AUDIT QUALITY DIFFERENTIALS FOR CONSTRAINING COSMETIC EARNINGS MANAGEMENT IN THE PRE-SOX ERA: AN ANALYSIS OF AUDIT FIRM SIZE AND BRAND

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ABSTRACT

Cosmetic earnings management (CEM) exists when a nine appears in the second digital position of the earnings number and management increases income through the use of discretionary accruals just enough to boost the second digit from nine to zero. The purpose of this earnings rounding is the resulting increase in the first (left-most) income digit by one. For example, unmanipulated income of $696 million would be managed upward with the earnings number reported at slightly above $700 million. Significant research shows that managers consistently practiced CEM in the U.S. for several decades before the 2000s but that it disappeared around the time of SOX's implementation. Another stream of research suggests that an audit quality differential exists between Big N and non-Big N audit firms with respect to their ability to constrain the use of discretionary accruals and thus restrict earnings management. This article contributes to the literature by assessing an historical aspect of audit quality between Big N and non-Big N firms by testing for the presence of an audit quality differential relative to constraining CEM during an extensive pre-SOX period. The results indicate little, if any, audit quality differential exists as the clients of both Big N and non-Big N auditors practiced significant levels of CEM as did the clients of each individual Big N firm. The results also show that, regardless of auditor size, smaller companies appeared to practice CEM more aggressively than larger entities.

INTRODUCTION

Kinnunen and Koskela (2003, p. 40) note that cosmetic earnings management (CEM) results from a company rounding income up by a small amount, "when such rounding yields an earnings number that seems abnormally larger than would be the case otherwise." For example, unmanipulated earnings of $4.94 million would be boosted through the use of discretionary accruals until it just exceeds $5.00 million. The objective of this relatively slight, but impactful, earnings manipulation is to enhance the first (left-most) income digit, which is frequently the only digit remembered by financial statement readers (Carslaw, 1988). For example, in the case above, if earnings had been reported at $4.94 million investors would have likely recalled it as $4 million something, while the upwardly managed earnings number would be remembered as $5 million something.

Even though these diminutive manipulations of income might seem harmless, Thomas (1989, p. 774) speculates that "small changes in reported earnings near user reference points have disproportionately large effects on firm value." Research shows that CEM consistently occurred in the U.S. at least from the 1920s through the 1990s (e.g., Cox et al., 2006; Guan et al., 2006; Jordan & Clark, 2015; Thomas, 1989) but vanished in the post-Sarbanes-Oxley (SOX) era (e.g., Aono & Guan, 2008; Lin & Wu, 2014; Wilson, 2012).

Numerous studies examine whether audit quality acts as a deterrent to earnings management, with audit quality often captured by the Big N (i.e., 8/7/6/5/4) versus non-Big N dichotomy. Compared to non-Big N firms, Big N auditors are often viewed as capable of performing better audits because of their supposedly superior training of personnel, economies of scale, greater industry specialization, etc. (e.g. Craswell et al. 1995, DeAngelo, 1981). Such an audit quality differential is documented in the U.S. as research (e.g., Becker et al., 1998; Francis & Krishnan, 1999; Krishnan, 2003; Reichelt & Wang, 2010) demonstrates that Big N auditors constrain their clients' use of discretionary accruals to manage earnings more aggressively than non-Big N auditors.

The current study tests for the presence of an audit quality differential in the U.S. based on the comparative ability of Big N versus non-Big N audit firms to constrain the practice of CEM. Examining a period of time when CEM was known to occur, the study shows relatively little, if any, audit quality differential existed as major groups of clients of both Big N and non-Big N auditors exhibited strong signs of CEM. Furthermore, no audit quality differential is observed among the individual Big N firms relative to their ability to restrict CEM as this form of earnings manipulation occurred at significant levels for the clients of each Big N firm.

The next section examines the literature concerning CEM as well as audit quality differentials relative to constraining earnings management. Then, the methodology and data collection are discussed. The final two sections present the results and conclusions drawn from the research.

LITERATURE REVIEW

Carslaw (1988) speculates that when the second digital position in the earnings number is high (e.g, nine), management frequently manipulates earnings to round up this second digit to zero, thus causing the first digit to increase by one. Carslaw (1988) theorizes that if this type of earnings management exists in practice, reported income numbers would be expected to possess an abnormally low proportion of nines and an unusually high frequency of zeros in the second digital position.

Carslaw (1988) tests his theory on a large sample of New Zealand entities with positive earnings and discovers precisely what he had posited. That is, nines occur in the second earnings position much less frequently than expected while zeros appear in this position at an unusually high rate. The numbers one through eight occur in the second position of earnings at their normal rates. Carslaw (1988) notes that this result provides direct evidence of goal oriented behavior as earnings are manipulated so that income can be rounded up to key benchmarks or reference points.

Following Carslaw's (1988) work, numerous researchers test for CEM in various countries using data from the 1980s and 1990s. For example, Thomas (1989) replicates Carslaw's study in

the U.S.; his results echo those of Carslaw (i.e., significantly smaller rates of nines and larger rates of zeros than typically expected in the second digital position of earnings). Thomas (1989) also examines entities with negative earnings and finds just the opposite effect (i.e., significantly more nines and less zeros than anticipated in the second earnings digit), suggesting that managers of companies with negative income frequently manipulate income to avoid having to increase the first digit by one.

Niskanen and Keloharju (2000) test for CEM with Finnish companies with positive income. They find that Finnish managers are quite aggressive in their earnings manipulation as the upward rounding of the second digit of income is more than just from nines to zeros. That is, Finnish managers boost the second earnings digit from as low as sixes and sevens to zeros and ones.

Van Caneghem (2002) replicates the previous CEM research for U.K. companies with positive earnings. His results are consistent with those of the prior research in that firms report unusually low rates of nines and high rates of zeros in the second position of the earnings number. He further adds to the CEM literature by showing that managers use discretionary accruals to increase income so that the second digit can be rounded up from nine to zero.

Kinnunen and Koskela (2003) examine 18 countries for the presence of CEM and find patterns of earnings rounding consistent with CEM in each country. They also discover that the degree of CEM practiced appears to be related to certain country-specific factors. For example, the aggressiveness of the CEM exhibited increases with the liberalism of a country's accounting policies.

Skousen et al. (2004) test Japanese entities with positive income for the existence of CEM. Their findings are consistent with those in other countries in that nines appear in the second digital position of earnings at an abnormally low rate while zeros occur at a much higher frequency than anticipated. Skousen et al. (2004) also learn that digits other the first digit appear to be the object of manipulation for Japanese managers. As an example, they find that nines appear significantly less often than anticipated while zeros occur much more often than expected in the third earnings position, suggesting that many managers round up the third digit of income to enhance the second digit by one.

Jordan and Clark (2015) test for the presence of CEM in U.S. companies with positive income for an extended period of time to determine when this form of manipulation began and to ascertain if any events (e.g., rule making bodies or laws) produced an apparent effect on management's propensity to engage in CEM. Using data going back to the 1920s, they discover that CEM consistently occurred in each unique decade from the 1920s through the 1990s, and no event during this time period seemed to deter management's proclivity for practicing CEM.

Subsequent to SOX's implementation, several studies test for the existence of CEM in the U.S. to ascertain whether SOX inhibited this form of earnings management. In particular, these projects test for CEM in unique periods before and after SOX became effective (e.g., Aono & Guan, 2008; Jordan & Clark, 2011; Lin & Wu, 2014). All these studies examine companies with positive income and find strong signs of CEM in the pre-SOX periods (i.e., abnormally low rates of nines and high rates of zeros reported in the second digital positon of earnings). However, in their post-SOX samples, the researchers discover little to no evidence of CEM as, in general, all

numbers (i.e., zero through nine) appear in the second earnings position at their anticipated rates. A fourth study (Wilson, 2012) examines data from one post-SOX year (2008) and finds no signs of CEM. As Jordan and Clark (2015, p. 648) note, the evidence suggests "that CEM existed continuously in the U.S. for many decades prior to SOX" but seems to have disappeared in the aftermath of the significant financial scandals occurring at the turn of the millennium and the advent of the corporate governance legislation (i.e., SOX) intended to restore integrity to the financial reporting process.

Two studies suggest that financial statement audits, and perhaps the quality of those audits, may be related to the propensity at which CEM occurs. Examining U.S. data, Guan et al. (2006) test for CEM in quarterly earnings figures for the decade immediately preceding SOX's implementation. They discover significant levels of CEM in all four quarters of the year; however, it is less severe in quarter four relative to quarters one through three. Since only the fourth quarter financial numbers are audited, Guan et al. (2006) speculate that, at least to a certain degree, audits inhibit managers' rounding of earnings to user reference points. The previously noted Kinnunen and Koskela (2003) study that tests for the existence of CEM in 18 nations during the period 1995-1999 shows that one of the country-specific factors associated with the severity of CEM is the amount spent on audit fees. Countries whose companies spend more on their audits experience lower levels of CEM compared to entities operating in nations where less is spent on auditing.

Craswell et al. (1995), DeAngelo (1981), and Krishnan (2003) provide a myriad of reasons why Big N auditors might provide better or higher quality audits than non-Big N firms (e.g., better staff training, greater industry expertise, etc.). Frequently, audit quality refers to an audit firm's prowess in restricting a client's use of discretionary accruals to manage earnings. Several U.S. studies present evidence suggesting that Big N audit firms indeed constrain their client's use of discretionary accruals more aggressively and thus provide audits of higher quality than non-Big N firms (e.g., Becker et al., 1998; Francis et al., 1999; Davidson & Neu, 1993; Krishnan, 2003; Lai, 2009).

The majority of non-U.S. studies, though, find little if any indication of an audit quality differential between Big N and non-Big N auditors (e.g., Huang & Liang, 2014; Maijoor & Vanstraelen, 2006; Piot & Janin, 2007; Thoopsamut & Jaikengkit, 2009; Vander Bauwhede & Willekens, 2004). Only a few non-U.S. studies find evidence of an audit quality differential based on the Big N versus non-Big N dichotomy (e.g., Chen et al., 2005; Van Tendeloo & Vanstraelen, 2008).

Khurana and Raman (2004) test for a quality differential between Big N and non-Big N auditors in four Anglo-American nations (i.e., U.S., Canada, Australia, and U.K.). They examine these four countries because the economic role of the audit is similar in each nation while the auditor's litigation risk exposure is greater in the U.S. than in the other three countries. The researchers find that the quality of Big N audits surpasses that of non-Big N audits in the U.S. only. Khurana and Raman (2004) conclude that the primary reason an audit quality differential exists in the U.S. and not in other nations is the higher risk of lawsuits faced by U.S. auditors coupled with the "deep pockets" associated with Big N firms.

The nexus of the CEM studies and the audit quality differential research provides the impetus for the current project. As noted previously, Guan et al. (2006) and Kinnunen and Koskela

(2003) provide some reason to believe that the incidence of CEM practiced could be affected by audit quality. Furthermore, significant research shows the presence of an audit quality differential for constraining discretionary accruals in the U.S. based on the Big N versus non-Big N dichotomy.

Only two studies examine whether audit quality, as captured by audit firm size, restricts the incidence of CEM. First, using the Big N/non-Big N auditor classification as a surrogate for audit quality, Van Caneghem (2004) examines a 1998 sample of U.K. companies. For his full sample of entities, he finds the classic pattern of CEM (i.e., significantly less nines and more zeros than normally expected in the second digital position of the income number). He then splits the sample according to the size of the companies' auditors (Big N versus non-Big N) and discovers that both groups exhibit the same signs of CEM as the full sample. Accordingly, Van Caneghem (2004) concludes that for his sample of U.K. companies, no audit quality (i.e., audit firm size) differential exists relative to constraining CEM. Still, he notes that his results might have been different in the U.S., where auditors face greater litigation risk than in the U.K. (e.g., see the Khurana & Raman (2004) study above).

Second, Jordan et al. (2011) test for an audit quality differential relative to constraining CEM in the U.S., but do so based on post-SOX (2008) data. The researchers understood that by examining a post-SOX period, no CEM would be expected for their overall sample. They were testing to see whether CEM exists in their subsamples segregated by auditor size (i.e., did the clients of non-Big N firms engage in CEM while the Big N clients did not, or vice versa). Their results show that neither group engaged in CEM. Jordan et al. (2011, p. 56) note that this does not indicate necessarily that "no audit quality differential exists between Big N and non-Big N auditors as the result may simply mean that the clients of neither group of auditors presently attempt to engage in CEM."

No study examines whether an audit quality differential relative to constraining CEM existed in the U.S. during the period of time when this form of earnings management was aggressively practiced in this country (i.e., prior to SOX). The current study fills this void in the literature. Some research (e.g., Francis & Yu, 2009; Knechel et al., 2007) suggests that audit quality differentials may even exist among the individual Big N firms.

As an example, Fuerman and Kraten (2009) examine the outcomes of 1,017 lawsuits filed against Big N firms during 1999-2004 relative to financial reporting issues. They surmise that the litigation outcome provides a surrogate measure of whether an audit failure occurred. Fuerman and Kraten (2009) find a differential among the Big N firms, with Ernst & Young outperforming the other firms relative to better litigation outcomes. Thus, the key research question in the present study involves ascertaining whether an audit quality differential existed in the pre-SOX period between Big N and non-Big N firms and/or among individual Big N firms with respect to their ability to constrain CEM.

The present study provides an historical analysis of audit quality differentials based on audit firm size and brand. Even though studies show that CEM does not currently occur in the U.S., it existed as a very real and pervasive form of earnings management for many decades, which provides a unique opportunity to add to the literature on audit quality differentials as captured by the Big N versus non-Big N dichotomy. Although examining audit quality differentials for deterring CEM in a pre-SOX setting is historical in nature, this study possesses continuing

relevance because the general topic of audit quality differentials based on audit firm size and brand is still a debated and unsettled issue. Numerous auditing studies explore historical issues because they add to the literature on a particular topic.

For example, one issue often examined in the auditing literature is whether nonaudit services impair auditor independence. Because of the SEC's 2003 prohibition of specific kinds of nonaudit services provided to audit clients, nonaudit service fees declined following the passage of SOX. Krishnan et al. (2011) used this decline to perform an historical analysis exploring the relationship between nonaudit services fees and earnings management. They posited that the audit firms with a larger decline would show greater earnings management in the pre-SOX period (2000-2001), and that the difference would be eliminated in the post-SOX period (2004-2005). Using discretionary accruals to proxy for earnings management, the results supported their hypothesis. But after further analysis, Krishnan et al. (2011) found that the reported results held only for negative discretionary accruals. They concluded that any impairment of auditor independence resulting from nonaudit services is observed only for downward earnings management, and that income-increasing earnings management is not associated with auditor provided nonaudit services. The key point here is that Krishnan et al.'s (2011) historical analysis of pre-SOX data provides relevant findings about the relationship between nonaudit services and earnings management. Even though audit firms are now greatly limited in the types of nonaudit services they can provide, research on whether nonaudit services impact auditors' ability or willingness to constrain earnings management is still relevant.

In a similar vein, even though research shows that CEM is not practiced in the post-SOX era, the present study examining audit quality differentials in deterring CEM in the pre-SOX era provides information of continuing historical relevance. In particular, a long debated topic in the auditing literature is whether an audit quality differential exists between Big N and non-Big N auditors in terms of their ability to constrain earnings management. If such an audit quality differential is observed relative to constraining CEM in the pre-SOX era (i.e., when CEM existed as a common form of earnings management), another piece of evidence is added to the literature suggesting that, indeed, such an audit quality differential exists. On the other hand, if the current study fails to find any real differences between Big N and non-Big N firms (or among individual Big N firms) relative to their ability to constrain CEM in the pre-SOX era, additional evidence is added to the literature indicating no audit quality differentials exist between Big N and non-Big N firms relative to constraining earnings management.

METHODOLOGY AND DATA

As discussed previously, CEM occurs when the second digital position of unmanipulated earnings is relatively high (e.g., nine) and management increases income just enough to boost the second digit to zero, thus enlarging the first (and most critical) digit by one. The telling sign of CEM is an under representation of nines in the second digital position of the earnings number and a corresponding overabundance of zeros in this position. The numbers one through eight should appear in the second position at their normal rates. Therefore, a key aspect of testing for CEM is comparing the observed frequencies of the numbers zero through nine occurring in the second

position of earnings for a large sample of companies with the expected distributions for these numbers.

Benford (1938) derived mathematical formulas for ascertaining the expected frequencies of numbers appearing in the various digital positions of real world data (i.e., not computer generated or fabricated by humans). He demonstrates that low numbers (e.g., ones or twos) occur more often than high numbers (e.g., eights or nines) in the left two digital positions. Starting in the third digital position from the left, all numbers zero through nine appear at nearly proportional frequencies (i.e., each number occurs about 10 percent of the time). In the number 53,627, five appears in the first digital position, with three in the second position, six in the third position, and so on. Table 1 presents Benford's expected distributions for numbers occurring in the first three digital positions of real world data.

As an example, the distributions in Table 1 (often known simply as Benford's Law) show that the normal frequency of twos in the first digital position is 17.61 percent, while the expected rate of eights as the second digit is 8.76 percent. As Nigrini (1996) suggests, conformity of a financial data set to Benford's Law does not guarantee the numbers are not manipulated, but lack of conformity with these expected distributions raises serious concerns about the data's naturalness. All prior studies testing for CEM use Benford's Law for evaluating the actual rates of the numbers zero through nine occurring in the second digital position of the earnings figure; accordingly, the current study uses it as well.

Table 1
Benford's Expected Digital Distributions

	Position of digit in number		
Digit	First	Second	Third
0		11.97%	10.18%
1	30.10%	11.39	10.14
2	17.61	10.88	10.10
3	12.49	10.43	10.06
4	9.69	10.03	10.02
5	7.92	9.67	9.98
6	6.70	9.34	9.94
7	5.80	9.04	9.90
8	5.12	8.76	9.86
9	4.58	8.50	9.83

Source: Nigrini & Mittermaier (1997).

Data are collected for all U.S. companies in COMPUSTAT's Annuals Fundamental files for the period 1950-1999. 1950 represents the start date for the sample as this is the earliest date for which COMPUSTAT data are available; the sample period ends in 1999 because prior research shows that CEM in the U.S. stopped in the early 2000s (e.g., Aono & Guan, 2008; Lin & Wu, 2014). The earnings figure examined is annual income before extraordinary items, and only company-years with positive income are included in the sample because, as Thomas (1989)

demonstrates, entities with positive earnings exhibit stronger tendencies than those with negative income to engage in CEM.

The statistical significance of the differences between the observed and anticipated (i.e., Benford's) distributions for the ten numbers (i.e., zero through nine) in the second digital position of income is determined using proportions tests and their resulting Z statistics. A rigorous alpha level of .01 helps ensure that differences between the actual and expected distributions occurring from chance are not erroneously deemed to be the result of earnings manipulation. That is, if testing at a .10 alpha level, at least one of the ten digits would be expected to produce a statistically significant difference merely due to chance. Even testing at a .05 alpha level results in a 50 percent probability that at least one digit would produce a statistically significant difference due to random occurrence.

To ascertain whether CEM exists during the period under study in general, the distributions of the numbers one through nine occurring in the second earnings position are examined for the entire sample. Then, to determine whether an audit quality differential exists relative to audit firm size, the sample is segregated into two subsamples, with one containing clients of Big N auditors only and the other one comprising strictly clients of non-Big N firms. The tests for CEM are run again for each of these two subsamples. To ascertain if an audit quality differential exists among individual Big N firms, the subsample of company-years with Big N auditors is further subdivided into five unique subgroups (i.e., groups for Arthur Andersen (AA), PricewaterhouseCoopers (PwC), Ernst & Young (E&Y), Klynveld Peat Marwick Goerdeler (KPMG), and Deloitte Touch Tohmatsu (Deloitte)).

During much of the 50-year time period (1950-1999) under study, precursor firms to the above merged Big N firms existed. For example, two separate firms (Arthur Young and Ernst & Whinney) existed until they merged into one firm in 1989 (i.e., E&Y). For consistency purposes, any company-years audited by the precursor firms are included in the subgroup for the resulting merged firm (i.e., as an example, audit clients of Arthur Young and Ernst & Whinney, or even Ernst & Ernst, prior to 1989 are included in the subgroup with the clients audited by E&Y). Tests for CEM are conducted for each of the five subgroups of Big N firms.

RESULTS

Table 2 shows the findings for the full sample of company-years for the period 1950-1999. The sample comprises clients of both Big N and non-Big N audit firms. The first two rows provide the observed counts and rates for each number (zero through nine) occurring in the second digital position of income. For example, nines appear as the second digit 9,177 times, representing 7.78 percent of the total 117,930 company-years. The third row contains the normal frequency, according to Benford's Law, at which each number is expected to occur in the second digital position of real world data (i.e., absent any intentional human interference). As an example, under ordinary circumstances nines would be expected in the second digital position of earnings 8.50 percent of the time. The final two rows in the table present the Z statistic and p-level for a two-tailed proportions test used for comparing the observed and expected rates for each number appearing in the second digital position of income. Staying with the analysis of nines, Table 2

shows that the Z statistic and significance level for the difference between the actual and expected rates of nines are -8.839 and .000, respectively.

Table 2
Distributions for Second Income Digit (Full Sample)

N = 117,930										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	15392	13589	12735	12388	11728	11314	10806	10618	10183	9177
Actual rate (%)	13.05	11.52	10.80	10.50	9.94	9.59	9.16	9.00	8.63	7.78
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	11.440	1.432	-.891	.833	-.968	-.880	-2.083	-.430	-1.516	-8.839
p-level	.000*	.152	.373	.405	.333	.379	.037	.667	.130	.000*
*significant at .01 level.										

To make sure the findings are not affected by potential rounding of the second earnings digit that may have occurred when including the data in the COMPUSTAT files, the sample excludes all company-years with income figures having less than three digits. Not surprisingly given the results of prior research testing for CEM during this period, the results in Table 2 depict a clear pattern of earnings rounding intended to boost the first income digit by one. In particular, following the classic form of CEM, nines occur in the second digital position of income much less often than anticipated while zeros appear in this position at an unusually high rate. The numbers one through eight occur in the second digital position at their anticipated frequencies (i.e., with statistical significance tested at the .01 level).

A primary emphasis of this study is ascertaining whether an audit quality differential exists between Big N and non-Big N auditors relative to their ability to constrain CEM. Panels A and B of Table 3 present the results when the full sample of company-years is separated between those with Big N auditors and those with non-Big N auditors, respectively. A difference in audit quality would be apparent if one group of auditors restricts the practice of CEM while the other group does not. However, it appears that neither Big N nor non-Big N auditors constrain their clients' tendencies to engage in CEM. In particular, for both groups, nines occur in the second position of income significantly less frequently than expected and zeros appear in this position far more often than anticipated. The numbers one through eight occur in the second earnings position at their normal, expected rates. Thus, similar to Van Caneghem's (2004) findings in the U.K., there seems to be no audit quality differential between Big N and non-Big N audit firms in the U.S. with respect to restricting CEM.

Table 3
Distributions for Second Income Digit (Big N and non-Big N Samples)

Panel A: (Big N clients), N = 99,284										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	12884	11479	10654	10418	9873	9564	9154	8910	8588	7760
Actual rate (%)	12.98	11.56	10.73	10.49	9.94	9.63	9.22	8.97	8.65	7.82
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	9.769	1.699	-1.504	.646	-.895	-.389	-1.294	-.717	-1.221	-7.723
p-level	.000*	.089	.132	.519	.371	.697	.196	.473	.222	.000*
Panel B: (non-Big N clients), N = 18,646										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2508	2110	2081	1970	1855	1750	1652	1708	1595	1417
Actual rate (%)	13.45	11.32	11.16	10.57	9.95	9.39	8.86	9.16	8.55	7.60
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	6.217	-.306	1.219	.592	-.358	-1.303	-2.241	.559	-.982	-4.396
p-level	.000*	.760	.223	.554	.720	.193	.025	.576	.326	.000*
*significant at .01 level.										

As noted earlier, some research (e.g., Francis & Yu, 2009; Fuerman & Kraten, 2009; Knechel et al., 2007) suggests that audit quality differentials may exist among individual Big N firms. To determine whether such an audit quality differential occurs relative to constraining CEM, the group of 99,284 company-years with Big N auditors is split into five subsamples based on their audit firm (i.e., KPMG, Deloitte, AA, E&Y, and PwC). Panels A, B, C, D, and E in Table 4 provide the results for these five firms. The number of company-years audited by these firms during the period under study ranges from 15,227 for KPMG to 24,762 for PwC.

With respect to constraining CEM, no audit quality differential seems to exist among the Big N firms. In particular, Table 4 shows that the clients of each audit firm engaged in significant CEM. That is, for each Big N firm, its clients' earnings figures contain abnormally low rates of nines and high frequencies of zeros as the second digit while the numbers one through eight occur in this digital position of income at approximately their expected frequencies.

The results of the study cover a number of decades in the pre-SOX era, and there is a question of whether separate time periods during this span could provide differing results. Gu et al. (2005) find that the variability of accounting accruals increased consistently from the 1950s to the 1990s, when they reached their zenith and leveled off. Thus, because the variability of accounting accruals increased steadily over time, a possibility exists that the incidence of various forms earnings management, like CEM, rose over time as well (i.e., since, as Van Caneghem (2002) shows, CEM is accomplished through the use of discretionary accruals).

Table 4
Distributions for Second Income Digit (Individual Big N Firms)

Panel A: (KPMG), N = 15,227										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2023	1719	1612	1627	1495	1463	1397	1339	1368	1184
Actual rate (%)	13.29	11.29	10.59	10.68	9.82	9.61	9.17	8.79	8.98	7.78
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	4.989	-.379	-1.150	1.016	-.857	-.245	-.688	-1.046	.964	-3.191
p-level	.000*	.705	.250	.310	.391	.806	.492	.295	.335	.001*
Panel B: (Deloitte), N = 17,955										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2295	2073	1921	1894	1811	1692	1664	1649	1569	1387
Actual rate (%)	12.78	11.55	10.70	10.55	10.09	9.42	9.27	9.18	8.74	7.72
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	3.340	.644	-.767	.508	.239	-1.105	-.321	.660	-.089	-3.711
p-level	.001*	.519	.443	.612	.811	.269	.749	.509	.929	.000*
Panel C: (AA), N = 20,202										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2565	2392	2208	2104	2060	1992	1800	1821	1711	1549
Actual rate (%)	12.70	11.84	10.93	10.41	10.20	9.86	8.91	9.01	8.47	7.67
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	3.171	2.004	.215	-.059	.779	.904	-2.088	-.117	-1.448	-4.230
p-level	.002*	.045	.830	.953	.436	.366	.037	.907	.148	.000*
Panel D: (E&Y), N = 21,138										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2799	2419	2223	2259	2093	2014	1913	1949	1809	1660
Actual rate (%)	13.24	11.44	10.52	10.69	9.90	9.53	9.05	9.22	8.56	7.85
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.685	.236	-1.686	1.211	-.610	-.688	-1.437	.903	-1.026	-3.360
p-level	.000*	.814	.092	.226	.542	.492	.151	.367	.305	.001*
Panel E: (PwC), N = 24,762										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	3202	2876	2690	2534	2414	2403	2380	2152	2131	1980
Actual rate (%)	12.93	11.61	10.86	10.23	9.75	9.70	9.61	8.69	8.60	8.00
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	4.649	1.102	-.074	-1.002	-1.462	.172	1.457	-1.906	-.846	-2.832
p-level	.000*	.270	.941	.317	.144	.863	.145	.057	.397	.005*
*significant at .01 level.										

In order to address this issue, the data are separated into three distinct decades (i.e., 1970s, 1980s, and 1990s). Data for the 1950s and 1960s are not examined due to an insufficient number of companies in COMPUSTAT for these decades to allow statistical testing. Table 5 presents the results for all companies for each decade and shows a clear pattern of CEM in each decade (i.e., significantly fewer nines and more zeros than expected in the second digital position of income).

Table 6 provides the results by decade for companies audited by Big N auditors; again, the classic pattern of CEM appears for each decade.

Table 5
Distributions for Second Income Digit (by Decade for All Companies)

Panel A: (1970-1979), N = 24,511										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	3216	2843	2653	2547	2384	2355	2246	2284	2124	1859
Actual rate (%)	13.12	11.60	10.82	10.39	9.73	9.61	9.16	9.32	8.67	7.55
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.540	1.019	-.273	-.188	-1.573	-.318	-.940	1.508	-.512	-5.335
p-level	.000*	.308	.785	.851	.116	.750	.347	.132	.609	.000*
Panel B: (1980-1989), N = 41,954										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	5510	4900	4495	4420	4264	4013	3777	3784	3595	3196
Actual rate (%)	13.13	11.68	10.71	10.54	10.16	9.57	9.00	9.02	8.57	7.62
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	7.334	1.859	-1.083	.698	.902	-.718	-2.366	-.139	-1.376	-6.470
p-level	.000*	.063	.279	.485	.367	.473	.018	.890	.169	.000*
Panel C: (1990-1999), N = 51,463										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	6665	5846	5587	5421	5080	4946	4783	4550	4464	4121
Actual rate (%)	12.95	11.36	10.86	10.53	9.87	9.61	9.29	8.84	8.67	8.01
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	6.849	-.210	-.165	.763	-1.192	-.447	-.351	-1.564	-.681	-3.997
p-level	.000*	.834	.869	.445	.233	.655	.726	.118	.496	.000*
*significant at .01 level.										

Table 6 Distributions for Second Income Digit (by Decade for Big N Clients)										
Panel A: (1970-1979), N = 18,952										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2505	2204	1997	1988	1833	1847	1747	1814	1623	1394
Actual rate (%)	13.22	11.63	10.54	10.49	9.67	9.75	9.22	9.57	8.56	7.36
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.280	1.026	-1.504	.257	-1.629	.340	.565	2.539	-.943	-5.637
p-level	.000*	.305	.133	.797	.103	.734	.572	.011	.346	.000*
Panel B: (1980-1989), N = 34,946										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	4571	4113	3714	3684	3552	3341	3164	3104	3018	2685
Actual rate (%)	13.08	11.77	10.63	10.54	10.16	9.56	9.05	8.88	8.64	7.68
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	6.385	2.225	-1.505	.676	.827	-.684	-1.828	-1.019	-.809	-5.465
p-level	.000*	.026	.132	.499	.408	.494	.068	.308	.418	.000*
Panel C: (1990-1999), N = 45,385										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	5808	5162	4943	4746	4488	4376	4243	3991	3947	3681
Actual rate (%)	12.80	11.37	10.89	10.46	9.89	9.64	9.35	8.79	8.70	8.11
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.421	-.101	.070	.182	-.994	-.194	.057	-1.822	-.469	-2.966
p-level	.000*	.919	.945	.856	.320	.846	.954	.068	.639	.003*
*significant at .01 level.										

Table 7 presents the findings by decade for entities audited by non-Big N auditors. The one surprising result in Table 7 is for the decade of the 1970s (see Panel A) where the clients of non-Big N auditors do not appear to engage in CEM, at least at a statistically significant level. There is some evidence of CEM as most of the high digits (i.e., five, six, seven, and nine) occur at below expected frequencies and the three lowest digits (i.e., zero, one, and two) occur at higher than expected frequencies; the discrepancies are just not large enough for statistical significance. Possible explanations for this could be that these non-Big N clients engaged in CEM less aggressively than the Big N clients during this period or that non-Big N firms constrained CEM through their audit practices in the 1970s. Perhaps a more likely possibility relates to the findings in the Gu et al. (2005) study above that the variability of accounting accruals increased over time. More specifically, of the three decades examined in the current analysis for the non-Big N clients, significant signs of CEM appear in the latter two decades (i.e., 1980s and 1990s) but not in the earliest decade (i.e., 1970s).

Table 7
Distributions for Second Income Digit (by Decade for non-Big N Clients)

Panel A: (1970-1979), N = 5,559										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	712	639	656	559	550	508	499	469	501	466
Actual rate (%)	12.81	11.49	11.80	10.06	9.89	9.14	8.98	8.44	9.01	8.38
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	1.904	.225	2.183	-.891	-.316	-1.319	-.909	-1.545	.642	-.289
p-level	.057	.822	.029	.373	.752	.187	.363	.122	.521	.772
Panel B: (1980-1989), N = 7,008										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	939	787	781	736	712	672	613	680	577	511
Actual rate (%)	13.40	11.23	11.14	10.50	10.16	9.59	8.75	9.70	8.23	7.29
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	3.667	-.403	.692	.178	.342	-.209	-1.685	1.915	-1.538	-3.606
p-level	.000*	.687	.489	.858	.732	.834	.092	.055	.124	.000*
Panel C: (1990-1999), N = 6,078										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	857	684	644	675	592	570	540	559	517	440
Actual rate (%)	14.10	11.25	10.60	11.11	9.74	9.38	8.88	9.20	8.51	7.24
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.096	-.314	-.692	1.702	-.731	-.748	-1.198	.405	-.678	-3.502
p-level	.000*	.753	.489	.089	.465	.454	.231	.686	.498	.000*
*significant at .01 level.										

In addition to showing that the variability of accounting accruals increased over time from the 1950s to the 1990s, Gu, et. al. (2005) also find that entity size is negatively related to the variability of accruals (i.e., smaller companies experience greater variability of accruals than larger entities). In addition, Johnson (2009) uses Benford's Law to show that companies with lower levels of capitalization (i.e., smaller entities) demonstrate a greater risk of engaging in earnings management behavior than larger companies. To assess the effects of entity size in the current study, the sample is divided into quintiles using a company's total assets as the measure of entity size. To reduce the noise created by combining entities across many years (e.g., a large entity in 1970 would be relatively small compared to another entity in 1999), the sample is first segregated by individual years. The quintiles based on asset size within each year are then identified and included in overall samples for particular quintiles. For example, the overall sample for quintile one comprises the largest companies for each individual year while the sample for quintile five comprises the smallest companies for each year. Table 8 presents the results for each of the five quintiles for the total sample and shows a clear pattern of CEM for each quintile.

Table 8
Distributions for Second Income Digit (by Size Quintile for All Companies)

Panel A: (Quintile one), N = 23,248										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	3020	2659	2527	2433	2371	2203	2097	2039	2031	1868
Actual rate (%)	12.99	11.44	10.87	10.47	10.20	9.48	9.02	8.77	8.74	8.04
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	4.783	.218	-.040	.166	.846	-.989	-1.665	-1.421	-.117	-2.530
p-level	.000*	.828	.968	.868	.398	.323	.096	.155	.907	.011*
Panel B: (Quintile two), N = 23,247										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2917	2741	2475	2434	2269	2261	2163	2096	2060	1831
Actual rate (%)	12.55	11.79	10.65	10.47	9.76	9.73	9.30	9.02	8.86	7.88
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	2.704	1.913	-1.133	.190	-1.358	.278	-.175	-.115	.535	-3.398
p-level	.007*	.056	.257	.850	.175	.781	.861	.908	.593	.001*
Panel C: (Quintile three), N = 23,248										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	3036	2686	2440	2379	2341	2203	2134	2185	2016	1828
Actual rate (%)	13.06	11.55	10.50	10.23	10.07	9.48	9.18	9.40	8.67	7.86
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.106	.775	-1.872	-.971	.191	-.989	-.831	1.896	-.465	-3.471
p-level	.000*	.438	.061	.331	.849	.323	.406	.058	.642	.001*
Panel D: (Quintile four), N = 23,248										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2964	2638	2575	2474	2271	2245	2151	2111	2014	1805
Actual rate (%)	12.75	11.35	11.08	10.64	9.77	9.66	9.25	9.08	8.66	7.76
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	3.651	-.195	.950	1.046	-1.316	-.057	-.448	.203	-.511	-4.012
p-level	.000*	.845	.342	.296	.188	.954	.654	.839	.609	.000*
Panel E: (Quintile five), N = 23,251										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	3232	2681	2541	2512	2298	2234	2103	2035	1921	1694
Actual rate (%)	13.90	11.53	10.93	10.80	9.88	9.61	9.04	8.75	8.26	7.29
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	9.058	.665	.227	1.854	-.733	-.308	-1.536	-1.518	-2.674	-6.628
p-level	.000*	.506	.820	.064	.464	.758	.125	.129	.007*	.000*
*significant at .01 level.										

One important outcome in Table 8, though, lends support to the findings in the Gu et al. (2005) and Johnson (2009) studies that smaller entities may exhibit a greater tendency to manage earnings than larger companies. In particular, quintiles one through four (i.e., Panels A through D in Table 8) demonstrate the classic pattern of CEM (i.e., significantly fewer nines and more zeros than expected in the second earnings digit). This suggests the upward manipulation of earnings was just enough to increase the second digit from nine to zero. However, for quintile five in Panel

E (which contains the smallest companies in the sample), the earnings rounding is more aggressive. That is, both eights and nines appear in the second digital position of earnings significantly less often than expected; zeros occur significantly more frequently than expected. Thus, the smaller companies rounded up the second digit over a wider range than their larger counterparts (i.e., from eights and nines to zeros rather than simply from nines to zeros). Table 9 presents the results by size quintile for the companies audited by Big N firms, and the patterns of CEM are similar (albeit not quite as strong) as those of the full sample of companies in Table 8.

Table 9
Distributions for Second Income Digit (for Big N Clients in Each Size Quintile)

Panel A: (Big N clients in quintile one), N = 22,331										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2908	2561	2431	2320	2273	2114	2022	1959	1941	1802
Actual rate (%)	13.02	11.47	10.89	10.39	10.18	9.47	9.05	8.77	8.69	8.07
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	4.834	.358	.019	-.189	.729	-1.017	-1.454	-1.382	-.348	-2.295
p-level	.000*	.720	.985	.850	.466	.309	.146	.167	.728	.022
Panel B: (Big N clients in quintile two), N = 21,731										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2714	2546	2327	2273	2128	2118	2049	1948	1921	1707
Actual rate (%)	12.49	11.72	10.71	10.46	9.79	9.75	9.43	8.96	8.84	7.86
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	2.349	1.502	-.802	.132	-1.154	.370	.439	-.378	.405	-3.397
p-level	.019	.133	.422	.895	.248	.712	.661	.705	.686	.001*
Panel C: (Big N clients in quintile three), N = 20,604										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2688	2417	2144	2107	2065	1966	1890	1926	1782	1619
Actual rate (%)	13.05	11.73	10.41	10.23	10.02	9.54	9.17	9.35	8.65	7.86
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	4.747	1.529	-2.175	-.946	-.025	-.611	-.812	1.528	-.552	-3.294
p-level	.000*	.126	.030	.344	.980	.541	.417	.126	.581	.001*
Panel D: (Big N clients in quintile four), N = 19,103										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	2429	2184	2062	2038	1851	1878	1790	1726	1660	1485
Actual rate (%)	12.72	11.43	10.79	10.67	9.69	9.83	9.37	9.04	8.69	7.77
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	3.162	.175	- .370	1.067	-1.554	.740	.131	-.010	-.331	-3.587
p-level	.002*	.861	.712	.286	.120	.459	.896	.992	.741	.000*
Panel E: (Big N clients in quintile five), N = 13,888										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	1928	1590	1522	1530	1386	1326	1249	1209	1148	1000
Actual rate (%)	13.88	11.45	10.96	11.02	9.98	9.55	8.99	8.71	8.27	7.20
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	6.930	.205	.286	2.248	-.183	-.473	-1.389	-1.361	-2.044	-5.476
p-level	.000*	.838	.775	.025	.855	.636	.165	.174	.041	.000*
*significant at .01 level.										

Table 10 shows the results for the companies audited by non-Big N firms within each size quintile. Not surprisingly, for quintile one Panel A shows that relatively few of the largest companies in the sample were audited by non-Big N firms (i.e., only 917 of the largest 23,248 companies were audited by non-Big N auditors). Panel E reveals that a much larger number of the smallest companies in the sample were audited by non-Big N auditors (i.e., 9,363 of the smallest 23,251 entities were audited by non-Big N auditors).

Table 10
Distributions for Second Income Digit (for non-Big N Clients in Each Size Quintile)

Panel A: (non-Big N clients in quintile one), N = 917										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	112	98	96	113	98	89	75	80	90	66
Actual rate (%)	12.21	10.69	10.47	12.32	10.69	9.71	8.18	8.94	9.81	7.20
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	.177	-.618	-.347	1.821	.607	.019	-1.152	-.046	1.071	-1.355
p-level	.860	.536	.729	.069	.544	.984	.249	.964	.284	.175
Panel B: (non-Big N clients in quintile two), N = 1,516										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	203	195	148	161	141	143	114	148	139	124
Actual rate (%)	13.39	12.86	9.76	10.62	9.30	9.43	7.52	9.76	9.17	8.18
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	1.664	1.765	-1.356	.200	-.902	-.269	-2.391	.936	.518	-.402
p-level	.096	.078	.175	.841	.367	.788	.017	.349	.605	.688
Panel C: (non-Big N clients in quintile three), N = 2,644										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	348	269	296	272	276	237	244	259	234	209
Actual rate (%)	13.16	10.17	11.20	10.29	10.44	8.96	9.23	9.80	8.85	7.90
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	1.858	-1.938	.489	-.208	.667	-1.196	-.164	1.321	.130	-1.063
p-level	.063	.053	.625	.835	.505	.231	.870	.186	.897	.288
Panel D: (non-Big N clients in quintile four), N = 4.145										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	535	454	513	436	420	367	361	385	354	320
Actual rate (%)	12.91	10.95	12.38	10.52	10.13	8.85	8.71	9.29	8.54	7.72
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	1.835	-.861	3.069	.161	.194	-1.751	-1.369	.530	-.473	-1.773
p-level	.067	.389	.002*	.872	.846	.080	.171	.596	.637	.076
Panel E: (non-Big N clients in quintile five), N = 9,363										
Second income digit	0	1	2	3	4	5	6	7	8	9
Actual count (n)	1304	1091	1019	982	912	908	854	826	773	694
Actual rate (%)	13.93	11.65	10.88	10.49	9.74	9.70	9.12	8.82	8.26	7.41
Expected rate (%)	11.97	11.39	10.88	10.43	10.03	9.67	9.34	9.04	8.76	8.50
Z statistic	5.818	.783	.007	.167	-.915	.073	-.710	-.718	-1.707	-3.756
p-level	.000*	.434	.995	.867	.360	.942	.477	.473	.088	.000*
*significant at .01 level.										

Table 10 for the non-Big N auditees presents different results from those of the clients of Big N auditors appearing in Table 9. For the non-Big N clients (i.e., Table 10), only quintile five, comprising the smallest entities, shows a clear pattern of CEM. Sample size may play a role in this outcome since the number of companies in quintiles one and two, the larger entities, for the non-Big N auditees is questionable for applying Benford's Law. However, there is no doubt that at certain levels of entity size, the clients of non-Big N auditors exhibit the same patterns and intensity of CEM as that demonstrated by the auditees of Big N firms. In particular, the majority of entities audited by non-Big N firms fall in quintile five, where the classic pattern of CEM occurs (i.e., see Panel E in Table 10). A final note of interest on the size issue is that both Tables 9 and 10 present evidence that the smaller entities, whether audited by Big N or non-Big N firms, appear more aggressive in their CEM behavior than larger companies. For the clients of both Big N and non-Big N auditors, the Z statistics in quintile five for zeros and nines are far larger than the Z statistics for these two digits in any other quintile.

SUMMARY AND CONCLUSION

Echoing the findings of previous research, the results of the current study demonstrate that significant levels of CEM existed in the U.S. throughout the second half of the 20th century. More importantly, though, the study provides evidence suggesting the pervasiveness of this form of earnings manipulation was largely unaffected by a traditional measure of audit quality. In particular, very noticeable levels of CEM were practiced by the clients of both Big N and non-Big N auditors as well as by the clients of each Big N firm. With respect to constraining CEM, there appears to be little, if any, audit quality differential in the U.S. based on audit firm size or brand.

As noted earlier, research (e.g., Jordan et al., 2011) shows that subsequent to SOX, CEM is no longer practiced in the U.S. by the clients of either Big 4 or non-Big 4 auditors. The findings in the current study suggest that prior to SOX, CEM was routinely practiced by the clients of both Big N and non-Big N auditors and by the clients of each individual Big N firm, thus adding to the literature on audit quality differentials (or lack thereof) based on audit firm size and brand. The present study also adds to the literature concerning the relationship between company size and the propensity to engage in earnings management. In particular, results suggest that, whether audited by Big N or non-Big N firms, smaller entities practiced CEM more aggressively than larger companies.

One final point relates to a limitation concerning the generalizability of this study's results. In addition to suggesting an audit quality differential may occur based on audit firm size, prior research also indicates the degree of industry specialization, even among Big N firms, may be positively related to audit quality (e.g., Green, 2008; Romanus et al., 2008; Stanley & DeZoort, 2007). Thus, there exists a possibility that audit quality, as captured by the degree of industry specialization, may have affected the rate at which CEM occurred during the period under study. Future research could address this question.

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