The Investment Opportunity Set and Industry Specialization by Auditors

Steven F. Cahan[a]*, Jayne M. Godfrey[b], Jane Hamilton[c], and Debra C. Jeter[d]

[a] *University of Auckland Business School, Private Bag 92019, Auckland, New Zealand*
[b] *Department of Accounting and Finance, Monash University, VIC 3800 Australia*
[c] *School of Business, La Trobe University, Bendigo, VIC 3550, Australia*
[d] *Owen Graduate School of Management, Vanderbilt University, Nashville, TN 37203 USA*

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* Corresponding author. Tel.: +64 9 373 7599 x87175, email: s.cahan@auckland.ac.nz

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Abstract

While auditor industry specialization has attracted widespread interest in the academic literature, one of the most fundamental questions remains unanswered: Why do some industries lend themselves to more intensive auditor specialization than others? 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 costly industry-specific investments that allow them to offer a differentiated product and 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), this creates unique knowledge requirements for the firm's auditor, 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.

1. Introduction

Anecdotal and empirical evidence (e.g., Berton 1995, Hogan and Jeter 1999, Casterella et al. 2004) suggests that audit firms seek recognition as industry specialists. Evidence also indicates that industry specialization is a differentiation strategy that allows the specialist auditor to earn audit fee premiums (Porter 1985, Mayhew and Wilkins 2003, Casterella et al. 2004, Ferguson et al. 2003, Francis et al. 2005). However, while the effects of industry specialization on audit fees, audit production costs, and audit quality have been widely examined, after more than two decades of research one of the most fundamental questions – i.e., why do some industries attract auditor specialization efforts to a greater degree than others? – has not been rigorously explored. Unlike prior studies, we do not examine the effects of industry specialization, but rather, we explain why specialization may occur in particular industries and we investigate this explanation empirically. Our explanation focuses on differences in the investment opportunity set (IOS) between and within industries.

We draw upon the argument that if a set of potential clients can be characterized on *n*-dimensions, audit firms will locate in the *n*-dimensional client space at a position that maximizes their expected profits (Chan et al. 2001). In equilibrium, audit firms will choose to differentiate themselves (i.e., specialize) by making an investment in "technology and human capital that is specific to a given set of specializations" (Chan et al. 2001, p. 9). Our interest lies in determining why that specialization is likely to be industry based, and why it is likely to vary across industries.

Mayhew and Wilkins (2003) suggest that audit firms have incentives to provide services that are not easily replicated by other audit firms. One way to do that is by making investments in industry-specific knowledge. Although acquiring this knowledge is costly, greater industry-specific knowledge can lead to a more clearly differentiated product, and the benefits of this specialized knowledge may not be limited to audit quality but may also extend to the auditors' ability to provide advice and counsel. Further, the cost of acquiring the knowledge creates a barrier to entry by other audit firms. Because of product differentiation and barriers to entry, specialization can benefit the auditor by leading to potentially higher fee premiums or enhanced growth in audit fee revenues, as well as potentially lower costs due to increased efficiency, effectiveness, and economies of scale. Under certain circumstances, the benefits of industry specialization will exceed the costs.

We argue that the levels of auditors' industry-specific knowledge vary across industries and that such knowledge is related to IOS available to companies in particular industries. In the vein of Smith and Watts (1992, p. 264), we view IOS as composed of "prospective investment opportunities and associated payoff distributions." While we recognize that IOS is by no means the only possible measure of industry-specific knowledge,[1] IOS affects a wide range of a firm's corporate policies, including those related to financing, dividends, and compensation (Smith and Watts 1992, Myers 1977). These are important policies that are likely to vary across industries and that are likely to

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[1] For example, prior studies (Eichenseher and Danos 1981, Danos and Eichenseher 1982) provide arguments that specialization is more likely in industries that are subject to extensive regulatory "red tape," such as healthcare or financial services (banking).

affect audit complexity. For example, expansion through acquisitions introduces consolidation issues, and investments in high growth areas raise revenue recognition issues for the auditor. Thus, we believe that IOS presents a unique combination of relevant attributes suitable for research into the topic of industry-specific knowledge and its relation to specialization.

We also recognize that IOS can vary for firms within an industry. As Gaver and Gaver (1993) and Myers (1997) suggest, there is a firm-specific dimension to IOS. *Ceteris paribus*, when the firm-specific component of IOS is more variable within an industry and firms have heterogeneous investment options, we expect that it will be more difficult for an auditor to specialize because it is harder to transfer knowledge and mitigate the cost per client of knowledge acquisition (e.g., training costs) among clients in that industry. Thus, we hypothesize that auditor industry specialization is positively related to the level of industry-specific IOS and negatively related to the variability of IOS within a given industry.

We use industry data from COMPUSTAT for the period 1986-2004 to test our hypotheses. We define industries based on three different classification schemes, i.e., 3-digit SIC codes, 3-digit NAICS codes, and Fama-French (1997) industries. In the spirit of Hogan and Jeter (1999), to measure auditor industry specialization, we use a two auditor concentration ratio. Further, we measure IOS in two ways using measures based on Baber et al. (1996) and Gaver and Gaver (1993). We use the median IOS in an industry to measure the level of industry-specific IOS and we use the standard deviation of IOS in an industry to measure its variability. Overall, 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 definition of industries that we use.

The rest of this paper is organized as follows. Section 2 provides an overview of the prior research on industry specialization by auditors. Section 3 develops our hypotheses, which link auditor specialization to the investment opportunity set. Section 4 describes the sample and method. Section 5 contains results, and section 6 summarizes and concludes.

2. Background

Although prior research into industry specialization has focused on its effects rather than its causes, there are a few notable exceptions. In this section, we discuss those studies and provide an overview of the literature on specialization effects. Recently, Mayhew and Wilkins (2003) and Casterella et al. (2004) use Porter's (1985) five forces framework to explain why auditors pursue specialization strategies. Under Porter's analysis, firms have incentives to specialize so that they can offer a unique or differentiated product to their clients. Their specialization provides the audit firms with competitive advantages. As Casterella et al. (2004) point out, this became particularly important after the deregulation of the audit market in the late 1970s and during the price wars that followed. Mayhew and Wilkins (2003) argue that audit firms specialize along *industry* lines because it allows them to offer a unique product to a fairly homogeneous group. Further, they note that specializing creates a competitive advantage for the audit firm in two ways – first, by decreasing the auditors' costs, and second, by providing more value for the clients. However, Casterella et al. (2004) and Mayhew and Wilkins (2003) do not test their conjectures empirically.

Industry 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 personnel training across more clients if their industry knowledge specialization is associated with a high number of clients in that industry. This was recognized early on by Eischenseher and Danos (1981), who argue that auditor concentration should be higher in industries where the auditor can use scale economies to reduce average production costs. As expected, they find higher auditor concentration in regulated industries (also see Danos and Eichenseher 1982).[2]

In addition, recent experimental research supports the notion that specialist auditors can lower audit costs by conducting more efficient and effective audits. For example, Low (2004) finds that specialist auditors make better assessments of risk and develop better audit plans and time budgets. Low (2004) also finds that specialist auditors are able to make higher quality changes to inherited audit programs, in terms of procedures, staff, and hours. Similarly, Owhoso et al. (2002) examine error detection in industry specialist and non-specialist audit teams. They find that, within specialist teams,

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[2] For example, regulated firms are often subject to capital requirements, which might cause managers of such firms to manipulate balance sheet amounts to comply with these requirements. An auditor knowledgeable in the industry would be more alert to check for, and identify, any such manipulations if a firm is near a cutoff point. Clients in regulated industries may also count on the audit firm to provide assistance in regulated form completion and other regulatory matters.

audit seniors and managers detect errors in work papers in a complementary way (i.e., seniors in specialist teams detect more mechanical errors while managers detect more conceptual errors, a finding not evident in non-specialist teams). Thus, compared to specialist auditors, non-specialist auditors are generally more likely to over-audit, which can lead to excessive fees, or under-audit, leading to more undetected errors.

Auditors' differentiation strategies can provide value to clients in several ways. First, industry specialists may be able to provide higher levels of assurance. As suggested above, industry specialists are more apt at detecting errors and should conduct better planned and more effective audits. Second, industry specialization can positively affect the quality of the financial reports. For example, Balsam et al. (2003) find that firms employing industry specialist auditors have higher earnings quality where earnings quality is measured using discretionary accruals and the earnings response coefficient. Also, Dunn and Mayhew (2004) find that the quality of disclosures is positively associated with auditor industry specialization. Third, while not explicitly part of the 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). Carcello et al. (1992) cite a survey where Fortune 1000 controllers identified industry knowledge and expertise as one of the primary factors in assessing audit quality, and Behn et al. (1997) find that industry specialization can lead to higher client satisfaction.

Finally, some evidence suggests that clients are willing to pay for audit services that are differentiated based on industry specialization. While studies based on non-US data (e.g., Craswell et al. 1995, DeFond et al. 2000, Ferguson and Stokes 2002) provide conflicting evidence, two recent studies using US data do find evidence of specialist premiums in some cases. Mayhew and Wilkins (2003) examine whether auditor industry specialization (measured by the audit firm's market share) affects audit fees for IPOs. They apply the law of diminishing marginal returns to argue that certain stages of an auditors' industry market share growth will lead to economies of scale and lower fees. They also argue that a dominant auditor (defined as a market leader with a market share that is 10 percent greater than the nearest competitor) offers a differentiated good and therefore can charge a premium. Consistent with their prediction, they find a negative and significant relation between the IPO audit fee and auditor market share but a positive (also significant) relation between the IPO audit fee and auditor dominance. Casterella et al. (2004) use a broader sample of listed firms. Based on Porter (1985), they focus on client size. They expect that small clients who use industry specialists will pay fee premiums because they have little bargaining power. However, they expect that large clients who use specialist auditors will pay lower fees because large clients will have more bargaining power. Their evidence supports these predictions.

Hogan and Jeter (1999) provide evidence on how auditor concentration has changed over time. They regress the three-firm auditor concentration ratio on time, whether the client's industry is regulated (0, 1), the four-firm concentration ratio for the client industry, client industry litigation risk, client industry size, client industry growth, and the number of Big 6 audit firms with a self-declared specialization in the client industry. They also include an interactive variable between regulated status and time. Hogan and Jeter (1999) find significant coefficients for all their variables. All the coefficients, except for the coefficients for the regulation/time interaction and litigation risk, are positive. The regulation/time interaction, in conjunction with their regulation variable, indicates that auditor concentration in regulated (nonregulated) industries is unchanged (increasing), in contrast to the findings of Danos and Eichenseher (1982) for an earlier time period.

This last finding is particularly relevant for purposes of the present research because it suggests that industry-specific knowledge requirements extend to nonregulated industries as well as to regulated industries. Equally important, Hogan and Jeter's (1999) finding that audit leaders' market shares increased over their sample period suggests that these knowledge requirements intensified during the period 1976 to 1993. The strong economic growth in the 1980s and early 1990s, along with the growth in information technology, served to expand the investment opportunity set for some nonregulated industries during this time period, allowing audit firms to invest more in industry-specific knowledge and to increase market share in these industries. Further, increases in globalization result in expanded investment opportunities, thus creating a need for more sophisticated, knowledgeable auditors competent in a wider range of skills. Also, rapid growth often goes hand in hand with a heightened risk level. These investment opportunities and the related risk effects are reflected in both the levels and variability of

IOS across firms in an industry. In the following section, we relate the specialization of auditors in particular industries to the level and variability of industry-specific IOS.

3. Hypotheses

While industry specialization can provide benefits to the auditor in the form of higher revenues and lower costs, auditors do not become specialists in all industries. This begs the question: Why do some industries draw more specialization efforts by auditors than others? In other words, what makes an industry an attractive target for specialization?

O'Keefe et al. (1994) suggest that the provision of 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), while important for conducting an audit, 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 entire client base. Thus, any differences in industry specialization by auditors across industries will relate to industry-specific or client-specific expertise (knowledge, tools, etc.). We argue that industry specialization by auditors relates positively to the level of *industry-specific* knowledge that is needed to audit the industry and to provide optimal audit and non-audit services (level of IOS in the industry). We also argue that auditors' industry specialization relates negatively to the level of *client-specific* knowledge necessary to audit an industry and provide optimal services, measured as the variability of industry-related knowledge (IOS variability within the industry).

Eichenseher and Danos (1981) hypothesize that inter-industry differences in specialized industry knowledge may lead to inter-industry differences in auditor concentrations because of economies of scale. Later, Danos and Eichenseher (1982) limit their focus for differentiating between industries with high and low levels of industry-specific knowledge to the regulated (or non-regulated) status of the industry. We extend their approach to argue that, *ceteris paribus*, any client environment with relatively high growth options, or high IOS, is likely to have characteristics that make auditing more complex, regardless of the regulatory status of the client's industry.

Myers (1977) contends that the firm's market 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. 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, p. 127). Smith and Watts (1992, p. 264) show that IOS can explain inter-industry differences in corporate policy decisions (e.g., financing, dividend, and compensation decisions).

Specifically, because growth options depend on the firm's future discretionary investments and are largely intangible, auditing a client firm with high growth options may require a deep understanding of the idiosyncrasies of the industry that the firm operates in and specific knowledge about the risks associated with the exercise and measurement of the growth options. This specialized knowledge will help the auditor in planning and executing the audit (Low 2004), detecting errors (Owhoso et al. 2002), and being able to identify earnings management attempts (Balsam et al. 2004). For example, the auditors' 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. In addition, the specialized knowledge will enhance the auditors' ability to advise, assist, and retain clientele since clients view the advisory facet of auditor services as critical (e.g., Behn et al. 1997).

Auditors familiar with the types of expenditures unique to a given industry are more likely to identify classification errors such as capitalization of items that should be expensed. Of course, many growth options are not capitalized in the financial statements (e.g., R&D; internally generated goodwill), and auditors may not regard the verification that such expenditures are value enhancing as within their realm of responsibility. However, at a more fundamental level, it is not possible to separate the recorded accounts from the environment in which the firm operates. For example, in establishing industry-specific benchmarks that can be used to assess the normalcy of a client's ratios, those benchmarks will reflect the industry's operating environment which, in turn, reflects the industry's growth opportunities. Moreover, in a rapidly changing environment, it is more difficult to determine what is "normal," but this is at least facilitated by increases in auditors' industry-specific knowledge. For example, if a given industry embraces a new technology with the result that ratios are altered, an auditor without industry-specific knowledge might err by comparing client ratios to old or outdated benchmark ratios.

At the extreme, the accounting system can provide warnings of financial distress, and is valuable if it facilitates the timely exercise of an abandonment option. Under these circumstances, auditing is a particularly valuable monitoring device when there are high growth options because the auditor reports on the accounting system's ability to provide early warnings of financial distress.[3]

Similarly, Anderson et al. (1993) explain that accounting information is used to determine payoffs to the different claimholders of the firms and, further, that the auditor must assess the appropriateness of the accounting methods. They note that when "unanticipated states" occur, the accounting methods are likely to be modified, and the auditor must determine if the modifications are consistent with GAAP as well as with the expectations of the various contracting parties. According to Anderson et al. (1993, p. 357), managers "employ auditors as one mechanism to ensure that resources directed to and from production-investment decisions are consistent with the intent of management decisions, and to insure that firm wealth is not deliberately expropriated by claimholders to an extent greater than the value of their claim."

We contend that auditor specialization is more valuable in industries with high IOS or growth options because it enables auditors to better conduct efficient, effective audits. Additionally, the fact that rapidly growing firms are likely to seek auditors capable of assisting in the growth process through their counsel and insight adds to the

[3] There is some confusion, expressed by various groups within the business community, about whether the auditor expresses an opinion about the health of the company or about the health of its financial statements. To the extent that the most informative type of audit opinion is viewed as the going-concern opinion, one might opt for the former definition, whereas a recognition that such opinions make up a very small fraction of all audit opinions issued would favor the latter view.

value of specialization skills in a setting of high growth options. Although these services are not related directly to the audit function, they are nonetheless valued by clients and thus play a nontrivial role in the cultivation of industry-specific expertise (Addams and Allred 2002, Wooten 2003).

Based on the above discussion, we expect that industry-specific knowledge can create opportunities for product differentiation, which allows less costly audits and/or higher audit fees. The higher costs of obtaining industry-specific knowledge in high IOS industries establish barriers to entry by other auditors. Nonetheless, we also recognize that, while auditors seek to capture growing revenue streams from clients in growing industries, they also need to guard against audit or client failures as growth bubbles may burst. On balance, we predict that:

H1 *As industry-specific IOS increases, the incidence of auditor specialization in that industry increases.*[4]

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 in an industry. We may think of 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

[4] While we examine whether an industry specialist exists, we do not examine which audit firm is most likely to be the specialist. Based on Porter (1985), there is likely to be a strong advantage for the first mover. However, we leave this issue for future research.

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 be able to benefit from greater scale economies or be able to pass fee reductions to their audit clients as a result of decreasing costs. Further, in this setting, it is easier for auditors to safeguard themselves from the potential costs associated with client or audit failures once they have acquired the desired level of expertise.

However, 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.

Between the hypothetical within-industry extremes of zero and complete variation in client firms' IOS, there is a region where clients have highly specific investments that are proprietary in nature, and these firms have incentives to use an industry specialist auditor to benefit from specialist advice and assurance and, potentially, lower audit fees. On the other hand, these client firms may also have potential incentives to avoid the market leading auditor in their industry because they do not want this proprietary information transferred to their competitors (e.g., Kwon 1996).

Overall, in industries where the IOS variability is high and firms' growth options are dissimilar, we expect that auditors investing in firm-specific knowledge will be unable to transfer their investment to other clients. Hence, 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 will be able to dominate the industry. As the variability of firms' IOS decreases within an industry, the ability to transfer industry specific knowledge and skills cost-effectively increases, and greater auditor specialization is to be expected. Consequently, we hypothesize:

H2 As client-specific IOS in an industry increases, the incidence of auditor specialization in that industry decreases.

4. Data, variables and method

4.1 Dependent variable

Similar to Hogan and Jeter (1999), we measure industry specialization using a ratio of auditor concentration. However, unlike Hogan and Jeter who use a three-audit firm concentration ratio, we use a two-audit firm ratio (*ACR2*) because we want a more restrictive definition of industry specialization and because by the end of our study (2004) there are only four large audit firms. Also, we note that this measure is consistent in principle with that used in the Mandated Study on Consolidation and Competition conducted by the U.S. General Accounting Office in July of 2003 (see GAO 2003, Appendix IV, Figure 13, for example).[5]

[5] As an alternative measure of industry specialization, we repeat our analyses using the market share for the leading auditor in each industry as the dependent variable. The results are qualitatively similar to those presented in section 5 except significance levels are somewhat lower.

4.2 IOS variables

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 a1. (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). Thus, the two measures of IOS that we use are: (1) a factor score based on all four of Baber's variables, and (2) a factor score based on four (of six) of Gaver and Gaver's variables.[6] We use these measures 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 four measures of IOS, i.e., two measures of

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[6] 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.

industry IOS (*IIOS_B*, *IIOS_G*) and two measures of within-industry IOS variability (*VIOS_B*, *VIOS_G*).

To measure *IIOS*, we use the industry median of the client firms' IOS factor scores based on the Baber et al. (1996) or Gaver and Gaver (1993) variables. Industries with high average IIOS measures are characterized as high IOS industries. 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 being 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.

4.3 Method

We test H1 and H2 using a multivariate model adopted from Hogan and Jeter (1999, p. 6, equation 3), i.e.:

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

$ACR2_{kt}$ is the market share of the two largest auditors 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) (*IIOS_B*) or (b) a factor score based on Gaver and Gaver (1992)

(*IIOS_G*). *VIOS* is the 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* is a linear time effect variable (time = l, 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.[7] *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.

We expect a positive coefficient for *IIOS* and a negative coefficient for *VIOS*. The remaining independent variables are control variables based on 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, and find a positive relation between *REG* and the three-audit firm concentration variable. Their

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[7] Following Hogan and Jeter (1999), we classify firms in the following two-digit SIC codes as regulated: 10 (metal mining), 12 (coal mining), 13 (oil and gas extraction), 14 (mining and quarrying of nonmetalic 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); Bohn and Choi (1996); and O'Brien (1997), we classify firms in the following two-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).

model's interaction between *REG* and *TIME* yields a negative coefficient which suggests 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 is negatively related to *LITRISK*. This suggests 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.[8]

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

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[8] We omit two of Hogan and Jeter's (1999) control variables. First, we delete their growth measure because this may be highly correlated with *IIOS*. 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 are interested in the auditor's specialties as measured using independent data.

We believe this approach is superior to the approach used by Hogan and Jeter (1999) for the purposes of this study. By combining the two market shares of the two merged firms in the pre-merger period and using the market share of the 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.

4.4 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 use 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 that has at least five firm-years with 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 *IIOS_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 *IIOS_G* at the industry level.[9] 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 *IIOS_B* and *VIOS_B*. Likewise, for each industry-year with at least five firms with *FAC_G* scores, we compute *IIOS_G* and *VIOS_G*.[10] 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 that we use.

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9 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.

10 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 3430 industry-years over the 21 year sample period. Using the 3-digit NAICS codes, we have 1513 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) 3322 industry-years based on the 3-digit SIC classification, 1479 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 which suggests 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.

5.0 Results

5.1 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. Further, both *IIOS_B* and *IIOS_G* have negative means and medians. However, we note that this does not imply that the overall economy has negative investment opportunities because 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, but in reality, the former is more important to the overall economy than the latter. Moreover, we view *IIOS_B* and *IIOS_G* as relative measures of IOS rather than absolute measures, i.e., *IIOS_B* and *IIOS_G* provide a relative rank of IOS across industries.[11] Also, the variability of *IIOS_B* and *IIOS_G* are roughly the same (mean *VIOS_B* = 0.550, mean *VIOS_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 (= 23.387^2). 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. First, the correlation between *IIOS_B* and *IIOS_G* is 0.721 which suggests that while the two measures overlap, there still is a unique component to each. Second, the correlations between the four IOS measures and the control variables are all significant. The highest correlation is between *IIOS_B* and *LITRISK* (r = 0.430) which suggests that growth opportunities are higher in high litigation industries. Third, the four IOS measures are negatively correlated with *CCR4* and *MEANSIZE*. This may reflect competition within an industry. That is, growing industries may attract new entrants that will reduce

[11] By construction, the mean of the firm-level factor scores used to compute *IIOS_B* (i.e., *FAC_B*)

available growth options. More concentrated industries and large industries may be more mature industries where IOS is lower on a relative basis. Fourth, 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. Fifth, firm concentration 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 *IIOS_B* (left column) and *VIOS_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 IIOS and VIOS have changed over time.

Insert Table 4

While purely descriptive, the rankings provided in Table 4 are not at odds with our priors. For example, the top 10 based on industry IOS (*IIOS_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

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and *IIOS_G* (I.e., *FAC_G*) will be equal to zero across all firms in our sample.

ranked industry based on *IIOS_B* in all four panels. On the other hand, many of the industries ranked in the bottom 10 based on *IIOS_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 10.

For the rankings based on *VIOS_B*, the bottom 10 industries appear to be mature, stable industries (e.g., railroad, water supply, mills, grocery stores) whereas the top 10 is harder to categorize and includes a wider variety of industries. Finally, while *IIOS_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 *IIOS_B* generally do not appear in the bottom (middle) [top] subsamples based on *VIOS_B* (drugs which appears in the top 10 based on *IIOS_B* and *VIOS_B* in all four years in an exception).

5.2 Multivariate tests

Table 5 summarizes the results from estimating equation (1) using the two alternative measures of IOS and using 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 use ACR3, no IOS variables, no *BIG* indicators, and data from the 1976-1993 period. Based on an a F-test, the two IOS variables provide incremental explanatory power relative to a base model that which 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 *IIOS_B* being positively related to *ACR2*. Also, we find a negative relation between *VIOS_B* and *ACR2*, which suggests that as firm specific IOS increases, the market share of the two leading auditors decreases. This supports H2 and is consistent with the view that it is more difficult for a single auditor to offer specialized services when IOS is variable within an industry and client firm growth opportunities are more unique to the specific firms.

Insert Table 5

In addition, all of the control variable coefficients are significant and signed as expected except for *TIME* and *LITRISK*. Consistent with 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.[12] However, also consistent with Hogan and Jeter (1999), *REG*TIME* is significant with a negative coefficient which suggests that industry specialization has increased faster in non-regulated industries over time.

For our models using the 3-digit NAICS and Fama-French industry definitions, we also find support for both H1 and H2. In each case, *IIOS_B* and *VIOS_B* coefficients are correctly signed and significant at the 0.001 level. For the model using the 3-digit NAICS codes, the *LITRISK* coefficient is significant and negative, which is consistent with Hogan and Jeter's (1999) finding and suggests that industry specialization is lower

[12] We ran our models without the *BIG* indicators included and *TIME* was consistently significant.

in high litigation risk industries. For the model using the Fama-French industry definitions, the main differences are that the adjusted R^2 is higher (64.4 percent) and *REG* is not significant. Also, as in the 3-digit SIC code model, *LITRISK* is not significant.

Table 5, panel B contains the results using the IOS measures based on Gaver and Gaver (1993). The sample sizes 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, *IIOS_G* is not significant. Between the two panels in Table 5, we find that IIOS is significant in five of the six models and VIOS is significant in all six models. Together, this provides strong support for both H1 and H2.

We conduct several sensitivity tests. First, to ensure that our results are not being driven by any particular Big N subperiod, we re-estimate equation (1) separately for each subperiod. Table 6 provides these results in abbreviated form, and panels A, B, C, and D show the results for *IIOS_B* and *VIOS_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 the various control variables, which are generally consistent with those in Table 5. The signs for *IIOS_B* and *VIOS_B* are remarkably robust across subperiods, but significance levels vary, possibly because of the smaller samples. Still, we generally find support for H1 and H2 across the Big 8, Big 5, and Big 4 subperiods. For the Big 6 subperiod, we find support for H2 but not for H1. Taken together, our results do not appear to be driven by any of the four subperiods in our sample.[13]

Insert Table 6

Second, since the number of firms in industries in our sample varies widely, we also introduce a control for the number of industry members. Other things equal, we expect it would be easier for an auditor to capture a dominant market share in industries with few firms than in industries with many 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). We expect a negative relation between *NFIRMS* and *ACR2*. While *NFIRMS* is insignificant (based on one-tailed tests) in all the models that we estimate, our results (untabulated) for our IIOS and VIOS measures are qualitatively unchanged from Table 5 whether we use the Baber et al. (1996) or Gaver and Gaver (1993) measures. Thus, our results are not affected by the number of firms in an industry.

Third, we estimate equation (1) without *CCR4*. Because *CCR4* has by far the most incremental explanatory power (e.g., t-statistics range from 21.74 to 41.86 in Table 5), *CCR4* may be sapping power from the other explanatory variables including our IIOS and VIOS measures. This would be a concern if IIOS and VIOS also affect the industry structure as represented by *CCR4*. Since IOS affects a firm's investment and financing

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13 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.

decisions, it is not unreasonable to expect that IOS will affect the growth and distribution of firms in an industry. Indeed, based on Table 3, all four IOS measures are negatively and significantly related to *CCR4*. This suggests that firms with high levels of industry IOS and high variability in industry IOS are less concentrated. Thus, by including *CCR4*, we may be obscuring the explanatory power of IIOS and VIOS which are more primitive constructs of industry structure.

Table 7 provides the estimation results where *CCR4* is omitted from our model. We estimate models with (panel A) and without (panel B) *NFIRMS* using *IIOS_B* and *VIOS_B*. The results using Gaver and Gaver (1993) measures are qualitatively identical. As expected, the t-statistics for *IIOS_B* and *VIOS_B* for the three models in Table 7, panel A generally increase relative to the models in Table 5, panel A. Further, *NFIRMS* has a negative coefficient and is highly significant in all three models. When *CCR4* and *NFIRMS* are excluded (i.e., Table 7, panel B), the t-statistics for *IIOS_B* and *VIOS_B* increase relative to Table 5, panel A in all but one case.[14] Overall, the results in Table 7, panels A and B suggest that the explanatory power of IIOS and VIOS increase when *CCR4* is excluded.

Insert Table 7

6.0 Conclusion

While auditor industry specialization has attracted widespread interest in the academic literature, one of the most fundamental questions remains unanswered. Specifically, it is not clear why some industries attract greater auditor specialization than others. 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 have to make industry-specific investments that allow them to offer a differentiated product and 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), it is more difficult to transfer knowledge between clients in that industry because each firm faces a unique set of investment opportunities and this creates unique knowledge requirements for the firm's auditor. Under these circumstances, knowledge cannot be easily transferred 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 IOS and auditor specialization but a negative relation between IOS variability within industry and auditor specialization.

We use industry level data collected from COMPUSTAT over the period 1986-2004. Our two measures of IOS are derived from a factor analysis of variables used by Baber et al. (1996) and variables used by Gaver and Gaver (1993). Within each industry, we use the median factor score to represent industry IOS and the standard deviation of the factor scores to represent IOS variability. We also use a two-audit firm concentration ratio to measure industry specialization. Our results provide strong evidence that auditor specialization is increasing in industry IOS levels and that auditor specialization is decreasing in within-industry IOS variability. These results are robust to the industry

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[14] The exception is for *IIOS_B* in the model using 3-digit SIC codes where *IIOS_B* is not significant.

classification scheme (i.e., 3-digit SIC codes, 3-digit NAICS codes, Fama-French classifications) and the IOS measures (i.e., Baber et al. 1996, Gaver and Gaver 1993) that are used.

We recognize several limitations with our study. First, auditor specialization can be measured in numerous ways (e.g., Neal and Riley 2004). While the measures we use – based on the auditor's market share as measured by their clients' total assets – are consistent with Hogan and Jeter (1999) and much of the prior literature, Neal and Riley (2004) note that different measures of auditor specialization can produce different results. Second, and similarly, IOS can be measured in different ways (e.g., Adam and Goyal 2003). While our results are highly consistent whether we use measures based on Baber et al. (1996) or Gaver and Gaver (1993), it is possible that both measures might be incomplete. Third, while we use three different industry classification schemes to categorize industries, these classifications might not align perfectly with the way that auditors define different industries, and as Ferguson et al. (2003) and Francis et al. (2005) suggest, industry specialization may be a local, rather than national, phenomenon. Fourth, the audit market has changed drastically in the past twenty years. Over that period the number of larger firms decreased from eight to four. As a result, it is not clear that being a specialist auditor in 1986 is the same as being a specialist auditor in 2002. For example, differentiation may be more important in a market with eight auditors than with four auditors. While we control for this theoretical concern to some extent by using *BIG* auditor designations and *TIME* as control variables in our regressions, this cannot completely control for changing perceptions.

Future research could provide valuable insights by refining the measures of specialization and IOS, and by investigating the optimal industry classification scheme to relate it most aptly to industry IOS levels and variability. Other avenues for future research include 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; and how auditors can spread the costs of acquiring that knowledge and skill base across their client-portfolios.

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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

Note:

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 specialization, IOS, and control variables

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

Notes:

Variable definitions: $ACR2_{kt}$ = market share of two largest auditors in industry *k*; *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

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

Notes:

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 = l, 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 level based on one-tailed tests, respectively.

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 IIOS_B		Ranked by VIOS_B	
SIC	Industry	SIC	Industry
Panel A. 1986 (first Big 8 year in sample)			
	Bottom 10		
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
	Middle 10		
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
	Top 10		
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 IIOS_B		Ranked by VIOS_B
SIC	Industry	SIC	Industry
Panel B. 1989 (first Big 6 year)			
	Bottom 10		
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
	Middle 10		
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
	Top 10		
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

SIC	Industry (Ranked by IIOS_B)	SIC	Industry (Ranked by VIOS_B)
Panel C. 1998 (first Big 5 year)			
	Bottom 10		
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
	Middle 10		
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
	Top 10		
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

SIC	Ranked by IIOS_B Industry	SIC	Ranked by VIOS_B Industry
Panel D. 2002 (first Big 4 year)			
	Bottom 10		
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 theatres	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
	Middle 10		
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
	Top 10		
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

		3-digit SIC		*3-digit NAICS*		*Fama-French*	
		Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Panel A. Baber et al. (1996) measures							
Constant		0.492	27.88***	0.563	23.62***	0.543	20.67***
IIOS_B	+	0.021	2.75***	0.037	3.08***	0.031	2.76***
VIOS_B	-	-0.016	-3.68***	-0.038	-5.42***	-0.032	-3.81***
TIME	+	-0.000	-0.29	0.001	-0.69	-0.001	-0.73
REG	+	0.037	4.39***	0.070	6.76***	0.006	0.50
*REG*TIME*	-	-0.002	-2.63***	-0.004	-4.42***	-0.003	-3.07***
CCR4	+	0.352	41.86***	0.329	24.77***	0.320	22.56***
LITRISK	-	0.005	1.16	-0.020	-2.71***	-0.006	-0.73
MEANSIZE	+	0.001	12.06***	0.001	3.63***	0.002	10.43***
BIG8	-	-0.139	-9.35***	-0.185	-9.41***	-0.190	-8.67***
BIG6	-	-0.085	-8.80***	-0.112	-8.60***	-0.117	-8.13***
BIG5	-	-0.041	-6.81***	-0.066	-7.95***	-0.059	-6.49
Adj. R^2		0.471		0.497		0.644	
F-statistic		278.67***		136.95***		146.74***	
No. of obs.		3430		1513		889	
F-stat. for *IIOS_B* and *VIOS_B*		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***
IIOS_G	+	0.018	2.73***	0.024	2.56***	0.012	1.11
VIOS_G	-	-0.019	-5.42***	-0.034	-6.59***	-0.021	-3.07***
TIME	+	0.000	0.05	0.001	-0.68	-0.008	-0.61
REG	+	0.049	5.74***	0.069	6.73***	-0.005	-0.46
*REG*TIME*	-	-0.003	-3.65***	-0.004	-4.70***	-0.003	-2.87***
CCR4	+	0.353	40.26***	0.334	23.86***	0.325	21.74***
LITRISK	-	0.002	0.33	-0.018	-2.54***	-0.003	-0.39
MEANSIZE	+	0.001	10.57***	0.001	3.50***	0.002	11.83***
BIG8	-	-0.143	-9.44***	-0.189	-9.65***	-0.179	-8.06***
BIG6	-	-0.089	-9.02***	-0.114	-8.79***	-0.112	-7.69***
BIG5	-	-0.047	-7.24***	-0.069	-8.18***	-0.058	-6.26***
Adj. R^2		0.460		0.489		0.629	
F-statistic		258.43***		129.57***		137.41***	
No. of obs.		3322		1479		885	
F-stat. for *IIOS_G* and *VIOS_G*		7.87***		22.20***		4.75***	

Notes:

$$AC2R_{kt} = \beta_0 + \beta_1 IIOS_{kt} + \beta_2 VIOS_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k{*}TIME + \beta_6 CCR4_{kt} + \beta_7 LITRISK_k + \beta_8 MEANSIZE_{kt} + \beta_9 BIG8_t + \beta_{10} BIG6_t + \beta_{11} BIG5_t + e$$

Variable definitions: $ACR2_{kt}$ = market share of two largest auditors in industry *k*; *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 = l, 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 level. 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 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
Panel A. Big 8 subperiod							
IIOS_B	+	0.023	1.27	0.084	2.61***	0.044	1.46*
VIOS_B	-	-0.020	-2.24**	-0.039	-2.24**	-0.020	-1.09
N		500		235		137	
Panel B. Big 6 subperiod							
IIOS_B	+	0.004	0.41	0.014	0.88	0.000	0.01
VIOS_B	-	-0.027	-3.12***	-0.033	-3.51***	-0.013	-1.01
N		1589		731		419	
Panel C. Big 5 subperiod							
IIOS_B	+	0.045	2.50***	0.042	1.55*	0.095	4.20***
VIOS_B	-	-0.002	-0.21	-0.040	-2.33***	-0.079	-4.63***
N		786		326		189	
Panel D. Big 4 subperiod							
IIOS_B	+	0.042	2.01**	-0.008	-0.22	0.050	1.59*
VIOS_B	-	-0.000	-0.04	-0.031	-1.42*	-0.039	-1.80**
N		545		221		144	

Notes:

$$AC2R_{kt} = \beta_0 + \beta_1 IIOS\_B_{kt} + \beta_2 VIOS\_B_{kt} + \beta_3 TIME_{kt} + \beta_4 REG_k + \beta_5 REG_k{*}TIME + \beta_6 CCR4_{kt} + \beta_7 LITRISK_k + \beta_8 MEANSIZE_{kt} + \beta_9 BIG8_t + \beta_{10} BIG6_t + \beta_{11} BIG5_t + e$$

Variable definitions: $ACR2_{kt}$ = market share of two largest auditors in industry k; *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 = l, 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 level. Tests are one-tailed.

Table 7
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

		3-digit SIC		*3-digit NAICS*		*Fama-French*	
		Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Panel A. NFIRMS included							
Constant		0.737	37.46***	0.747	28.28***	0.658	21.24***
IIOS_B	+	0.046	4.77***	0.072	5.09***	0.052	3.84***
VIOS_B	-	-0.022	-4.24***	-0.048	-5.81***	-0.032	-3.17***
TIME	+	-0.001	-0.70	-0.002	-1.41*	-0.002	-1.02
REG	+	0.020	2.02***	0.060	4.93***	0.004	0.32
*REG*TIME*	-	-0.002	-2.33***	-0.004	-3.99***	-0.004	-3.01***
LITRISK	-	0.005	0.90	-0.053	-5.69***	-0.017	-1.65**
MEANSIZE	+	0.001	8.32***	0.000	1.52*	0.003	12.61***
NFIRMS	-	-0.001	-18.28***	0.000	-6.53***	0.000	-8.66***
BIG8	-	-0.175	-10.11***	-0.217	-9.47***	-0.206	-7.76***
BIG6	-	-0.115	-10.20***	-0.137	-9.01***	-0.126	-7.24***
BIG5	-	-0.056	-7.91***	-0.079	-8.14***	-0.064	-5.86***
Adj. R^2		0.272		0.338		0.481	
F-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***
IIOS_B	+	-0.008	-0.81	0.057	4.07***	0.065	4.66***
VIOS_B	-	-0.031	-5.71***	-0.051	-6.14***	-0.041	-3.88***
TIME	+	-0.002	-1.44	-0.002	-1.74	-0.003	-1.65
REG	+	0.004	0.38	0.058	4.72***	-0.011	-0.73
*REG*TIME*	-	-0.002	-2.07**	-0.004	-3.96***	-0.004	-3.11***
LITRISK	-	-0.010	-1.86**	-0.084	-10.34***	-0.060	-6.52***
MEANSIZE	+	0.001	8.03***	0.000	0.25	0.003	11.98***
BIG8	-	-0.184	-10.10***	-0.226	-9.71***	-0.223	-8.11***
BIG6	-	-0.123	-10.39***	-0.144	-9.36***	-0.141	-7.79***
BIG5	-	-0.063	-8.51***	-0.084	-8.55***	-0.075	-6.63***
Adj. R^2		0.200		0.292		0.437	
F-statistic		86.84***		63.41***		70.02***	
No. of obs.		3430		1479		885	

Notes:

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

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

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 = l, 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 level. Tests are one-tailed where a sign is predicted, two-tailed otherwise.