CLIENT SIMILARITY AND ITS IMPLICATIONS FOR
AUDIT QUALITY AND PRODUCTION COSTS

By

STEPHEN V. BROWN

A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2012

المنارة للاستشارات

www.manaraa.com

© 2012 Stephen V. Brown

www.manaraa.com

ACKNOWLEDGEMENTS

I am especially grateful to my dissertation committee for their assistance: W. Robert Knechel (chair), Stephen Asare, Praveen Pathak, and Jennifer Wu Tucker. I would also like to thank workshop participants at Arizona State University, Florida International University, Southern Methodist University, the University of Florida, the University of Illinois at Urbana–Champaign, the University of Kentucky, the University of South Carolina, and the University of Virginia for their feedback on portions of this paper.

www.manaraa.com

TABLE OF CONTENTS

المنارة للاستشارات
www.manaraa.com

المنارة للاستشارات

www.manaraa.com

LIST OF TABLES

المنارة للاستشارات
www.manaraa.com

LIST OF FIGURES

www.manaraa.com

Abstract of Dissertation Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy

CLIENT SIMILARITY AND ITS IMPLICATIONS FOR
AUDIT QUALITY AND PRODUCTION COSTS

By

Stephen V. Brown

December 2012

Chair: W. Robert Knechel
Major: Business Administration

The current work focuses on the implications of the commonality among clients of an auditor. In Chapter 2, I examine the degree of compatibility between clients and their auditors to test whether companies systematically prefer specific auditors based on this criterion. Using both financial statements and narrative disclosures, I introduce two new measures of compatibility based on how similar a client is to other clients of the same auditor. My results strongly support the idea that auditor-client compatibility can predict the particular auditor a client will choose to engage. When compatibility is lower, clients are more likely to change auditors and pick a new auditor with relatively high auditor-client fit. Interquartile changes in compatibility increase the probability of switching auditors by as much as 19 percent. Audit quality, as captured by discretionary accruals, increases as auditor-client compatibility increases. However, SEC enforcement actions, indicative of a severe audit failure, become more prevalent as compatibility improves.

In Chapter 3, I use the similarity measures from Chapter 2 to proxy for the opportunities to specialize that arise from greater client commonality, finding strong evidence that higher client overlap is associated with lower audit fees. This relationship is incrementally stronger in industries for which the auditor has greater economic

www.manaraa.com

incentives. Because the financial statements and narrative disclosures are distinct disclosure channels, I explore the effect on audit fees when the two channels portray inconsistent messages about the degree of client commonality. When the financial statements are relatively unusual compared to peer clients, but the narrative disclosures do not reflect this dissimilarity, I expect the auditor to assess higher audit risk. Consistent with this prediction, the auditor charges higher audit fees under this condition. On the other hand, when the narrative disclosures are more unique than the financial statements reflect, audit fees are lower, which I argue is due to the greater, more useful firm-specific information contained in the text relative to the financial statements.

المنارة للاستشارات
www.manaraa.com

CHAPTER 1
INTRODUCTION

There is little doubt that relationships between companies are important. A tighter bond between a firm and its suppliers can reduce costs, improve the timeliness of deliveries, and decrease the time-to-market of new products. Closer relationships among competitors can improve profitability, as in the case of an oil cartel, or give rise to antitrust litigation. Managers with close ties to political figures might receive preferential treatment for their firm, while those who steer clear of government lobbying could pay a substantial financial cost. A substantial amount of research in accounting examines the relationships between variables—such as client size and audit costs—but does not fully explore the relationships between observations. Such a limitation is implicit in any study that includes only characteristics of the observation in the empirical model while excluding measures of how the observation relates to entities beyond itself. In this work, I investigate the strength of the bond between clients and their auditor, specifically testing its implications for which auditor a client will engage, the resulting quality of the audit process, and audit production costs.

I focus on the auditor-client relationship in particular due to its importance for both regulators and researchers. Generally Accepted Auditing Standards (GAAS) in the U.S. and the International Standards on Auditing both require the auditor to be independent of the client in fact and in appearance, a feature at the core of auditing's value proposition. The closer the relationship between the auditor and client, the more likely independence issues will arise. This concern is reflected in recent discussions about mandatory auditor rotation by the Public Company Accounting Oversight Board (PCAOB). The PCAOB is gathering public comments on a potential new requirement

المنارة للاستشارات
www.manaraa.com

that auditors be changed after a given number of years due to fear that the relation auditor-client bond will strengthen to the point of impairing independence of the audit process. While I do not specifically address the issue of independence in this work, my results have value for regulators considering the costs and benefits of mandatory auditor rotation.

Another important feature of the auditor-client relationship explored in many prior studies is specialization of the audit process. The typical line of reasoning is that auditors can customize (“specialize”) their normal audit process for any client or set of clients. Customization can take the form of modifications to the audit workflow, employee training, shifting personnel onto engagements to maximize the usefulness of prior on-the-job experience, or in a variety of other ways. This specialization is typically costly for the auditor, but has potential benefits, such as higher audit quality, more efficient audits, and improved marketability of the product to new customers. While a significant amount of research has examined specialization, the main weakness of the empirical approach is a lack of adequate proxies for specialization. Papers in this area normally rely on strong assumptions about the meaning of market share within an industry to proxy for specialization—assumptions that may be difficult to justify (Gramling and Stone 2001). To address this concern, I develop a more direct measure of specialization based on explicit features of the auditor’s client base.

A major innovation in the current work is the implementation of two measures of similarity between one company and another; one measure is based on the company’s financial statements and the other on its narrative, textual disclosures contained in its annual report. Taken together, these two approaches give a comprehensive view of

المنارة للاستشارات
www.manaraa.com

how a company's economic status and disclosure decisions imply a given relationship with other firms. For the financial statement similarity measure, I use an existing algorithm from the cluster analysis literature in a novel way within an accounting setting. For the narrative disclosure score, I extend a measure already used in an accounting context, adapting it to allow comparisons among multiple companies. Both of the measures have multiple potential uses within an auditing context and for accounting research more broadly. For the purposes of this work, I use the similarity of one company to the existing clients of an auditor as a proxy for how much the company has in common with the auditor's current client base.

Chapter 2 considers the basic question of whether clients tend to select an auditor with which they are more compatible and the implications of auditor-client compatibility for audit quality. I use the similarity measures as a proxy for auditor-client compatibility based on the argument that when a company has relatively more in common with an auditor's clients, it has a better fit with that auditor than an alternative with less inter-client similarity. This chapter develops the similarity measures, validates them, tests their sensitivities to various implementations, and compares them with alternatives. I find that clients on average prefer a more-compatible auditor, and they are more likely to switch to a new auditor when compatibility is lower. More importantly, this compatibility has implications for audit quality. One broad measures of audit quality is increasing in auditor-client compatibility, meaning that the quality is higher when the client fits better with that auditor. On the other hand, I also find evidence that severe audit failures are more likely with the compatibility is high.

المنارة للاستشارات
www.manaraa.com

In Chapter 3, the similarity measures proxy for potential specialization by an auditor because greater commonality among its client base provides more opportunities to customize the audit process for a particular group of clients, with a higher possible payoff to that specialization. I find support for this prediction in the form of lower audit fees for clients having more in common with an auditor's other clients. This result is somewhat unique in the audit literature, since most specialization studies find higher audit fees, purportedly a result of higher audit quality by specialist auditors. However, my approach is a more powerful and direct measure of potential specialization than existing proxies based on industry market share. The uniqueness of my measure provides support for an alternative outcome of specialization—more efficient audit processes.

Chapter 4 concludes the current work by summarizing the key findings of the other chapters and discussing their implications for both regulators and researchers.

للاستشارات المنارة
www.manaraa.com

CHAPTER 2
AUDITOR-CLIENT COMPATIBILITY AND SELECTION OF AUDIT FIRM

Introductory Remarks

Clients have preferences about the audit process, its outcomes, and the nature of the relationship with their auditor. I define *auditor-client compatibility* as the ability of the auditor to satisfy these preferences, given its own preferences and constraints.[1] If client preferences vary across companies, and auditors have varied abilities to meet clients' needs, the degree of fit between the two entities will also vary. Prior literature has examined variations in this compatibility in a broad sense, such as the choice of a Big4 auditor versus a smaller firm or an industry specialist versus a non-specialist. In this paper, I examine the typical auditor-client compatibility observed among Big4 firms, the occurrence of auditor changes when compatibility is relatively lower, and the implications of fit for audit quality.[2]

I find clients tend to be with auditors where the compatibility is better; depending on the proxy used, anywhere from 51 to 59 percent of clients are with the two best-fitting auditors among the Big4. I observe the same selection preferences among clients switching to a new auditor. And the worse the fit with the incumbent auditor, the greater the probability the client will choose to switch to a new auditor. When examining the association between fit and audit quality, I find some evidence that discretionary accruals are lower when the auditor-client compatibility is better. On the other hand, there is a greater occurrence of SEC enforcement actions for these higher levels of auditor-client compatibility.

[1] In this paper, I use the term "fit" interchangeably with "compatibility."

[2] Chapter 3 of this work addresses the association between auditor-client fit and audit fees.

www.manaraa.com

The degree to which a client and a specific auditor are well-matched is generally not externally observable. However, to the extent a company has similar audit preferences as other companies, they would presumably choose the same auditor, subject to various constraints on that choice. Therefore, in this study I compare the similarity of a company to other current clients of the auditor as a proxy for how well that company fits into the auditor's client base. If the company of interest is very similar to other clients already audited by the audit firm, the auditor is likely to have developed expertise and cost advantages related to that "type" of client. Therefore, when the similarity to existing clients is high, I consider this a more compatible fit than those situations where there is very low similarity between the company and the auditor's existing clients.

I specifically introduce two measures of inter-company similarity, one based on financial statements and one on narrative, textual disclosures. Each source of information provides variation in what managers are disclosing and how they choose to disclose it. The financial statement similarity proxy relies on the Mahalanobis distance, used extensively in the cluster analysis literature to divide objects into groups based on sets of numbers associated with each object. The set of numbers I use is motivated by financial components known to be important in an audit context, including proxies for effort, complexity, and risk. The narrative disclosure similarity measure extends the pairwise similarity score introduced in Brown and Tucker (2011) as a proxy for year-over-year changes in MD&A. As the source of narrative disclosures, I use the business description, MD&A, and footnotes contained in the mandatory annual report. Using each

المنارة للاستشارات
www.manaraa.com

measure, I calculate the similarity of each client-year to other clients in the same auditor-industry-year (the "reference group").

The primary contribution of this study is the introduction of two measures of how similar a company is to a reference group of other companies. The financial statement measure, based on the Mahalanobis distance, has been used in other contexts before, but not in the accounting literature. While the financial statement similarity score is used in Brown and Tucker (2011), I extend this formerly pairwise, year-over-year measure to allow for comparison of one entity to a group. Defranco et al. (2011) develops a measure of accounting system comparability based on the relationship between earnings and returns. My measure can be used in settings outside of financial statement comparability and can be adapted to whichever financial statement variables are important in a given context. While the current paper focuses on auditors and their clients, there are many other potential applications of these measures in any fields of research where either financial statement information or narrative disclosures are available.

Within the audit context, I contribute to the lack of literature on the fit of specific auditors and their clients. Some literature has looked at misalignments given *types* of auditors, such as audit firm size (e.g., Shu 2000; Landsman et al. 2009). However, there is a much more limited literature on the compatibility of specific auditors with a specific client. What literature exists tends to be narrowly focused, such as research on the effects on a client of hiring a former audit partner (e.g., Lennox and Park 2007). I broaden the existing research on auditor choice by considering the suitability of a specific auditor for a client. This research is relevant to the debate on mandatory auditor

المنارة للاستشارات
www.manaraa.com

switching, since forcing an auditor change could have negative implications for the engagement if the client is currently with a first-best choice of auditor. My findings are also important for researchers who are considering aspects of the auditor-client relationship, since prior literature typically only contains controls for auditor types (e.g., Big4/non-Big4, industry specialist/non-specialist) rather than considering the specific auditor being engaged.

The rest of the paper proceeds as follows. The next section develops the hypotheses and discusses prior literature. Following that section is the rationale and foundation for the similarity measures, a demonstration of how they are calculated, and a discussion of observed trends. A description of the design and results of the empirical tests follows, while the next section examines these results for their sensitivity to changes in the similarity measures. The final section contains the conclusion.

Hypotheses and Prior Literature

Auditor-Client Compatibility and Selection of Auditor

To make predictions about the choice of an auditor based on auditor-client compatibility requires two conditions: (1) variation in client preferences regarding the audit and auditor, and (2) variation in auditors' abilities to satisfy those preferences. If auditors are all essentially equivalent (no auditor variation), clients would randomly choose between them. On the other hand, if auditors vary but clients all have the same preferences, then all the clients would strictly prefer the "one" auditor that best suited their uniform preferences, which is a condition not observed in the U.S. audit market. Therefore, the only situation which would lead to predictable patterns in auditor choice is the one in which both clients and auditors have variation within their respective groups.

المنارة للاستشارات
www.manaraa.com

The literature has documented substantial evidence of variation in client preferences and auditor capability. For example, a large, multinational client is more likely to choose a BigN auditor (Chaney et al. 2004), at least in part because a smaller auditor does not have the resources and capability of auditing such a company. A large number of studies have also focused on industry specialization as a differentiator of both demand and supply. Industry specialists are those auditors that have invested significantly in developing expertise in auditing a particular industry, typically proxied for by having higher market share in that industry. Specialists are typically better at detecting errors (Owhoso et al. 2002), and are associated with clients having higher earnings response coefficients (Balsam et al. 2003; Gul et al. 2009) and lower discretionary accruals (Krishnan 2003). They are also better at improving audit quality through knowledge spillover from non-audit services they provide (Lim and Tan 2008).

Beyond variation in quality, there are also cost structure differences among specialists. While most studies have found specialists charge higher audit fees (Gramling and Stone 2001), there is also the possibility of cost savings through the same expertise (Cahan et al. 2008; Craswell et al. 1995; Willenborg 2002). Audits by industry specialists also tend to be more efficient (Cairney and Young 2006). Client preferences for certain quality levels and cost structures will lead them to choose an auditor with structural characteristics that best meet their needs.[3]

While most prior literature has focused on broad categories of auditor (e.g., Big4 or non-Big4, specialist or non-specialist), some studies have examined client

[3] Investor preference can also play a role in the decision. Switches to larger auditors and specialist auditors are associated with positive market reactions (Fried and Schiff 1981; Knechel et al. 2007; Nichols and Smith 1983).

المنارة للاستشارات

www.manaraa.com

motivations for choosing a *specific* auditor. For instance, Lennox and Park (2007) find that a company is more likely to engage a particular auditor when a former employee of that auditor is now on the management team of the client. Research on client-auditor disagreements about accounting treatments finds that a client is more likely to switch auditors in the presence of more conservative accounting treatments, presumably in an effort to find an auditor who is more amenable to the company's preferences (DeFond and Subramanyam 1998; Krishnan 1994). Bamber and Iyer (2007) find that auditors who more strongly identify with the client will be more likely to allow the desired accounting treatment. While this "opinion shopping" may sound disreputable, Dye (1991) shows that the firm may simply be trying to better communicate its internal information to the market. The broad conclusion is that interpersonal relationships and opinion shopping are just two ways a client can find one auditor to be a more compelling alternative than others.

Given sufficient variation among clients and auditors, each of them will attempt to maximize their respective utilities by choosing a counterparty that best matches its preferences. While auditors can appear very similar on the surface, there are likely to be subtle differences that make one auditor a better fit than another. Considering all a client's needs and preferences, one specific auditor will likely provide a higher net benefit to the client.[4] Therefore, I predict in alternative form:

> H1: Clients will tend to be with an auditor having a higher degree of auditor-client compatibility than one with a poorer compatibility.

[4] The decision is also subject to various constraints. For example, Coca-Cola is unlikely to choose the same auditor as PepsiCo due to competitive concerns. I do not specifically address this issue in this paper, but the effect will be to shift a client away from its apparent best fit, thus working against my findings.

المنارة للاستشارات
www.manaraa.com

Auditor-Client Compatibility and Auditor Switching

Under H1, clients on average will prefer higher compatibility with their auditors; I now examine the outcome when the fit is suboptimal. Johnson and Lys (1990) demonstrate companies are more likely to switch auditors as the client's operating, investing, and financing activities change over time. They interpret this higher likelihood of switching as a rational, efficient response to temporal changes in the company's audit preferences. In effect, the auditor-client compatibility that was utility-maximizing in the past has shifted such that another auditor may now be a better fit.

Shu (2000) examines auditor-client fit based on whether the client is with a BigN auditor when an empirical model would predict a non-BigN auditor, or vice versa, finding clients are more likely to change auditors when there is a mismatch between the two. I extend this concept to examine whether such mismatches with a specific auditor are more likely to lead to auditor switches. Based on the degree of fit between the auditor and client, I expect that poor compatibility is more likely to lead to an auditor switch than better compatibility. Therefore, I predict in alternative form:

> H2: Clients having relatively poorer compatibility with their current auditor will be more likely to change auditors.

Once a client has made the decision to change auditors, it will need to choose from the remaining available auditors. For example, if the company always limits itself to Big4 auditors, a maximum of three auditors remain, subject to further constraints such as the auditor choices of close competitors and non-audit service providers. Combining the first two hypotheses leads to the expectation that, after deciding the benefits of changing auditors will exceed the switching costs, a company will generally prefer a

المنارة للاستشارات
www.manaraa.com

new auditor that has a better compatibility from among the remaining options.[5]

Therefore, in alternative form, I expect:

> H3: A client switching auditors will tend to choose a new auditor that has a relatively higher degree of compatibility among the non-incumbent auditors.

Effect of Changes in Auditor-Client Compatibility

If compatibility affects audit quality and cost, then the degree of auditor-client compatibility should lead to changes in observable audit process outcomes. Hammersley (2006) shows "matched" specialists—defined as those operating within their industry of expertise—are more likely to process experimental cues regarding misstatements than mismatched specialists. Low (2004) shows that a similar industry-based mismatch affects the audit planning and risk assessments occurring before the audit even begins. These experimental studies imply that audit quality will be higher when there is a better fit between the auditor and client. Johnstone, Li, and Luo (2011) find that clients within the same supply chain—a measure of relatedness, if not similarity—tend to have higher audit quality.

On the other hand, a sizable literature finds decreased audit quality when the auditor more closely identifies with the client. In essence, the auditor-client compatibility has become so good that the auditor's independence is compromised. Lennox (2005) shows that companies are more likely to receive a clean audit opinion if the auditor becomes affiliated with the client by hiring its former auditors. Menon and Williams (2004) find clients employing former audit partners in executive positions tend to report higher levels of discretionary accruals. Based on existing evidence about the relation

[5] I do not predict that the new auditor will necessarily have a better fit than the previous auditor, primarily because of the endogenous nature of compatibility —a client may appear to become a better fit for an auditor over time as the auditor's preferences modify the client's observable financial statements and related disclosures.

www.manaraa.com

between compatibility and audit quality, I expect that switching to an auditor with a better fit will change audit quality in the years following such a change. However, I do not make a signed prediction. Therefore, in alternative form:

H4: Audit quality is associated with auditor-client compatibility.

Measurement of Auditor-Client Compatibility

When clients are closely related to one another, auditors have the opportunity to specialize in those companies for both reputational and audit production reasons.[6] While prior literature typically uses an "all-or-nothing" industry membership test to organize clients into similar groups, I introduce continuous proxies for the degree of compatibility between a company and an auditor's existing client base. I base these measures on two existing streams of academic research that study inter-entity similarity, the two being differentiated by the nature of the underlying data. The first stream is cluster analysis, along with related fields such as factor analysis, and is primarily concerned with grouping similar entities together based on a small set of numeric data (e.g., financial statement accounts). The second stream is the information retrieval literature, which uses documents as the underlying data (e.g., narrative disclosures).

I develop client-year measures of similarity for both financial statement and narrative textual disclosures since they represent different, but complimentary, signals. While the accounting systems and underlying economics are not separately observable, their joint effect is reflected in the financial statements. The narrative disclosures also provide economic and accounting system information, but contain additional information about management's interpretation of past events and expectations about the future.

[6] Gramling and Stone (2001) summarize the industry specialization literature, which generally finds differences in both quality and audit fees for industry specialists versus non-specialists.

www.manaraa.com

The narrative disclosures are especially flexible, giving the opportunity for management to communicate more firm-specific information or otherwise influence the market's view of the company. These two signals are each necessary to better understand the other and, taken together, provide a more comprehensive view of how the clients of an auditor relate to one another.

Financial Statement Similarity

Algorithms used in cluster analysis of numeric data include the Euclidean distance, city-block distance, Chebychev distance, and Mahalanobis distance (Hair et al. 2006). Of these, the Mahalanobis distance-squared (D^2) is particularly sophisticated in its ability to weight each variable equally according to its individual scale, as well as account for covariances among the various components. Introduced in Mahalanobis (1936), the D^2 statistic imposes few restrictions on the underlying variables, only requiring non-degenerate distributions. After scaling and accounting for covariance of the variables, an observation's distance from the group is larger when the variables for the observation are jointly more "unusual." The D^2 measure is the generally preferred algorithm in cluster analysis, when available (Hair et al. 2006).

Outside of the accounting literature, D^2 has been used in management to compare the distance between countries along multiple dimensions, including economic, financial, political, cultural, demographic, and geographic location (Berry et al. 2010). Climatologists have used the measure to look for boundaries between different regional climates (Mimmack et al. 2001). And chemists have used it for multivariate calibration, pattern recognition and process control (De Maesschalck et al. 2000).

Prior accounting literature has used the D^2 measure to a limited extent. Rege (1984) uses it to test the effectiveness of a discriminant function in classifying data into

للاستشارات المنارة
www.manaraa.com

two groups of likely and unlikely takeover targets. If the distance between the two groups is significant then the discriminant function is considered effective. Iyer (1998) also employs the statistic in a discriminant function context to maximize the distance between subgroups. Guilding and McManus (2002) use the measure to test for potentially influential outlying observations. However, all these studies use the measure in a statistical context and do not examine the properties of the distance itself.[7] Due to the D^2 measure's power and flexibility, I use it as my primary measure of financial statement similarity.

Because there is limited theoretical guidance on which variables might be appropriate for determining financial statement similarity, I use financial variables having well-known significance in an audit context. Client size, complexity, and risk are important aspects of the audit (Hay et al. 2006). I include company size as the log of total assets (*SIZE*) to capture the scope and potential importance of the client. The combination of inventory and receivables proxies for audit risk inherent to the company (*IRISK*). Total accruals is a known audit risk factor and possible indicator of audit quality, so *TACC* is calculated as in Defond and Subramanyam (1998). Cash and equivalents (*CASH*) is a proxy for liquidity, while return on assets (*ROA*) measures profitability; both are indicators of higher client stability and lower risk. All measures except *SIZE* are scaled by total assets.[8]

[7] The abnormal accrual model could also be conceptualized as a distance measure. It empirically models the relationship between total accruals and various explanatory variables to attempt detection of accrual levels that are unusual-looking relative to peer companies.

[8] Other potential inputs, various permutations of those inputs, and alternative measurement approaches are described in the robustness section.

www.manaraa.com

To calculate the D^2 distance for my sample, I gather these five variables from Compustat, only using observations having assets greater than $1 million, with no fiscal year end change, and not in the utilities or financial services industries. The sample begins in 1997, when EDGAR data is first widely available for my narrative similarity scores, and ends in 2009. I include former Arthur Andersen clients only after they have not engaged Andersen for at least one year to limit the potential confounding effect of this one-time event.

The concept of similarity is with respect to some group of other objects and is undefined for a single observation on its own. I call these other observations the *reference group*, which I define as other clients in the same auditor-industry-year. [9] I exclude any reference groups that do not have at least five observations; the similarity score is unlikely to be reliable if there are too few observations in the group. Because the reference groups are rarely large enough for non-Big4 auditors, I explicitly limit the sample to Big 4 clients. Finally, I do not allow companies in the reference group in the year that they switch auditors.

Each observation in the sample has n = 5 financial statement variables, which are contained in the transposed vector, $x^T = (x_1, x_2, \ldots, x_n) = (SIZE, IRISK, TACC, CASH, ROA)$. An observation is contained in an auditor-industry-year group having mean

[9] Hogan and Jeter (1999) document the increasing importance of auditor restructuring along industry lines at the national level to take better advantage of internal teams of experts. While client compatibility can also vary at the auditor office level, there are few offices with enough clients to calculate my similarity measures within an industry. Calculating the scores at the office-industry level would lead to a 63% reduction in sample size (and a 30% reduction if calculated at the office-sector level).

www.manaraa.com

values of the same variables, $\mu^T = (\mu_1, \mu_2, \ldots, \mu_n)$. Finally, the group has a covariance matrix, Σ, for the five inputs. The Mahalanobis distance-squared is then calculated as:[10]

$$D^2 = (x - \mu)^T \Sigma^{-1} (x - \mu)$$

The scores are calculated within a GICS industry due to the general lack of comparability across industries. I generate the ($x - \mu$) portion of the measure by subtracting the auditor-industry-year mean for each variable from the variables for the company-year being analyzed. I compute the Σ covariance matrix at the industry-year level to account for different scales and covariances across industries and over time that are unlikely to vary significantly between auditors.[11] Because D^2 is a measure of dissimilarity, I convert it to a similarity measure by taking the inverse. The natural log reduces skewness and outliers:

$$SIM_{FS} = ln\left(\frac{1}{D^2}\right)$$

Narrative Disclosure Similarity

The information retrieval literature has developed numerous methods for measuring the similarity of two documents, often in the context of matching a user's Internet search query to the closest applicable web pages (Singhal 2001). Assuming the ability to map a document into a numeric representation, the D^2 measure is also conceptually possible in a document context. However, practical considerations limit its

[10] The Euclidian distance between observations is a special case of the Mahalanobis distance. If the covariance matrix (Σ) is the identity matrix, the square root of D^2 simplifies to the familiar $[(x-\mu)^T(x-\mu)]^{½}$, which is the Pythagorean theorem if the vector has length two.

[11] Multicollinearity is not problematic as it would be in a regression. However, as the variables approach nearly perfect multicollinearity, the covariance matrix will not be invertible, which can be a concern when using a small vector of variables in a small industry. While unusual in my sample, I exclude industry-years that do not have at least ten company-year observations (twice the number of variables). This restriction is almost always met given the earlier restriction of at least five observations with an *auditor*-industry-year.

المنارة للاستشارات
www.manaraa.com

usefulness. When mapping a list of words from narrative text into variable vectors, the high dimensionality makes calculation of the D^2 measure impractical.[12]

Given these computational challenges, I instead use the Vector Space Model (VSM) from the document retrieval literature that can better accommodate large sets of long text. The VSM maps a document into a numeric vector (Salton et al. 1975). There are numerous ways to calculate the similarity of these document vectors. The most common approach is to calculate the cosine of the angle between any two vectors (Singhal 2001), an approach used in the accounting literature by Brown and Tucker (2011). They use the VSM cosine statistic to measure year-over-year dissimilarities in MD&A as a proxy for changes in narrative disclosure. Because they are interested in the differences between just two documents at a time, they only calculate pairwise similarity scores. In contrast, I aggregate these pairwise scores to get a measure of the similarity between one narrative disclosure and the disclosures issued by a reference group of clients within the same auditor-industry-year. Due to its relative ubiquity in information retrieval and its presence in existing accounting literature, I use the VSM-based cosine similarity score as my measure of narrative disclosure similarity.[13]

To calculate the similarity of clients along a narrative disclosure dimension, I use important items from the annual report to ensure the disclosures are reviewed by the

[12] For example, a covariance matrix using the 98,519 unique words for the MD&A in my sample would contain 9.7 billion elements. The matrix would then need to be inverted. The large size of the matrix arises not primarily from the number of documents, but from the unique words used in those documents. While the two are positively correlated, calculating the D^2 measure on a subset of documents would not generally address the computational difficulties.

[13] While I cannot feasibly calculate the D^2 statistic for documents, I *can* do the reverse and calculate the VSM similarity for financial statements. Using such an approach, Jaffe (1986) uses vectors of different categories of patent applications to examine R&D spending overlap within industries. I avoid this approach because the VSM does not account for variances and covariances of the variable components, which reduces its statistical power.

www.manaraa.com

auditor, not voluntary, and considered important by the capital markets and regulators. Within the 10-K, the longest disclosure items tend to be the business description, Management's Discussion & Analysis (MD&A), and the financial statement footnotes. Excluding exhibits, there are an average of 6,338 words in the business description, 7,054 in the MD&A, and 8,623 in the footnotes (see Table B-1), comprising 17, 18, and 21 percent, respectively, of the length of the typical 10-K.[14]

I use multiple 10-K items because there is considerable variation in the characteristics of each disclosure along several dimensions: (1) subject matter, (2) time-horizon, and (3) audit requirements. First, the topics discussed in each item are different. Item 101 of Regulation S-K requires the 10-K item 1 contain a detailed narrative description of the business, including industrial and geographic segments, principal products and services, R&D spending, and competitive conditions. Item 303(a) requires that the MD&A contain a discussion of liquidity, capital resources, results of operations, off-balance sheet arrangements, and contractual obligations. Even though there is some topical overlap, the footnote content is typically determined by GAAP. Second, the MD&A is intended to be an interpretation of past and future operations "through the eyes of management" (SEC 2003). Given certain conditions, any forward-looking statements receive Safe Harbor protection (Item 303(c) of Regulation S-K). In contrast, regulations do not broadly require footnotes to explicitly contain interpretive or forward-looking statements. Third, the footnotes are audited, while the business

[14] The footnotes and MD&A seem particularly important to stakeholders, given the large number of accounting standards requiring or encouraging specific footnote disclosures and the relatively frequent guidance by the SEC on MD&A (e.g., SEC 1987; 1989; 2003). Prior studies have demonstrated the usefulness of footnotes (e.g., Shevlin 1991; Amir 1993; Wahlen 1994; Riedl and Srinivasan 2010). Other research has shown some of the potential information contained in MD&A (e.g., Feldman et al. 2010; Feng Li 2010; Sun 2010). Of the three narrative disclosures, the business description is relatively unexplored except in studies of the full 10-K as a single document (e.g., Li 2008).

المنارة للاستشارات
www.manaraa.com

description and MD&A are not audited but are only reviewed for material misstatements and consistency with facts known to the auditor (AU Sections 550; 551). While all narrative disclosures are somewhat flexible, the lack of an explicit audit of the business description and MD&A gives management the greatest flexibility to choose the topics and quality of discussion. Because all three have distinct characteristics, I use each as a separate source of narrative disclosure.

For the narrative disclosure sample, I use 10-K's filed electronically via the SEC's EDGAR system for fiscal years 1997 through 2009. As in the financial statement sample, the disclosures in the text samples are by Big4 clients having at least five other observations available for comparison within the same auditor-industry-year reference group. Appendix A describes the selection and extraction process, which yields 33,355 business description, 31,280 MD&A, and 14,439 footnote observations.

Treating the three narrative disclosure items of the annual report as separate data sets, I calculate the similarity score for each using an extension of the approach in Brown and Tucker (2011) that allows for a comparison of a company to its peers. The process, summarized in Appendix B, produces three variables—SIM_{BUS}, $SIM_{MD\&A}$, and SIM_{NOTES}—that proxy for the degree of similarity between one client and other clients in the same auditor-industry-year. Higher similarity scores correspond to greater auditor-client compatibility.

Patterns in Client Similarity

Panel A of Table 2-1 contains descriptive statistics for the financial statement and narrative disclosure similarity measures. Higher similarity scores indicate greater

www.manaraa.com

similarity in relation to the reference group.[15] SIM_{FS} is always negative because of the log transformation. The sample contains the largest number of observations for this similarity measure since the financial statement components used to construct SIM_{FS} are available for nearly all company-years in Compustat. The narrative disclosure similarities (SIM_{BUS}, $SIM_{MD\&A}$, and SIM_{NOTES}) are approximately centered around zero.[16] Similarity scores are significantly higher for companies in the top quartile of size than for those in the bottom quartile (untabulated), indicating that bigger clients tend to be at the "core" of the auditor's portfolio in terms of their similarity.

The four similarity scores are not directly comparable to one another because of variations in how they are calculated (e.g., a score of 0.20 for MD&A is not necessarily larger than a score of 0.15 for footnotes). To compare across measures, I standardize each of them to have a mean of zero and standard deviation of one. In Figure 2-1, I plot these values against auditor tenure—the number of years with the current auditor. A tenure value of zero corresponds to the year before an auditor change and a value of one is the first year after a switch. For visual comparability, all scores are adjusted to begin at zero when auditor tenure is zero. The graph ends in year ten of the audit engagement since a decreasing number of observations after this point leads to heightened volatility in the graph.

All similarity measures increase over the length of the auditor-client relationship, indicating auditor-client compatibility improves over time. Auditors might find this trend

---

[15] The average auditor-industry-year reference group size is 38 clients for financial statements, 23 for the business description, 22 for MD&A, and 12 for the footnotes.

[16] As noted in Appendix B, I maximize the sample size for making the length adjustment by using all available observations, including non-Big4 auditors. After restricting the study sample to only Big4 clients, the mean is slightly above zero.

www.manaraa.com

beneficial to the extent that it improves the quality or reduces the effort involved in the audit engagement. Likewise, clients might benefit from adopting best practices arising from the auditor's expertise developed in similar client engagements.

The business description experiences a rapid increase in similarity during the first two years of the engagement, after which point the similarity becomes more stable. MD&A similarity also increases quickly in the first two years and then rises more slowly until approximately year seven. The trends in financial statement and footnote similarities are highly correlated, which is not surprising since those disclosures are intended to be closely aligned by regulation. Both of these measures increase gradually over time, with no sudden jump in the early years of the relationship.

To test for the statistical significance of these trends, I compare the means of similarity for engagements with a short tenure (less than four years) to those with a long tenure (nine or more years). In all cases, the similarity scores are significantly higher for longer-tenure clients than for shorter ones. I perform a related test using year-over-year changes in similarity and find that the annual changes for long-tenure clients are not as large as the changes seen in newer clients.[17] These patterns all demonstrate that auditor-client compatibility is not just a static component of the relationship, but at least partially a function of the length of auditor tenure.

Validation of Similarity Measures

Table 2-2 shows the Pearson pairwise correlations among the similarity measures. I limit the correlations to those observations with scores available for all four disclosures

[17] The t-statistics for the difference in means of the financial statements, business description, MD&A, and footnotes are: 24.10, 4.61, 5.13, and 8.72, respectively. The corresponding t-statistics for the difference in changes are: 6.55, 2.94, 2.29, and 1.63.

المنارة للاستشارات
www.manaraa.com

(narrative and financial), although the unrestricted correlations are similar. The four similarity scores are all positively correlated with one another, indicating they measure related constructs. The correlations are higher among the three narrative disclosures (ranging from 0.61 to 0.72) than they are with the financial statements (from 0.05 to 0.11).

As a means of validation, the table also contains the correlations between the similarity measures and various proxies for client differences, which I expect to be negative. For each variable used to produce SIM_{FS} (*SIZE*, *IRISK*, *TACC*, *CASH*, and *ROA*), I calculate the client's absolute difference from the mean for the auditor-client-year, calling them |*SIZEDIFF*|, |*IRISKDIFF*|, |*TACCDIFF*|, |*CASHDIFF*|, and |*ROADIFF*|.[18] The correlations with SIM_{FS} are all significant, ranging from -0.25 to -0.42. More importantly, the significant correlations between these difference variables and all the narrative disclosure scores are also negative, indicating the proper functioning of the narrative scores even though they did not explicitly include any financial statement variables. Of all the difference variables, |*ROADIFF*| and |*TACCDIFF*| have the highest negative correlation with SIM_{FS}, so client profitability and accruals appear to be important determinants of financial statement similarity. On the other hand, |*IRISKDIFF*| has the most negative correlation with the three narrative similarities, consistent with the importance of the numerous risk-related disclosures in annual report items (e.g., Kravet and Muslu 2010; Campbell et al. 2010).

[18] These difference variables should be negatively correlated with SIM_{FS} by design, but these correlations document the SIM_{FS} measure is working as expected. Performing a series of univariate correlation tests is also substantially different from the joint difference measure produced using the D^2 technique.

المنارة للاستشارات
www.manaraa.com

For an alternative measure of client difference, I use the absolute value of unexpected discretionary accruals. Following DeFond and Jiambalvo (1994), I estimate accruals with a cross-sectional modified Jones model run within SIC 2-digit industries. The residual from this model is *DACC*, the unexpected discretionary accruals. As expected, all the similarity scores are significantly negatively correlated with the absolute value of *DACC*.

As a final validation, I expect that auditor-client compatibility will not change dramatically over short time periods because of the general stability in financial statements, related disclosures, and client portfolios. Large changes in the similarity measure from year to year are unlikely if the similarity measure is capturing the desired construct. In untabulated analysis, I calculate the autocorrelation coefficient for SIM_{FS} (0.55), SIM_{BUS} (0.93), $SIM_{MD\&A}$ (0.92), and SIM_{NOTES} (0.92), demonstrating a high degree of time-series stability in all four measures.

Analysis of Auditor-Client Alignment

Sample

For the hypotheses tests, I collect additional data from Compustat for each observation with at least one similarity score available. The other variables, summarized in Table 2-1, begin in 1997, corresponding with the earliest availability of the narrative disclosure data, and end in 2009. Auditor tenure is calculated based on the current auditor information in Compustat beginning in 1974.

Typical Auditor-Client Alignment

If clients and auditors randomly choose to enter into an audit engagement without regard to auditor-client alignment, one would expect approximately a 25% probability that a client would be with each of the Big4 auditors. According to the first hypothesis, a

المنارة للاستشارات
www.manaraa.com

client is more likely to be with an auditor having other clients similar to itself and are least likely to be with an auditor having a less similar set of clients. Table 2-3, Panel A contains a summary of auditor-client alignment using each of the similarity scores. For financial statements, more clients are with the auditor having the best fit (26%) than with the worst fit (24%). When examining the business description, 27% of clients are with the auditor they are most aligned with, but only 23% are with the auditor with which they are least aligned. The MD&A pattern is even stronger, with 30% of clients being with the most aligned auditor and just 21% with the least aligned auditor. The strongest pattern occurs when using the footnotes, where 32% of clients are using the most similar auditor and only 20% are with the least similar auditor. In each case, the probabilities monotonically decline as auditor-client alignment decreases.

To evaluate the statistical significance of these patterns, I compare the average auditor-client alignment rank with the expected rank under the null of a random distribution.[19] Since the ranks range from one to four, the null hypothesis would predict an average rank of 2.5.[20] Comparing the average rank of each score to the null of 2.5 gives a test of the tendency of clients to be with a more closely aligned auditor than with a less aligned one, without requiring them to necessarily be with the *most* similar auditor. Table 2-3, Panel B shows the average rank of the incumbent auditor based on auditor-client alignment. The average ranks are 2.47 ($t = 5.67$) when using the financial

[19] An alternate approach would be to model the alignment rank using an ordered logit/probit, which would also allow me to control for other factors. Unfortunately, I am unaware of any existing model in the literature that would be useful for this purpose. Two streams of literature—the choice of an industry specialist auditor and the choice of a BigN/Non-BigN auditor—would seemingly be the most relevant for developing such a model. However, modeling the rank using a wide variety of variables from these literatures did not yield a model with a statistically significant fit.

[20] The expected average rank under the null is: $(1 + 2 + 3 + 4) / 4 = 2.5$

www.manaraa.com

statements, 2.43 (t = 10.86) for the business description, 2.36 (t = 21.42) for MD&A, and 2.29 (t = 19.56) for the footnotes, all of which are significantly less than 2.5. The overall conclusion is that, based on the contents of their disclosures, clients are significantly more likely to be with better-fitting auditors than with poorer-fitting ones.

Likelihood of Auditor Change

Although clients tend to be with better-aligned auditors, the simple descriptive analysis in the previous section does not address whether this pattern occurs because clients and auditors jointly choose an engagement that already has a higher alignment, or whether clients merely become more similar to their auditor over time as a side effect of the audit process. Therefore, in this section and the next, I undertake several analyses surrounding auditor switches to address these two possible explanations. First, I model the decision to change auditors, using important variables from the existing auditor switching literature, and then augment this model with my auditor-client alignment measures. The basic logit model predicts a switch in the subsequent year using current-year variables (firm and year subscripts are suppressed):

$$SWITCH = a_0 + a_1 SIZE + a_2 IRISK + a_3 GROWTH + a_4 MODOPIN + a_5 TENURE10 + a_6 ROA + a_7 LOSS + a_8 CASH + a_9 ACQUIS + industry + year + \varepsilon \quad (2\text{-}1)$$

The dependent variable, *SWITCH*, is an indicator set to one if the client will change auditors in the subsequent year; all other variables are measured in the current year. Because I expect larger firms to change auditors less frequently, I start by including the natural log of total assets (*SIZE*) in the model. Following Landsman et al. (2009), I include a variety of controls for audit and financial risk. As proxies for audit risk, I include growth, inherent risk, the nature of the audit opinion, and auditor tenure.

www.manaraa.com

GROWTH in assets is associated with greater litigation risk for the auditor. Inherent audit risk (*IRISK*) is defined as receivables plus inventories, scaled by total assets. *MODOPIN* is a dummy set to one for anything other than a clean opinion with no modifying language. I expect all these elements of audit risk to be negatively associated with the probability of an auditor switch. As in Landsman et al. (2009), *TENURE10* is the number of years the client has engaged its current auditor, with a maximum value of 10 years. I predict this variable will be positively associated with auditor changes, both because of the general stability of most auditor-client relationships and the higher risk accompanying the early learning years of the engagement.

To proxy for financial risk, I include both return on assets (*ROA*) and a dummy set to one when ROA is less than zero (*LOSS*). I expect that both of these controls will be positively associated with auditor switches. On the other hand, higher cash and equivalents scaled by total assets (*CASH*) proxies for the relative lack of financial risk for a client.[21] Because M&A activity can lead to an increased likelihood of changing auditors when the previously separate entities engaged different auditors, I include a dummy set equal to one when the current client has engaged in acquisition activity during the prior year that exceeds ten percent of total assets (*ACQUIS*).[22] The correlations among these variables are presented in Panel A of Table 2-4. The correlations with the similarity scores imply larger (*SIZE*), more profitable (*ROA*), and less risky companies (*IRISK*) are more likely to have a better fit with their auditor. This

[21] I omit the leverage variable in Landsman et al. (2009) since it is not significant in their study or mine. I also leave out their measure of absolute discretionary accruals because this variable also proxies for the relative "unusualness" of the client relative to the industry, which is my construct of interest. However, including it does not change my conclusions.

[22] I winsorize all controls other than dummies and log-transformed variables at the 1st and 99th percentiles.

المنارة للاستشارات
www.manaraa.com

pattern would arise if these types of companies are more likely to be able to engage their preferred auditor, a potential constraint for peers that may not be able to engage their first-best choice if that auditor declines the engagement due to concerns about audit or financial risk.

I augment Equation 2-1 with each of my proxies for auditor-client fit as measured in the year before the switch and present the results in Table 2-4, Panel B. The controls are generally consistent with prior literature. All similarity measures except for SIM_{BUS} are negatively related to auditor switches. SIM_{FS} (t = 4.72), $SIM_{MD\&A}$ (t = 3.40) and SIM_{NOTES} (t = 3.78) have negative coefficients, supporting the prediction in the second hypothesis that clients having a poorer fit with their auditor are more likely to switch to a new auditor. Holding all the other variables at their means, an interquartile decrease in financial statement similarity is associated with a 9.2 percent higher probability of switching. The increase for MD&A is 11.8 percent and for footnotes is 18.9 percent. This result explains one of the mechanisms through which the patterns in Table 2-3 may occur: clients tend to be with a better-fitting auditor because they are more likely to change auditors when the fit is poor. Since the coefficient on SIM_{BUS} is insignificant, the fit observed by examining the discussion of operating results and risks in the MD&A and the detailed accounting disclosures in the footnotes appear to be better predictors of an auditor switch than the general business description text.

Auditor Choice Conditional on Decision to Switch Auditors

Hypothesis 3 predicts company behavior following the decision to switch auditors, a situation in which the client has already decided the net benefits of a change outweigh the switching costs. Table 2-3, Panel C, summarizes the average rank of the new auditor. Consistent with the earlier results for incumbent auditors, these clients tend to

المنارة للاستشارات
www.manaraa.com

choose a new auditor with better auditor-client fit. To test the statistical significance of this pattern, I compare the average rank of the new auditor to the prediction under the null.[23] In Table 2-3, Panel D, the average rank of the financial statements is 1.96 (t = 1.91; p-value = 0.028), the business description is 1.94 (t = 2.11; p-value = 0.018), the MD&A is 1.86 (t = 4.85), and the footnotes is 1.89 (t = 2.19; p-value = 0.015). Therefore, all similarity measures imply clients are significantly more likely to choose a better-fitting auditor when switching among the Big4.

While these tests may seem to overlap with the earlier tests of typical auditor-client fit, they provide insight into whether the commonly observed pattern is due to (1) a decision made by clients to choose an auditor with better fit or (2) clients becoming more aligned with their auditors as the auditors' preferences gradually affect the clients' disclosures over time. Consistent with the tenure-related increase in auditor-client fit demonstrated in Figure 2-1, fit could be solely the *result* of the engagement rather than a causal factor. However, the patterns in Table 2-3 appear to support the first of these explanations: fit is relevant in the auditor selection process and is not merely an outcome of the audit process itself.

Changes in Audit Quality Conditional on Auditor-Client Fit

To test whether audit quality is affected by auditor-client fit, I compare the audit quality of engagements with better fit to those with poorer fit. There are multiple empirical proxies for audit quality; I start the analysis by examining discretionary accruals before considering the existence of Accounting and Auditing Enforcement Releases (AAER's) issued by the SEC.

[23] A random choice among auditors would imply a rank of (1 + 2 + 3)/3 = 2.

المنارة للاستشارات
www.manaraa.com

Discretionary accruals

Signed discretionary accruals are often used as a proxy for audit quality, with income-decreasing accruals representing conservatism and income-increasing accruals corresponding to aggressive accounting practices. For such a proxy, I use discretionary accruals (*DACC*) as defined in DeFond and Subramanyam (1998). Of the four similarity measures, SIM_{FS} has a positive univariate correlation of 0.10 with *DACC* (untabulated), while the others are uncorrelated. I test for differences in discretionary accruals between clients having the best auditor-client fit (i.e., a rank of one in Table 2-3) and those having the worst fit. *DACC* is lower for better-fitting auditors based on the business description (t = 1.50; p-value = 0.067) and MD&A (t = 1.73; p-value = 0.042). Discretionary accruals are insignificantly lower for the financial statement and footnote samples. When focusing on changes that occur in the first year after the switch (rather than levels), there is a significantly larger decrease in discretionary accruals for better-fitting auditors than for less compatible ones. However, this pattern only occurs for the financial statement measure, while the other measures are insignificant.

Accounting and Auditing Enforcement Releases

AAER's indicate the presence of a severe misstatement, and therefore represents extreme instances of poor audit quality. The advantage of AAER's is that a significant problem truly exists, which may not be the case with extreme levels of continuous proxies such as discretionary accruals. The disadvantage is a relatively small sample size given their severe nature. I rely on a highly-developed logistic model of AAER's described by Dechow et al. (2011):

www.manaraa.com

$$AAER = a_0 + a_1 RSST\_ACC + a_2 CH\_REC + a_3 CH\_INV + a_4 SOFT\_ASSETS + a_5 CH\_CS + a_6 CH\_ROA + a_7 ISSUE + \varepsilon \quad (2\text{-}2)$$

The AAER data is a hand-collected dataset provided by the authors of Dechow et al. (2011) that covers all AAER's issued starting in 1982. Since the actual AAER is issued later—and sometimes much later—than the misstatement itself, I only consider fiscal year 2003 and earlier, which is the last year with at least 50 AAER's available. *AAER* is an indicator set to one if the SEC has issued an AAER that covers a particular fiscal year. The first four independent variables proxy for various aspects of accruals quality. *RSST_ACC* measures accruals as described in Richardson et al. (2005). *CH_REC* and *CH_INV* are the change in accounts receivables and change in inventory, respectively, scaled by assets. *SOFT_ASSETS* are scaled total assets after removing fixed assets and cash equivalents. The next two variables are performance-related. *CH_CS* measures year-over-year change in cash sales and *CH_ROA* is the change in return on assets. Finally, *ISSUE* is an indicator variable set to one if the firm issued securities during the year.[24] The pairwise correlations of these variables are in Table 2-5, Panel A.

Using Equation 2-2 as a starting point, I add each of the auditor-client fit measures in turn, with the results of these tests in Panel B of Table 2-5.[25] Hypothesis 4 anticipates a cross-sectional association between audit quality and auditor-client fit, although it does not make a directional prediction. The coefficients on SIM_{FS} (t = 2.83), SIM_{BUS} (t =

[24] All variables except *ISSUE* are winsorized at the 1st and 99th percentiles.

[25] The controls for this test are consistent with, but weaker than, those in Dechow et al. (2011), a condition that arises because my sample period begins after theirs.

المنارة للاستشارات
www.manaraa.com

2.40; p-value = 0.016) and $SIM_{MD\&A}$ (t = 2.77) are significantly positive, while SIM_{NOTES} is not significant. These results generally support the conclusion that a company is *more* likely to receive an AAER as it becomes more similar to other clients of the auditor. Rather than implying higher audit quality arising from this similarity, the risk of major misstatements actually increases. Such a pattern could be explained by opinion shopping, where companies are looking for well-fitting auditors because they are more likely to be able to use a preferred accounting treatment. An alternative explanation is that some audit production-related efficiencies arising due to increasing overlap among clients is actually decreasing audit quality.

Robustness and Sensitivity Analyses

Alternative Inputs for Financial Statement Similarity

Because it is a new measure, I use a variety of alternative inputs for the financial statement similarity score to judge the sensitivity of SIM_{FS}. Because large companies empirically occur less frequently than smaller companies, including *SIZE* as an input could cause the similarity measure to proxy for large clients rather than similarity more generally. I first remove *SIZE* from the input variables, leaving the four other inputs in place. As a second alternative, I include return volatility as an additional input to the original set to capture risk from a market perspective. Finally, I count the number of non-missing/non-zero financial statement variables in Compustat as a measure of audit effort and complexity, since additional financial statement items are likely to increase the scope and intricacy of the audit.[26] None of these changes make a difference in the

[26] The number of reporting segments is frequently used to proxy for audit complexity, but is unavailable for many companies in Compustat. Counting the number of variables serves as a broadly available alternative.

www.manaraa.com

qualitative results. Based on these modifications and others not reported here, the measure seems quite stable and insensitive to the exact mix of input variables.

Clients Switching from Non-Big4 Auditors

Conditional on switching auditors, Hypothesis 3 predicts clients will prefer a better-fitting auditor. My primary test explicitly excludes clients switching from a non-Big4 auditor. I now perform a similar test for clients switching from a non-BigN auditor to a Big4 auditor (i.e., "upward switches"), ignoring the forced changes by Arthur Andersen clients. Because these clients have four auditors from which to choose, the null would predict an average rank of 2.5. Only the footnote sample mean of 2.25 (t = 2.26; p-value = 0.01) implies upward switchers are more likely to choose a better-fitting auditor. None of the other measures are significant. However, in all cases, the magnitudes of the average auditor ranks are similar to those observed in Panel C of Table 2-3. Overall, there may be some constraints on upward switchers' ability to choose the best-fitting auditor, but the lack of statistical significance could be due to smaller sample sizes.

I also examine former Arthur Andersen clients that switched to a Big4 firm following that auditor's collapse. The patterns in this subsample seem the most random of the subsets. Based on my proxies of auditor fit, none of the ranks are significantly different than what is expected under a random auditor selection (the MD&A measure is slightly significant, with a p-value of 0.09). Because the sample sizes are not dramatically smaller than those in Table 2-3, the former Andersen clients appear unlikely to be with an auditor with greater compatibility. This result is not surprising because of the capacity constraints induced by the rapid auditor turnover affecting so many large clients at once.

المنارة للاستشارات
www.manaraa.com

Overall, the choices of clients switching among the Big4 most clearly support the idea that companies choose better-fitting auditors when making a switch. The patterns for upward-switching clients are similar, despite more limited formal significance. However, in the resource-constrained environment following Arthur Andersen's collapse, its former clients seemed unable to choose auditors with high compatibility.

Accounting System Comparability

While I consider a broad notion of client similarity using multiple financial statement variables and narrative disclosure language, De Franco et al. (2011) specifically examine the comparability of accounting systems between companies. For each company, they regress 16 quarters of earnings (an accounting system output) on returns (the net economic events) to estimate the "accounting function" for that company. To determine the similarity between any two observations, they use the fitted accounting function to predict earnings for each observation using actual returns. They interpret the difference between the two predicted earnings values as a measure of the difference in accounting systems. Aggregating these differences for all pairs of observations gives a measure of accounting system similarity for each company within an industry-year (*COMPACCT-IND*). They construct an alternative measure using only earnings by regressing 16 quarters of earnings of one company on the earnings of another. Aggregating the R^2 from each regression also gives a proxy for accounting system similarity (*COMPACCT-R2*). As a sensitivity test to my primary D^2 metric, I calculate these two measures as described in more detail in De Franco et al. (2011) as an alternative to SIM_{FS}.

The *COMPACCT-IND* variable is uncorrelated with the four primary similarity scores I use in the current study. Nor is it correlated with most of my alternative proxies

المنارة للاستشارات
www.manaraa.com

for client differences (|*SIZEDIFF*|, |*IRISKDIFF*|, |*TACCDIFF*|, |*CASHDIFF*|, and *DACC*), with the exception of a -0.06 correlation with |*ROADIFF*|. In contrast, *COMPACCT-R2* has correlations of 0.07, 0.08, and 0.04 with SIM_{BUS}, $SIM_{MD\&A}$ and SIM_{NOTES}, respectively. As an alternative test of auditor changes, I separately include the two accounting comparability measures in the base switch Equation 2-1. They are both negative but insignificant. When examining changes in audit quality, I find an increase in the probability of receiving an AAER as COMPACCTIND increases, but only at the 5 percent significance level; COMPACCTR2 is insignificant.

Concluding Remarks

I find strong evidence that auditor-client compatibility helps predict which auditor a client will choose to engage. When the fit is poorer, clients are more likely to change auditors and choose a compatible auditor from among their remaining options. An interquartile shift in similarity with the current auditor's client base can change the probability of switching auditors by as much as 19 percent. Descriptively, auditor-client fit is a concave function of auditor tenure; compatibility with the incumbent auditor increases over time, but at a decreasing rate. Based on discretionary accruals, overall audit quality increases as auditor-client compatibility increases. However, severe audit failures in the form of AAER's appear to increase as fit improves.

The similarity measures I introduce have additional applications within accounting research. Chapter 3 of this work uses the same measures to look at the effect on audit fees when an auditor's clients have different amounts of overlap in their audit processes. Beyond auditing, the measures can be used to isolate firm-specific disclosures from disclosures that are similar among a set of companies. Econometrically, it is possible to implement a matched-pair design based on having

المنارة للاستشارات
www.manaraa.com

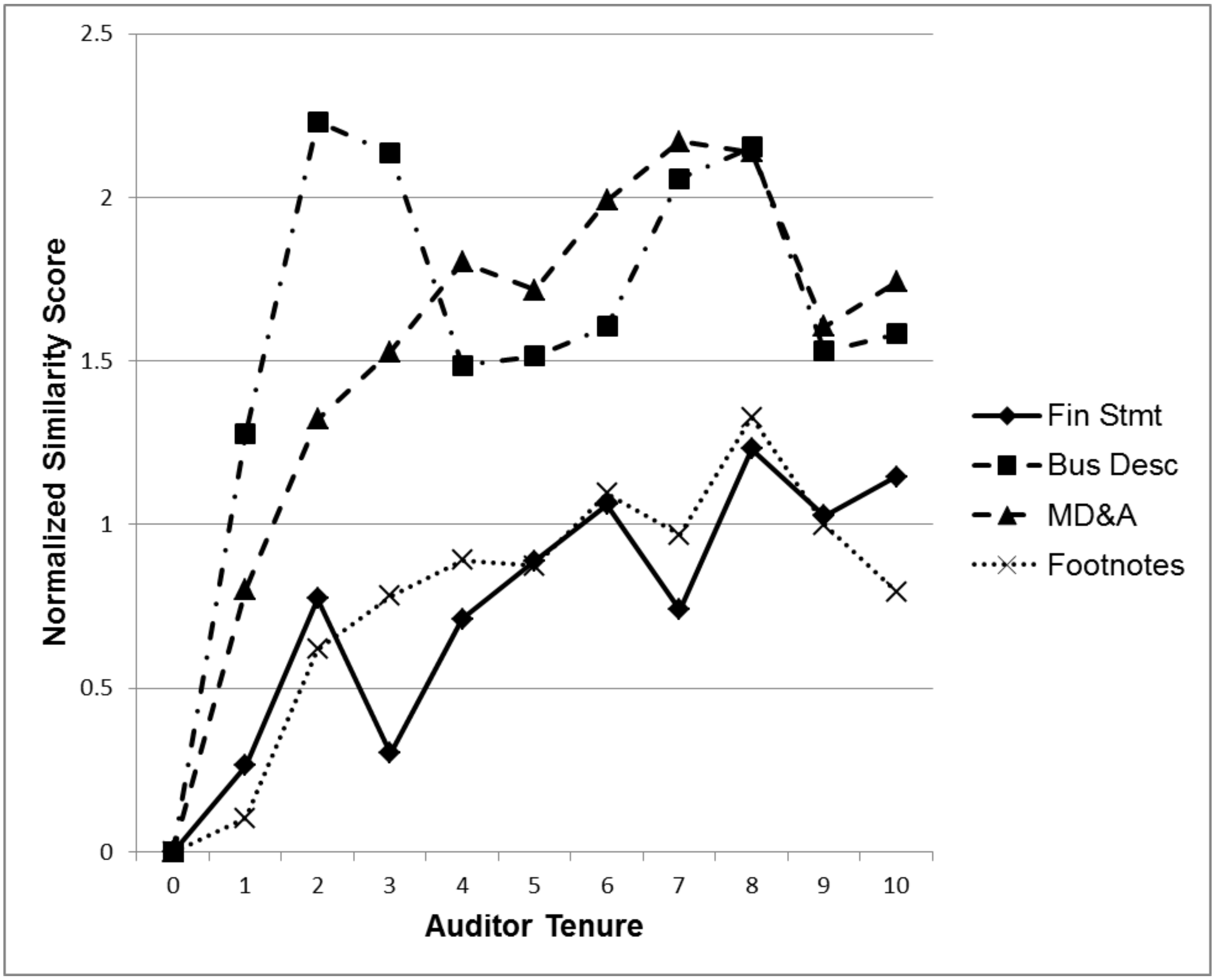
similar narrative disclosures.[27] Another possibility is studying how disclosures propagate throughout an industry by monitoring when a specific disclosure becomes similar to other existing disclosures of peer firms. The similarity measures have potential usefulness in any context in which the relationships among a set of companies is of interest.

My findings have several implications for both regulators and researchers. With the PCAOB continuing to consider requiring mandatory auditor rotation (PCAOB 2011), requiring an auditor change could force auditors and clients into less compatible engagements, which will potentially lead to changes in audit quality. On the other hand, the higher number of SEC enforcement actions as fit increases may imply fewer severe failures if clients switch to less-compatible auditors. For researchers, prior literature has directly examined the effect of auditor type, such as auditor size and specialization, implicitly assuming auditors are indistinguishable within these groups (e.g., all BigN auditors are essentially the same). My findings indicate more heterogeneity among a particular category of auditors than previously thought. Therefore, depending on the nature of the research question, it may be worthwhile to consider the differential effects of specific audit firms rather than examining them in broad categories.

[27] The Mahalanobis measure is already used for this purpose. For example, the psmatch2 Stata library.

المنارة للاستشارات
www.manaraa.com

Figure 2-1. Trend in normalized similarity score over auditor tenure.



This figure plots the proxies for auditor-client compatibility on the Y-axis against the number of years a client has engaged the incumbent auditor (“auditor tenure”) along the X-axis. The normalized similarity score, used only in this graph, is standardized to have a mean of zero and standard deviation of one, and then adjusted to begin at zero in the first year of the engagement. The auditor switch occurs when tenure equals one; auditor tenure of zero indicates the year before the switch.

www.manaraa.com

Table 2-1. Descriptive statistics.

Panel A: Similarity measures and components

Variable	Mean	Std dev	25%	Median	75%	N
SIM_{FS}	(2.164)	1.235	(2.689)	(1.978)	(1.402)	57,035
SIM_{BUS}	0.002	0.077	(0.053)	(0.017)	0.040	33,355
$SIM_{MD\&A}$	0.002	0.087	(0.057)	(0.024)	0.038	31,280
SIM_{NOTES}	0.000	0.048	(0.029)	(0.013)	0.011	14,439
SIZE	5.743	2.120	4.256	5.657	7.146	59,110
IRISK	0.249	0.195	0.088	0.213	0.367	58,553
TACC	(0.066)	0.476	(0.097)	(0.048)	(0.004)	57,460
CASH	0.210	0.243	0.026	0.104	0.318	59,106
ROA	(0.085)	0.365	(0.082)	0.022	0.069	59,067

للاستشارات المنارة
www.manaraa.com

Table 2-1. Continued.
Panel B: Model variables

Variable	Mean	Std dev	25%	Median	75%	N
SWITCH	0.070					54,149
GROWTH	0.310	1.228	-0.057	0.058	0.241	58,799
MODOPIN	0.332					59,110
TENURE	8.847	7.868	3.000	6.000	12.000	59,110
LOSS	0.398					59,110
ACQUIS	0.125					59,110
AAER	0.008					59,110
RSST_ACC	0.034	0.302	-0.059	0.026	0.114	53,446
CH_REC	0.012	0.069	-0.010	0.006	0.032	58,431
CH_INV	0.007	0.046	-0.002	0.000	0.013	58,402
SOFT_ASSETS	0.502	0.260	0.290	0.523	0.714	59,048
CH_CS	0.220	1.112	-0.052	0.080	0.259	54,434
CH_ROA	0.000	0.225	-0.047	-0.001	0.037	55,279
ISSUE	0.917	0.276	1.000	1.000	1.000	59,110
DACC	-0.002	0.336	-0.049	-0.003	0.045	57,460
|DACC|	0.089	0.184	0.021	0.047	0.098	57,410
RETVOL	0.167	0.122	0.093	0.138	0.205	44,011
CSITEMS	150.226	34.960	125.000	146.000	173.000	59,110

Subscripts: *FS* = Financial Statements, *BUS* = Business Description, *MD&A* = Management's Discussion & Analysis, *NOTES* = Footnotes to Financial Statements.
Panel A: *SIM* = similarity to other clients in the auditor-industry-year reference group. *SIZE* = log of total assets. *IRISK* = receivables plus inventory, scaled by assets. *TACC* = total accruals. *CASH* = cash and equivalents, scaled by assets. *ROA* = income before extraordinary items, scaled by assets.
Panel B: *SWITCH* = 1 if an auditor change in following year. *GROWTH* = change in assets, scaled by prior year assets. *MODOPIN* = 1 for non-standard opinion. *TENURE* = number of years with current auditor. *LOSS* = 1 if *ROA* < 0. *ACQUIS* = 1 if acquisition activity in current year exceeds 10% of assets. *AAER* = 1 if accounting misstatement in current year. *RSST_ACC* = accruals as in Richardson et al. (2005). *CH_REC* = change in receivables. *CH_INV* = change in inventory. *SOFT_ASSETS* = assets after removing fixed assets and cash. *CH_CS* = change in cash sales. *CH_ROA* = change in return on assets. *ISSUE* = 1 if securities issued during year. *DACC* = discretionary accruals from cross-sectional modified Jones model. *RETVOL* = return volatility. *CSITEMS* = # of non-missing/non-zero variables in Compustat.

المنارة للاستشارات
www.manaraa.com

Table 2-2. Correlations between similarity and difference measures.

	SIM_{FS}	SIM_{BUS}	$SIM_{MD\&A}$	SIM_{NOTES}
SIM_{BUS}	0.10			
$SIM_{MD\&A}$	0.11	0.72		
SIM_{NOTES}	0.05	0.61	0.66	
|*SIZEDIFF*|	-0.25	0.00	-0.06	-0.02
|*IRISKDIFF*|	-0.27	-0.13	-0.11	-0.13
|*TACCDIFF*|	-0.35	-0.06	-0.04	-0.08
|*CASHDIFF*|	-0.31	-0.11	-0.04	-0.12
|*ROADIFF*|	-0.42	-0.08	-0.06	-0.08
|*DACC*|	-0.27	-0.06	-0.05	-0.08

Correlations in bold are significant at the 1% level. Those within dashed box are expected to be negative. Based only on observations with valid values for all four similarity scores. |*SIZEDIFF*|, |*IRISKDIFF*|, |*TACCDIFF*|, |*CASHDIFF*|, |*ROADIFF*| = absolute difference of the variable from the mean of the auditor-industry-year reference group. Other variables defined in Table 2-1.

المنارة للاستشارات
www.manaraa.com

Table 2-3. Auditor selection based on auditor-client compatibility.

Panel A: Rank of incumbent auditor, based on similarity to each auditor's client base

	Fin stmt			Bus desc			MD&A			Footnotes		
	Freq	%	Cml	Freq	%	Cml	Freq	%	Cml	Freq	%	Cml
1 (Sim)	13,870	26	26	8,027	27	27	8,352	30	30	3,427	32	32
2	13,833	25	51	7,695	26	53	7,041	25	55	2,850	27	59
3	13,622	25	76	7,352	25	77	6,710	24	79	2,331	22	80
4 (Diff)	12,961	24	100	6,751	23	100	5,802	21	100	2,099	20	100
Total obs	54,286			29,825			27,905			10,707		

Panel B: Average rank of incumbent auditor

	Avg rank	t-stat
Financial statements	2.47 ***	5.67
Business description	2.43 ***	10.86
MD&A	2.36 ***	21.42
Footnotes	2.29 ***	19.56

Panel C: Rank of new auditor following a Big4-to-Big4 auditor change

	Fin stmt			Bus desc			MD&A			Footnotes		
	Freq	%	Cml	Freq	%	Cml	Freq	%	Cml	Freq	%	Cml
1 (Sim)	557	36	36	285	36	36	314	41	41	110	41	41
2	510	33	68	266	34	70	245	32	73	79	29	70
3 (Diff)	495	32	100	237	30	100	205	27	100	80	30	100
Total obs	1,562			788			764			269		

المنارة للاستشارات
www.manaraa.com

Table 2-3 Continued.

Panel D: Average rank of new auditor following a Big4-to-Big4 auditor change

	Avg rank	t-stat
Financial statements	1.96 **	1.91
Business description	1.94 **	2.11
MD&A	1.86 ***	4.85
Footnotes	1.89 **	1.99

Panel A: Freq = number of times an auditor of a given rank is engaged by a client. Rank 1 corresponds to the most compatible auditor while rank 4 indicates the most incompatible auditor. % = percentage of client-years engaging that rank. Cml = cumulative total of the % column.
Panel B: Avg Rank = average rank of the auditor engaged by a client. Random choice (null) is 2.5.
Panel C: Similar to Panel A, but only for clients changing from one Big4 auditor to another Big4 auditor in the year of the change.
Panel D: Similar to Panel B, but only for clients changing auditors.

المنارة للاستشارات
www.manaraa.com

Table 2-4. Probability of auditor change.

Panel A: Pairwise Pearson correlations

	SIM_{FS}	SIM_{BUS}	$SIM_{MD\&A}$	SIM_{NOTES}	*SIZE*	*IRISK*	*GROWTH*	*TENURE10*	*ROA*
SIZE	0.22	0.26	0.10	0.19					
IRISK	-0.04	-0.21	-0.15	-0.14	-0.11				
GROWTH	-0.09	-0.03	0.00	-0.03	-0.01	-0.14			
TENURE10	0.07	0.04	0.04	0.08	0.22	0.06	-0.17		
ROA	0.30	0.06	0.04	0.10	0.40	0.16	0.06	0.11	
CASH	-0.07	-0.03	0.10	-0.09	-0.37	-0.39	0.20	-0.11	-0.28

www.manaraa.com

Table 2-4. Continued.
Panel B: Logit model of auditor switch in subsequent year

		Fin stmt			Bus desc			MD&A			Footnotes		
	Exp	Coef	z-stat		Coef	z-stat		Coef	z-stat		Coef	z-stat	
(Intercept)		-1.810	-10.46	***	-0.681	-2.54	**	-0.489	-1.93	*	-0.440	-0.98	
SIZE	-	-0.248	-18.87	***	-0.390	-19.92	***	-0.390	-19.40	***	-0.437	-13.90	***
IRISK	+	0.205	1.66	*	-0.018	-0.11		-0.045	-0.27		-0.217	-0.86	
GROWTH	?	-0.074	-3.75	***	-0.053	-2.04	**	-0.040	-1.59		-0.073	-1.81	*
MODOPIN	+	0.419	10.14	***	0.241	4.14	***	0.243	4.10	***	0.330	3.70	***
TENURE10	-	-0.039	-6.42	***	-0.032	-3.81	***	-0.031	-3.70	***	-0.024	-1.89	*
ROA	-	-0.042	-0.81		-0.154	-2.22	**	-0.163	-2.32	**	-0.167	-1.57	
LOSS	+	0.345	7.92	***	0.437	7.38	***	0.410	6.80	***	0.361	3.84	***
CASH	-	-0.596	-5.76	***	-0.923	-6.34	***	-0.975	-6.62	***	-1.270	-5.53	***
ACQUIS	+	0.043	0.74		-0.024	-0.29		0.021	0.26		0.071	0.60	
SIM_{FS}	-	-0.076	-4.72	***									
SIM_{BUS}	-				-0.430	-0.99							
$SIM_{MD\&A}$	-							-1.324	-3.40	***			
SIM_{NOTES}	-										-4.922	-3.78	***
Year FE		Yes			Yes			Yes			Yes		
Industry FE		Yes			Yes			Yes			Yes		
Obs		52,232			29,778			27,761			12,850		
Pseudo-R^2		0.07			0.09			0.09			0.11		

Panel A: Correlations in bold are significant at the 1% level. *TENURE10* = same as *TENURE* but with a maximum value of 10 years, for compatibility with Landsman et al. (2009). Other variables defined in Table 2-1.
Panel B: The results of a logistic regression with dependent variable of *SWITCH,* indicating an auditor change in the following year. Variables defined in Table 2-1.

المنارة للاستشارات
www.manaraa.com

Table 2-5. Probability of receiving an AAER.

Panel A: Pairwise Pearson correlations

	SIM_{FS}	SIM_{BUS}	$SIM_{MD\&A}$	SIM_{NOTES}	*RSST_ACC*	*CH_REC*	*CH_INV*	*SOFT_ASSETS*	*CH_CS*
RSST_ACC	0.07	0.01	0.04	0.01					
CH_REC	0.00	-0.01	-0.03	-0.03	0.31				
CH_INV	0.01	0.00	0.02	-0.01	0.21	0.32			
SOFT_ASSETS	0.06	-0.20	-0.26	-0.24	0.00	0.09	0.08		
CH_CS	-0.02	-0.02	-0.01	-0.03	0.18	0.16	0.12	-0.07	
CH_ROA	0.10	0.01	0.02	0.00	0.32	0.13	0.07	-0.04	0.12

www.manaraa.com

Table 2-5. Continued.
Panel B: Logit model of future AAER being issued for current year financial statements

		Fin stmt			Bus desc			MD&A			Footnotes		
	Exp	Coef	z-stat		Coef	z-stat		Coef	z-stat		Coef	z-stat	
(Intercept)		-6.767	-14.9	***	-7.287	-9.93	***	-6.492	-12.08	***	-7.206	-6.86	***
RSST_ACC	+	0.424	1.97	**	0.177	0.70		0.273	1.11		-0.168	-0.41	
CH_REC	+	1.692	2.21	**	2.162	2.35	**	2.630	2.78	***	2.253	1.53	
CH_INV	+	1.979	1.89	*	1.822	1.45		1.180	0.89		1.298	0.63	
SOFT_ASSETS	+	2.007	7.96	***	1.747	5.70	***	1.638	5.25	***	2.125	4.26	***
CH_CS	+	0.031	0.6		0.015	0.23		0.024	0.38		-0.082	-0.63	
CH_ROA	-	-0.605	-2.08	**	-0.456	-1.40		-0.603	-1.88	*	-0.190	-0.38	
ISSUE	+	1.456	3.52	***	2.014	2.83	***	1.287	2.54	**	1.716	1.70	*
SIM_{FS}	?	0.149	2.83	***									
SIM_{BUS}	?				2.181	2.40	**						
$SIM_{MD\&A}$	?							2.215	2.77	***			
SIM_{NOTES}	?										-2.943	-0.83	
Year FE		Yes			Yes			Yes			Yes		
Industry FE		Yes			Yes			Yes			Yes		
Obs		28,676			16,575			15,132			6,495		
Pseudo-R^2		0.04			0.03			0.03			0.04		

Panel A: Correlations in bold are significant at the 1% level. Variables defined in Table 2-1.
Panel B: The results of a logistic regression with dependent variable of *AAER*, indicating an SEC enforcement action was released for the current year. Model based on Dechow et al. (2011). Variables defined in Table 2-1.

www.manaraa.com

CHAPTER 3
SPECIALIZATION THROUGH CLIENT COMMONALITY AND ITS EFFECT ON AUDIT PRODUCTION COSTS

Introductory Remarks

Each engagement within an auditor's portfolio has both idiosyncratic and non-idiosyncratic features deriving from the extent to which the audits have elements in common. A portion of each accounting disclosure of a client is due to the economic and accounting choices of that company, while other portions are the result of common factors such as auditor preferences, industry norms, macroeconomic conditions, and accounting standards. In this paper, I argue the non-idiosyncratic, overlapping components represent opportunities for the auditor to reduce production costs by improving audit technology and reliance on common knowledge spillover, which I refer to collectively as specialization. I use the similarity of each client to other clients within the same auditor-industry-year as a proxy for potential opportunities to specialize in that group of companies.

Following the approach in Chapter 2, I calculate the commonality between clients based on the similarities of both their financial statement and narrative disclosures contained within the annual report. Using two separate measures derived from different sources and based on different calculation approaches allows for a broader proxy of commonality than either would provide on its own. The financial statement similarity measure is based on the Mahalanobis distance, used in the cluster analysis literature to divide observations into groups based on numeric characteristics of each observation.[1] The narrative disclosure commonality measure uses the business description, MD&A,

[1] I typically use the term "similarity" in this paper, although the context occasionally calls for the term "distance." In the current context, distance is the conceptual inverse of similarity.

المنارة للاستشارات
www.manaraa.com

and footnote items contain in the mandatory annual report as a proxy for how similar the company's disclosure choices are to the choices of peer companies.

In my first hypothesis, I argue the degree of commonality among clients of an auditor can affect audit production costs through its effect on both labor and audit technology. Commonality influences labor costs through knowledge spillovers between engagements and changes to the mix of more senior and less experienced labor. Production costs are also a function of audit technology, which is easier to implement and more effective when client overlap is greater. Given the opportunity for reduced production costs, I first predict that a client having more in common with its peer clients has lower audit fees. I find strong evidence of this association for both financial statement and narrative disclosure similarity. The effect is also economically significant: an increase in similarity from the 25^{th} to the 75^{th} percentile is associated with a decrease in audit fees of 4.3 to 8.3 percent.

My second hypothesis is that the relationship between client similarity and fees is stronger when the auditor has greater financial incentives to take advantage of overlap in its portfolio. The auditor is unlikely to make the necessary investments solely because of the opportunity to do so, but will also consider how economically meaningful the investment might be for overall profitability. In support of this hypothesis, I document an incrementally negative effect for financial statement similarity when an industry provides a higher percentage of the auditor's revenues.

Finally, having two primary measures for client commonality allows me to examine situations in which the two proxies are inconsistent in their portrayal of similarity. I consider two types of inconsistency between the financial statements and

المنارة للاستشارات
www.manaraa.com

corresponding narrative disclosures: pooled textual disclosures and differentiated textual disclosures. A *pooled* disclosure occurs when a company has unusual-looking financial statements relative to its peers, but the accompanying textual disclosures do not reflect those financial differences. The accompanying text should either reflect the atypical financial statements or explain why the differences are not a true representation of the company's situation. However, the text does not appear to do so, representing an incremental risk factor for the auditor and possibly eroding the production efficiencies predicted to be associated with greater client commonality. I proxy for each type of inconsistency by focusing on firms that are in opposing terciles of similarity for financial statements and narrative disclosures. As predicted, I find that pooled text disclosures are associated with higher audit fees than clients without such inconsistency.

The second type of inconsistency—a *differentiated* disclosure—occurs when a company has fairly typical financial statements relative to its peers, but the textual disclosures seem to contain more uncommon, possibly firm-specific, information. The prediction in this case is less clear than a pooled disclosure since differentiation can be the result of a client who is (1) unjustifiably trying to differentiate itself from its peers or (2) attempting to provide additional, firm-specific information that can be useful and risk-reducing to both auditors and investors. In contrast to pooled disclosures, I generally find that differentiated disclosures are associated with lower audit fees than clients not having this type of inconsistency.

My study makes several contributions to the literature. First, I provide empirical proxies of auditor specialization that have several advantages over existing measures. The proxies are at the client level, rather than the auditor-industry level, which allows a

المنارة للاستشارات
www.manaraa.com

more direct mapping into client-level audit fees. This approach also allows for the existence of subgroups within an auditor-industry, since auditors do not necessarily orient their practices around the broad groups provided by third party industry classification systems. Because my proxies rely explicitly on client characteristics, I avoid the use of market share measures that are likely confounded by competitive pricing strategies and other audit market features, making my measures easier to interpret as proxies for the underlying specialization construct. Although interpreted in an audit context for the current study, the proxies are general purpose measures of overlap among companies, providing many potential applications outside of the audit setting.

My second contribution is to the limited literature on the relation between auditors and clients' narrative disclosures. Few audit-related studies consider the role of narrative disclosures in conveying information about the client,[2] even as the PCAOB has recently proposed substantially increasing the role of the auditor in reviewing these communications (PCAOB 2011). In this study, I show the usefulness of narrative disclosures in examining the implications of how clients of an auditor relate to one another. In a third contribution, an extensive literature has looked at the relationship between specific client financial statement elements and the audit, without a higher-level understanding of what the broader financial data mean for the auditor's client portfolio. The measures I develop allow for a research design that simultaneously considers multiple dimensions of client commonality. I further combine the multiple disclosure channels used by the client to look for inconsistencies, which provides more

[2] One exception is Dunn and Mayhew (2004), which finds that clients of industry specialists have higher quality narrative disclosures.

المنارة للاستشارات
www.manaraa.com

nuanced insights than those provided by studies examining only one disclosure mechanism.

The rest of the paper proceeds as follows. The next section develops the hypotheses. The section after that describes the rationale and foundation for the similarity measures, followed by a section that explains the sample and calculations of the measures. A description of the results of the empirical tests follows. The next section contains alternative similarity measures and other robustness tests, and the final section concludes.

Hypotheses and Prior Literature

Production Costs and Audit Fees

Simunic (1980) presents a widely-used model of audits in which fees charged to clients are a function of production costs ("effort") and any expected losses due to potential audit failure ("risk"). Production costs—primarily labor in an audit setting—are composed of the quantity and unit cost of resources consumed to provide a given level of audit quality. For example, the size of the client corresponds to a higher quantity of resources required; as such, client assets and sales are positively related to the quantity of labor hours expended (O'Keefe, Simunic, et al. 1994). Since there is a non-zero probability that an audit will fail by not detecting or reporting a material financial statement error, the auditor must either charge a higher fee to insure against the possible loss or expend greater effort to reduce the risk. For instance, Hackenbrack and Knechel (1997) show that the labor mix shifts towards more senior, costly auditor employees when audit risks are higher. Overall, prior literature has documented a very

المنارة للاستشارات
www.manaraa.com

strong, positive relation between audit production costs (both effort and risk) and audit fees (Causholli et al. 2010).[3]

Specialization and Audit Fees

An extensive literature has examined the effect an auditor's specialization in a group of clients has on audit fees. The "group" is typically implemented as some category of industry, leading to the customary term *industry specialization*. Studies in this area variously predict both a decrease and an increase in audit fees due to industry specialization, although the archival evidence has generally supported the latter.

Industry specialists are expected to charge *lower* fees when non-idiosyncratic audit components lead to knowledge sharing and investments in overlapping audit technology that are associated with lower production costs due to having a more efficient and less risky audit. Earlier studies have occasionally acknowledged the possibility of this negative relationship (e.g., Craswell et al. 1995; Willenborg 2002) and some archival results support this prediction. For example, Mayhew and Wilkins (2003) find that auditors who have larger industry market share, but do not dominate the industry, charge lower fees to clients initially going public. Experimental evidence also lends credence to the potential for lower fees (e.g., Owhoso et al. 2002; Low 2004).

However, most studies in the area proxy for specialization using industry market share and typically find *higher* fees for specialists (Gramling and Stone 2001). The general interpretation is that the same knowledge sharing and audit technology described under the negative prediction improve audit quality or auditor reputation (e.g.,

[3] Lower production costs do not necessarily lead to lower audit fees if the auditor is retaining the entire increase in profit margin. However, as long as the audit market is sufficiently competitive, at least some portion of these lower costs will be passed along to the client.

www.manaraa.com

Ward et al. 1994). Since clients are presumably willing to pay more for higher actual—or perceived—quality, specialization should be associated with higher audit fees.

Given the two divergent predictions, the choice of proxy for specialization is especially critical. For example, the offsetting effects could lead to no discernable relationship (e.g., Palmrose 1986). On the other hand, if the proxy better captures the quality and reputational effects of specialization, a positive relation will dominate, as appears to be the case when using industry market share. Market share-based proxies could also be measuring the competitive strategy of an auditor in the audit market for a particular industry rather than specialization per se (Numan and Willekens 2012). Minutti-Meza (2011) argues that studies documenting a positive relation between industry specialists and audit quality are the result of uncontrolled client characteristics, and finds no improvement in audit quality for specialist clients once fully matching on these attributes. Gramling and Stone (2001) note the link between market share and specialization is typically vague and that “existing research offers little justification for applying existing market share and market specialization measures as proxies for industry expertise” (p. 14). In the current study, I develop measures that more directly proxy for having a production process specialized for a subset of clients so that I can better address the negative relation between specialization and fees.

Opportunities to Lower Production Costs

Commonality and idiosyncrasies among clients of an auditor can affect audit production costs through their effect on both labor and audit technology. One effect on labor costs is that fewer idiosyncrasies will likely require less planning and oversight due to decreased risk and complexity, thus shifting the labor mix to lower-level, less expensive personnel (Hackenbrack and Knechel 1997). There is also the potential for

المنارة للاستشارات
www.manaraa.com

knowledge overlap, which includes familiarity with certain "types" of clients, rules-of-thumb, and other relevant on-the-job experience (e.g., Beck and Wu 2006). Research in organizational behavior has found that knowledge gained by performing job tasks is transferred within an organization (e.g., Darr et al. 1995). Experimental evidence suggests that specialist auditors are better at detecting errors (Owhoso et al. 2002) and assessing audit risk (Low 2004). However, archival auditing studies have not found strong empirical evidence to support learning-by-doing or learning over time (Causholli et al. 2010; Davis et al. 1993; O'Keefe et al. 1994), possibly due to the specific proxies chosen.

Increased client overlap could also affect the auditor's ability to develop specialized audit technology. Audit technology is a set of fixed investments by an auditor in innovations such as customized workflow, employee training, specialized software, decision aids, and the formation of in-house consulting groups (Dowling 2009; Sirois and Simunic 2010).[4] Higher-quality audit technology is "better at identifying and directing effort to problem areas of individual clients" (Blokdijk et al. 2006, 29). A higher degree of client commonality could provide more input into the current audit. For example, analytical procedures have better predictive ability when based on similar peer firms (Minutti-Meza 2010). These techniques are likely to be more accurate when based on a larger number of more similar reference clients. Cahan et al. (2008) argue that homogenous investment opportunity sets among clients are a specific type of client overlap that creates such an opportunity to invest in audit technology. I extend this line of reasoning to examine client overlap in a more general sense. If there is greater client

[4] Note that audit technology is not necessarily implemented using computerized systems.

المنارة للاستشارات
www.manaraa.com

overlap, there will be more common audit components to extract, and thus it will be less costly and more effective to develop common technologies based on those similarities.[5]

The lack of archival evidence notwithstanding, organizational theory and experimental studies suggest a greater ability to transfer knowledge within the audit firm will lead to lower audit risk and more efficient audits. Both of these outcomes will result in an audit with lower production costs, albeit with potentially higher audit quality. Therefore, I predict in alternative form:

> H1: Clients having higher overlap with other clients of the auditor pay lower audit fees.

Incentives to Lower Production Costs

The first hypothesis derives from the opportunities inherent in client overlap, but audit firms and individuals will only invest in additional audit technology and develop common knowledge when there are incentives to do so. Economic incentives are likely to be highest for those clients that are relatively more important to the auditor's overall profitability. For example, an industry that provides audit fees that are higher than other industries might give the auditor greater incentives to develop audit technology appropriate for that industry. In contrast, if an industry represents a very small portion of the fee portfolio, the auditor is less likely to make investments in technological improvements for that group of clients, even in the presence of strong opportunities. I expect greater incentives to develop specialized audit technology and knowledge will accentuate the relation between opportunities and fees predicted in the first hypothesis. Supporting the significance of stronger portfolio incentives, Knechel, Niemi, and Zerni

[5] While some technology and knowledge can be broadly applied, such as audit standards and firm-wide policies, I specifically focus on components that are relevant to subgroups of clients to provide adequate cross-sectional variation.

المنارة للاستشارات
www.manaraa.com

(2012) find that partner specialization is associated with higher compensation for economically important sectors. Therefore, the next alternative hypothesis is:

> H2: The negative relation between client overlap and audit fees is stronger in industries that are economically important to the auditor.

Inconsistent Signals of Commonality

Given multiple consistent signals of the true underlying client overlap, the prior hypotheses make predictions about the relationship between commonality and audit fees. For the purposes of this study, I use the financial statements and the narrative disclosures in the annual report as two broad disclosure channels. Bamber and Cheon (1998) show cross-sectional variation in management's choice of channels for disclosing earnings forecasts, along with differential investor reaction to those choices. Therefore, an incremental effect beyond the earlier predictions can arise if these disclosure channels are not in agreement with one another regarding the degree of underlying similarity.

One type of disclosure inconsistency occurs when the quantitative financial statements seem to represent a company that is relatively unusual for the industry, but the accompanying qualitative narrative disclosures make the client appear very typical. If the financials are dissimilar, one would expect that the accompanying text would either reflect these differences or explain why the differences are not a true representation of management's view of the company's position. In either case, the narrative disclosures should appear different from other clients of the auditor. Narrative disclosures give the company greater flexibility and discretion than is usually available in the financial statements. Under this flexible regime, the company is apparently choosing to downplay the differences in the underlying financials. I call this situation

المنارة للاستشارات
www.manaraa.com

pooled text inconsistency. Inappropriately differentiated disclosures could cause additional risk for the auditor or require more effort to attain the same level of assurance. But even if the differences are justified, verifying the propriety of the claims will take additional effort by the auditor:

> H3a: Clients with dissimilar financial statements but similar narrative disclosures ("pooled text") pay higher fees than other clients.

A second type of inconsistency is when the financial statements indicate a client is relatively similar to other companies, but the narrative disclosures make the client appear more unusual. The client may be attempting to unjustifiably differentiate itself from other companies, as might occur before an upcoming equity offering. On the other hand, narrative differences could represent firm-specific disclosures that improve the quality of information available about the company. For example, Tasker (1998) shows that managers will use a more flexible disclosure channel when the financial statements are relatively less informative. This improvement in the information environment represents a potentially positive situation for the auditor. I call this type of inconsistency the *differentiated text* condition. Because there are both beneficial and problematic potential reasons for differentiated narrative disclosures, it is an empirical question as to the relation between this type of inconsistency and audit fees. Stated in alternative form, my final hypothesis is:

> H3b: Clients with highly similar financial statements but dissimilar narrative disclosures ("differentiated text") pay different fees than other clients.

Sample

Financial Statements

As in Chapter 2, I use the Mahalanobis distance-squared (D^2) measure to calculate the commonality of financial statements among clients of an auditor. This

المنارة للاستشارات
www.manaraa.com

proxy is ideally suited to determining the similarity of small sets of variables. By selecting a limited number of key financial statement variables, the measure provides the aggregate distance of one company's financial statement variables from all the other financial statements in the same auditor-industry-year.

To calculate the similarity between one observation and a set of appropriate peers, I define the *reference group* as the set of client-years with the same auditor and industry. I exclude any reference groups that do not have at least five observations; the similarity score is unlikely to be reliable if there are too few observations in the group. Because the reference groups are rarely large enough for non-Big4 auditors, I explicitly limit the sample to Big 4 clients. Finally, I do not allow companies in the reference group in the year that they switch auditors. These restrictions leave 32,412 observations in my financial statement sample.

Because there is no theoretical guidance on which variables are appropriate for the financial statement similarity measure, I use financial statement variables having well-established relationships in an audit context. Based on the empirical audit fee model components described in Hay et al. (2006), I include proxies for audit effort, audit complexity, and client risk. To focus on the client's financial statement similarity, I avoid engagement- or auditor-specific variables and client-related variables that are not included in the financial statements. As a distance-based measure, using unscaled variables would cause the D^2 metric to be so heavily influenced by the size of the companies that it would effectively become a proxy for client size. Because client size typically explains a large portion of audit fees and large firms are more uncommon by definition than smaller firms, I do not directly include proxies for size and also scale all

المنارة للاستشارات
www.manaraa.com

variables to remove a direct size effect. Correlations with size are normally observed in financial data (e.g., between size and profitability), which ensure client size has an indirect effect on the measure without overwhelming other patterns in the data.[6]

I gather the necessary financial statement variables from Compustat, only using observations with assets greater than $1 million, with no fiscal year end change, not in the financial or utility sectors, and having all data fields required to calculate the similarity scores. The sample begins in 2000, when audit fee data is first widely available, and ends in 2009.

I count the number of non-missing/non-zero financial statement variables in Compustat as a measure of audit effort and complexity (*CSITEMS*), since additional financial statement items are likely to increase the scope and intricacy of the audit.[7] I use long-term debt to proxy for the risk due to the client's leverage (*LEV*). The combination of inventory and receivables proxies for inherent audit risk (*IRISK*). Audit fee models usually include a measure of profitability, frequently some variant of income or a profit/loss dummy. Departing somewhat from prior literature, I include separate variables for revenues (*REV*) and operating expenses (*EXP*) to give the income statement roughly the same representation in the vector as the balance sheet.[8] All measures are scaled by total assets. I regress the natural log of audit fees on these

[6] Chapter 2 includes *SIZE* in the set of input variables. Size is excluded in the current paper because of its well-documented, dominant effect on audit fees, which is the dependent variable in the current context.

[7] The number of reporting segments is frequently used to proxy for audit complexity, but is unavailable for many companies in Compustat. Counting the number of variables serves as a broadly available alternative. To my knowledge, this variable has not been used before in the audit fee literature, but is potentially superior to existing alternatives.

[8] In an untabulated robustness test, I use income before extraordinary items (*INC*) in place of *REV* and *EXP*, with no change in the qualitative conclusions.

المنارة للاستشارات
www.manaraa.com

scaled variables to verify they are all highly significant in the expected directions and consistent with prior literature.

Narrative Disclosures

I use three important items from the mandatory annual report as separate sources of narrative disclosures with which I proxy for client commonality. I select the business description, MD&A, and footnotes from the annual report because of their relative importance and length within the context of the 10-K. Each provides variation in topical coverage, time horizon, and the level of auditor assurance provided. Using three distinct disclosures provides insights beyond using either a single disclosure item or the annual report in its entirety. For example, to the extent that liquidity and results of operations is more strongly related to audit fees than product market competition, I would expect the MD&A similarity measure to have stronger results than the business description. While I make no specific predictions about which narratives have a stronger relationship with audit production costs, I leave the disclosures disaggregated to ensure I can observe differences across the various items.

To proxy for the commonality among clients, I use the same Vector Space Model (VSM) procedure as in Chapter 2, which is an extension of the approach in Brown and Tucker (2011). The VSM maps documents into numeric vector representations, where each element of the vector is a weighted count of the number of times a particular word occurs in the document. Taking the dot product of any two document vectors yields the cosine of the angle between those vectors, a measure of similarity that ranges from zero (completely dissimilar) to one (identical documents). I calculate this dot product between the observation of interest and every other client in the same auditor-industry-year. I average the top five most similar clients (i.e., the five with the highest cosine

المنارة للاستشارات
www.manaraa.com

measures) and correct for mechanical biases using the procedure described in Appendix B of Chapter 2.[9]

For the narrative disclosure sample, I use 10-K's and 10-K405's filed electronically via the SEC's EDGAR system for fiscal years 2000 through 2009. As in the financial statement sample, the disclosures in the text samples are by Big4 clients having at least five other observations available for comparison within the same auditor-industry-year reference group. These filters yield 23,146 business description, 22,146 MD&A, and 10,666 footnote observations. There are fewer observations in the narrative disclosure samples than in the financial statement sample. This difference is primarily due to unavailable reports on EDGAR, items included by reference to other locations, and textual idiosyncrasies that lead to problems extracting the 10-K items of interest. The substantial drop in the number of footnote observations, as compared to the business description and MD&A samples, is because many companies attach financial statements and footnotes as an exhibit to the report in a variety of unpredictable ways, making their automated extraction difficult.

Treating the three narrative disclosure items of the annual report as separate data sets, I calculate the similarity score for each using the same approach described in Chapter 2. The process, summarized in Appendix B, produces three variables—SIM_{BUS}, $SIM_{MD\&A}$, and SIM_{NOTES}—that proxy for the amount of commonality between firm *i* and its five closest peers in the same auditor-industry-year. Higher similarity scores correspond to greater commonality.

---

[9] Chapter 2 averages *all* the scores within the auditor-industry-year, rather than the five most similar. Therefore, when correcting for the mechanical bias in the current chapter, I also include the first three powers of the number of clients in the auditor-industry-year. In the next draft, I plan to make these two chapters consistent by always using the full set of clients and only using the five most similar in a sensitivity test. Doing so does not change the qualitative results.

www.manaraa.com

Analysis of Similarity

Audit Fee Model

The tests rely on the following base audit fee model developed from the audit fee meta-analysis in Hay et al. (2006):

$$LNFEES = a_0 + a_1 SIZE + a_2 CSITEMS + a_3 IRISK + a_4 LOSS + a_5 LEV + a_6 DELAY$$
$$+ a_7 NAS + a_8 BUSY + a_9 OPIN + a_{10} ICMW + a_{11} TENURE + a_{12} INDSPEC$$
$$+ industry + year + \varepsilon$$

I include controls for various client attributes, some of which are also used to calculate client similarity. The natural log of client assets is *SIZE*. I proxy for client complexity by counting the number of non-zero/non-missing items for that client-year in Compustat (*CSITEMS*). Inherent risk (*IRISK*) is receivables plus inventory, scaled by total assets. *LOSS*, a dummy set to one for negative net income, proxies for financial weakness. Finally, leverage (*LEV*) is long-term debt scaled by total assets.

I also control for auditor and engagement attributes. If the number of days between fiscal year end and the issuance of the 10-K is more than 90 days, then *DELAY* is set to one as a proxy for audit complexity. The log of the dollar amount of non-audit services is *NAS.*[10] Clients with a December 31 fiscal year end date could lead to increased resource constraints, so *BUSY* is a dummy set to one for these companies. Audits leading to anything other than a standard opinion might be associated with additional audit effort or risk. Therefore, *OPIN* is a dummy set to one for non-standard opinions, almost always a clean opinion with modified language. I construct a similar measure for internal control, setting *ICMW* to one if the auditor has noted a material

[10] I first add 1 to the non-audit fees to avoid taking the log of 0.

المنارة للاستشارات
www.manaraa.com

weakness in internal control. *TENURE* is the number of years the client has been with the current auditor, according to Compustat. To ensure my measures capture a construct distinct from traditional proxies for industry specialization, I include *INDSPEC*, a dummy set to one when the current auditor receives at least 32.5% of the total fees available within the client's GICS industry and year.[11] Finally, I control for industry and year fixed effects. All controls are expected to be positive, except *INDSPEC* which is unpredicted. For these variables, Table 3-1 contains descriptive statistics in Panel A and correlations in Panel B. The patterns are consistent with prior audit fee literature.

Hypothesis 1

To test the first hypothesis regarding client similarity and audit fees, I augment the base model with one or more of the similarity variables. H1 predicts the coefficients on these similarity variables will be negative. I begin by testing the model with SIM_{FS} to assess the relationship between fees and financial statement similarity, with the results in Table 3-2.[12] The coefficient on SIM_{FS} is significantly negative (t = -9.41), as predicted, so fees are lower as the financial statements of a client are more similar to other clients of its auditor. All control variables are significant and in the expected direction except for *LEV*, which is insignificant. While size, complexity, and risk are still important determinants of audit fees, it appears that financial statement overlap with other clients is also relevant.

[11] Since the literature has not extensively explored GICS industries in a specialization context, I use the sample's 75th percentile as a cutoff. I prefer GICS to SIC as the similarity scores are calculated using this categorization. Results are qualitatively unchanged when using a more typical 30% cutoff based on SIC 2-digit codes.

[12] All standard errors are heteroscedasticity-consistent using a Huber-White adjustment.

www.manaraa.com

I now turn to the three narrative disclosure similarity measures. For this test, I leave SIM_{FS} in the model as a control for underlying economic similarity and then alternately test the coefficients on SIM_{BUS}, $SIM_{MD\&A}$, and SIM_{NOTES}. Each of the narrative coefficients is significantly negative (t = -9.98, t = -4.77, and t = -2.86, respectively). The results are qualitatively unchanged if SIM_{FS} is excluded from these models. Once again, the control variables are as expected, with the exception of *LEV*. Overall, there is strong evidence that the similarity of client narrative disclosures is negatively related to audit fees, even after controlling for the similarity of the underlying financial statements.

As an evaluation of the economic significance of the of the effect, moving from the 25th to the 75th percentile of SIM_{FS} decreases audit fees by a range of 2.8% in the footnote model to 3.8% in the business description model. Corresponding changes in SIM_{BUS}, $SIM_{MD\&A}$, and SIM_{NOTES} are associated with additional declines in audit fees of 4.5%, 2.1%, and 1.5%, respectively. The largest combined effect is in the business description model where combined interquartile changes in both the financial statements and business description are associated with an 8.3% decrease in fees. Even the smallest economic effect—the footnotes—is a combined 4.3%. By comparison, the economic effect of being an industry specialist based on market share (*INDSPEC*) increases audit fees by a range of 4.7% to 8.8%, depending on which of the four models in Table 3-2 is considered. Therefore, the relation between client commonality and audit fees is both statistically and economically significant.

Hypothesis 2

The second hypothesis predicts the negative relation in H1 is magnified in industries that are more economically important to the auditor. Chung and Kallapur (2003) measure individual client importance by calculating the client's audit fees scaled

المنارة للاستشارات
www.manaraa.com

by total fees received by the auditor in that year. My tests require a measure of the importance of a group of clients, rather than one specific client.[13] Therefore, as a proxy for economic importance I use portfolio share (*PORTSHR*), the audit fees received from a particular industry-year divided by the auditor's total fees from all industries in the same year. In keeping with the industry specialization literature, I include in the model the importance of the industry (*IMPIND*), which is a dummy set to one if the portfolio share exceeds 2.8% (the upper quartile of *PORTSHR*). The industry specialization literature has previously used this measure as a proxy for an industry's economic importance to the auditor (Neal and Riley Jr. 2004).

To test H2, I expand the model for the first hypothesis by adding a main term for *IMPIND* and its interaction with each similarity score. The interaction coefficients will be negative under H2's prediction that greater economic incentives accentuate the negative relation between similarity and fees. As shown in Table 3-3, the significant *IMPIND* main effects are positive, consistent with other studies, indicating that higher portfolio share is associated with higher fees.

Focusing first on financial statement similarity, the coefficient on SIM_{FS} remains negative (t = -7.68) as found in the test of H1. The interaction of *IMPIND* and SIM_{FS} is also negative (t = -3.54), supporting the economic incentive hypothesis. Moving on to the narrative disclosure similarities, I retain SIM_{FS} in the model to control for underlying financial statement similarity. I then add each narrative disclosure score and its interaction with *IMPIND* to the model. The main effects remain significant, as previously found, but none of the interactions are significant.

[13] Using their measure directly would bias in favor of a result in my setting since fees would effectively be both a dependent and independent variable.

المنارة للاستشارات
www.manaraa.com

While I can easily reject the H2 null for financial statements, the results for the narrative disclosures are not significant. One ex-post interpretation for this outcome is that financial statements are quantitative, which should allow for specific technological improvements that would be more difficult to implement for soft, qualitative disclosures. In other words, while narratives *proxy* for underlying client similarity, it may be difficult to implement audit technology that specifically leverages this type of overlap. Financial statements are also likely to be more stable than text, which should more easily allow for technology improvements. In untabulated analysis, I use *PORTSHR* in place of *IMPIND* as an alternative measure of industry importance. The conclusions do not change for the financial statements, MD&A, or footnotes, but the business description has significantly negative coefficients on both the main and interaction terms. Supporting the importance of stability within the narrative disclosures, the business description is the most stable of the three textual items and it also has the strongest support for H2 in this alternative analysis.[14]

Overall, I find some empirical evidence that the negative similarity-fees relationship is incrementally negative as an industry becomes more important to the auditor's revenue stream. As portfolio share increases, the auditor may gain more knowledge and streamline its process for these clients. Alternatively, the auditor may not have a different cost structure due to technological investments, but is just more willing or able to charge lower fees to retain these economically important clients.

[14] Using the raw year-over-year disclosure modification score from Brown and Tucker (2011), the business description has an average modification score of only 0.09, as compared to much larger annual modification scores of 0.16 for MD&A and 0.14 for the footnotes.

المنارة للاستشارات
www.manaraa.com

Hypothesis 3

The final hypotheses examine the consistency between financial statements and narrative disclosures. To test these hypotheses, I split the financial statement similarity and each of the narrative disclosure similarities into terciles. I am particularly interested in misalignment between the lowest and highest terciles of the financials and text, so I create dummies indicating when such misalignments occur. For each narrative disclosure type, I set the corresponding *POOLTEXT* variable to one when financial statement similarity is low (SIM_{FS} is in the bottom tercile) and narrative similarity is high (SIM_{BUS}, $SIM_{MD\&A}$, or SIM_{NOTES} is in the top tercile). These indicators correspond to the riskiest type of disclosure inconsistency—*pooled text*—since the financial statements portray a very atypical company for the industry, while its narrative disclosures are very similar to its peers.

I then create *DIFFTEXT* dummies set to one when financial statement similarity is high (SIM_{FS} is in the top tercile) and narrative similarity is low (SIM_{BUS}, $SIM_{MD\&A}$, or SIM_{NOTES} is in the bottom tercile). While still inconsistent, these *differentiated text* misalignments have potentially benign—and potentially beneficial—explanations. Examining each of the narrative disclosures in separate models, I expand the base audit fee model to include the respective *POOLTEXT* and *DIFFTEXT* dummy for that disclosure type. In each model, I also control for SIM_{FS} and the similarity of the textual disclosure being examined. H3a predicts the coefficient on *POOLTEXT* is positive and H3b predicts the coefficient on *DIFFTEXT* is nonzero (although a null result would not be unexpected).

Table 3-4 presents the results of the test. Consistent with the earlier tests of H1, all the financial statement and narrative disclosure similarity scores are significantly

المنارة للاستشارات
www.manaraa.com

negative. As predicted by H3a, the coefficients on *POOLTEXT* for the business description, MD&A, and footnotes are all significantly positive (t = 5.05, t = 4.43, and t = 2.40, respectively). These results support the prediction that inconsistency in the form of pooled text (dissimilar financials, similar text) is associated with higher audit fees. Relative to other clients, the findings are consistent with pooled text clients either (1) representing higher idiosyncratic risk to the auditor or (2) leading to a lower willingness to implement technological improvements to take advantage of client commonality.

Turning to the test of differentiated narrative disclosures, $DIFFTEXT_{BUS}$ is significantly negative (t = -2.50, p-value = 0.012), as is $DIFFTEXT_{MD\&A}$ (t = -2.73). $DIFFTEXT_{NOTES}$ is negative, but insignificant (t = -1.07), potentially due to the much smaller sample size for the footnotes. The hypothesis makes only weak predictions about these coefficients because it is unclear whether differentiated text increases, decreases, or does not affect the risk and efficiency associated with auditing these inconsistent clients. However, the results support the idea that differentiated disclosures reduce risk or increase audit efficiency, even when they are inconsistent with the financial statements.

Alternative Measures and Sensitivity Analyses

Larger Reference Groups

The primary narrative disclosure measures are calculated based on the similarity to the five clients that are most similar to the observation. To test the sensitivity of the results to this choice, I construct textual similarities using *all* clients in the auditor-industry-year. These three alternative measures have correlations with the original measures that range from 0.91 to 0.94.

www.manaraa.com

Compared with the original test of H1, the negative relation between client similarities and audit fees is qualitatively similar for the business description (t = -6.24), but somewhat weaker for the MD&A (t = -1.97; p-value = 0.048) and footnotes (t = -2.27; p-value = 0.023). The patterns for the second hypothesis are unchanged. For the final hypotheses regarding disclosure consistency, the results are qualitatively unchanged except that $DIFFTEXT_{MD\&A}$ is now slightly less significant (t = -2.02; p-value = 0.044) and $DIFFTEXT_{BUS}$ is no longer significant.

Overall, the results are slightly weaker in a few cases as the reference group is expanded to include more dissimilar clients. The changes in significance could be due to additional measurement error in the proxies as less relevant peers affect the calculations. This pattern is also consistent with auditors either explicitly or implicitly taking into account the similarity of more narrowly constructed client subgroups than the GICS industry as defined by Standard & Poor's.

Minimum Reference Group Size

Rather than requiring the auditor-industry-year to have at least five clients, I alternatively require at least ten clients from which to choose the five most similar. The results are qualitatively unchanged for the business description and MD&A samples, but weaker for the footnote sample. These changes in significance seem to be attributable to a reduction in sample size from 9,806 observations to only 6,317.

Accounting System Comparability

As an alternative to my approach, I also examine the accounting system comparability measures from De Franco et al. (2011). For each company, they regress 16 quarters of earnings (an accounting system output) on returns (the net economic events) to estimate the "accounting function" for that company. To determine the

المنارة للاستشارات
www.manaraa.com

similarity between any two observations, they use the fitted accounting function to predict earnings for each observation using actual returns. They interpret the difference between the two predicted earnings values as a measure of the difference in accounting systems. Aggregating these differences for all pairs of observations gives a measure of accounting system similarity for each company within an industry-year (*COMPACCT-IND*). They construct an alternative measure using only earnings by regressing 16 quarters of earnings of one company on the earnings of another. Aggregating the R^2 from each regression also gives a proxy for accounting system similarity (*COMPACCT-R2*). As a sensitivity test to my primary D^2 metric, I calculate these two measures as described in more detail in De Franco et al. (2011) as an alternative to SIM_{FS}.

As an alternative test of H1, I separately include the two accounting comparability measures in the base audit fee model. They are both significantly negative (t = -5.01 for *COMPACCT-IND* and t = -2.14 for *COMPACCT-R2*). These results hold whether or not I include SIM_{FS} in the model, although SIM_{FS} has a much higher economic magnitude and a more negative t-statistic in both cases. I find no support for the second hypothesis when using these alternative measures. However, they strongly support H3a and H3b regarding disclosure consistency. Using *COMPACCT-IND*, all of the *POOLTEXT* and *DIFFTEXT* coefficients are qualitatively similar to the original tests except that $DIFFTEXT_{NOTES}$ also becomes significantly negative, making it consistent with the business description and MD&A results.

Using the relation between earnings and returns, De Franco et al. (2011) develop an empirical proxy that is directly related to their theoretical construct. However, even though the statistical significance of their measures are similar to mine, SIM_{FS} is much

المنارة للاستشارات
www.manaraa.com

more strongly related to audit pricing in terms of economic magnitude than their measures of accounting comparability. Therefore, depending on the context, each approach could provide unique insights as proxies for company similarity. The advantages of my approach are that it requires no knowledge about the functional form of the relationship, requires less time series data, and can include an arbitrary number of economic dimensions in the similarity score.[15]

Concluding Remarks

I introduce measures of financial statement and narrative disclosure similarity as proxies for audit client overlap. As predicted, I find higher commonality among clients is associated with lower audit fees, which I interpret as reduced production costs arising from increased audit efficiency and reduced risk due to greater potential for improved audit technology and shared knowledge. These patterns are stronger when the auditor has higher financial incentives to profit from the non-idiosyncratic elements of the audit. I also find that inconsistencies between financial statements and narrative disclosures are associated with higher fees when these differences are consistent with the client attempting to reduce its apparent financial differences with peer companies. In contrast, I find lower audit fees when the narrative disclosures differ from financial statements in a manner consistent with the client revealing differentiating firm-specific information.

The measures I develop in this paper have additional potential applications in audit research. For example, client commonality could be relevant to a company that is choosing whether to keep their incumbent auditor or switch to a new one. A company might look for an auditor that already audits similar firms (or dissimilar firms if

[15] The DeFranco et al. (2011) approach can only be used as an alternative to SIM_{FS}, the financial statement similarity, and not as a proxy for narrative disclosure similarity.

المنارة للاستشارات
www.manaraa.com

knowledge spillover is a competitive concern). Outside of audit research, the financial statement and narrative disclosure inconsistency result could have implications for a company's information environment. There could also be econometric applications when the research design calls for a control company that is very similar to the original observation. While somewhat related to other measures of company similarity, such as the accounting comparability measure in De Franco et al. (2011), I provide a broader alternative that could be preferable in certain research contexts.

In addition to the contribution provided by the measures themselves, the proxies allow me to explore topics that were previously difficult to examine empirically. I provide a more direct proxy for the potential of specialization than merely using the prevalent industry market share measures, which can be difficult to interpret. This paper is also one of the few to integrate narrative disclosures as an empirical proxy for elements of the audit.

المنارة للاستشارات
www.manaraa.com

Table 3-1. Audit fee model variables.

Panel A: Descriptive statistics

Variable	Mean	Std dev	25%	Median	75%
LNFEES	13.384	1.332	12.403	13.367	14.269
AT	3,590.358	13,797.860	110.045	439.236	1,771.330
SIZE	6.119	2.050	4.701	6.085	7.479
CSITEMS	165.494	33.216	142.000	164.000	188.000
IRISK	0.235	0.185	0.085	0.199	0.341
LOSS	0.383				
LEV	0.198	0.302	0.001	0.119	0.300
DELAY	0.253				
NAS	11.260	3.575	10.692	12.024	13.190
BUSY	0.710				
OPIN	0.474				
ICMW	0.030				
TENURE	9.712	8.567	3.000	7.000	13.000
INDSHR	0.254	0.111	0.171	0.244	0.325
PORTSHR	0.022	0.015	0.011	0.019	0.028
INDSPEC	0.249				
PORTSPEC	0.282				
Observations	33,006				

www.manaraa.com

Table 3-1. Continued.

Panel B: Pairwise Pearson correlations of continuous variables in audit fee model

	LNFEES	*SIZE*	*CSITEMS*	*IRISK*	*LEV*	*NAS*	*TENURE*	*INDSHR*	*PORTSHR*
SIM_{FS}	0.02	0.13	0.11	0.10	0.07	0.02	0.05	0.01	-0.10
SIM_{BUS}	0.11	0.27	0.06	-0.17	0.10	-0.05	0.03	0.09	0.09
$SIM_{MD\&A}$	0.02	0.18	-0.02	-0.16	0.03	-0.05	0.03	0.01	-0.02
SIM_{NOTES}	0.01	0.20	-0.03	-0.16	0.08	-0.04	0.06	0.04	0.13
LNFEES		0.75	0.77	0.03	0.12	0.28	0.31	0.09	0.03
SIZE			0.65	-0.07	0.19	0.38	0.33	0.06	0.10
CSITEMS				0.12	0.16	0.28	0.36	0.04	-0.03
IRISK					-0.09	0.06	0.10	-0.04	-0.09
LEV						0.06	-0.01	-0.03	0.07
NAS							0.18	0.02	-0.02
TENURE								0.08	0.01
INDSHR									0.32

Panel A: For each client: *LNFEES* = log of audit fees. *AT* = total assets. *SIZE* = log of *AT*. *CSITEMS* = # of non-missing/non-zero variables in Compustat. *IRISK* = receivables plus inventory, scaled by *AT*. *LOSS* = 1 if net income < 0. *LEV* = long-term debt, scaled by *AT*. *DELAY* = 1 if 10-K filed > 90 days after fiscal year end. *NAS* = log of non-audit fees. *BUSY* = 1 if 12/31 fiscal year end. *OPIN* = 1 for non-standard opinion. *ICMW* = 1 if material weakness in internal control. *TENURE* = number of years with the current auditor. *INDSHR* = % of industry's fees provided to the current auditor. *PORTSHR* = % of current auditor's fees provided by the client's industry-year. *INDSPEC* = 1 if *INDSHR* >= 32.5%. *IMPIND* = 1 if *PORTSHR* >= 2.8% (economically important industry). See Table 2-1 for descriptive statistics for *SIM* measures.

Panel B: Correlations in bold are significant at the 5% level. *SIM* = similarity of observation to other clients in the financial statement (*FS*), business description (*BUS*), MD&A (*MD&A*), and footnote (*NOTES*) reference groups. See Table 2-2 for correlations of *SIM* measures.

www.manaraa.com

Table 3-2. OLS regression of audit fees on client similarity.

		LNFEES			LNFEES			LNFEES			LNFEES		
	Exp	Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat	
(Intercept)		8.169	296.35	***	8.275	268.65	***	8.392	268.73	***	8.426	182.00	***
SIZE	+	0.414	135.46	***	0.391	109.64	***	0.371	100.40	***	0.383	73.19	***
CSITEMS	+	0.009	44.70	***	0.009	42.46	***	0.009	42.87	***	0.009	28.30	***
IRISK	+	0.534	21.25	***	0.463	17.14	***	0.440	16.09	***	0.446	11.47	***
LOSS	+	0.173	21.85	***	0.170	19.36	***	0.157	17.68	***	0.160	12.61	***
LEV	+	-0.016	-0.84		-0.034	-2.12	**	-0.026	-1.69	*	0.005	0.23	
DELAY	+	0.022	2.40	**	0.112	7.75	***	0.117	7.86	***	0.064	2.89	***
NAS	+	0.021	16.14	***	0.018	12.28	***	0.018	12.01	***	0.013	6.50	***
BUSY	+	0.071	9.21	***	0.093	10.98	***	0.088	10.04	***	0.100	8.12	***
OPIN	+	0.105	13.97	***	0.100	11.74	***	0.095	10.95	***	0.079	6.49	***
ICMW	+	0.512	24.07	***	0.445	18.45	***	0.446	18.15	***	0.448	13.19	***
TENURE	+	0.003	6.50	***	0.002	5.50	***	0.002	3.75	***	0.002	2.39	**
INDSPEC	?	0.084	10.16	***	0.073	7.79	***	0.067	7.03	***	0.046	3.36	***
SIM_{FS}	-	-0.016	-9.41	***	-0.015	-8.52	***	-0.013	-7.41	***	-0.011	-4.35	***
SIM_{BUS}	-				-0.339	-9.98	***						
$SIM_{MD\&A}$	-							-0.158	-4.77	***			
SIM_{NOTES}	-										-0.245	-2.86	***
Years		Yes			Yes			Yes			Yes		
Industries		Yes			Yes			Yes			Yes		
Adj R^2		0.808			0.822			0.810			0.803		
Model F		5,729			4,111			3,666			1,632		
Obs		32,412			21,450			20,530			9,806		

H1 predicts negative coefficients on the *SIM* measures. Variables defined in Table 3-1. Standard errors are Huber-White-adjusted. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, in a two-tailed test.

المنارة للاستشارات
www.manaraa.com

Table 3-3. Regression of fees on client similarity conditional on auditor incentives.

	LNFEES			LNFEES			LNFEES			LNFEES		
	Coef	t-stat		Coef	t-stat		Coef	t-stat		Coef	t-stat	
(Intercept)	8.169	293.82	***	8.268	268.16	***	8.385	268.46	***	8.416	180.52	***
SIZE	0.414	135.42	***	0.391	109.62	***	0.371	100.26	***	0.383	73.21	***
CSITEMS	0.009	44.81	***	0.009	42.47	***	0.009	42.90	***	0.009	28.34	***
IRISK	0.533	21.24	***	0.464	17.15	***	0.440	16.11	***	0.446	11.47	***
LOSS	0.173	21.79	***	0.170	19.36	***	0.157	17.68	***	0.160	12.62	***
LEV	-0.015	-0.79		-0.034	-2.13	**	-0.026	-1.68	*	0.006	0.24	
DELAY	0.022	2.45	**	0.112	7.74	***	0.117	7.84	***	0.064	2.89	***
NAS	0.021	16.14	***	0.018	12.26	***	0.018	12.00	***	0.013	6.49	***
BUSY	0.071	9.24	***	0.093	10.98	***	0.088	10.06	***	0.100	8.12	***
OPIN	0.104	13.90	***	0.099	11.70	***	0.094	10.90	***	0.079	6.45	***
ICMW	0.513	24.11	***	0.445	18.46	***	0.446	18.16	***	0.449	13.20	***
TENURE	0.003	6.47	***	0.002	5.50	***	0.002	3.74	***	0.002	2.40	**
INDSPEC	0.077	8.67	***	0.065	6.53	***	0.060	5.91	***	0.038	2.66	***
ECONIMP	-0.010	-0.59		0.027	2.19	**	0.024	1.92	*	0.027	1.59	
SIM_{FS}	-0.014	-7.68	***	-0.015	-8.50	***	-0.013	-7.39	***	-0.011	-4.31	***
$ECONIMP*SIM_{FS}$	-0.009	-3.54	***									
SIM_{BUS}				-0.337	-8.08	***						
$ECONIMP*SIM_{BUS}$				-0.006	-0.09							
$SIM_{MD\&A}$							-0.151	-4.03	***			
$ECONIMP*SIM_{MD\&A}$							-0.022	-0.33				
SIM_{NOTES}										-0.317	-2.86	***
$ECONIMP*SIM_{NOTES}$										0.149	0.95	

المنارة للاستشارات
www.manaraa.com

Table 3-3. Continued.

Years	Yes	Yes	Yes	Yes
Industries	Yes	Yes	Yes	Yes
Adj R^2	0.809	0.822	0.810	0.803
Model F	5,270	3,787	3,374	1,502
Obs	32,412	21,450	20,530	9,806

H2 predicts negative coefficients on the interaction terms. *IMPIND* = 1 if *PORTSHR* >= 2.8% (economically important industry). Other variables defined in Table 3-1. Standard errors are Huber-White-adjusted. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, in a two-tailed test.

www.manaraa.com

Table 3-4. Regression of fees on client similarity conditional on disclosure consistency.

		LNFEES			LNFEES			LNFEES		
	Exp	Coef	t-stat		Coef	t-stat		Coef	t-stat	
(Intercept)		8.287	267.89	***	8.400	267.85	***	8.427	182.24	***
SIZE	+	0.391	109.56	***	0.370	100.24	***	0.382	73.14	***
CSITEMS	+	0.009	42.48	***	0.009	43.06	***	0.009	28.42	***
IRISK	+	0.459	16.99	***	0.433	15.85	***	0.442	11.36	***
LOSS	+	0.170	19.31	***	0.157	17.64	***	0.160	12.61	***
LEV	+	-0.033	-2.05	**	-0.027	-1.75	*	0.005	0.23	
DELAY	+	0.111	7.72	***	0.117	7.87	***	0.065	2.93	***
NAS	+	0.018	12.33	***	0.018	12.00	***	0.013	6.49	***
BUSY	+	0.094	11.05	***	0.088	10.01	***	0.100	8.12	***
OPIN	+	0.099	11.68	***	0.095	10.99	***	0.079	6.49	***
ICMW	+	0.445	18.48	***	0.446	18.23	***	0.451	13.27	***
TENURE	+	0.002	5.45	***	0.002	3.77	***	0.002	2.43	**
INDSPEC	?	0.073	7.84	***	0.069	7.23	***	0.048	3.49	***
SIM_{FS}	-	-0.012	-6.14	***	-0.010	-5.46	***	-0.009	-3.48	***
SIM_{BUS}	-	-0.415	-11.31	***						
$POOLTEXT_{BUS}$	+	0.077	5.05	***						
$DIFFTEXT_{BUS}$	?	-0.033	-2.50	**						
$SIM_{MD\&A}$	-				-0.225	-6.35	***			
$POOLTEXT_{MD\&A}$	+				0.064	4.43	***			
$DIFFTEXT_{MD\&A}$	?				-0.036	-2.73	***			
SIM_{NOTES}	-							-0.323	-3.54	***
$POOLTEXT_{NOTES}$	+							0.050	2.40	**
$DIFFTEXT_{NOTES}$	?							-0.022	-1.07	

www.manaraa.com

Table 3-4. Continued.

Years	Yes	Yes	Yes
Industries	Yes	Yes	Yes
Adj R^2	0.822	0.810	0.803
Model F	3,801	3,384	1,503
Obs	21,450	20,530	9,806

H3a predicts a positive coefficient on *POOLTEXT*. H3b predicts the coefficient on *DIFFTEXT* is nonzero. *POOLTEXT (DIFFTEXT)* = 1 if observation is in the lowest (highest) tercile of financial statement similarity and the highest (lowest) tercile of narrative disclosure similarity. Other variables defined in Table 3-1. Errors are Huber-White-adjusted. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, in a two-tailed test.

المنارة للاستشارات

www.manaraa.com

CHAPTER 4
CONCLUSION

I find broad evidence that clients systematically choose their auditor and that the relationship between a client and its auditor has implications for both audit quality and costs. Clients tend to prefer auditors that are more compatible with them, and are even more likely to switch auditors when the compatibility is poor. General measures of audit quality improve when auditor-client compatibility increases, even though severe audit failures appear to also increase. When the compatibility is higher, audit fees tend to be lower, which I argue is indicative of lower production costs for the auditor that arise through specialization of the audit process to a specific set of clients. Reinforcing this interpretation, the fees are even lower when the auditor has stronger incentives to develop these specialized processes. As further support, fees are higher in the presence of inconsistencies among the client's disclosure channels, which I interpret as a constraint on auditor specialization. I use the similarity of a client to other clients of the same auditor to proxy for auditor-client compatibility and the commonality among a set of clients.

I develop two novel measures of how similar one company is to a set of other companies. I take a broad approach by using both financial statements and narrative disclosures as sources of information, and then introduce two distinct algorithms appropriate to the structure of each information signal. The Mahalanobis D^2 measure has been used to a limited extent in accounting research, but solely for statistical purposes and not as a construct of interest. This measure is appropriate for any setting in which a researcher has a small set of numeric variables. No specific (known) relationship among the variables is necessary, other than them being relevant for the

www.manaraa.com

context at hand. For example, no assumptions about an earnings-return relationship is necessary, as is required in one of the few accounting similarity scores currently available (De Franco et al. 2011). The Mahalanobis distance is robust to correlations among the variables and is not affected by the scale of those variables. In this study, my basic analysis uses five variables known to be important in an audit context. However, the measure seems quite robust to various input variables, with no changes to my qualitative results when various variables are removed or added to the input set. Overall, the D^2 approach seems very useful when constructing a single summary measure of similarity and dissimilarity among a set of financial statements.

While the Mahalanobis distance is very powerful and robust, it is not feasibly implemented when the set of input variables is extremely large, as is the case when long textual items are used as an information source. In this situation, I provide an alternative that can handle extremely large quantities of information. In fact, the Vector Space Model (VSM) approach I use is implemented by Internet search engines that need to compare many billions of documents. In the current context, I extend the method introduced to the accounting literature in Brown and Tucker (2011), which analyzes only two documents, so that I can compare one company to others. The similarity scores I produce are correlated with other known measures of similarity, such as discretionary accruals, simple differences of the company from the mean of the industry, and even the Mahalanobis distance. These correlations with a variety of financial statement constructs are significant despite the fact that the language-based sources of the similarity measures contain no references to the financial statement variables (they are intentionally stripped out of the calculations). My findings

المنارة للاستشارات
www.manaraa.com

demonstrate the VSM approach is continuing to show promise as a measure of narrative disclosure similarity.

The two similarity algorithms have additional applications within accounting research. For example, a common econometric problem is to match a “treated” observation (e.g., a company receiving an SEC enforcement action) with an “untreated” observation. A common approach is to match on size and industry, which can produce matches that are not very close, other than along the size dimension (and sometimes the observations are not even very similar in size). The Mahalanobis approach is already used to perform a match along multiple dimensions, as in the psmatch2 command within the Stata software package. However, I provide a new alternative based on narrative disclosures that could pair companies who have made very similar disclosure decisions even if they are not that similar financially.

Another area of recent focus in accounting research is on the implications of networks. One example is social networks, which we observe when individuals are connected through board memberships, social clubs, and alma maters. Another example is in studies of how accounting standards and other disclosures become diffused throughout an economy. These timely topics are concerned with how various entities are connected to one another. Rather than using the traditional econometric approach of assuming independence between observations, they seek to exploit this dependence. My measures provide another means for researchers to study these connections, because they explicitly proxy for the degree of connectedness among observations. For instance, the narrative disclosure similarity score could be used to detect when a specific accounting disclosure spreads throughout an industry.

المنارة للاستشارات
www.manaraa.com

While showing promise for future research, my findings also have implications for regulators. One persistent issue raised in the United States is the potential for mandatory rotation of auditors after a specific number of years, a rule already in place in other countries. There are obvious potential benefits for audit quality under a mandatory rotation regime because independence in fact and appearance are potentially better preserved. However, a trickier issue is assessing the costs of such rotations. My results show that clients do not randomly choose among auditors of a given type (e.g., Big4 auditors). Therefore, a non-voluntary auditor change has the potential to move a client away from the "first-best" auditor for that company; in other words, auditors are not fungible. Auditor switching costs are already documented due to the learning process that takes place in the first years of an audit engagement. However, my studies point to other costs of forcing clients to leave their preferred auditors. These costs take the form of both changes in audit quality and audit fees.

Overall, my findings contribute to our understanding of the nature of the auditor-client relationship, especially given a relative lack of literature on the mechanisms by which specific clients are connected to specific auditors. These conclusions have implications for both regulators and researchers. In addition, I contribute novel measures of inter-company similarity that have broad potential applications in a variety of studies, even those outside of auditing research.

المنارة للاستشارات
www.manaraa.com

APPENDIX A
EXTRACTION OF ANNUAL REPORT ITEMS

To gather the business description, MD&A, and footnotes sample, I begin by downloading all 10-K's and 10-K405's available on the SEC's EDGAR system that meet the following requirements: (1) fiscal years between 1997 and 2009, (2) assets greater than $1 million, (3) no change in fiscal year-end, (4) not in the utilities or financial services industries, and (5) engaging a Big4 auditor. As described in Table A1, this initial screen leaves 41,782 annual reports.

I next screen out any unusually short annual reports since these typically belong to holding companies, firms that are winding down, and other atypical observations. I use a cutoff of 50,000 characters for this purpose (approximately the 4th percentile of 10-K length). This value filters out most of the unwanted observations without losing a substantial number of desired reports. I use characters instead of words because the tables and numbers contained in the report make it difficult to split the document into "words" at this point in the process. These filters leave 40,149 annual reports.

I begin the item extraction process by stripping all HTML formatting and data tables as in Li (2008; 2010). I then split each annual report into its component items, keeping only the business description, MD&A, and footnotes (the financial statements are removed when data tables are discarded).

I remove any narrative disclosures that contain language indicating the relevant section has been omitted as permitted by regulation. I skip disclosures that are included by reference, either to an external document or an attached exhibit, since the variety of alternate locations dramatically increases the difficulty in obtaining that data. The footnotes, in particular, are frequently included by reference. I drop any remaining items

www.manaraa.com

that do not contain at least 150 characters. Items shorter than this cutoff have typically been omitted or included by reference, but do so using somewhat unusual wording that my initial string search did not recognize.

I split each item into words, keeping disclosures with at least 500 words. Items shorter than this length are relatively unusual and are unlikely to provide a meaningful comparison to disclosures by peers in the auditor-industry-year reference group. Finally, I exclude items exceeding 20,000 words because these frequently indicate problems splitting the 10-K into separate items. For example, the extraction process might erroneously treat the entire annual report as the business description due to misspellings and other idiosyncratic document features. Archival studies frequently handle outliers such as these through deletion, winsorization, or robust techniques during the empirical analysis. However, doing so in the current study would allow these outliers to be in reference groups and therefore have an undesirable influence on the calculation of the similarity scores.

There are fewer observations in the narrative disclosure samples than in the financial statement sample, primarily due to unavailable reports on EDGAR, items included by reference to other locations, and textual idiosyncrasies that lead to problems extracting the 10-K items of interest. The substantial drop in the number of footnote observations, as compared to the business description and MD&A samples, is because many companies attach financial statements and footnotes as an exhibit to the report in a variety of unpredictable ways, making their automated extraction difficult.

المنارة للاستشارات
www.manaraa.com

Table A-1. Narrative disclosure sample selection process.

	Reports		
10-K available on EDGAR; fiscal years 1997-2009; Compustat assets > $1M; no FYE change; excl. financials and utilities; Big4 auditor	41,782		
Less: Short reports (<50,000 characters)	(1,633)		
Total annual reports available	40,149		
	Bus desc	**MD&A**	**Footnotes**
Less: Item not succesfully extracted	(1,918)	(936)	(1,166)
Less: Item specifically omitted	(10)	(41)	(117)
Less: Item included by reference	(23)	(2,840)	(10,516)
Less: Short items (<150 characters)	(1,277)	(1,173)	(3,415)
Less: < 500 or > 20,000 words	(886)	(1,257)	(7,227)
Less: < 5 other clients in auditor-industry-year	(2,680)	(2,622)	(3,269)
Total items available	33,355	31,280	14,439

www.manaraa.com

APPENDIX B

CALCULATION OF NARRATIVE DISCLOSURE SIMILARITY SCORE

As described in Brown and Tucker (2011), the Vector Space Model (VSM) maps a document into a vector, v, with each vector element, w_i, representing the weighted frequency of a word in that document. The weighted frequency is zero if the word does not occur in that document and the length of the vector is n, the number of unique words in all documents of the sample:

$$v = (w_1, w_2, \ldots, w_n)$$

For example, assume there are only two documents in the sample: (1) "Earnings have increased." and (2) "Earnings have decreased." The length of each document vector is four, since there are four unique words in the sample: w_1 corresponds to "earnings," w_2 to "have," w_3 to "increased," and w_4 to "decreased." The two documents are then represented as:

$$v_1 = (1, 1, 1, 0) \qquad \text{"}\textit{Earnings have increased.}\text{"}$$

$$v_2 = (1, 1, 0, 1) \qquad \text{"}\textit{Earnings have decreased.}\text{"}$$

The vectors allow for various comparisons between documents in the sample (Manning and Schütze 1999). The cosine of the angle, θ, between any two vectors, v_i and v_j, is a proxy for the similarity of any two underlying documents, $SIM_{DOC,i,j}$:

$$SIM_{DOC,i,j} = \cos(\theta) = \frac{v_i}{\|v_i\|} \cdot \frac{v_j}{\|v_j\|} = \frac{v_i \cdot v_j}{\|v_i\| \|v_j\|},$$

where $(\cdot)$ is the vector dot product operator, $\|v_i\|$ is the length of v_i, and $\|v_j\|$ is the length of v_j. SIM_{DOC} ranges from zero (completely dissimilar documents) to one (identical documents). I stem all words using the Porter stemming algorithm to reduce the dimensionality of the data, which in turn limits the computing time and resources

المنارة للاستشارات
www.manaraa.com

required (e.g., “earnings,” “earned,” and “earn” are all converted to “earn”).[1] Consistent with Brown and Tucker (2011), I use the term frequency-inverse document frequency (TF-IDF) algorithm to decrease the weight on frequently used words and increase the weight on uncommon words.[2] Therefore, instead of a raw frequency count, each document vector element is the frequency count of the word multiplied by a weight based on the relative prominence of that word in the entire sample.

Because Brown and Tucker (2011) are interested in the differences between just two documents at a time, they only calculate pairwise similarity scores. In contrast, I aggregate these pairwise scores to get a measure of the similarity between one narrative disclosure and the disclosures issued by the client reference group. As with the financial statement similarities, the reference group contains other clients of the same auditor, within the same GICS industry and year. To combine the pairwise $SIM_{DOC,i,j}$ scores between client i and all other clients j in the same auditor, industry, and year, I average the pairwise similarities to get $SIM_{DOC,i}$ for each observation in my sample.

I calculate the $SIM_{DOC,i}$ similarity measure for each observation in the business description ($RAWSIM_{BUS}$), MD&A ($RAWSIM_{MD\&A}$) and footnote ($RAWSIM_{NOTES}$) samples. However, Brown and Tucker (2011) show that these raw scores are positively related to document length because of the mechanics of the calculation, rather than due

[1] Even with the reduced dimensions, the calculations take over one week to run on a 2.66 GHz, quad-core machine, while occupying most of the 6 gigabytes of working memory.

[2] I do not use a “stop word” list to remove extremely common (i.e., unimportant) words, such as “the” and “a,” from the sample as in Li (2010). These words will receive a weight of zero, or very close to it, via the TF-IDF weighting procedure. Brown and Tucker (2011) find no substantial difference in their conclusions between using the TF-IDF approach and a simple frequency count combined with a stop word list. I generate the TF-IDF weights independently for each type of narrative disclosure.

المنارة للاستشارات
www.manaraa.com

to any meaningful underlying relation. They control for this relationship by regressing the raw similarity on the first five powers of the number of words in the observation *i* document (LEN_{BUS}, $LEN_{MD\&A}$, and LEN_{NOTES} in the current study)—in the current study I use the first three powers because the magnitudes of the coefficients rapidly approach zero after this point.[3] In order to maximize the sample size for making this adjustment, I use all available observations, including those from non-Big4 auditors; for all other tests in the paper, I use only clients of Big4 auditors.

Regressing the raw similarity scores on the first three powers of the document length yields a residual that represents the variation in the raw similarity scores that cannot be explained by these factors. I label these residuals SIM_{BUS}, $SIM_{MD\&A}$, and SIM_{NOTES}, producing the similarity scores I use in my analysis. Descriptive data for these measure components are in Table B1.

[3] Hanley and Hoberg (2012) use the VSM to measure the similarity of an IPO prospectus to all the recent IPO's experiencing litigation problems. However, they do not control for document length, making it difficult to ascertain the validity of their measure.

المنارة للاستشارات
www.manaraa.com

Table B-1. Calculation of narrative disclosure similarity measures.

Variable	Mean	Std dev	25%	Median	75%	Obs
SIM_{BUS}	0.002	0.077	(0.053)	(0.017)	0.040	33,355
$SIM_{MD\&A}$	0.002	0.087	(0.057)	(0.024)	0.038	31,280
SIM_{NOTES}	0.000	0.048	(0.029)	(0.013)	0.011	14,439
$RAWSIM_{BUS}$	0.108	0.085	0.045	0.087	0.148	36,035
$RAWSIM_{MD\&A}$	0.113	0.095	0.044	0.086	0.155	33,902
$RAWSIM_{NOTES}$	0.054	0.061	0.021	0.037	0.064	17,708
LEN_{BUS}	6,338	3,739	3,602	5,471	8,252	36,253
$LEN_{MD\&A}$	7,054	3,870	3,984	6,437	9,401	34,131
LEN_{NOTES}	8,623	4,018	5,423	7,934	11,178	18,083

Subscripts: *BUS* = Business Description, *MD&A* = Management's Discussion & Analysis, *NOTES* = Footnotes to Financial Statements.
Variables: *SIM* = similarity of observation to other clients in the reference group, adjusted for *LEN*; higher value indicates more similarity. *RAWSIM* = *SIM* before adjustment. *LEN* = # of words in the observation's text.

www.manaraa.com

LIST OF REFERENCES

Amir, E. 1993. The Market Valuation of Accounting Information: The Case of Postretirement Benefits Other Than Pensions. *The Accounting Review* 68 (4): 703–724.

Balsam, S., J. Krishnan, and J. S. Yang. 2003. Auditor Industry Specialization and Earnings Quality. *Auditing* 22 (2): 71–97.

Bamber, E. M., and V. M. Iyer. 2007. Auditors' Identification with Their Clients and Its Effect on Auditors' Objectivity. *Auditing* 26 (2): 1–24.

Bamber, L. S., and Y. S. Cheon. 1998. Discretionary Management Earnings Forecast Disclosures: Antecedents and Outcomes Associated with Forecast Venue and Forecast Specificity Choices. *Journal of Accounting Research* 36 (2): 167–190.

Beck, P. J., and M. G. H. Wu. 2006. Learning by Doing and Audit Quality. *Contemporary Accounting Research* 23 (1): 1–30.

Berry, H., M. F. Guillén, and N. Zhou. 2010. An Institutional Approach to Cross-National Distance. *Journal of International Business Studies* 41 (9): 1460–1480.

Blokdijk, H., F. Drieenhuizen, D. A. Simunic, and M. T. Stein. 2006. An Analysis of Cross-Sectional Differences in Big and Non-Big Public Accounting Firms' Audit Programs. *Auditing* 25 (1): 27–48.

Brown, S. V., and J. W. Tucker. 2011. Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications. *Journal of Accounting Research* 49 (2): 309–346.

Cahan, S., J. Godfrey, J. Hamilton, and D. Jeter. 2008. Auditor Specialization, Auditor Dominance, and Audit Fees: The Role of Investment Opportunities. *The Accounting Review* 83 (6): 1393–1423.

Cairney, T. D., and G. R. Young. 2006. Homogenous Industries and Auditor Specialization: An Indication of Production Economies. *Auditing* 25 (1): 49–67.

Campbell, J. L., H. Chen, D. S. Dhaliwal, H.-M. Lu, and L. Steele. 2010. The Information Content of Mandatory Risk Factor Disclosures in Corporate Filings. *Working Paper*.

Causholli, M., M. De Martinis, D. Hay, and W. R. Knechel. 2010. Audit Markets, Fees and Production: Towards an Integrated View of Empirical Audit Research. *Journal of Accounting Literature* 29: 167–215.

Chaney, P. K., D. C. Jeter, and L. Shivakumar. 2004. Self-Selection of Auditors and Audit Pricing in Private Firms. *The Accounting Review* 79 (1): 51–72.

المنارة للاستشارات
www.manaraa.com

Chung, H., and S. Kallapur. 2003. Client Importance, Nonaudit Services, and Abnormal Accruals. *The Accounting Review* 78 (4): 931–955.

Craswell, A. T., J. R. Francis, and S. L. Taylor. 1995. Auditor brand name reputations and industry specializations. *Journal of Accounting and Economics* 20 (3): 297–322.

Darr, E. D., L. Argote, and D. Epple. 1995. The Acquisition, Transfer, and Depreciation of Knowledge in Service Organizations: Productivity in Franchises. *Management Science* 41 (11): 1750–1762.

Davis, L. R., D. N. Ricchiute, and G. Trompeter. 1993. Audit Effort, Audit Fees, and the Provision of Nonaudit Services to Audit Clients. *The Accounting Review* 68 (1): 135–150.

Dechow, P., W. Ge, C. Larson, and R. Sloan. 2011. Predicting Material Accounting Misstatements. *Contemporary Accounting Research* 28 (1): 17–82.

DeFond, M. L., and J. Jiambalvo. 1994. Debt Covenant Violation and Manipulation of Accruals. *Journal of Accounting and Economics* 17 (1-2): 145–176.

DeFond, M. L., and K. R. Subramanyam. 1998. Auditor changes and discretionary accruals. *Journal of Accounting and Economics* 25 (1): 35–67.

Dowling, C. 2009. Appropriate Audit Support System Use: The Influence of Auditor, Audit Team, and Firm Factors. *The Accounting Review* 84 (3): 771–810.

Dunn, K. A., and B. W. Mayhew. 2004. Audit Firm Industry Specialization and Client Disclosure Quality. *Review of Accounting Studies* 9 (1): 35–58.

Dye, R. A. 1991. Informationally motivated auditor replacement. *Journal of Accounting and Economics* 14 (4): 347–374.

Feldman, R., S. Govindaraj, J. Livnat, and B. Segal. 2010. Management's tone change, post earnings announcement drift and accruals. *Review of Accounting Studies* 15 (4): 915–953.

De Franco, G., S. P. Kothari, and R. S. Verdi. 2011. The Benefits of Financial Statement Comparability. *Journal of Accounting Research* 49 (4): 895–931.

Fried, D., and A. Schiff. 1981. CPA Switches and Associated Market Reactions. *The Accounting Review* 56 (2): 326–341.

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

المنارة للاستشارات

www.manaraa.com

Guilding, C., and L. McManus. 2002. The Incidence, Perceived Merit and Antecedents of Customer Accounting: An Exploratory Note. *Accounting, Organizations and Society* 27 (1-2): 45–59.

Gul, F. A., S. Y. K. Fung, and B. Jaggi. 2009. Earnings quality: Some evidence on the role of auditor tenure and auditors' industry expertise. *Journal of Accounting and Economics* 47 (3): 265–287.

Hackenbrack, K., and W. R. Knechel. 1997. Resource allocation decisions in audit engagements. *Contemporary Accounting Research* 14 (3): 481–499.

Hair, J. F., W. C. Black, B. J. Babin, R. E. Anderson, and R. L. Tatham. 2006. *Multivariate Data Analysis*. 6th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Hammersley, J. S. 2006. Pattern Identification and Industry-Specialist Auditors. *The Accounting Review* 81 (2): 309–366.

Hanley, K. W., and G. Hoberg. 2012. Litigation risk, strategic disclosure and the underpricing of initial public offerings. *Journal of Financial Economics* 103 (2): 235–254.

Hay, D. C., W. R. Knechel, and N. Wong. 2006. Audit Fees: A Meta-analysis of the Effect of Supply and Demand Attributes. *Contemporary Accounting Research* 23 (1): 141–191.

Iyer, V. M. 1998. Characteristics of Accounting Firm Alumni Who Benefit Their Former Firm. *Accounting Horizons* 12 (1): 18–30.

Jaffe, A. B. 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. *The American Economic Review* 76 (5): 984–1001.

Johnson, W. B., and T. Lys. 1990. The market for audit services : Evidence from voluntary auditor changes. *Journal of Accounting and Economics* 12 (1-3): 281–308.

Johnstone, K. M., C. Li, and S. Luo. 2011. Client Supply Chain Relationships, Audit Firm Selection, and Implications for Audit Quality and Pricing. *Working Paper*.

Knechel, W. R., V. Naiker, and G. Pacheco. 2007. Does Auditor Industry Specialization Matter? Evidence from Market Reaction to Auditor Switches. *Auditing* 26 (1): 19–45.

Knechel, W. R., L. Niemi, and M. Zerni. 2012. Empirical Evidence on the Implicit Determinants of Compensation in Big four Audit Partnerships. *Working Paper*.

المنارة للاستشارات

www.manaraa.com

Kravet, T. D., and V. Muslu. 2010. Informativeness of Risk Disclosures in Corporate Annual Reports. *Working Paper*.

Krishnan, G. V. 2003. Does big 6 auditor industry expertise constrain earnings management? *Accounting Horizons* 17: 1–16.

Krishnan, J. 1994. Auditor Switching and Conservatism. *The Accounting Review* 69 (1): 200–215.

Landsman, W., K. Nelson, and B. Rountree. 2009. Auditor Switches in the Pre- and Post-Enron Eras: Risk or Realignment? *The Accounting Review* 84 (2): 531–558.

Lawrence, A., M. Minutti-Meza, and P. Zhang. 2011. Can Big 4 versus Non-Big 4 Differences in Audit-Quality Proxies Be Attributed to Client Characteristics? *The Accounting Review* 86 (1): 259–286.

Lennox, C. 2005. Audit quality and executive officers' affiliations with CPA firms. *Journal of Accounting and Economics* 39 (2): 201–231.

Lennox, C., and C. Park. 2007. Audit Firm Appointments, Audit Firm Alumni, and Audit Committee Independence. *Contemporary Accounting Research* 24 (1): 235–258.

Li, F. 2008. Annual Report Readability, Current Earnings, and Earnings Persistence. *Journal of Accounting and Economics* 45 (2-3): 221–247.

———. 2010. The Information Content of Forward-Looking Statements in Corporate Filings—A Naïve Bayesian Machine Learning Approach. *Journal of Accounting Research* 48 (5): 1049–1102.

Lim, C.-Y., and H.-T. Tan. 2008. Non-audit Service Fees and Audit Quality: The Impact of Auditor Specialization. *Journal of Accounting Research* 46 (1): 199–246.

Low, K.-Y. 2004. The Effects of Industry Specialization on Audit Risk Assessments and Audit-Planning Decisions. *The Accounting Review* 79 (1): 201–219.

De Maesschalck, R., D. Jouan-Rimbaud, and D. L. Massart. 2000. The Mahalanobis Distance. *Chemometrics and Intelligent Laboratory Systems* 50 (1): 1–18.

Mahalanobis, P. C. 1936. On the Generalized Distance in Statistics. *Proceedings of the National Institute of Sciences of India* 2 (1): 49–55.

Manning, C. D., and H. Schütze. 1999. *Foundations of Statistical Natural Language Processing*. Cambridge, Mass: MIT Press.

المنارة للاستشارات
www.manaraa.com

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* 22 (2): 33–52.

Menon, K., and D. D. Williams. 2004. Former Audit Partners and Abnormal Accruals. *The Accounting Review* 79 (4): 1095–1118.

Mimmack, G. M., S. J. Mason, and J. S. Galpin. 2001. Choice of Distance Matrices in Cluster Analysis: Defining Regions. *Journal of Climate* 14 (12): 2790–2797.

Minutti-Meza, M. 2010. Does Auditor Industry Specialization Improve Audit Quality? Evidence from Comparable Clients. *Working Paper*.

Neal, T. L., and R. R. Riley Jr. 2004. Auditor Industry Specialist Research Design. *Auditing* 23 (2): 169–177.

Nichols, D. R., and D. B. Smith. 1983. Auditor Credibility and Auditor Changes. *Journal of Accounting Research* 21 (2): 534–544.

Numan, W., and M. Willekens. 2012. An empirical test of spatial competition in the audit market. *Journal of Accounting and Economics* 53 (1–2): 450–465.

O'Keefe, T. B., R. D. King, and K. M. Gaver. 1994. Audit Fees, Industry Specialization, and Compliance with GAAS Reporting Standards. *Auditing* 13 (2): 41–55.

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 (2): 241–261.

Owhoso, V. E., W. F. Messier Jr., and J. G. Lynch Jr. 2002. Error Detection by Industry-Specialized Teams during Sequential Audit Review. *Journal of Accounting Research* 40 (3): 883–900.

Palmrose, Z.-V. 1986. Audit Fees and Auditor Size: Further Evidence. *Journal of Accounting Research* 24 (1): 97–110.

PCAOB. 2011. *Concept Release on Auditor Independence and Audit Firm Rotation*. *PCAOB Release No. 2011-006*.

Public Company Accounting Oversight Board. 2011. *Concept Release on Possible Revisions to Pcaob Standards Related to Reports on Audited Financial Statements*. *PCAOB Release No. 2011-003*.

Rege, U. P. 1984. Accounting Ratios to Locate Take-Over Targets. *Journal of Business Finance & Accounting* 11 (3): 301–311.

المنارة للاستشارات

www.manaraa.com

Richardson, S. A., R. G. Sloan, M. T. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics* 39 (3): 437–485.

Riedl, E., and S. Srinivasan. 2010. Signaling Firm Performance Through Financial Statement Presentation:: An Analysis Using Special Items. *Contemporary Accounting Research* 27 (1): 289–332.

Salton, G., A. Wong, and C. S. Yang. 1975. A Vector Space Model for Automatic Indexing. *Communications of the ACM* 18 (11): 613–620.

Securities and Exchange Commission. 1987. *Concept Release on Management's Discussion and Analysis of Financial Condition and Operations*. *Release No. 33-6711*.

———. 1989. *Management's Discussion and Analysis of Financial Condition and Results of Operations; Certain Investment Company Disclosures*. *Release No. 33-6835*.

———. 2003. *Commission Guidance Regarding Management's Discussion and Analysis of Financial Condition and Results of Operations*. *Release No. 33-8350*.

Shevlin, T. 1991. The Valuation of R&D Firms with R&D Limited Partnerships. *The Accounting Review* 66 (1): 1–21.

Shu, S. Z. 2000. Auditor resignations: clientele effects and legal liability. *Journal of Accounting and Economics* 29 (2): 173–205.

Singhal, A. 2001. Modern Information Retrieval: A Brief Overview. *Bulletin of the IEEE Computer Society Technical Committee on Data Engineering* 24 (4): 35–43.

Sirois, L.-P., and D. A. Simunic. 2010. Auditor Size and Audit Quality Revisited: The Importance of Audit Technology. *Working Paper*.

Sun, Y. 2010. Do MD&A Disclosures Help Users Interpret Disproportionate Inventory Increases? *The Accounting Review* 85 (4): 1411–1440.

Tasker, S. C. 1998. Bridging the Information Gap: Quarterly Conference Calls as a Medium for Voluntary Disclosure. *Review of Accounting Studies* 3 (1): 137–167.

Wahlen, J. M. 1994. The Nature of Information in Commercial Bank Loan Loss Disclosures. *The Accounting Review* 69 (3): 455–478.

Ward, D. D., R. J. Elder, and S. C. Kattelus. 1994. Further Evidence on the Determinants of Municipal Audit Fees. *The Accounting Review* 69 (2): 399–411.

المنارة للاستشارات
www.manaraa.com

Willenborg, M. 2002. Discussion of "Brand Name Audit Pricing, Industry Specialization, and Leadership Premiums post-Big 8 and Big 6 Mergers." *Contemporary Accounting Research* 19 (1): 111–116.

www.manaraa.com

BIOGRAPHICAL SKETCH

Stephen V. Brown has a Bachelor of Science in computer science from the University of North Florida in Jacksonville, Florida, where he also earned a Master of Business Administration with a concentration in accounting. He was a computer analyst and programmer before becoming licensed as a Certified Public Accountant in the State of Florida. His Ph.D., from the University of Florida, is in business administration with a concentration in accounting.

المنارة للاستشارات

www.manaraa.com