value of the firm and the number of growth-oriented mutual funds that hold the firm's shares in year i . We exclude these variables for theoretical and practical reasons. Baber et al. (1996) note that the correlation between the variance of total returns and future investments is low and further that the variance cannot be computed for relatively new firms. Baker (1993) expresses concerns regarding the use of the mutual fund measure.

We rely on these scores to compute both an industry-specific IOS measure (*IIOS*) and our IOS variability measure (*VIOS*), and we label the measures using the suffix “_B” for the Baber et al. based measures and “_G” for the Gaver and Gaver based measures. Consequently, we have two measures of industry IOS (*IIOS_B*, *IIOS_G*) and two measures of within-industry IOS variability (*VIOS_B*, *VIOS_G*).

Industry IOS is measured as the median of a given industry’s client firm IOS factor scores. Higher *IIOS* measures reflect higher underlying IOS, on average. To measure *VIOS*, we use the within-industry standard deviation of the IOS variable. When IOS is extremely variable, this suggests that a large component of IOS is firm-specific. For example, if two industries have mean *IIOS* scores of 2 and one of the industries has two firms with scores of 3 and 1 while both firms in the second industry have scores of 2, the first industry has more firm-specific (i.e., unique) IOS. Thus, our *VIOS* measure may be viewed as analogous to the measure of firm-specific risk used in the finance literature where firm-specific risk is measured as the standard deviation of the residuals from a market-model regression.

Method

We test H1 and H2 using the following multivariate model:

$$\begin{aligned}
 ACR2_{kt} = & \beta_0 + \beta_1 IIOS_{kt} + \beta_2 VIOS_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k * TIME + \\
 & \beta_6 CCR4_{kt} + \beta_7 LITRISK_{kt} + \beta_8 MEANSIZE_{kt} + \beta_9 BIG8_t + \beta_{10} BIG6_t + \\
 & \beta_{11} BIG5_t + e
 \end{aligned} \tag{1}$$

$ACR2_{kt}$ is the market share of the two largest auditors (measured in terms of total client assets) in industry k . *IIOS* is the median value of IOS in industry k where IOS is

measured using (a) a factor score based on Baber et. al. (1996) (*I IOS_B*) or (b) a factor score based on Gaver and Gaver (1992) (*I IOS_G*). *V IOS* is the standard deviation of IOS in industry *k* where IOS is measured using (a) a factor score based on Baber et. al. (1996) (*V IOS_B*) or (b) a factor score based on Gaver and Gaver (1992) (*V IOS_G*). *TIME* is a linear time effect variable (time = 1, 2, ..., 21). *REG* is equal to 1 if industry *k* is regulated, and 0 otherwise. *CCR4* is the four-firm industry concentration ratio for industry *k* in year *t*. *LITRISK* is equal to 1 if industry *k* is a high litigation-risk industry, 0 otherwise.¹⁰ *MEANSIZE* is the average size, measured as the square root of total assets (measured in millions), of all firms in industry *k* in year *t*. *BIG8*, *BIG6*, and *BIG5* are indicator variables where *BIG8* equals 1 for 1986-1989, *BIG6* equals 1 for 1990-1996, and *BIG5* equals 1 for 1997-2001 and the measures are 0 otherwise.

Based on H1 and H2, we expect a positive coefficient for *I IOS* and a negative coefficient for *V IOS*. The remaining independent variables are control variables adopted from Hogan and Jeter (1999). Hogan and Jeter find a positive relation between *TIME* and the three-audit firm concentration ratio, which indicates that specialization increases over time. They also control for regulation because regulation may lead to economies of scale,

¹⁰ Following Hogan and Jeter (1999), we classify firms in the following 2-digit SIC codes as regulated: 10 (metal mining), 12 (coal mining), 13 (oil and gas extraction), 14 (mining and quarrying of nonmetallic minerals), 20 (food and kindred products), 29 (petroleum refining and related industries), 40 (railroad transportation), 41 (transit, passenger transportation), 42 (motor freight transportation), 44 (water transportation), 45 (air transportation), 46 (pipelines, except natural gas), 48 (communications), 49 (electric, gas and sanitary services), 60 (depository institutions), 61 (nondepository credit institutions), 62 (security and commodity brokers, dealers), 63 (insurance carriers), 64 (insurance agents, brokers and service) and 67 (holding and other investment offices).

Also, based on Hogan and Jeter (1999), we classify firms in the following 2-digit SIC codes as relatively high litigation-risk industries: 28 (chemicals and allied products), 35 (industrial and commercial machinery and computer equipment), 36 (electronic and other electrical equipment and components, except computer equipment), 38 (measuring, analyzing and controlling instruments), 60 (depository institutions), 67 (holding and other investment offices) and 73 (business services).

and find a positive relation between *REG* and the three-audit firm concentration variable. Their model's interaction between *REG* and *TIME* yields a negative coefficient, suggesting that specialization has increased more in non-regulated industries in their sample. Further, they find that the three-audit firm concentration ratio is positively related to *CCR4* and *MEANSIZE* and negatively related to *LITRISK*. These findings suggest that auditor concentration is higher in industries where industry firms are concentrated or large, and is lower where the industry is more prone to litigation.¹¹

We use the *BIG* indicators to control for the effects of audit firm mergers and the demise of Arthur Andersen, which together reduced the number of large audit firms from eight to four during our test period. Our market share measures are sensitive to the number of auditors serving a market. For example, assuming equal market shares, in a market with eight auditors, each auditor would have a 12.5 percent market share, but in a market with five auditors, each auditor would have a 20 percent market share. Thus, our *BIG* indicators allow for different intercepts depending on the number of large auditors that were active at the time. Keeping in mind that an observation is defined at the industry rather than firm level, the *BIG* indicators capture the adjustment to the intercept, which represents the 2002-2004 period when there were only four large audit firms. Hence, we expect that each of the *BIG* indicators will have a negative coefficient because more large auditors in the marketplace should be associated with lower market shares on

¹¹ We omit two of Hogan and Jeter's (1999) control variables. First, we delete their growth measure because this may be correlated with *ILOS* but also because their growth measure is relatively crude (they use a binary variable to identify rapid growth industries). Second, we delete their measure that captures the audit firms' declared specialties because, unlike Hogan and Jeter, we are not interested in the *declared* specialties but rather in the auditor's specialties as measured using independent data.

average, with the coefficient on *BIG8* being the most negative and the coefficient on *BIG5* being the least negative.

We believe this approach is more appropriate to this study than the approach used by Hogan and Jeter (1999). By combining the market shares of the two merged firms in the pre-merger period and using the market share of the combined or “artificial” firm in their tests, Hogan and Jeter (1999) treat the merged firms as if they had been merged throughout the test period. However, this masks the real audit market structure. In particular, it is unlikely in the pre-merger period that the two audit firms were acting in unison; rather, they would have been competing against one another.

Data

We use three different industry classification schemes to identify industry membership, i.e., 3-digit SIC codes, 3-digit NAICS codes, and Fama-French (1997) classifications. We include all firms on COMPUSTAT at the end of 2004, and we collect data for the period 1984-2004. Because some of our variables include lagged measures, our test period is 1986-2004. We first compute our *ACR2* measure for each industry-year with at least five firm-years of data on total assets and auditor. These computations involve 170,396 firm-year observations, and we do this separately for each of our three industry classification schemes.

Next, at the firm level, we compute the six measures used in the IOS factor analyses (i.e., prior investment intensity, geometric growth in market value of assets, ratio of market value to book value of assets, ratio of R&D expenditure to book value of assets, ratio of market value to book value of equity, EP ratio) for all firm-years with

sufficient data. We then run two factor analyses using all firm-years with sufficient data. First, we factor analyze the firm-level variables used by Baber et al. (1996), i.e., prior investment intensity, geometric growth in market value of assets, ratio of market value to book value of assets, and ratio of R&D expenditure to book value of assets, using 90,894 firm-year observations. The resulting factor scores (FAC_B) are used to compute $I IOS_B$ at the industry level. Second, we factor analyze the firm-level variables used by Gaver and Gaver (1993), i.e., the market to book value of total assets, R&D expenditure to book value of assets, the market to book value of equity, and EP ratio, using 84,298 firm-year observations. The resulting factor scores (FAC_G) are used to compute $I IOS_G$ at the industry level.¹² The difference in the number of firms used in the two factor analyses arises because not all firms have share price data that are needed to compute the EP ratio.

For each industry-year with at least five firms with FAC_B scores, we compute $I IOS_B$ and $V IOS_B$. Likewise, for each industry-year with at least five firms with FAC_G scores, we compute $I IOS_G$ and $V IOS_G$.¹³ We do this for each industry-year with sufficient data for every industry in each of our three classification schemes. Since the number of industries differs across our three classification schemes and since the number of firms with IOS data varies depending on the industry definition, the number of industries used in our tests varies depending on which classification scheme we use.

¹² We use the maximum number of firms to compute our specialization measure to get the most comprehensive measure of audit market structure. If we compute $ARC2$ using only those firms with IOS data, we ignore a large part of the market. Thus, our tests assume that the IOS for the firms with the data to compute the IOS measures is representative of the IOS for all firms in the same industry. This is supported by Smith and Watts (1992) who argue that there is a significant industry component in individual firms' IOS.

¹³ We repeat our tests with a minimum of 10 firms per industry with IOS data. Our results are qualitatively unchanged.

Table 1 provides data on the maximum number of industry-years used in our tests for each classification scheme. Using the 3-digit SIC codes, we have 3,430 industry-years over the 21 year sample period. Using the 3-digit NAICS codes, we have 1,513 industry-years, and using the Fama-French industry classifications, we have 889 industry-years. These numbers reflect the numbers used in the tests involving *IIOS_B* and *VIOS_B*. Because not all firms have share price data for computing the EP ratio, the number of industry-years for the tests involving *IIOS_G* and *VIOS_G* are slightly lower. For these tests, we have (untabulated) 3,322 industry-years based on the 3-digit SIC classification, 1,479 industry-years based on the 3-digit NAICS classification, and 885 industry-years based on Fama-French classifications.

Insert Table 1

Table 1 also provides the mean and median number of firms within each industry by year. In all three panels, the mean number far exceeds the median, suggesting that a few industries have a large number of firms. However, the median remains relatively stable over the sample period for all three industry classification schemes.

V. RESULTS

Descriptive statistics

Table 2 provides descriptive statistics for *ACR2*, the IOS variables, and control variables. The mean (median) for *ACR2* is 63.2 percent (62.5 percent) which suggests that the average market share for the two largest auditors is around 63 percent across all industry-years. This varies from 24.1 percent to 100 percent, and the standard deviation of *ACR2* is 14.7 percent. *IIOS_B* and *IIOS_G* are relative measures of IOS rather than

absolute measures, i.e., *I IOS_B* and *I IOS_G* provide a relative rank of IOS across industries.¹⁴ Also, the variability of *I IOS_B* and *I IOS_G* are roughly the same (mean *V IOS_B* = 0.550, mean *V IOS_G* = 0.591).

The mean four-firm concentration ratio (*CCR4*) is 49.7 percent, and the mean of *MEANSIZE* is 23.387, indicating that the mean of the average firm size within industries is 546.95 million (= 23.387²). Further, 22.9 percent of the industry-year observations are regulated, and 21 percent are from high litigation risk industries.

Insert Table 2

Table 3 provides the correlations between the IOS and the control variables. The correlation between *I IOS_B* and *I IOS_G* is 0.721, which suggests that while the two measures overlap, there still is a unique component to each. The four IOS measures and the control variables are all significantly correlated. The highest correlation is between *I IOS_B* and *LITRISK* ($r = 0.430$), suggesting that growth opportunities are higher in high litigation industries. The four IOS measures are negatively correlated with *CCR4* and *MEANSIZE*, which could reflect competition within an industry. More concentrated industries and large industries may be more mature industries where IOS is lower on a relative basis. The correlations between *MEANSIZE* and the four other control variables are significant, suggesting that the mean size of firms in an industry is growing over time, is higher in regulated industries, is higher in industries where the firms are more concentrated, and is lower in industries that have high litigation risk. Firm concentration

¹⁴ By construction, the mean of the firm-level factor scores used to compute *I IOS_B* (i.e., *FAC_B*) and *I IOS_G* (i.e., *FAC_G*) will be equal to zero across all firms in our sample. Also, note that the means and medians in panel A are based on equally-weighted industries. For example, a large, growing industry with positive IOS is weighted the same as a small, declining industry with negative IOS.

is higher in regulated industries, and *CCR4* and *LITRISK* are negatively and significantly correlated, which indicates that firm concentration is lower in high litigation industries.

Insert Table 3

Table 4 identifies the top, middle, and bottom 10 industries ranked by *I IOS_B* (left column) and *V IOS_B* (right column). We show the top, middle, and bottom 10 industries for 1986 (the first Big 8 year in our sample), 1989 (the first Big 6 year), 1998 (the first Big 5 year), and 2002 (the first Big 4 year) to give some sense of how *I IOS* and *V IOS* have changed over time.

Insert Table 4

While purely descriptive, the rankings provided in Table 4 are not at odds with our expectations. For example, the top ten based on industry IOS (*I IOS_B*) includes several high tech and medical related industries, and six of these (i.e., communication equipment; computer and office equipment; drugs; laboratory apparatus and analytical, optical; research, development, and testing services; surgical, medical, and dental instruments) appear in at least three of the four years. Further, drugs (3-digit SIC 283) is the highest ranked industry based on *I IOS_B* in all four panels. On the other hand, many of the industries ranked in the bottom ten based on *I IOS_B* are related to financial services, insurance, natural resources, and transportation, although the exact membership is not as stable over time as for the top ten.

For the rankings based on *V IOS_B*, the bottom ten industries appear to be mature, stable industries (e.g., railroad, water supply, mills, grocery stores) whereas the top ten are harder to categorize and include a wider variety of industries. Finally, while *I IOS_B*

and *VIOS_B* are positively correlated ($r = 0.486$ in Table 3), based on Table 4, the overlap is not extreme. That is, the industries that appear in the bottom (middle) [top] subsamples based on *I IOS_B* generally do not appear in the bottom (middle) [top] subsamples based on *V IOS_B* (drugs, which appears in the top ten based on *I IOS_B* and *V IOS_B* in all four years, is an exception).

Multivariate tests

Table 5 summarizes the results from estimating equation (1) using the two alternative measures of IOS and the three alternative industry classification schemes. Panel A contains the results for the IOS measures based on Baber et al. (1996). Where industries are based on the 3-digit SIC codes, the model has an adjusted R^2 of 47.1 percent. This is considerably higher than the 30 percent R^2 reported by Hogan and Jeter (1999), who included *ACR3*, no IOS variables, no *BIG* indicators, and data from the 1976-1993 period. Based on an F-test, the two IOS variables provide incremental explanatory power relative to a base model that excludes the two variables (F -statistic = 7.89, $p < 0.01$). Consistent with our first hypothesis, specialist auditors appear to be capturing a bigger share of those industries with higher levels of industry IOS, as evidenced by *I IOS_B* being positively related to *ACR2*. Also, we find a negative relation between *V IOS_B* and *ACR2*, suggesting that as firm-specific IOS increases, the market share of the two leading auditors decreases. This relation is consistent with H2 and with an argument that it is more difficult for a single auditor to benefit by offering specialized services when IOS is variable within the industry and when client-firm growth opportunities are largely unique to specific firms.

Insert Table 5

In addition, all of the control variable coefficients are significant and signed as expected except for *TIME* and *LITRISK*. As in Hogan and Jeter (1999), auditor specialization increases with the regulatory status of the industry, firm concentration in the industry, and the mean size of firms in the industry. In our model, *TIME* is not significant because our *BIG* indicators subsume its explanatory power.¹⁵ However, also consistent with Hogan and Jeter (1999), the coefficient on *REG*TIME* is significant and negative, suggesting that industry specialization has increased faster in non-regulated industries over recent years.

For our models using the 3-digit NAICS and Fama-French industry definitions, we find support for both H1 and H2. In each case, *ILOS_B* and *VLOS_B* coefficients are signed as predicted and significant at the 0.001 level. The coefficient on *LITRISK* is not consistent across specifications (significant and negative using the 3-digit NAICS codes, but not using the other two classification schemes). This inconclusive relation between *LITRISK* and auditor concentration is not particularly surprising since this variable is likely to capture aspects of the industry leading both *toward* specialization (barriers to entry are likely to be easier to protect) and *away from* specialization (risks may be prohibitive, and discourage significant investments). For the model using the Fama-French industry definitions, the main differences (compared to the other classification schemes) are that the adjusted R^2 is higher (64.4 percent) and *REG* is not significant.

¹⁵ We also estimated our models with the *BIG* indicators omitted, and the coefficient on *TIME* was consistently significant in that specification.

Table 5, panel B presents the results using the IOS measures based on Gaver and Gaver (1993). As mentioned previously the sample sizes here are slightly smaller because some firms did not have the share price data needed to compute the EP ratio component of the Gaver and Gaver IOS measure. The results are consistent with those reported in Table 4, panel A except that in the Fama-French model, *I IOS_G* is not significant. Between the two panels in Table 5, we find that *I IOS* is significant in five of the six models and *V IOS* is significant in all six models. Together, these results provide strong support for both H1 and H2.

Next, we conduct several sensitivity tests. First, since the number of firms in industries in our sample varies widely, we introduce a control for the number of industry members. Other things equal, one might conjecture that it would be easier for an auditor to capture a dominant market share in industries with few firms than in industries with many firms (suggesting a negative relation between auditor concentration and number of firms). That is, in the former, an auditor may only need one or two large clients to capture a major share of the market. Consequently, we include a variable representing the number of firms in industry k in year t (*NFIRMS*) in equation (1). The coefficient on *NFIRMS* is insignificant (based on one-tailed tests), and our results (untabulated) for our *I IOS* and *V IOS* measures are qualitatively unchanged from Table 5 (whether we use the Baber et al. (1996) or Gaver and Gaver (1993) measures). Thus, our results do not appear to be affected by the number of firms in an industry.

Second, we estimate equation (1) without *CCR4* because of a concern that *I IOS* and *V IOS* may also affect the industry structure as represented by *CCR4*. Since IOS

affects a firm's investment and financing decisions, it is not unreasonable to expect that IOS will affect the growth and distribution of firms in an industry. Table 6 provides the estimation results where *CCR4* is omitted from our model. We estimate models with (panel A) and without (panel B) *NFIRMS* using *I IOS_B* and *V IOS_B*. The results using Gaver and Gaver (1993) measures are qualitatively identical. The t-statistics for *I IOS_B* and *V IOS_B* for the three models in panel A of Table 6 generally increase relative to the models in Table 5, panel A. Further, the coefficient on *NFIRMS* is negative and significant in all three models. When *CCR4* and *NFIRMS* are excluded (i.e., Table 6, panel B), the t-statistics for *I IOS_B* and *V IOS_B* increase relative to Table 5, panel A in all but one case.¹⁶ Overall, the results in Table 6, panels A and B suggest that the explanatory power of *I IOS* and *V IOS* increase when *CCR4* is excluded, and that our main results are robust to its inclusion or exclusion.

Insert Table 6

Third, we re-estimate equation (1) separately for each Big N subperiod to see if our results are consistent across time. However, consistent with Hogan and Jeter (1999), for the Big 8 and Big 6 subperiods we use the three-auditor concentration ratio instead of the two-auditor ratio.¹⁷ Table 7 provides these results in abbreviated form, and panels A, B, C, and D show the results for *I IOS_B* and *V IOS_B* for the Big 8, Big 6, Big 5, and Big 4 subperiods, respectively (untabulated results using the Gaver and Gaver (1993) measures are qualitatively similar). To conserve space, we do not present the results for

¹⁶ The exception is for *I IOS_B* in the model using 3-digit SIC codes where *I IOS_B* is not significant.

¹⁷ We repeat the analysis for the Big 8 and Big 6 subperiods using the two-auditor ratio and obtain qualitatively similar results.

the various control variables, which are generally consistent with those in Table 5. The signs for *I IOS_B* and *V IOS_B* are remarkably robust across subperiods, but significance levels vary, possibly because of the smaller samples.¹⁸ Still, we find general support for H1 and H2 in the Big 8, Big 5, and Big 4 subperiods. For the Big 6 subperiod, our findings are consistent with H2 in both sign and significance levels but insignificant for H1 (though still of consistent sign).

Insert Table 7

VI. CONCLUSION

A report of the GAO issued in July 2003 highlighted both the importance to clients of industry specialization in choosing an auditor and the extreme levels of specialization in recent years, measured using a two-auditor concentration ratio, in some industries. In this study, we posit that IOS plays an important role in determining whether an industry is an attractive target for auditor specialization. We argue that when industry-specific IOS is high, auditors must make industry-specific investments to offer a differentiated product and to create entry barriers for other audit firms. However, when a large component of IOS is unique to specific firms within an industry (i.e., IOS is highly variable within the industry), the transfer of knowledge between clients in that industry is hampered because each firm faces a unique set of investment opportunities, creating unique knowledge requirements for the firm's auditor. Under these circumstances,

¹⁸ We are not surprised that our results are weaker for the subperiods than in aggregate as it takes time for auditors' client portfolios to adjust to merger influences such as client incompatibilities or over-reliance on a particular industry. Thus, the subperiods may be too short to capture the equilibrium portfolios. In contrast, data aggregated over the subperiods as in Table 5 are more likely to capture general, enduring associations.

knowledge cannot be transferred easily to other firms in the industry, and the costs of acquiring the knowledge cannot be spread across those firms. Thus, we expect a positive relation between industry levels of IOS and auditor specialization, but a negative relation between IOS variability within industries and auditor specialization. Using industry level data over the period 1986-2004, we present evidence consistent with these predictions. Our results are robust to the industry classification scheme and the IOS measures that are chosen.

The findings contribute not only to the academic literature, but also offer some new insights into the GAO's concern that specialization limits the auditor choices available to client firms (For example, the GAO suggests evaluating "ways to increase accounting firm competition in certain industries by limiting market shares" (GAO 2003, 53)). Our analysis suggests that industry specialization is, at least in part, a rational response to industry-specific knowledge requirements. As a result, limiting market share could reduce the auditor's incentives to acquire this knowledge, which ultimately could lead to lower quality audits.

Directions for future research include examining in greater depth the causes of variation in industry IOS levels and variability, the precise nature of the knowledge and skills necessary to effectively and efficiently audit high IOS or high-variance IOS firms, an exploration of the explicit linkage between auditor technology and the investment opportunity set, and how auditors can spread the costs of acquiring that knowledge and skill base across their client-portfolios.

REFERENCES

- Adam, T., and V.K. Goyal. 2003. The investment opportunity set and its proxy variables: Theory and evidence. Working paper. Hong Kong University of Science and Technology.
- Addams, H.L., and A. Allred. 2002. Why the fastest-growing companies hire and fire their auditors. *CPA Journal* 72 (5): 62-63.
- Addams, H., and B. Davis. 1994. Privately held companies report reasons for selecting and switching auditors. *CPA Journal* 64 (8): 38-41.
- Baber, W.R., S.N. Janakiraman, and S.H. Kang. 1996. Investment opportunities and the structure of executive compensation. *Journal of Accounting and Economics* 21: 297-318.
- Balsam, S., J. Krishnan, and J.S. Yang. 2003. Auditor industry specialization and earnings quality. *Auditing: A Journal of Practice and Theory* 22: 71-97.
- Behn, B.K., J.V. Carcello, D.R. Hermanson, and R.H. Hermanson. 1997. The determinants of audit client satisfaction among clients of Big 6 firms. *Accounting Horizons* 11: 7-24.
- Bell, T., F. Marrs, I. Solomon, and H. Thomas. 1997. Auditing organizations through a strategic-systems lens. KPMG monograph.
- Cairney, T., and G. Young. 2004. Homogeneous industries and auditor concentration: An indication of production economics. Working paper. Georgia Southern University.
- Casterella, J.R., J.R. Francis, B.L. Lewis, and P.L. Walker. 2004. Auditor industry specialization, client bargaining power, and audit pricing. *Auditing: A Journal of Theory and Practice* 23: 123-140.
- Chan, D.K., A. Ferguson, D.A. Simunic, and D. Stokes. 2001. A spatial analysis and test of oligopolistic competition in the market for assurance services. Working paper. University of British Columbia.
- Craswell, A., J. Francis, and S. Taylor. 1995. Auditor brand name reputation and industry specialization. *Journal of Accounting and Economics* 20: 297-322.
- Danos P., and J.W. Eichenseher. 1982. Audit industry dynamics: Factors affecting changes in client-industry market shares. *Journal of Accounting Research* 20: 604-616.

- DeFond, M.L., J.R. Francis, and T.J. Wong. 2000. Auditor industry specialization and market segmentation: Evidence from Hong Kong. *Auditing: A Journal of Theory and Practice* 19: 49-66.
- Dunn, K.A., and B.W. Mayhew. 2002. Audit firm industry specialization and client disclosure quality. *Review of Accounting Studies* 9: 35-58.
- Eichenseher J.W., and P. Danos. 1981. The analysis of industry-specific auditor concentration: Towards an explanatory model. *The Accounting Review* 56: 479-492.
- Fama, E. F., and D. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43: 153–193.
- Ferguson, A., J.R. Francis and D.J. Stokes. 2003. The effects of firm-wide and office-level industry expertise on audit pricing. *The Accounting Review* 78: 429-448.
- , and D. Stokes. 2002. Brand name audit pricing, industry specialization and industry leadership premiums post Big 8 and Big 6 mergers. *Contemporary Accounting Research* 19: 77-110.
- Francis, J.R., K. Reichelt and D. Wang. 2005. The pricing of national and city-specific reputations for industry expertise in the U.S. audit market. *The Accounting Review* 80: 113-136.
- Gaver, J.J., and K.M. Gaver. 1993. Additional evidence on the association between the investment opportunity set and corporate financing, dividend and compensation policies. *Journal of Accounting and Economics* 16: 125-160.
- General Accounting Office (GAO). 2003. Public accounting firms: Mandated study on consolidation and competition. *GAO report* 03-864.
- Godfrey, J.M., and J. Hamilton. 2005. The impact of R&D intensity on demand for specialist auditor services. *Contemporary Accounting Research* 22: 55-93.
- Hogan C.E., and D.C. Jeter. 1999. Industry specialization by auditors. *Auditing: A Journal of Practice & Theory* 18: 1-17.
- International Standard on Auditing (ISA) 315. *Understanding the Entity and its Environment and Assessing the Risks of Material Misstatements*. October 2003.
- Krishnan, J., and J. Krishnan. 1997. Litigation risk and auditor resignations. *The Accounting Review* 79: 1095-1118.

- Kwon, S. Y.. 1996. The impact of competition within the client's industry on the auditor selection decision. *Auditing: A Journal of Practice & Theory* 15: 53-69.
- Low, K.Y.. 2004. The effect of industry specialization on audit risk assessments and audit-planning decisions. *The Accounting Review* 79: 201-209.
- Mayhew, B.W., and M.S. Wilkins. 2003. Audit firm industry specialization as a differentiation strategy: Evidence from fees charged to firms going public. *Auditing: A Journal of Theory and Practice* 22: 33-52.
- Myers, S., 1977. Determinants of corporate borrowing. *Journal of Financial Economics* 5: 147-175.
- Neal, T.L., and R.R. Riley, 2004. Auditor industry specialist research design. *Auditing: A Journal of Practice and Theory* 23: 169-177.
- O' Keefe T.B., D.A. Simunic, and M.T. Stein. 1994. The production of audit services: Evidence from a major public accounting firm. *Journal of Accounting Research* 32: 241-261.
- Owhoso, V.E., W.F. Messier, and J. Lynch. 2002. Error detection by industry-specialized teams during the sequential audit review. *Journal of Accounting Research* 40: 883-900.
- Porter, M.E.. 1985. *Competitive advantage; creating and sustaining superior performance*. New York, NY, Free Press.
- Skinner, D.J.. 1993. The investment opportunity set and accounting procedure choice. *Journal of Accounting and Economics* 16: 407-445.
- , and R. G. Sloan. 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7: 289–312.
- Smith, C.W. and J.B. Warner. 1979. On financial contracting: an analysis of bond covenants. *Journal of Financial Economics* 7: 117-161.
- , and R.L. Watts. 1992. The investment opportunity set and corporate financing, dividend and compensation policies. *Journal of Financial Economics* 32: 263-292.
- Wooten, T.C. 2003. Research about audit quality. *CPA Journal* 73 (1): 48-51.

Zhang, L.. 2006. Independent directors, investment opportunities and earnings conservatism. Working paper. The George Washington University, Washington, DC.

TABLE 1
Number of Industries and Firm Observations per Industry by Year

Panel A. 3-digit SIC codes

Year	# of 3-digit SIC industries with 5 or more firms	Mean # of firms per industry used to calculate auditor specialization measures	Median # of firms per industry used to calculate auditor specialization measures
1986	162	41.40	23.5
1987	168	40.57	23.5
1988	170	39.59	23.5
1989	171	38.51	22
1990	166	39.61	23
1991	174	39.20	23
1992	169	41.04	24
1993	177	42.28	25
1994	175	46.12	25
1995	185	49.09	25
1996	187	49.50	24
1997	195	46.75	23
1998	200	47.13	22
1999	196	47.53	22
2000	193	46.20	21
2001	197	42.85	19
2002	190	42.17	19
2003	188	40.03	19
2004	167	36.12	17
All years	3430	43.10	23

Panel B. 3-digit NAICS codes

Year	# of 3-digit NAICS industries with 5 or more firms	Mean # of firms per industry used to calculate auditor specialization measures	Median # of firms per industry used to calculate auditor specialization measures
1986	75	95.07	55
1987	80	90.48	51
1988	80	88.41	51
1989	81	85.58	48
1990	82	85.05	44.5
1991	81	87.84	45
1992	81	90.05	50
1993	81	96.68	53
1994	81	104.93	56
1995	81	115.78	61
1996	82	116.94	66
1997	81	115.32	63

1998	82	116.93	56.5
1999	82	116.02	54.5
2000	81	112.61	57
2001	81	106.00	50
2002	75	109.16	49
2003	75	102.44	45
2004	71	88.13	39
All years	1513	101.34	53

Panel C. Fama-French industries

Year	# of Fama-French industries with 5 or more firms	Mean # of firms per industry used to calculate auditor specialization measures	Median # of firms per industry used to calculate auditor specialization measures
1986	46	157.57	115.5
1987	46	158.87	123
1988	45	158.22	128
1989	46	151.78	119
1990	46	152.46	117
1991	47	152.77	112
1992	47	156.30	121
1993	47	167.94	133
1994	47	182.06	135
1995	47	201.09	143
1996	46	209.24	147.5
1997	46	204.13	144.5
1998	47	205.11	133
1999	47	203.40	135
2000	47	195.32	127
2001	48	180.25	119
2002	48	172.00	115
2003	48	161.52	108
2004	48	131.96	78.5
All years	889	173.78	124

The numbers above reflect the number of industry-years for tests where the Baber et al. (1996) measures of IOS are used. The corresponding numbers for tests using the Gaver and Gaver (1993) IOS measures are 3322 based on 3-digit SIC code industries, 1479 based on 3-digit NAICS industries, and 885 based on Fama-French (1997) industries.

TABLE 2
Descriptive Statistics for Specialization, IOS, and Control Variables

Variable	Mean	Std.Dev.	Minimum	Median	Maximum
<i>Panel A. Specialization measure</i>					
<i>ACR2</i>	0.632	0.147	0.241	0.625	1.000
<i>Panel B. IOS measures</i>					
<i>IIOS_B</i>	-0.323	0.257	-0.910	-0.385	1.840
<i>VIOS_B</i>	0.550	0.429	0.017	0.422	3.948
<i>IIOS_G</i>	-0.221	0.301	-0.823	-0.293	1.468
<i>VIOS_G</i>	0.591	0.517	0.008	0.457	7.587
<i>Panel C. Control variables</i>					
<i>REG</i>	0.229	0.420	0.000	0.000	1.000
<i>CCR4</i>	0.497	0.202	0.052	0.494	0.992
<i>LITRISK</i>	0.210	0.408	0.000	0.000	1.000
<i>MEANSIZE</i>	23.387	20.145	2.782	17.348	236.648

Variable definitions: $ACR2_{kt}$ = market share of two largest auditors in industry k (measured in terms of total client assets); $IIOS_B$ ($IIOS_G$) = median value of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) (Gaver and Gaver 1993); $VIOS_B$ ($VIOS_G$) = standard deviation of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) (Gaver and Gaver 1993); $REG_k = 1$ if industry k is regulated, and 0 otherwise; $CCR4_{kt}$ = the four-firm industry concentration ratio for industry k in year t ; $LITRISK_k = 1$ if industry k is a high litigation-risk industry, 0 otherwise; $MEANSIZE_{kt}$ = the average size, measured by square root of total assets (measured in millions) of all firms in industry k in year t .

Sample size is 3430 industry years where industries are based on 3-digit SIC codes. Descriptive statistics based on the other industry classifications (i.e., 3-digit NAICS, Fama-French) are similar and are not tabulated.

TABLE 3
Pairwise Correlations for IOS and Control Variables

	<i>IIOS_B</i>	<i>VIOS_B</i>	<i>IIOS_G</i>	<i>VIOS_G</i>	<i>TIME</i>	<i>REG</i>	<i>CCR4</i>	<i>LITRISK</i>
<i>VIOS_B</i>	0.486***							
<i>IIOS_G</i>	0.721***	0.354***						
<i>VIOS_G</i>	0.328***	0.362***	0.392***					
<i>TIME</i>	-0.106***	-0.102***	-0.052***	-0.122***				
<i>REG</i>	-0.121***	-0.053***	-0.168***	-0.122***	0.027*			
<i>CCR4</i>	-0.166***	-0.163***	-0.111***	-0.093***	0.054***	-0.164***		
<i>LITRISK</i>	0.430***	0.268***	0.268***	0.195***	0.005	-0.240***	-0.093***	
<i>MEANSIZE</i>	-0.212***	-0.248***	-0.248***	-0.228***	0.294***	0.386***	-0.050***	-0.112***

Variable definitions: *IIOS_B* (*IIOS_G*) = median value of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) (Gaver and Gaver 1993); *VIOS_B* (*VIOS_G*) = standard deviation of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) (Gaver and Gaver 1993); *TIME* = a linear time effect variable (time = 1, 2, ..., 21); $REG_k = 1$ if industry k is regulated, and 0 otherwise; $CCR4_{kt}$ = the four-firm industry concentration ratio for industry k in year t ; $LITRISK_k = 1$ if industry k is a high litigation-risk industry, 0 otherwise; $MEANSIZE_{kt}$ = the average size, measured by square root of total assets (measured in millions) of all firms in industry k in year t .

Sample size is 3430 industry years where industries are based on 3-digit SIC codes. Pairwise correlations based on the other industry classifications (i.e., 3-digit NAICS, Fama-French) are similar and are not tabulated.

*, **, and *** indicate significance at 0.10, 0.05, and 0.01 levels, respectively, based on one-tailed tests.

TABLE 4
Top, Middle, and Bottom 10 3-digit SIC Industries by *IIOS_B* and *VIOS_B* in 1986 (Big 8), 1989 (Big 6), 1998 (Big 5), and 2002 (Big 4)

Ranked by <i>IIOS_B</i>		Ranked by <i>VIOS_B</i>	
SIC	Industry	SIC	Industry
<i>Panel A. 1986 (first Big 8 year in sample)</i>			
<i>Bottom 10</i>			
138	Oil and gas field services	401	Railroads
440	Water transportation	511	Paper and paper products
162	Heavy construction, except highway and street	335	Rolling, drawing, and extruding of nonferrous
160	Heavy construction other than building construction contractors	122	Bituminous coal and lignite mining
131	Crude petroleum and natural gas	291	Petroleum refining
505	Metals and minerals, except petroleum	493	Combination electric and gas, and other utility
470	Transportation services	531	Department stores
346	Metal forgings and stampings	252	Office furniture
122	Bituminous coal and lignite mining	566	Shoe stores
331	Steel works, blast furnaces, and rolling	220	Textile mill products
<i>Middle 10</i>			
345	Screw machine products, and bolts, nuts, screws, rivets, and washers	251	Household furniture
807	Medical and dental Laboratories	308	Miscellaneous plastics products
451	Air transportation, scheduled, and air courier	344	Fabricated structural metal products
209	Miscellaneous food preparations and kindred	201	Meat products
571	Home furniture and furnishings stores	353	Construction, mining, and materials handling
507	Hardware, and plumbing and heating equipment	306	Fabricated rubber products, not elsewhere
251	Household furniture	506	Electrical goods
541	Grocery stores	508	Machinery, equipment, and supplies
394	Dolls, toys, games and sporting and athletic	533	Variety stores
521	Lumber and other building materials dealers	282	Plastics materials and synthetic resins, synthetic
<i>Top 10</i>			
271	Newspapers: publishing, or publishing and printing	632	Accident and health insurance and medical
565	Family clothing stores	283	Drugs
484	Cable and other pay television services	329	Abrasive, asbestos, and miscellaneous
562	Women's clothing stores	470	Transportation services
495	Sanitary services	233	Women's, misses', and juniors' outerwear
870	Engineering, accounting, research, management, and related services	781	Motion picture production and allied services
384	Surgical, medical, and dental instruments	679	Miscellaneous investing
632	Accident and health insurance and medical	616	Mortgage bankers and brokers
483	Radio and television broadcasting stations	399	Miscellaneous manufacturing industries
283	Drugs	343	Heating equipment, except electric and warm air

Ranked by <i>IIOS_B</i>		Ranked by <i>VIOS_B</i>	
SIC	Industry	SIC	Industry
<i>Panel B. 1989 (first Big 6 year)</i>			
<i>Bottom 10</i>			
616	Mortgage bankers and brokers	505	Metals and minerals, except petroleum
615	Business credit institutions	493	Combination electric and gas, and other utility
501	Motor vehicles and motor vehicle parts	491	Electric services
245	Wood buildings and mobile homes	614	Personal credit institutions
314	Footwear, except rubber	333	Primary smelting and refining of nonferrous
122	Bituminous coal and lignite mining	633	Fire, marine, and casualty insurance
614	Personal credit institutions	494	Water supply
621	Security brokers, dealers, and flotation	243	Millwork, veneer, plywood, and structural wood
571	Home furniture and furnishings stores	263	Paperboard mills
633	Fire, marine, and casualty insurance	327	Concrete, gypsum, and plaster products
<i>Middle 10</i>			
596	Nonstore retailers	289	Miscellaneous chemical products
735	Miscellaneous equipment rental and leasing	344	Fabricated structural metal products
738	Miscellaneous business services	550	Automotive dealers and gasoline service stations
452	Air transportation, nonscheduled	495	Sanitary services
562	Women's clothing stores	332	Iron and steel foundries
363	Household appliances	720	Personal services
160	Heavy construction other than building construction contractors	267	Converted paper and paperboard products
267	Converted paper and paperboard products	820	Educational services
421	Trucking and courier Services, except air	565	Family clothing stores
731	Advertising	399	Miscellaneous manufacturing industries
<i>Top 10</i>			
382	Laboratory apparatus and analytical, optical	999	Nonclassifiable establishments
366	Communications equipment	359	Miscellaneous industrial and commercial
104	Gold and silver ores	358	Refrigeration and service industry machinery
873	Research, development, and testing services	489	Communications services
384	Surgical, medical, and dental instruments	807	Medical and dental laboratories
357	Computer and office equipment	873	Research, development, and testing services
302	Rubber and plastics footwear	283	Drugs
807	Medical and dental laboratories	100	Metal mining
499	Electric, gas, and sanitary services	287	Agricultural chemicals
283	Drugs	512	Drugs, drug proprietaries, and druggists' sundries

Ranked by <i>IIOS_B</i>		Ranked by <i>VIOS_B</i>	
SIC	Industry	SIC	Industry
<i>Panel C. 1998 (first Big 5 year)</i>			
<i>Bottom 10</i>			
521	Lumber and other building materials dealers	494	Water supply
154	General building contractors-nonresidential	571	Home furniture and furnishings stores
501	Motor vehicles and motor vehicle parts	493	Combination electric and gas, and other utility
221	Broadwoven fabric mills, cotton	263	Paperboard mills
631	Life insurance	162	Heavy construction, except highway and street
162	Heavy construction, except highway and street	491	Electric services
152	General building contractors-residential	332	Iron and steel foundries
314	Footwear, except rubber	272	Periodicals: publishing, or publishing and printing
615	Business credit institutions	566	Shoe stores
633	Fire, marine, and casualty insurance	347	Coating, engraving, and allied services
<i>Middle 10</i>			
335	Rolling, drawing, and extruding of nonferrous	202	Dairy products
327	Concrete, gypsum, and plaster products	499	Electric, gas, and sanitary services
506	Electrical goods	503	Lumber and other construction materials
750	Automotive repair, services, and parking	599	Retail stores, not elsewhere classified
628	Services allied with the exchange of securities	308	Miscellaneous plastics products
201	Meat products	531	Department stores
352	Farm and garden machinery and equipment	874	Management and public relations services
138	Oil and gas field services	870	Engineering, accounting, research, management, and related services
517	Petroleum and petroleum products	285	Paints, varnishes, lacquers, enamels, and allied
245	Wood buildings and mobile homes	353	Construction, mining, and materials handling
<i>Top 10</i>			
873	Research, development, and testing services	482	Telegraph and other message communications
366	Communications equipment	100	Metal mining
355	Special industry machinery, except metalworking	140	Mining and quarrying of nonmetallic minerals, except fuels
382	Laboratory apparatus and analytical, optical	873	Research, development, and testing services
482	Telegraph and other message communications	655	Land subdividers and developers
357	Computer and office equipment	281	Industrial inorganic chemicals
384	Surgical, medical, and dental instruments	152	General building contractors-residential
737	Computer programming, and data processing	283	Drugs
830	Social services	732	Consumer credit reporting agencies, mercantile
283	Drugs	358	Refrigeration and service industry machinery

Ranked by <i>HIOS_B</i>		Ranked by <i>VIOS_B</i>	
SIC	Industry	SIC	Industry
<i>Panel D. 2002 (first Big 4 year)</i>			
<i>Bottom 10</i>			
104	Gold and silver ores	204	Grain mill products
616	Mortgage bankers and brokers	750	Automotive repair, services, and parking
153	Operative builders	493	Combination electric and gas, and other utility
635	Surety insurance	401	Railroads
783	Motion picture theaters	655	Land subdividers and developers
501	Motor vehicles and motor vehicle parts	265	Paperboard containers and boxes
499	Electric, gas, and sanitary services	221	Broadwoven fabric mills, cotton
633	Fire, marine, and casualty insurance	352	Farm and garden machinery and equipment
452	Air transportation, nonscheduled	541	Grocery stores
614	Personal credit institutions	451	Air transportation, scheduled, and air courier
<i>Middle 10</i>			
329	Abrasive, asbestos, and miscellaneous	138	Oil and gas field services
267	Converted paper and paperboard products	122	Bituminous coal and lignite mining
363	Household appliances	734	Services to dwellings and other buildings
160	Heavy construction other than building construction contractors	517	Petroleum and petroleum products
531	Department stores	731	Advertising
371	Motor vehicles and motor vehicle equipment	800	Health services
504	Professional and commercial equipment	621	Security brokers, dealers, and flotation
232	Men's and boys' furnishings, work clothing	599	Retail stores, not elsewhere classified
376	Guided missiles and space vehicles and parts	799	Miscellaneous amusement and recreation
302	Rubber and plastics footwear	208	Beverages
<i>Top 10</i>			
355	Special industry machinery, except metalworking	782	Motion picture distribution and allied services
361	Electric transmission and distribution equipment	366	Communications equipment
873	Research, development, and testing services	274	Miscellaneous publishing
367	Electronic components and accessories	873	Research, development, and testing services
382	Laboratory apparatus and analytical, optical	351	Engines and turbines
737	Computer programming, data processing	283	Drugs
366	Communications equipment	202	Dairy products
357	Computer and office equipment	359	Miscellaneous industrial and commercial
351	Engines and turbines	365	Household audio and video equipment, and audio
283	Drugs	874	Management and public relations services

TABLE 5
Summary Statistics from Regression of ACR2 on Industry IOS, Within-Industry IOS Variability, and Control Variables

	<i>3-digit SIC</i>		<i>3-digit NAICS</i>		<i>Fama-French</i>		
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic	
<i>Panel A. Baber et al. (1996)</i>							
<i>measures</i>							
Constant	0.492	27.88***	0.563	23.62***	0.543	20.67***	
<i>I IOS</i> _{<i>B</i>}	+	0.021	2.75***	0.037	3.08***	0.031	2.76***
<i>V IOS</i> _{<i>B</i>}	-	-0.016	-3.68***	-0.038	-5.42***	-0.032	-3.81***
<i>TIME</i>	+	-0.000	-0.29	0.001	-0.69	-0.001	-0.73
<i>REG</i>	+	0.037	4.39***	0.070	6.76***	0.006	0.50
<i>REG</i> * <i>TIME</i>	-	-0.002	-2.63***	-0.004	-4.42***	-0.003	-3.07***
<i>CCR4</i>	+	0.352	41.86***	0.329	24.77***	0.320	22.56***
<i>LITRISK</i>	-	0.005	1.16	-0.020	-2.71***	-0.006	-0.73
<i>MEANSIZE</i>	+	0.001	12.06***	0.001	3.63***	0.002	10.43***
<i>BIG8</i>	-	-0.139	-9.35***	-0.185	-9.41***	-0.190	-8.67***
<i>BIG6</i>	-	-0.085	-8.80***	-0.112	-8.60***	-0.117	-8.13***
<i>BIG5</i>	-	-0.041	-6.81***	-0.066	-7.95***	-0.059	-6.49
<i>Adj. R</i> ²		0.471		0.497		0.644	
<i>F</i> -statistic		278.67***		136.95***		146.74***	
No. of obs.		3430		1513		889	
<i>F</i> -stat. for <i>I IOS</i> _{<i>B</i>} and <i>V IOS</i> _{<i>B</i>}		7.89***		15.16***		7.73***	

Panel B. Gaver and Gaver
(1993) measures

Constant		0.502	28.53***	0.558	24.11***	0.518	19.81***
<i>IIOS_G</i>	+	0.018	2.73***	0.024	2.56***	0.012	1.11
<i>VIOS_G</i>	-	-0.019	-5.42***	-0.034	-6.59***	-0.021	-3.07***
<i>TIME</i>	+	0.000	0.05	0.001	-0.68	-0.008	-0.61
<i>REG</i>	+	0.049	5.74***	0.069	6.73***	-0.005	-0.46
<i>REG*TIME</i>	-	-0.003	-3.65***	-0.004	-4.70***	-0.003	-2.87***
<i>CCR4</i>	+	0.353	40.26***	0.334	23.86***	0.325	21.74***
<i>LITRISK</i>	-	0.002	0.33	-0.018	-2.54***	-0.003	-0.39
<i>MEANSIZE</i>	+	0.001	10.57***	0.001	3.50***	0.002	11.83***
<i>BIG8</i>	-	-0.143	-9.44***	-0.189	-9.65***	-0.179	-8.06***
<i>BIG6</i>	-	-0.089	-9.02***	-0.114	-8.79***	-0.112	-7.69***
<i>BIG5</i>	-	-0.047	-7.24***	-0.069	-8.18***	-0.058	-6.26***
<i>Adj. R²</i>			0.460		0.489		0.629
<i>F-statistic</i>			258.43***		129.57***		137.41***
<i>No. of obs.</i>			3322		1479		885
<i>F-stat. for IIOS_G and VIOS_G</i>			7.87***		22.20***		4.75***

Model:

$$ACR2_{kt} = \beta_0 + \beta_1 IIOS_{kt} + \beta_2 VIOS_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k * TIME + \beta_6 CCR4_{kt} + \beta_7 LITRISK_k + \beta_8 MEANSIZE_{kt} + \beta_9 BIG8_t + \beta_{10} BIG6_t + \beta_{11} BIG5_t + e$$

Variable definitions: $ACR2_{kt}$ = market share of two largest auditors in industry k (measured in terms of total client assets); $IIOS$ = median value of IOS in industry k where IOS is measured using (a) a factor score based on Baber et. al. (1996) ($IIOS_B$) or (b) a factor score based on Gaver and Gaver (1992) ($IIOS_G$); $VIOS$ = standard deviation of IOS in industry k where IOS is measured using (a) a factor score based on Baber et. al. (1996) ($VIOS_B$) or (b) a factor score based on Gaver and Gaver (1992) ($VIOS_G$); $TIME$ = a linear time effect variable (time = 1, 2, ..., 21); $REG_k = 1$ if industry k is regulated, and 0 otherwise; $CCR4_{kt}$ = the four-firm industry concentration ratio for industry k in year t ; $LITRISK_k = 1$ if industry k is a high litigation-risk industry, 0 otherwise; $MEANSIZE_{kt}$ = the average size,

measured by square root of total assets (measured in millions) of all firms in industry k in year t ; $BIG8 = 1$ if year is 1986-1988, 0 otherwise; $BIG6 = 1$ if year is 1989-1997, 0 otherwise; $BIG5 = 1$ if year is 1998-2001, 0 otherwise.

Industries are based on 3-digit SIC codes, 3-digit NAICS codes, or Fama-French (1997) industry classifications.

*, **, and *** indicate significance at 0.10, 0.05, and 0.01 levels respectively. Tests are one-tailed where a sign is predicted, two-tailed otherwise.

TABLE 6
Summary Statistics from Regression of ACR2 on Industry IOS, Within-Industry IOS Variability, and Control Variables with CCR4 Excluded Using Baber et al. (1996) IOS Measures

		<i>3-digit SIC</i>		<i>3-digit NAICS</i>		<i>Fama-French</i>	
		Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
<i>Panel A. NFIRMS</i>							
<i>included</i>							
Constant		0.737	37.46***	0.747	28.28***	0.658	21.24***
<i>IIO</i> _{<i>B</i>}	+	0.046	4.77***	0.072	5.09***	0.052	3.84***
<i>VIO</i> _{<i>B</i>}	-	-0.022	-4.24***	-0.048	-5.81***	-0.032	-3.17***
<i>TIME</i>	+	-0.001	-0.70	-0.002	-1.41*	-0.002	-1.02
<i>REG</i>	+	0.020	2.02***	0.060	4.93***	0.004	0.32
<i>REG*TIME</i>	-	-0.002	-2.33***	-0.004	-3.99***	-0.004	-3.01***
<i>LITRISK</i>	-	0.005	0.90	-0.053	-5.69***	-0.017	-1.65**
<i>MEANSIZE</i>	+	0.001	8.32***	0.000	1.52*	0.003	12.61***
<i>NFIRMS</i>	-	-0.001	-18.28***	0.000	-6.53***	0.000	-8.66***
<i>BIG8</i>	-	-0.175	-10.11***	-0.217	-9.47***	-0.206	-7.76***
<i>BIG6</i>	-	-0.115	-10.20***	-0.137	-9.01***	-0.126	-7.24***
<i>BIG5</i>	-	-0.056	-7.91***	-0.079	-8.14***	-0.064	-5.86***
<i>Adj. R</i> ²		0.272		0.338		0.481	
<i>F</i> -statistic		117.02***		69.50***		75.83***	
No. of obs.		3430		1479		885	

Panel B. NFIRMS

excluded

Constant		0.724	35.13***	0.752	28.06***	0.676	21.02***
<i>IIOS_B</i>	+	-0.008	-0.81	0.057	4.07***	0.065	4.66***
<i>VIOS_B</i>	-	-0.031	-5.71***	-0.051	-6.14***	-0.041	-3.88***
<i>TIME</i>	+	-0.002	-1.44	-0.002	-1.74	-0.003	-1.65
<i>REG</i>	+	0.004	0.38	0.058	4.72***	-0.011	-0.73
<i>REG*TIME</i>	-	-0.002	-2.07**	-0.004	-3.96***	-0.004	-3.11***
<i>LITRISK</i>	-	-0.010	-1.86**	-0.084	-10.34***	-0.060	-6.52***
<i>MEANSIZE</i>	+	0.001	8.03***	0.000	0.25	0.003	11.98***
<i>BIG8</i>	-	-0.184	-10.10***	-0.226	-9.71***	-0.223	-8.11***
<i>BIG6</i>	-	-0.123	-10.39***	-0.144	-9.36***	-0.141	-7.79***
<i>BIG5</i>	-	-0.063	-8.51***	-0.084	-8.55***	-0.075	-6.63***
<i>Adj. R</i> ²		0.200		0.292		0.437	
<i>F</i> -statistic		86.84***		63.41***		70.02***	
No. of obs.		3430		1479		885	

Models:

$$ACR2_{kt} = \beta_0 + \beta_1 IIOS_B_{kt} + \beta_2 VIOS_B_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k * TIME + \beta_6 LITRISK_k + \beta_7 MEANSIZE_{kt} + \beta_8 NFIRMS_t + \beta_9 BIG8_t + \beta_{10} BIG6_t + \beta_{11} BIG5_t + e \quad (\text{panel A})$$

$$ACR2_{kt} = \beta_0 + \beta_1 IIOS_B_{kt} + \beta_2 VIOS_B_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k * TIME + \beta_6 LITRISK_k + \beta_7 MEANSIZE_{kt} + \beta_8 BIG8_t + \beta_9 BIG6_t + \beta_{10} BIG5_t + e \quad (\text{panel B})$$

Variable definitions: $ACR2_{kt}$ = market share of two largest auditors in industry k ; $IIOS_B$ = median value of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) ($IIOS_B$); $VIOS_B$ = standard deviation of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) ($VIOS_B$); $TIME$ = a linear time effect variable (time = 1, 2, ..., 21); REG_k = 1 if industry k is regulated, and 0 otherwise; $MEANSIZE_{kt}$ = the average size, measured by square root of total assets (measured in millions) of all firms in industry k in year t ; $NFIRMS$ = number of firms in industry k ; $BIG8$ = 1 if year is 1986-1988, 0 otherwise; $BIG6$ = 1 if year is 1989-1997, 0 otherwise; $BIG5$ = 1 if year is 1998-2001, 0 otherwise.

Industries are based on 3-digit SIC codes, 3-digit NAICS codes, or Fama-French (1997) industry classifications.

*, **, and *** indicate significance at 0.10, 0.05, and 0.01 levels respectively. Tests are one-tailed where a sign is predicted, two-tailed otherwise.

TABLE 7
Summary Statistics from Regressions of ACR2/ACR3 on Industry IOS, Within-Industry IOS Variability, and Control Variables by Subperiod Using Baber et al. (1996) IOS Measures

		3-digit SIC		3-digit NAICS		Fama-French	
		Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
<i>Panel A. Big 8 subperiod</i>							
<i>IIOS_B</i>	+	0.011	0.60	0.055	1.79**	0.063	2.08**
<i>VIOS_B</i>	-	-0.031	-3.38**	-0.050	-3.10***	-0.031	-1.61*
<i>N</i>		500		235		137	
<i>Panel B. Big 6 subperiod</i>							
<i>IIOS_B</i>	+	0.007	0.70	0.009	0.62	0.005	0.34
<i>VIOS_B</i>	-	-0.025	-4.06***	-0.043	-4.81***	-0.042	-3.61***
<i>N</i>		1589		731		419	
<i>Panel C. Big 5 subperiod</i>							
<i>IIOS_B</i>	+	0.045	2.50***	0.042	1.55*	0.095	4.20***
<i>VIOS_B</i>	-	-0.002	-0.21	-0.040	-2.33***	-0.079	-4.63***
<i>N</i>		786		326		189	
<i>Panel D. Big 4 subperiod</i>							
<i>IIOS_B</i>	+	0.042	2.01**	-0.008	-0.22	0.050	1.59*
<i>VIOS_B</i>	-	-0.000	-0.04	-0.031	-1.42*	-0.039	-1.80**
<i>N</i>		545		221		144	

Model:

$$ACR3_{kt} = \beta_0 + \beta_1 IIOS_B_{kt} + \beta_2 VIOS_B_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k * TIME + \beta_6 LITRISK_k + \beta_7 MEANSIZE_{kt} + \beta_8 NFIRMS_t + e \quad (\text{panels A and B})$$

$$ACR2_{kt} = \beta_0 + \beta_1 IIOS_B_{kt} + \beta_2 VIOS_B_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k * TIME + \beta_6 LITRISK_k + \beta_7 MEANSIZE_{kt} +$$

$$\beta_8 NFIRMS_t + e$$

(panels C and D)

Variable definitions: $ACR2_{kt}$ ($ACR3_{kt}$) = market share of two (three) largest auditors in industry k ; $IIOS_B$ = median value of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) ($IIOS_B$); $VIOS_B$ = standard deviation of IOS in industry k where IOS is measured using a factor score based on Baber et. al. (1996) ($VIOS_B$); $TIME$ = a linear time effect variable (time = 1, 2, ..., 21); REG_k = 1 if industry k is regulated, and 0 otherwise; $CCR4_{kt}$ = the four-firm industry concentration ratio for industry k in year t ; $LITRISK_k$ = 1 if industry k is a high litigation-risk industry, 0 otherwise; $MEANSIZE_{kt}$ = the average size, measured by square root of total assets (measured in millions) of all firms in industry k in year t . For economy, only the coefficients for $IIOS_B$ and $VIOS_B$ are reported.

The model is estimated for the Big 8 (1986-1989), Big 6 (1989-1997), Big 5 (1998-2001), Big 4 (2002-2004) subperiods.

Industries are based on 3-digit SIC codes, 3-digit NAICS codes, or Fama-French (1997) industry classifications.

*, **, and *** indicate significance at 0.10, 0.05, and 0.01 levels respectively. Tests are one-tailed.