EARNINGS MANAGEMENT AROUND EARNINGS BENCHMARKS

by

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(Under the Direction of Kenneth M. Gaver)

ABSTRACT

Chapter 1 examines the earnings management around earnings benchmark literature. The earnings benchmarks are the earnings level (loss avoidance), earnings changes (earnings improvement), and the analyst forecast benchmark. Chapter 1 documents (1) that firms' management have incentives to meet or beat the three earnings benchmarks, (2) methods firms' management are using to manage earnings to beat these benchmarks, (3) whether the market sees through earnings management to beat benchmarks, (4) and which benchmarks are the most important to firms. Chapter 1 also presents avenues for future research. Chapter 2 examines whether firms just above and just below the three earnings benchmarks have differing levels of discretionary accruals. If discretionary accruals are a measure of earnings management, then firms above (benchmark beaters) and firms below a benchmark should have differing levels of discretionary accruals. I find that after I remove firms with incentives to beat an alternative benchmark from the firms that just missed the loss avoidance benchmark, firms just above the benchmark have significantly higher discretionary accruals. I find similar results for the earnings changes and analyst forecast benchmarks. Chapter 3 asks why there are so many firms just below an earnings benchmark, assuming firms have incentives to beat a benchmark. This chapter examines whether firms just above and just below the three earnings benchmarks have differing levels of flexibility and market sensitivity to earnings announcements. I use net operating assets (NOA) and change in total accruals (ΔTACC) to proxy for a firm's ability or flexibility to manage earnings. I use the earnings response coefficient (ERC) and analysts' stock recommendations to proxy for a firm's incentives to beat a threshold. I hypothesize that firms above a threshold will have beginning-of-the-year levels of NOA and ΔTACC that are lower than firms below a threshold (Flexibility Hypothesis). I hypothesize that firms above a threshold will have higher ERCs and overall stock recommendations (high = buy recommendations) than firms below a threshold (Market Sensitivity Hypothesis). Results support the flexibility hypothesis using NOA, when I limit the sample of firms above a benchmark to potential earnings managers. Results support the market sensitivity hypothesis using analyst stock recommendations.

INDEX WORDS: Abnormal accruals, discretionary accruals, earnings benchmarks, earnings management, earnings management constraints, earnings thresholds, market sensitivity to earnings announcements.

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DEDICATION

I would like to dedicate this dissertation to my wife Doris, my daughters, Ellie, Abigail, Lilyanne, and Ginevieve, my parents, Dean and Uela, my brothers and sisters, Matthew, Mark, Timothy, Janice, Evelyn, Sarah, Uel, Jewel, John, Mary, Pearl, and Nathan, my mother-in-law, Sarah Rowse, my father-in-law, Van Rowse, my brothers- and sisters-in-law for all their love, fasting, prayers, and encouragement throughout the whole process.

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CHAPTER 1

LITERATURE REVIEW

I. INTRODUCTION

In this review, I will be focusing on earnings management around three earnings benchmarks. The three benchmarks are the earnings level benchmark (loss avoidance), earning changes benchmark (earnings improvement benchmark), and the analyst forecast benchmark. The earning level benchmark describes managers that wish to avoid reporting losses and focuses on firms around the zero earnings level. The earnings changes benchmark describes managers that want to increase earnings as compared to a prior period and focuses on firms with small positive or negative earnings changes. The analyst forecast benchmark describes managers that want to meet or beat analysts' forecast of earnings and focuses on just missing and meeting or beating the forecast by a few cents.

Other papers have reviewed the earnings management literature (e.g., Schipper 1989, Dechow and Skinner 1999, McNichols 2000, Healy and Whalen 2000). Schipper (1989 p. 92) defines earnings management as "purposeful intervention in the external financial reporting process, with the intent of obtaining some private gain." Firms manage earnings because they have some incentive to do so. Healy and Whalen (p. 368) state that "earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers." Burgstahler and Dichev (1997) state that "studies of earnings management typically consider a specific incentive for earnings management (e.g. incentives related to executive bonus plans) and then test whether earnings have been managed assuming a particular earnings management method (e.g. management of accruals)."

This review focuses on firms that manage earnings because they have incentives to beat an earnings benchmark. I will discuss evidence that supports earnings management around earnings benchmarks and what methods firms are using to manage earnings. These benchmarks have been considered as early as Ball and Brown (1968). Ball and Brown show that firms have capital market rewards for beating earnings changes benchmarks. Since Ball and Brown, there has also developed a large literature that documents firms' incentives for beating one of the benchmarks (i.e. Barth, Elliot, and Finn 1999, Myers and Skinner 1999, Bartov, Givoly, and Hayn 2002, Kasznik and McNichols 2003). With the market incentives as support, the late 90's had a surge in literature that looked at earnings management around these benchmarks.

Hayn (1995) uses a cross-sectional distribution approach to provide evidence that firms manage earnings to beat the earnings level benchmark. Hayn documents that there are too few firms just below the earnings level benchmark and too many firms just above. Burgstahler and Dichev (1997) compliment and extend her research by showing similar results for the earnings level benchmark and the earnings changes benchmark. Holland and Ramsay (2003) support the external validity of Hayn (1995) and Burgstahler and Dichev (1997) by showing similar results for large Australian firms. Degeorge, Patel, and Zeckhauser (1999) add in the analyst forecast benchmark and find similar cross sectional results. Table 1.1 includes the time periods examined for each of the cross-sectional distribution studies. The cross sectional distribution approach encourages research that examines earnings management around the earnings benchmarks. McNichols (2000 p. 337) states that "the distribution approach per se is silent on the approach applied to manipulate earnings." Many studies throughout the late 1990's and the early part of this decade have addressed how firms are actually managing earnings to beat benchmarks and I include these studies in this review.

Degeorge et al. (1999) take an initial look at which benchmark is most important for firms to meet. They conclude that meeting the earnings level benchmark is the most important, followed by the earnings changes benchmark, and finally the analyst forecast benchmark. Recent research questions the validity of this hierarchy and I also review this literature.

The remainder of the paper proceeds as follows. Section II presents the incentives firm management has to beat benchmarks. Section III reports evidence and methods of earnings management around benchmarks. Section IV discusses whether the market sees through earnings management to achieve benchmarks. Section V presents findings on which benchmark is the most important for firms' management. Section VI provides ideas for future research, summarizes, and concludes the paper.

II. INCENTIVES FOR FIRMS TO BEAT BENCHMARKS

A – Capital Market Incentives

Graham, Harvey, and Rajgopal (2004) survey 312 financial executives from public companies. They ask executives which earnings benchmarks are important to them and find that roughly two thirds or more (depending on the benchmark) of the respondents agree that all three benchmarks are important (Graham et al. 2004 Table 3). Over 80% of the executives surveyed agreed that meeting earnings benchmarks helped them to 'build credibility with the capital market' and 'maintain or increase stock price' (Graham et al. 2004 Table 4).

DeAngelo, DeAngelo, and Skinner (1996) report that firms that have an annual earnings decline after nine or more years of annual earnings increases have abnormal returns of -14% in the decline year. Similarly, Barth, Elliott, and Finn (1999) find that firms with consecutive years of earnings increases have higher price-earnings multiples[1] than firms without consecutive increases. They also find that price-earnings multiple decrease significantly when earnings first decline after a period of consecutive increases. Myers and Skinner (1999) find similar results using consecutive quarters of earnings increases.

Kasznik and McNichols (2002) find that firms that meet or beat analysts' forecasts in the current year have higher abnormal returns than firms that do not. They also show that firms that have met or beat analysts' forecasts in the preceding two years have higher abnormal returns than firms that meet or beat in the current year. Firms that meet or beat in the preceding three years have even higher abnormal returns. Mikhail, Walther, and Willis (2004) find that firms that have repeated large positive or negative earnings surprises have high cost of equity capital, but the costs are higher for firms with negative earnings surprises.

Brown and Caylor (2004) examine quarterly earnings information. They run regressions with 3-day cumulative abnormal returns on the earnings announcement date as the dependent variable, and use dummy variables for the eight combinations of whether firms met or did not meet the three benchmarks. They find that firms meeting or beating at least one or any combination of the three benchmarks have a positive valuation consequence.

B – CEO/Upper Management Compensation

Matsunaga and Park (2001) test whether beating the three earnings benchmarks effects a CEO's cash compensation. Their results suggest that CEO bonus payments give CEOs an economic incentive to beat the analyst forecast benchmark and the earnings changes benchmark. They do not find evidence of a relationship between CEO bonus payments and loss quarters. This evidence is consistent with Gaver and Gaver (1998), which shows that gains flow through to compensation, but losses do not. Adut, Cready, and Lopez (2003) show that compensations committees examine characteristics of each restructuring charge before deciding whether to shield executives' compensation from the charge. Adut et al. (2003) provides evidence that, under certain circumstances, even restructuring charge losses generated by firms can affect CEO compensation.

In summary, evidence from accounting research shows that firms have capital market incentives to beat all three earnings benchmarks. Also, CEOs (or Upper Management) have incentives to beat all three benchmarks, with conditional incentives to beat the loss avoidance benchmark.

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[1] Barth et al. (1999) define earnings multiple as either the coefficient on net income where price is the dependent variable and net income is an independent variable or the coefficient on change in earnings when returns is the dependent variable and change in earnings is an independent variable.

III. EARNINGS MANAGEMENT TO BEAT BENCHMARKS

A – Insurance and Banking industries (Regulated)

Beaver, McNichols, and Nelson (2003) examine the earnings levels of property-casualty insurance firms. They find that there are too many firms with small positive earnings levels and too few firms with small negative earnings levels, based on the smoothness of the rest of the earnings level distribution. In the insurance industry, the claim loss reserve is a target for observing earnings management. The claim loss reserve if understated (overstated) will boost (depress) the reported net income number for property-casualty insurers. The claim loss reserve account is trued up when actual claims are made. A loss reserve development is reported for the ten years following the recording of the initial reserve. The loss reserve development can be used to determine how much the claim loss reserve was over or understated at initial recording. Beaver et al. (2003) find that property-casualty insurers use the loss reserve to help them to get from below the earning level threshold to above the threshold. This results holds for both public and mutual property-casualty insurers.

Beatty, Ke, and Petroni (2002) examine publicly and privately held banks and focus specifically on the earnings changes benchmark. Beatty et al. (2002) state that publicly held banks have diffuse ownership and privately held banks have more concentrated ownership. The authors argue that the diffuse ownership of publicly held banks and cost of monitoring leads the publicly held bank owners to rely on simple heuristics to value firms. Beatty et al. (2002) focus on earnings changes as a heuristic. Using the cross-sectional distribution approach, Beatty et al. (2002) find that publicly held banks have too few firms with small negative changes in earnings and too many firms with small positive changes in earnings than would be expected under a normal distribution. The authors also find that publicly held banks are more likely than privately held banks to use discretionary loans loss provisions and realized security gains and losses to move from just missing the earnings changes benchmark to just beating the earnings changes benchmark.

B – Other Firms

Moehrle (2002) examines whether firms use restructuring charge reversals to meet the three earnings benchmarks. Similar to the insurance and banking industries, Moehrle (2002) focuses on a specific account and avoids problems associated with using discretionary accruals as a measure for earnings management. Moehrle (2002) finds evidence that firms use restructuring charge reversals in periods where pre-reversal earnings fall short of the earnings level and analyst forecast benchmark. He also finds some evidence that firms use restructuring charge reversals when pre-reversal earnings are short of the earnings changes benchmarks.

Phillips, Pincus, and Rego (2003, hereafter PPR) examine the deferred tax expense account (DTE) around the three earnings benchmarks. PPR posit that firms have more discretion in their GAAP reported earnings than they do with their earnings reported for tax purposes. They state that "the exercise of managerial discretion to manage income upward should generate temporary book-tax differences and, hence, deferred tax expense will be useful in detecting such earnings management." (PPR p. 492) PPR examine the firms just above and just below the three earnings benchmarks. They label the firms just above a benchmark as earnings managers and firms below as non-earnings managers. PPR use probit models to determine whether deferred tax expense is incrementally useful in explaining whether a firm is classified as an earnings manager or not. PPR also include total accruals, discretionary accruals, and cash flows as control variables in their probit model. PPR find that deferred tax expense is incrementally useful in classifying earnings management firms around the earnings changes benchmark. Total accruals and discretionary accruals using the forward-looking Jones model (Dechow, Richardson, and Tuna 2003) are also incrementally useful. The results for deferred tax expense hold after controlling for firm performance, though the results are not significant for the accrual measures. PPR also find that deferred tax expense is incrementally useful in classifying earnings management firms around the earnings level benchmark, as are the accrual measures. PPR find no evidence that deferred tax expense or abnormal accrual measures are incrementally useful in classifying earnings management firms around the analyst forecast benchmark.

The results of PPR rely on a major assumption: firms just above any of the three benchmarks are earnings managers. Burgstahler and Dichev (1997 p. 101) "estimate that 8-12% of firms with small pre-managed earnings decreases manipulate earnings to achieve earnings increases, and 30-44% of firms with small pre-managed losses manage earnings to create positive earnings." Dechow, Richardson, and Tuna (2003) estimate using a linear (exponential) approximation that 90% (85%) of firms that beat the earnings level benchmark are expected to be there by chance, and 10%(15%) are firms that potentially have managed earnings. The evidence in Burgstahler and Dichev (1997) and Dechow et al. (2003) provides argument against assuming all firms above the earnings benchmarks are earnings managers. The deferred tax expense account may be linear in nature and may increase with the level of earnings. Research is needed to examine whether increased levels of deferred tax expense are due to earnings management or whether the increase is due to the increase in earnings from below the benchmark to above.

Dechow, Richardson, and Tuna (2003, hereafter DRT) look at the earnings level benchmark. They posit that if firms are managing earnings to beat the earning level benchmark, then firms above the earnings level benchmark should have higher levels of discretionary accruals than firms below the benchmark. Their results do not support their expectations. They posit that their lack of results may be because 1) their model of discretionary accruals cannot detect earnings management or 2) firms do not use discretionary accruals to get from below the benchmark to above. DRT perform additional analysis to address these possible limitations. They address the low power by (1) using a better measure of discretionary accruals (forward-looking model) which has a higher r-squared than models used in existing literature, (2) looking at the persistence of discretionary accruals, (3) testing whether the discretionary accruals correlate with SEC enforcement actions, and (4) showing that firms with high levels of discretionary accruals have lower levels of future earnings and stock returns. The authors cannot rule the first explanation of low power, even after the additional analysis. However, DRT do find some evidence that firms may not use discretionary accruals to surpass an earnings benchmark. They show that the break in the distribution may be caused (A) exchange listing requirements being biased towards profitable firms and (B) investors using different valuation models for profit and loss firms, which accentuates the break in the distribution when scaling by market value of equity.

DRT only examine the earning levels benchmark, which they label the loss avoidance benchmark. They do not examine discretionary accrual levels around the earnings changes and analyst forecast benchmarks. DRT also assume that loss avoidance only pertains to those firms whose earnings are just below the benchmark. According to this position, firms with large negative earnings would not use their discretion to make the loss smaller.

Hansen (2004a) provides an additional explanation for the level of discretionary accruals being similar for firms above and below all three earnings benchmarks. Management of firms below a benchmark may be using their discretionary accruals to help them meet an alternative benchmark. For example, many dot.com firms in the mid-to-late 90's were not profitable. These dot.com firms with losses may have focused on a secondary benchmark of either having a positive earnings change over the prior year or beating an analyst forecast. Small loss firms may be using their discretionary accruals to achieve a positive earnings increase or to beat an analyst forecast. Hansen (2004) expects that if firms below a benchmark with alternative incentives to beat an additional benchmark are deleted from the sample, firms above the benchmark will have higher discretionary accruals than firms below the benchmark. Results support the expectation for all three earnings benchmarks.

Roychowdhury (2003) also provides an explanation for the results of Dechow et al. (2003). Firms' management may be using real activities to manage earnings to beat the earning level benchmark. Roychowdhury (2003) find that firms just above the earnings level benchmark (1) offer price discounts to give a short term boost to sales, (2) overproduce to lower their cost of goods sold number, and (3) reduce discretionary expenses (e.g. selling & administrative and research & development). Rather than using accruals to beat the earnings level benchmark, firms' management may use real activities to beat the benchmark.

Altamuro, Beatty, and Weber (2002) examine firms that were required to restate earnings as a result of the Security and Exchange Commission (SEC) issuing Staff Accounting Bulletin (SAB) 101. SAB 101 deals with revenue recognition. They test whether firms that were required to restate earnings as a result of SAB 101 were more likely to miss or beat the three earnings benchmarks prior to restatement than a control sample matched on industry and asset size. They find that for the years prior to restatement, SAB 101 firms were (1) less likely to report small losses, (2) less likely to report small negative earnings changes, and (3) more likely to report small profits than control firms. The authors provide this as evidence that firms were using revenue recognition prior to restatement to help them beat the earnings level and earnings changes benchmark.

Doyle and Soliman (2002) examine whether firms use pro forma earnings to beat the analyst forecast benchmark. The authors define earnings reported on a pro forma basis as the "practice of excluding items from GAAP earnings deemed by management to be transitory, non-recurring, non-cash, or simply uninformative of the firm's core operating performance." Doyle and Soliman (2002) posit that firms can use pro forma earnings to be 'informative' or to be 'opportunistic' and examine whether firms are being 'opportunistic'. The authors define 'pro forma use' as firms that exclude expenses from their pro forma number so pro forma earnings are greater than GAAP earnings. They test and find evidence that the likelihood of meeting or beating the analyst forecast increases with the use of pro forma earnings.

Dhaliwal, Gleason, and Mills (2004) examine whether firms use income tax expense to meet or beat the analyst forecast benchmark. The authors state that “tax expense is one of the last accounts closed before earnings are announced because other income-related changes impact the tax accounts.” The authors’ proxy for earnings management is the difference between a firm’s actual effective tax rate (ETR) at year-end and the estimate of ETR at the third quarter. The estimate of ETR at the third quarter is an annual estimate that incorporates tax planning for the fourth quarter. The authors’ proxy for ‘earnings before tax expense management’ is the net income that would have been reported had the third quarter ETR estimate been used. The authors find that firms will lower their annual ETR from the third to fourth quarter as the earnings minus tax expense management fall short of analysts’ forecast.

Dhaliwal et al. (2004) focus on the analyst forecast benchmark. They do not examine the earnings level and earnings changes benchmark. Not examining the earnings level benchmark in tax research is acceptable because taxes or ETRs for loss firms can be confounding. Additional research is needed to see if firms’ management use ETRs to help the firm meet the earnings changes benchmark. If firms are not using ETRs to meet this additional benchmark, it would be interesting to document what firm characteristics may cause results to differ from the analyst forecast benchmark.

In summary, recent research suggests that there are many ways for firms to manage earnings to meet or beat benchmarks. The options include manipulating real activities (e.g. R&D expenditures) to manipulating accruals. Future research may try to aggregate these methods to better describe earnings management around earnings benchmarks.

IV. FIRMS' REWARDS AFTER EARNINGS MANAGEMENT

Section II discusses incentives that firms' management have to meet or beat benchmarks. This section discusses whether firms that manage earnings have rewards for meeting and beating earnings benchmarks.

Gleason and Mills (2004) follow up the study by Dhaliwal, Gleason, and Mills (2004) to see if the market reward to meeting the analyst forecast benchmark is affected when firms' management use tax expense to manage earnings. The authors compare firms that meet or beat the analyst forecast benchmark using tax expense management to those that meet or beat using no management. The authors find that the reaction (measured using cumulative size-adjusted returns) for firms using tax expense management to meet or beat the forecast is positive but smaller than firms that meet or beat the analyst forecast without tax expense management. Firms that meet or beat the forecast had more positive reactions than firms that missed the forecast, regardless of whether tax expense management was involved. These findings are interesting because the market appears to see through the earnings management but does not fully discount for the tax expense earnings management.

Similarly, Bartov, Givoly, and Hayn (2002) show that firms that meet or beat analysts' earnings forecast in the current quarter have higher returns than firms that fail to meet or beat. They show that although the premium is smaller, it still exists even when firms likely meet or beat forecasts either through earnings management or through managing expectations.

Bhojraj, Hribar, and Picconi (2003) define firms with high earnings quality as firms with high research and development expenditures, high advertising expenditures, and low total accruals. They find that firms that beat the analyst forecast benchmark and have low quality earnings have higher one year size adjusted returns than firms that missed the analyst forecast benchmark and have high quality earnings. Interestingly, firms that miss the analyst forecast benchmark and have high quality earnings have higher two-year and three-year cumulative size adjusted returns than firms that beat the analyst forecast and have low quality earnings. The results of Bhojraj et al. (2003) suggest that managing earnings to beat the analyst forecast will give firms benefit in the short run, but not over a longer horizon.

The evidence in Gleason and Mills (2004), Bartov et al. (2002), and Bhojraj et al. (2003) suggests that firms receive market rewards in the short run for beating the analyst forecast, even when these firms manage earnings. Additional research is needed to examine whether similar results will be found around the earnings level and the earnings changes benchmark.

V. BENCHMARK IMPORTANCE

Degeorge et al. (1999) examine the three earnings benchmark distributions conditional upon meeting or missing the other two benchmarks to determine which benchmark is the most important for firms. Their tests place earnings level benchmark as the most important, followed by earnings changes, and finally, analyst forecast benchmark. Dechow et al. (2003) examine the kink in the cross sectional distribution of firms, to see whether the kink is changing throughout time. They find that the kink is declining for the earnings level and earnings changes distribution, but increasing for the analyst forecast benchmark. They provide this as initial evidence that the hierarchy of benchmark importance is shifting from the earnings level to the analyst forecast benchmark.

Recent evidence shows that the importance of meeting the analyst forecast benchmark has increased in recent years (Brown 2001; Bartov, Givoly, and Hayn 2002; Lopez and Rees 2002; Matsumoto 2002). Brown and Caylor (2004) further explore the hierarchy of earnings benchmarks using data from 1985-2002. Similar to Burgstahler and Dichev (1997), Brown and Caylor calculate a standardized difference for the group of firms just below a benchmark (actual numbers of observations in the interval just below a benchmark minus the expected number of observations divided by an estimate of the standard deviation of the difference). The benchmark with the most negative standardized difference is regarded as the most important benchmark for firms to beat. Brown and Caylor (2004) run regressions of the standardized difference on year to see how the importance of each benchmark has changed over time. They find that from 1985-1993 the earnings changes benchmark is the most important, followed by the earnings level benchmark, and finally the analyst forecast benchmark. Although this period covers years examined by Degeorge et al. (1999), the importance of the earnings levels and earnings changes benchmarks is reversed. Brown and Caylor (2004) find that for the period from 1996-2002 the analyst forecast benchmark becomes the most important benchmark, followed by the earnings changes benchmark, and finally the earnings level benchmark. The importance of the earnings level benchmark and the earnings changes benchmark has remained constant over time, based on the slope coefficient from their regression of standardized difference on year.

Brown and Caylor (2004) also examine the incremental valuation consequences of meeting one benchmark as compared to meeting none, and meeting a third benchmark as compared to having met the other two benchmarks. They measure valuation consequences by using market adjusted cumulative abnormal returns regressed on dummy variables that describe the eight different combinations of making and missing the three benchmarks and an interaction term of unexpected earnings and the dummy variables. Brown and Caylor (2004) find that prior to 1993, it is hard to determine which benchmark has the largest incremental valuation consequence. From 1993-2002 it is clear that meeting or beating the analyst forecast benchmark has the largest incremental valuation consequence, whether you compare meeting one benchmark to meeting none or meeting a third benchmark as compared to meeting the other two benchmarks. Results from standardized differences or incremental valuation consequences support analyst forecasts as being the most important benchmark.

Graham et al. (2004) survey financial executives from public companies and find that 84% agree that the earnings changes benchmark is important. They report that 69% of the executives agree that the analyst forecast benchmark is important. They also find that 65% agree that the earnings level benchmark is important. Graham et al. (2004) add yet another hierarchy to the mix, with the earnings changes benchmark being first, followed by the analyst forecast benchmark, and finally the earnings level benchmark. Graham et al. (2004, Table 3) also perform a similar analysis conditional upon firm characteristics. For example, they show that large, profitable, public firms that list on the New York Stock Exchange (NYSE), that have high sales growth, high debt to asset ratios, actively guide analysts, and have large analyst following are more likely to agree that the analyst consensus forecast is important.

More research is needed that examines the earnings benchmark hierarchy conditional on firm characteristics. Similar to Graham et al. (2004), additional insight may be gained by examining the hierarchy based on prominent firm characteristics. Small vs. large firms, high leverage vs. low leverage firms, and high vs. low analyst following are a few examples of characteristics that may provide different earnings benchmark hierarchy.

VI. FUTURE RESEARCH, SUMMARY AND CONCLUSION

A –Firms below benchmarks

Burgstahler and Dichev (1997 p. 112) examine the earnings level benchmark and "conjecture that the extent of earnings management is likely to be a function of the ex ante costs of earnings management. In other words, earnings manipulators are likely to be firms which faced relatively lower ex ante costs of earnings management. Therefore, given that earnings manipulators moved from slightly negative earnings to slightly positive earnings, firms with slightly negative earnings likely are those which faced higher ex ante earnings management costs than firms with slightly positive earnings."

If firms truly face incentives to beat the three earnings benchmarks, then why are there any firms just below a benchmark? What keeps firms just below a benchmark from moving to meet or slightly beat a benchmark? Burgstahler and Dichev (1997) begin to address these questions. They posit that (1) working capital accruals ostensibly offers the most readily available means by which earnings can be managed, (2) marginal manipulation of working capital accruals are more easily 'buried' when firms report high levels of current assets and current liabilities and this reduces the costs of managing earnings, and (3) firms just above an earnings benchmark offer a fruitful group to search for earnings managers. Burgstahler and Dichev (2004 p. 114-115) offer limited evidence in support of this idea. In Figure 5 and 6, they show that firms just above the earnings level benchmark have higher levels of current assets and current liabilities than firms just below the benchmark. However, they neglect to investigate whether this condition holds for alternative benchmarks.

Hansen (2004b) also addresses why there are so many firms just below the three benchmarks. He examines constraints that might be keeping firms below a benchmark from managing earnings and whether firms below a benchmark have the same market sensitivity to earnings announcements as firms above. Hansen (2004b) finds that firms just below the earnings change and the analyst forecast benchmarks do not have the same flexibility, as measured by beginning-of-the-year net operating assets scaled by sales, to manage earnings that firms just above these benchmarks do. Hansen also finds that firms just below the earnings change and analyst forecast benchmark have lower market sensitivity to earnings announcements, as measured by analyst stock recommendations, than firms just above.

Additional research is needed to address other characteristics that possibly constrain firms from managing earnings. Hansen (2004b) tests to see whether change in total accruals from the prior year is a measure of constraint around earnings benchmarks, but results do not support this measure. Levels of working capital accruals, current assets, and current liabilities are a few possibilities for potential constraints. Research is also needed to examine differences in incentives for firms just above and just below benchmarks. Examining firm characteristics that affect incentives to manage earnings may prove fruitful.

B – Industry earnings benchmarks

Beaver et al. (2003) discuss the incentives that property-casualty insurers have to manage earnings. They state that the incentives will change with the ownership structure of the firm. They discuss that in a public insurance company there is agency/incentive conflicts between owners and managers and between owners and policyholders. In a private (mutual) insurance company there are agency/incentive conflicts between owners and policyholders (owners and managers). The agency problems for insurers seem somewhat similar to agency problems in non-regulated industries. Beaver et al. (2003) focus on property-casualty insurers that are managing earnings around the earnings level benchmark. Incentives for insurers suggest that they would also benefit from meeting or beating the earnings changes benchmark. Beaver et al. (2003) do not investigate whether the earnings changes benchmark is important to property casualty insurers and whether the cross-sectional distribution of earnings changes supports the importance. If results do not hold for this alternative benchmark, it would be interesting to know why.

Similary, Beatty et al. (2002) focus on earnings changes for publicly held firms and argue that earnings changes is a heuristic that diffuse ownership can use to value firms. Beatty et al. (2002) do not address the earnings level benchmark for publicly held banks. Again, regulators and diffuse ownership should be interested in the additional benchmark of earnings levels. If cross-sectional distributions of earnings levels do not support the importance of the earnings levels benchmark to banks, it would be interesting to know why. If banks do not use loans loss provisions and realized security gains and losses to meet or beat the earnings level benchmark, it would also be interesting to know why.

Industry earnings standards or norms also affect firms. This may translate into firms not only trying to meet the three earnings thresholds already mentioned, but also earnings thresholds set by other firms within the same industry. I also leave industry earnings benchmarks to future research.

C – Multiple Thresholds

Many of the results presented above look at earnings management around only one threshold. As in the insurance and banking industry, one benchmark is examined while the other two benchmarks are not discussed. Sometimes a benchmark is not examined because of the situation or context. For example, examining tax issues around the earnings level benchmark would likely not be fruitful because of the difference in taxes for profit and loss firms. However, many of the studies would benefit from examining whether results hold around the alternative earnings benchmarks. If results do not hold, examining what features of the sample that cause one benchmark to be more important to a firms' management will benefit our understanding of the benchmark literature. This will also help to explain sample features that cause the hierarchy of benchmark importance to change.

D – Summary and Conclusion

This review examines earnings management around three earnings benchmark. This paper provides evidence that firms' management have capital market incentives and also compensation incentives to meet the three earnings benchmarks. In the banking industry, management appears to use loan loss reserve and security gain realizations to help firms meet earnings benchmarks. In the insurance industry, management appears to use loss reserves to meet earning benchmarks. Outside of regulated industries, firms' management appear to use restructuring charges, aggressive revenue recognition, pro forma earnings, deferred tax expense, tax expense (ETR), discretionary (abnormal) accruals, and real activities to help firms meet earnings benchmarks. Research supports that firms receive rewards for meeting the analyst forecast benchmark, even after managing earnings to do so. Evidence is split on which earnings benchmark is the most important for firms' management and more research is needed to solidify a hierarchy of importance. I discuss ideas for future research and provide (1) characteristics of firms that miss benchmarks, (2) industry specific benchmarks, and (3) research examining multiple benchmarks as promising areas of future research.

Table 1.1

Time Periods of Cross Sectional Earnings Benchmarks Studies

Author	Earnings Interval	Time Period
Hayn (1995)	Annual	1963-1990
Burgstahler and Dichev (1997)	Annual	1976-1994
Holland and Ramsay (2003) – Australian Firms	Annual	1990-2000
Degeorge, Zeckhauser, and Patel (1999)	Quarterly	1974-1996
Brown and Caylor (2004)	Quarterly	1985-2002

CHAPTER 2

ADDITIONAL EVIDENCE ON DISCRETIONARY ACCRUAL LEVELS OF BENCHMARK BEATERS

I. INTRODUCTION

The SEC and investors are increasingly concerned with firms managing earnings to meet benchmarks (Niemeier 2001, Turner 2001). For example, William Donaldson, Chairman of the Securities and Exchange Commission (SEC), in a speech to the National Press Club in July 2003 (Donaldson 2003) stated that:

> "During the boom years [mid-1990s through early 2000], corporate America increasingly emphasized a short-term focus, fueled by an obsession with quarter-to-quarter earnings…Analysts, some tainted by conflicts of interest, became cheerleaders for the game of 'hitting the numbers'. And winning that game, rather than creating the conditions for sound, long-term strength and performance, became the primary goal. Finally, the perception that uninterrupted earnings growth was the hallmark of sound corporate progress caused too many managers to adjust financial results—in ways that were sometimes large and sometimes small, but in all cases unacceptable—to meet projected results."

These concerns make earnings management both an interesting and important area of accounting research. Burgstahler and Dichev (1997) provide strong circumstantial evidence that earnings management exists, showing that there is a paucity of firms in the cross-sectional distribution of earnings reporting small losses. They also show a similar paucity of firms reporting small earnings decreases in the distribution of earnings changes. McNichols (2001) states that the distribution approach, however, is silent on how firms actually manipulate earnings. Beaver, McNichols, and Nelson (2003) and Gaver and Paterson (2004) find that property-casualty insurers use their loss reserve estimates to manipulate earnings around benchmarks. Using a much broader cross-section of firms, I investigate whether firms just above and just below three earnings benchmarks have differing levels of discretionary accruals.

Dechow, Richardson, and Tuna (2003) investigate earnings management as an explanation of the 'kink' in the cross sectional distribution of earnings levels, using discretionary accruals[2] to operationalize earnings management. They examine whether firms use discretionary accruals to avoid a small loss. Dechow et al. refer to this as a 'loss avoidance strategy'. They find that, although firms with earnings just above zero (benchmark beaters) have higher discretionary accruals than the rest of the firms in their sample, the discretionary accruals of the benchmark beaters do not differ significantly from those of small loss firms. Dechow et al. state that if firms use discretionary accruals to achieve positive earnings, then there is no apparent reason, assuming that loss avoidance is paramount, why small loss firms would exhibit discretionary accruals at levels comparable to those of benchmark beaters. In other words, to shift income from future periods into the current period to make the current loss smaller would seem like a futile gesture, assuming that loss avoidance is an overriding objective.

However, if managers of small loss firms have other earnings objectives, this finding might be understandable. Degeorge, Patel, and Zeckhauser (1999) argue that a hierarchy of earnings benchmarks can exist for firms, with loss avoidance heading the list, followed by an earnings improvement benchmark, and thereafter by an analysts'

[2] I use discretionary accruals and abnormal accruals synonymously throughout the paper. The term 'abnormal accruals' is often used in the literature because the residual includes the nondiscretionary as well as discretionary accruals related to unexpected or unmodeled events.

forecasts benchmark.[3] This suggests that a potential explanation for the Dechow et al. (2003) anomaly is that firms with small losses strive to report a diminishing string of reported losses (earnings improvement benchmark) or try to meet or beat analysts' loss forecasts (analyst forecast benchmark).

There is evidence that firms pay heed to objectives other than loss avoidance. For example, Myers and Skinner (1999) and Barth, Elliot, and Finn (1999) find that firms behave as if maintaining consecutive strings of increases in quarterly earnings is an important goal. Additionally, Matsumoto (2002) finds that firms have incentives to meet or beat analysts' forecasts. However, these studies do not specifically examine whether loss firms strive to meet the earnings improvement and analyst forecast benchmarks. Nor do they examine the pattern of discretionary accruals of firms reporting earnings near the earnings increase and analysts' forecast thresholds.

I examine the properties of discretionary accruals for small loss firms. I hypothesize that firms with small losses may still use discretionary accruals to maintain (or establish) positive earnings *changes*, or to meet or exceed analysts' forecasts, even when positive earnings is unattainable. If evidence supports the hypothesis, this could explain why Dechow et al. (2003) found that there is no significant difference in the level of discretionary accruals between small loss and small profit firms.

To conduct the investigation, I create switches for the three benchmarks (loss avoidance, earnings improvement, and analyst forecast). I leave one switch on and turn

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[3] Whether or not loss avoidance still heads the hierarchy among benchmarks is open to debate. Hayn (1995) finds that the occurrence of losses has been increasing over time, suggesting that loss avoidance has waned in importance during the last decade. More recently, Brown and Caylor (2003) conclude that the ordering among the benchmarks may have changed, with meeting analysts' forecasts becoming more important.

off the other two and compare the level of discretionary accruals around the benchmark that is turned on. I estimate discretionary accruals using the modified cross-sectional Jones Model (Dechow, Sloan, and Sweeney 1995; DeFond and Subramanyam 1998) and also the forward-looking abnormal accruals model (Dechow et al. 2003; Phillips, Pincus, and Rego 2003). For the loss avoidance benchmark (switch on), I identify firms with small losses that also have incentives to beat the earnings improvement benchmark (switch off) and the analyst forecast benchmark (switch off). After removing these firms, I find that firms with small profits have discretionary accruals that are significantly higher than the resulting sample of firms with small losses. These results provide an explanation for the anomalous findings of Dechow et al. (2003). In particular, their result seems to be driven by firms from the small loss sample that have strong alternative incentives to manipulate discretionary accruals to beat the earnings improvement benchmark.

Next, I shift focus to my second earnings benchmark—earnings improvement. I examine whether firms that report small positive changes in earnings (as compared to the previous year's earnings) have higher levels of discretionary accruals than firms with small negative changes in earnings (earnings improvement benchmark). For the full sample of firms with small earnings changes, I do not find that firms with small positive earnings changes have discretionary accruals that are higher than firms with small negative earnings changes. However, I find that firms with small positive earnings changes have higher discretionary accruals than firms with small negative earnings changes, after I delete from the small negative earnings change sample firms that have strong alternative incentives to either 1) make a small profit or 2) meet or beat analysts' forecasts.

Finally, I examine the analyst forecast benchmark. I investigate whether firms that meet or just beat analysts' forecasts have higher discretionary accruals than firms that just miss analysts' forecasts. I find that firms that meet or just beat analyst's forecast have a higher level of discretionary accruals than firms that just missed analysts' forecasts, after I delete from the just miss analysts' forecasts sample firms that have a strong alternative incentive to 1) beat the loss avoidance benchmark or 2) beat the earnings improvement benchmark.

In this study I show that a second benchmark (earnings improvement) impacts observed discretionary accruals around the loss avoidance benchmarks. Secondly, I show that the loss avoidance and the analyst forecast benchmark also affect observed discretionary accruals around the earnings improvement benchmark. Finally, I show that the loss avoidance and earnings improvement benchmarks impact observed discretionary accruals around the analyst forecast benchmark. After accounting for these impacts, evidence suggests that firms record discretionary accruals in a manor consistent with earnings management. Thus, the 'loss avoidance' strategy put forth in Dechow et al. (2003) appears to be a portion of a more complex story where firms close to one earnings benchmark may face incentives to meet different benchmarks as well.

The remainder of the paper proceeds as follows. Section II presents the research design. Section III reports the results. Section IV summarizes and concludes the paper.

II. RESEARCH DESIGN

A – Sample

The sample includes of all firm-years in the Compustat 2002 annual database with necessary data to compute discretionary accruals. Consistent with DeFond and Subramanyam (1998), I exclude financial institutions (SIC 6000 to 6999) from the sample. Hribar and Collins (2002) find that studies that measure accruals using changes in a series of balance sheet accounts have a potential for measurement error in accrual estimates. I avoid this potential for measurement error by restricting the sample to the post-fiscal-year 1987 years with accrual data from the statement of cash flows. (i.e., FAS 95 data)

B – Earnings Levels Classification (Loss Avoidance)

I form my small profit sample similar to Burgstahler and Dichev (1997) and Dechow et al. (2003). I scale net income (Compustat Data 172) in year *t* by market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-1*. I place firms in net income classes (*ni_class*) with the width of each *ni_class* equaling 0.01 (e.g., *ni_class -15* contains firm-years with -0.15 ≤ Scaled Net Income < -0.14). *Ni_class* 0 includes all firm-years where 0 ≤ Scaled Net Income < 0.01.

C – Earnings Changes Classification (Earnings Improvement)

Consistent with Burgstahler and Dichev (1997), I calculate a firm's current change in earnings by subtracting net income (Compustat Data 172) in year *t-1* from net income in year *t* and scaling that amount by the market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-2*. I place firms in change-in-net-income classes (*chgni_class*) with the width of each *chgni_class* equaling 0.01, similar to *ni_class* (e.g., *chgni_class* -15 contains firm-years with -0.15 ≤ Scaled Change-in-net-income < -0.14). Consistent with *ni_class*, *chgni_class* 0 includes all firm-years where 0 ≤ Scaled Change-in-net-income < 0.01.

D – Analyst Forecast Error Classification

I calculate a firm's analyst forecast error by subtracting the most recent median I/B/E/S forecast of annual earnings per share for the current year from actual earnings per share for the current year (also obtained from I/B/E/S). I collect the median I/B/E/S forecast of annual earnings per share from the I/B/E/S Summary History File in the month that actual earnings are reported, or in the month prior to actual earnings being reported if there is no consensus forecast in the month that actual earnings are reported. I place firms in analyst forecast error classes (*forecasterror_class*) with the width of each *forecasterror_class* equaling two cents (e.g., *forecasterror_class* -15 contains all firm-years where -0.30 ≤ Forecast Error < -0.28). *Forecasterror_class* 0 includes all firm-years where 0 ≤ Forecast Error < 0.02.

E – Discretionary Accruals

I measure discretionary accruals using the modified cross-sectional Jones model (Dechow et al. 1995; DeFond and Subramanyam 1998) and the forward-looking model (Dechow et al. 2003; Phillips et al. 2003). For the modified cross-sectional Jones model, nondiscretionary accruals are a function of property, plant, and equipment and changes in revenue estimated by the following model:

$$ACCR_{j,t}/TA_{j,t-1} = \alpha + \beta_1 \cdot [(\Delta REV_{j,t} - \Delta REC_{j,t})/TA_{j,t-1}] + \beta_2 \cdot [PPE_{j,t}/TA_{j,t-1}] + e_{j,t} \qquad (1)$$

where: $ACCR_{j,t}$ = total accruals for firm j in year t. (Compustat Data 123 – Compustat Data 308 or Income before extraordinary items – Cash Flow from Operations),

$TA_{j,t-1}$ = total assets for firm j in year $t-1$. (Compustat Data 6),

$\Delta REV_{j,t}$ = change in net revenue (Compustat Data 12),

$\Delta REC_{j,t}$ = change in accounts receivable (Compustat Data 302), and

$PPE_{j,t}$ = property, plant, and equipment (Compustat Data 7).

I estimate the model separately for each two-digit SIC code and calendar year and eliminate from the sample any combination of two-digit SIC code and calendar year with less than ten observations. I define nondiscretionary accruals and discretionary accruals as the fitted value from Eq. (1) and the residual, respectively. Similar to Dechow et al. (2003), I exclude observations from the sample where total accruals or any of the independent variables are in the extreme 1% of their respective distributions.

The forward-looking discretionary accrual model has advantages over the cross-sectional Jones model. Bernard and Skinner (1996) state that Jones Model improperly classifies nondiscretionary accruals as discretionary and this can lead to erroneous results. Dechow et al. (2003) show that the forward-looking model has a mean adjusted R^2 of 0.20, which is consistent with R^2s from industry-specific models (Beatty, Ke, and Petroni 2002). The higher R^2 suggests that more of the variation in total accruals is explained by the variables in the model. In other words, the residual of the regression contains smaller amounts of nondiscretionary accruals. I include this model in my analysis as my primary measure of discretionary accruals. The forward-looking model is estimated as follows:

$$ACCR_{j,t} = \alpha + \beta_1 \cdot [\Delta REV_{j,t} - (1-k)\, \Delta REC_{j,t}] + \beta_2 \cdot (PPE_{j,t}) + \beta_3 \cdot ACCR_{j,t-1} + \beta_4 \cdot GR\_Sales + e_{j,t} \qquad (2)$$

where: $ACCR_{j,t-1}$ = total accruals for firm j in year $t-1$, *GR_Sales* = the change in sales for firm *j* from year *t* to *t+1*, scaled by year *t* sales, and

k = the slope coefficient from a regression of *ΔREC on ΔREV*.

The forward-looking model makes three adjustments to the modified cross-sectional Jones model. Phillips et al. (2003 p. 503) describe the changes as follows: First, the model does not assume that all credit sales are discretionary. The forward-looking model treats part of the increase in credit sales as expected (a nondiscretionary accrual) by regressing $\Delta REC_{j,t}$ on $\Delta REV_{j,t}$ and winsorizing the estimated parameter *k* so it ranges from 0 to 1. Hence, the forward-looking model reduces the change in sales in Equation (2) by less than 100 percent of the increase in receivables. Second, the model assumes a portion of total accruals is predictable and is captured by including last year's accruals (i.e., lagged total accruals) in the model. Third, the modified Jones model treats increases in inventory made in anticipation of higher sales as an abnormal accrual rather than as a rational increase in inventory. The forward-looking model includes next year's sales growth to correct for the 'rational' increase in inventory. The forward-looking model uses future period data to estimate current period normal and abnormal accruals. Dechow et al. (2003) note that this is not a problem when the objective is simply to separate accruals into their non-discretionary and discretionary components.

Table 2.1 contains descriptive statistics for firms just above and just below the benchmarks. Table 2.1 also contains statistics for all the other firms. Mean and median total accruals are negative for firms around the benchmarks. Firms around the loss avoidance benchmark (*ni_class* -1 & *ni_class* 0) have mean Total Assets, MVE, PPE, and Sales that appear to be consistent with *All Other Firms*. Firms around the earnings improvement benchmark (*chgni_class* -1 and *chgni_class* 0) have mean Total Assets, MVE, PPE, and Sales that are at least twice the mean for *All Other Firms*. Firms that Meet or Just Beat the Analyst Forecast (forecasterror_class 0) have a mean MVE that is nearly twice that of *All Other Firms.* The high MVE for firms just above the earnings improvement benchmark and analyst forecast benchmark adds some evidence to the argument that these firms have market incentives to meet or just beat these benchmarks.

III. RESULTS

A – Primary Results

First I confirm that my sample is consistent with Dechow et al. (2003). I examine the loss avoidance benchmark and compare discretionary accruals for the small profit sample (*ni_class* 0) to the small loss firms (*ni_class* -1). Table 2.2, Panel A reports results based on the modified cross-sectional Jones model, and Panel B reports results based on the forward-looking model. Table 2.2 shows that firms in *ni_class* 0 have discretionary accruals that are significantly higher than all other firms in the sample. Consistent with Dechow et al. (2003), discretionary accruals for firms in *ni_class* -1 are not significantly different than *ni_class* 0. As previously stated, these results are not consistent with a simple 'loss avoidance strategy'.

I next test whether there are similar results for the earnings improvement benchmark and the analyst forecast benchmark. Table 2.3 and Table 2.4 report results for the earnings changes benchmark and analyst forecast benchmark, respectively. In each table, Panel A reports results using the modified cross-sectional Jones model, and Panel B uses the forward-looking model. Table 2.3 indicates that firms in *chgni_class* 0 have discretionary accruals that are significantly higher than all other firms in the sample.

Discretionary accruals for firms in *chgni_class* -1, however, are not significantly different than *chgni_class* 0. This result is consistent with the findings for the loss avoidance benchmark found in Table 2.2. Table 2.4 shows similar findings for the analyst forecast benchmark. Firms in *forecasterror_class* 0 have significantly higher discretionary accruals than all other firms in the sample, but not significantly different for firms in *forecasterror_class* -1. Results from all three benchmarks cast doubt that managers use discretionary accruals to meet or slightly beat benchmarks. I hypothesize that the failure to find a difference between discretionary accruals of firms just above a benchmark and firms just below arises because firms missing one benchmark use discretionary accruals to meet an alternative benchmark.

To test this hypothesis, I start with the loss avoidance benchmark. As illustrated in Figure 1, Panel A, I identify the portion of firms from the small loss sample (*ni_class* -1) that have incentives to increase discretionary accruals to beat the earnings improvement benchmark (*chgni_class* = 0 or *chgni_class* ≥ 0). I delete these firms with the alternative incentive to beat the earnings improvement benchmark from my small loss sample and test the difference in the level of discretionary accruals. I delete these firms from the small loss sample because these firms may be inflating discretionary accrual levels because they may be using discretionary accruals to meet an alternative earnings benchmark. Table 2.5, panels B and C report the results for *chgni_class* = 0 and *chgni_class* ≥ 0, respectively.

When I delete firms with an alternative incentive to just beat the earnings improvement benchmark (*chgni_class* = 0), discretionary accruals above and below the loss avoidance benchmark are not significantly different (Panel B). However, using *chgni_class* = 0 as my filter for deleting firms does not control for the possibility that small loss firms may have an incentive to make the loss as small as possible. I propose and use *chgni_class* ≥ 0 to eliminate firms attempting to make the loss as small as possible. Panel C shows that after deleting small loss firms with an alternative earnings improvement benchmark (*chgni_class* ≥ 0), firms in the small profit sample (*ni_class* 0) have significantly higher discretionary accruals than the small loss sample (*ni_class* -1).

I next delete firms with an additional incentive to beat the analyst forecast benchmark (*forecasterror_class* = 0 or *forecasterror_class* ≥ 0). Results reported in Panel D and Panel E do not support my hypothesis. These results suggest that small loss firms are not using discretionary accruals to meet or beat analysts' forecasts. Finally, I delete from the small loss sample all firms that have the alternative earnings improvement benchmark (*chgni_class* = 0 or *chgni_class* ≥ 0), analyst forecast benchmark (*forecasterror_class* = 0 or *forecasterror_class* ≥ 0), or both. After deleting these firms, the small profit sample has discretionary accruals that are significantly higher than the small loss sample (Table 2.5, Panel G). Again this result appears to be driven by the *chgni_class* ≥ 0 filter. Therefore, after removing the alternative incentive of maintaining earnings improvement, firms appear to be using discretionary accruals to meet the loss avoidance benchmark.

I repeat these tests by identifying and removing alternative incentives from the firms just below the earnings improvement benchmark and the analyst forecast benchmark. I illustrate this in Figure 1, Panel B and Panel C for the earnings improvement and analyst forecast benchmark, respectively. After identifying and removing firms, I test the difference in the level of discretionary accruals for the firms just above and just below the earnings improvement and analyst forecast benchmark. I report results in Tables 6 and 7.

Table 2.6 reports the results for the earnings improvement benchmark (earnings changes). Panel B shows that when I delete firms with an incentive to just beat the loss avoidance benchmark (*ni_class* = 0) from the firms with small negative earnings change (*chgni_class* -1), the mean and median discretionary accruals for the firms with small negative earnings change (*chgni_class* -1) decrease. The decrease is in the expected direction but the difference from the sample firms with small positive earnings change (*chgni_class* 0) is insignificant. Table 2.6, Panel C reports the results when all firms that beat the loss avoidance benchmark (*ni_class* ≥ 0) are deleted from the firms with small negative earnings change (*chgni_class* -1). Although discretionary accruals for the small positive earnings change sample (*chgni_class* 0) are higher that the small negative earnings change sample (*chgni_class* -1) after I delete these firms (*ni_class* ≥ 0), I do not focus on these results because deleting all firms with *ni_class* ≥ 0 leaves only loss firms in my small negative earnings change sample.

Table 2.6, Panel E shows that when I delete firms with an alternative incentive to beat the analyst forecast benchmark (*forecasterror_class* ≥ 0) from the small negative earnings change (*chgni_class* -1) sample, firms with small positive earnings changes (*chgni_class* 0) have discretionary accruals which are marginally higher than the remaining firms with small negative earnings change. In other words, firms from the small negative earnings improvement (*chgni_class* -1) sample with alternative incentives appear to be using discretionary accruals to meet those incentives and are inflating the discretionary accruals for the small negative earnings changes sample.

The results in Table 2.6, Panel H show that when I delete firms with an alternative incentive to beat the loss avoidance benchmark (*ni_class* 0), analyst forecast benchmark (*forecasterror_class* ≥ 0), or both (*ni_class* 0 and *forecasterror_class* ≥ 0) from the small negative earnings change sample (*chgni_class* -1), firms with small positive earnings changes (*chgni_class* 0) have significantly higher discretionary accruals than firms with small negative earnings changes (*chgni_class* -1). Consistent with the loss avoidance benchmark reported in Table 2.5, firms trying to be beat the earnings change benchmark appear to be using discretionary accruals to meet or beat this benchmark.

Table 2.7 reports the results for the analyst forecast benchmark. Panel H shows that when I delete firms with an alternate incentive to meet or beat the loss avoidance benchmark (*ni_class* 0), earnings changes benchmark (*chgni_class* ≥ 0), or both (*ni_class* 0 and *chgni_class* ≥ 0) from the sample of firms that just missed analysts forecasts (*forecasterror_class* -1), the level of discretionary accruals for firms that met or slightly beat the analyst forecast benchmark (*forecasterror_class* 0) is significantly higher than for the firms that slightly missed the analyst forecast (*forecasterror_class* -1). The results for the analyst forecast benchmark are consistent with the loss avoidance and the earnings improvement benchmark.

B – Supplemental Analysis

In the tests reported to this point, I delete firms with alternative incentives from just below a benchmark and compare the discretionary accrual levels for these firms to the full sample of firm just above a benchmark. Using Figure 1 as a reference, I compare the full sample of firms just above a benchmark with the 'white-space' for firms just below a benchmark. In this section, I perform tests to compare the 'white-space' for firms above the benchmark with the ‘white-space’ for firms just below the benchmark. Table 2.8 contains this analysis for the three benchmarks. Panels A and B provide results for the loss avoidance benchmark. After I delete firms with alternative incentives to meet the earnings improvement and analyst forecast benchmark from just above and just below the loss avoidance benchmark, the discretionary accruals for the small profit sample remain significantly and marginally significantly higher than the small loss sample, as reported in Panel A and Panel B respectively.

Panel C and D provide results for the earnings improvement benchmark. Consistent with Panel A and B, after I delete firms with alternative incentives to meet the loss avoidance and analyst forecast benchmark from just above and just below the earnings improvement benchmark, the discretionary accruals for the small positive earnings changes sample remain marginally significantly higher than the small positive earnings changes sample.

Finally, Panels E and F provide results for the analyst forecast benchmark. Unlike the loss avoidance and earnings improvement benchmark, after I delete firms with alternative incentives to meet the loss avoidance and earnings improvement benchmark from just above and just below the analyst forecast benchmark, the discretionary accruals for the just meet or beat analysts’ forecast sample is not significantly different than the just missed analysts’ forecast sample.

In summary, results from comparing the discretionary accruals of the ‘white-space’ firms above and below the loss avoidance and earnings improvement benchmark are consistent with results from comparing the full sample of firms above the benchmark with the ‘white-space’ firms below. The results are not consistent for the analyst forecast benchmark. Firms can meet or beat analysts' forecast by guiding the analysts' forecast downward or by managing earnings upwards. Matsumoto (2002) finds that both mechanisms play a role for firms in meeting or beating analysts' forecasts. Analyst guidance may factor into the inconsistent results for the analyst forecast benchmark. I leave this question to future research.

IV. CONCLUSIONS AND SUMMARY

In their conclusion, Dechow et al. (2003 pg. 24) state: "another possibility [to explain lack of results for discretionary accruals of small profit firms as compared to small loss firms] is that we are measuring discretionary accruals correctly, but that the earnings management story is more complex than the one we test…We leave the examination of more complex earnings management stories to future research." I provide a more complex story for discretionary accruals around the loss avoidance benchmark and also around the earnings improvement and analyst forecast benchmark.

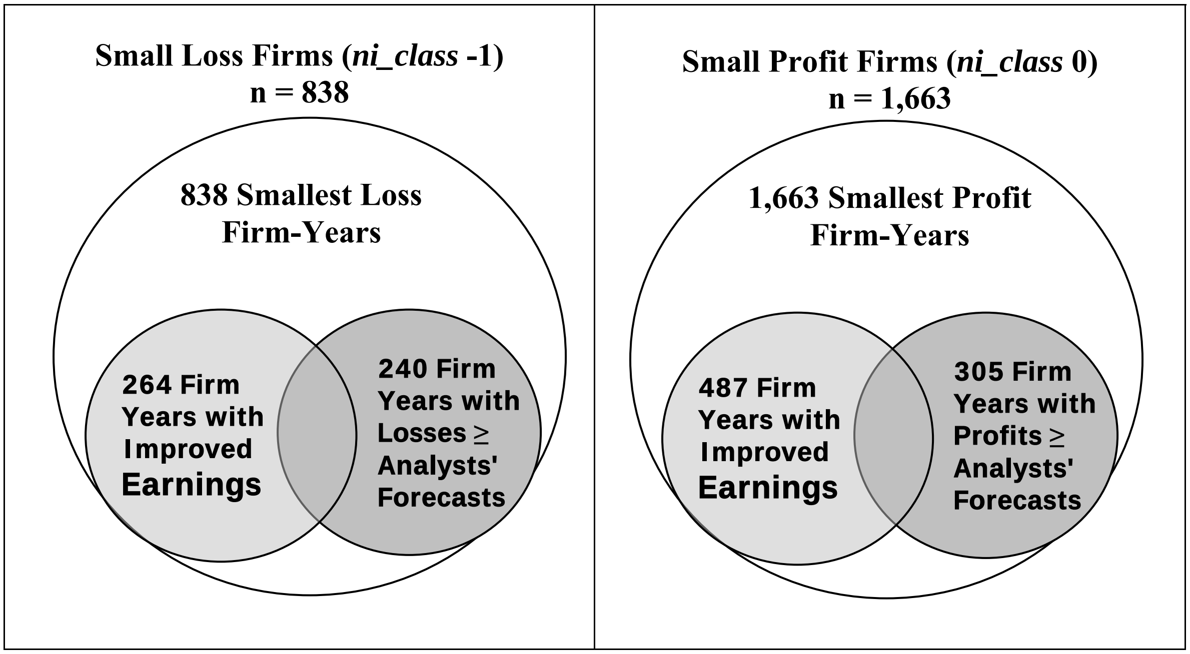
First, I replicate the findings of Dechow et al. (2003). I use a more recent sample and find results consistent with their results for the loss avoidance benchmark. I also find similar results for the earnings improvement and analyst forecast benchmark. Next, I identify firms with small losses that also have alternative incentives to beat the earnings improvement benchmark and the analyst forecast benchmark. When I remove firms from the small loss sample that have incentives to manage earnings to meet the earnings improvement benchmark, firms with small profits report higher discretionary accruals than firms with small losses. In essence, I create switches for the three benchmarks (loss avoidance, earnings improvement, and analyst forecast) and leave one switch on while turning off the other two. The benchmark that is turned on is not confounded by alternative incentives to meet a second or third benchmark. When I examine the loss avoidance benchmark and delete the earnings improvement benchmark, I find that firms appear to be using discretionary accruals to manage earnings.

I find similar results when I examine the earnings improvement benchmark. When I 'turn on' the earnings improvement benchmark and delete firms from the small negative earnings changes sample with incentives to manage earnings to meet or beat the other two benchmarks (loss avoidance and analyst forecast), firms with small positive earnings changes have higher discretionary accruals than firms with small negative earnings changes. Firms also appear to use discretionary accruals to avoid small negative earnings changes.

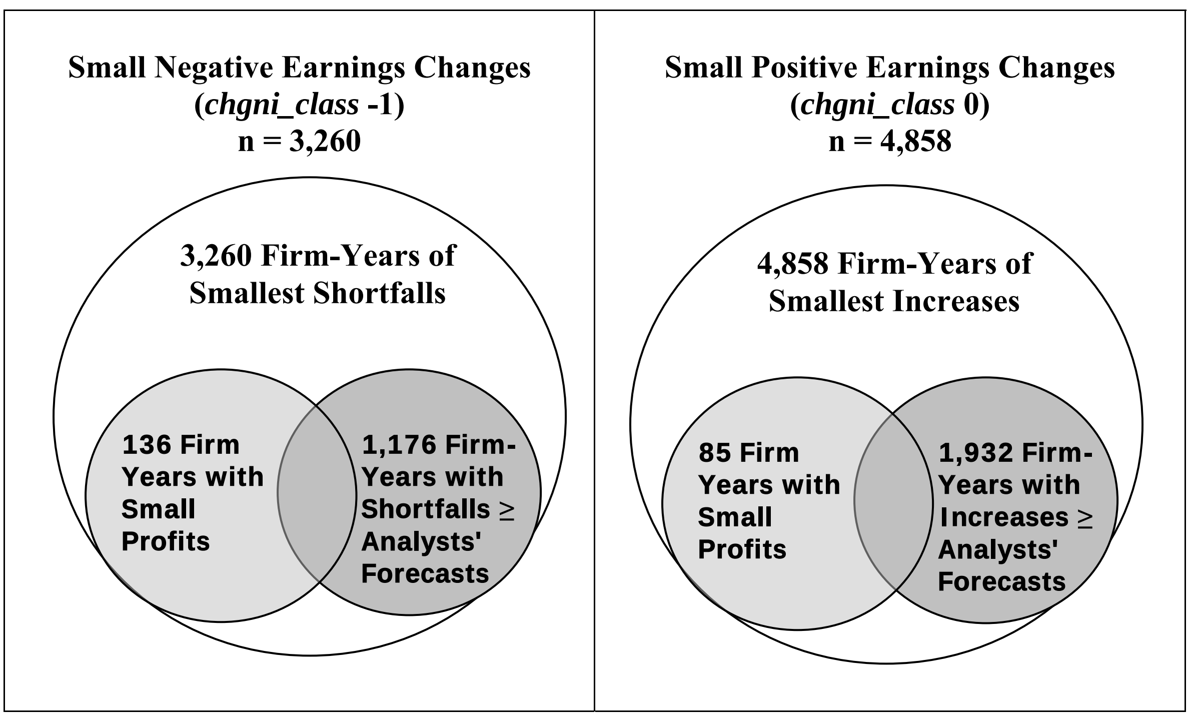
Finally, I find that firms that just meet or beat the analyst forecast have higher discretionary accruals than firms that just missed the analyst forecast, after I delete firms from the just missed analyst forecast sample with incentives to manage earnings to meet or beat additional benchmarks (loss avoidance and earnings improvement).

My results provide evidence to: (1) why firms with small losses have discretionary accruals that are not significantly different from that of firms with small profits, (2) why firms with small negative earnings changes have discretionary accruals that are not significantly different from that of firms with small positive earnings changes, and (3) why firms that just missed an analysts' forecast have discretionary accruals that are not significantly different from that of firms that met or just beat an analysts' forecast. The small loss sample just below the loss avoidance benchmark contains firms that could be managing discretionary accruals to meet another benchmark (earnings improvement). The small negative earnings changes sample just below the earnings improvement benchmark contains firms that could be managing discretionary accruals to meet other benchmarks (loss avoidance and analyst forecast). The just missed analyst's forecast sample just below the analyst forecast benchmark contains firms that could be managing discretionary accruals to meet other benchmarks (loss avoidance and earnings improvement). After controlling for these alternative benchmarks, results suggest that firms record discretionary accruals in a manor consistent with earnings management. These findings suggest a more 'complex earnings management story' than the loss avoidance strategy.

Panel A: Loss Avoidance Benchmark



Panel B: Earning Improvement Benchmark



Panel C: Analyst Forecast Benchmark

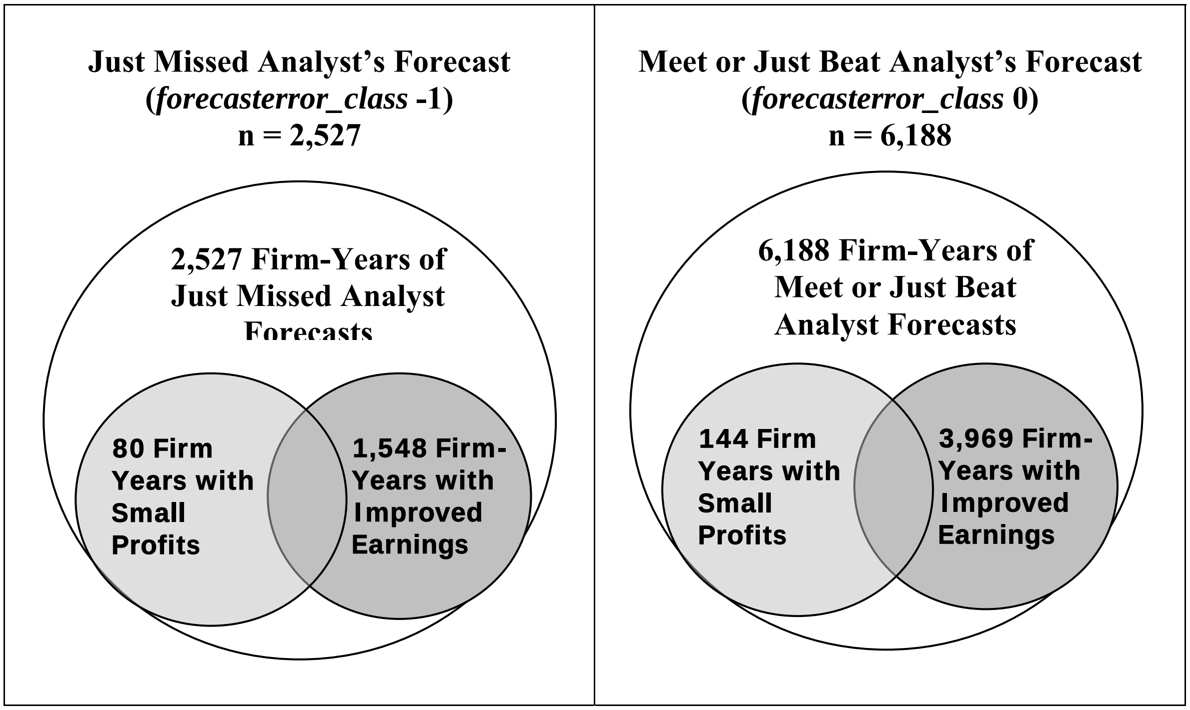


Figure 2.1
Firm-Year Observations Above and Below the Earnings Benchmarks

Table 2.1 Descriptive Statistics - Initial Sample

Panel A - Loss Avoidance Benchmark

	Small Loss Firms (n = 838) *Ni_class* = -1		Small Profit Firms (n = 1,663) *Ni_class* = 0		All Other Firms (n = 47,149)	
	Mean	Median	Mean	Median	Mean	Median
Total Assets	1,844.36	123.34	1,683.13	97.99	1,696.15	118.98
MVE	2,200.30	140.66	1,887.93	81.44	1,783.12	94.69
PPE	1,120.38	47.53	1,112.63	38.42	1,223.32	51.49
Sales	1,366.10	124.16	1,401.78	92.40	1,475.01	132.58
ΔAcc Rec	6.00	(0.25)	(4.23)	(0.34)	(12.94)	(0.50)
Accruals	(139.18)	(4.64)	(115.03)	(2.83)	(91.30)	(4.16)

Panel B - Earnings Improvement Benchmark

	Small Negative Earnings Changes (n = 3,260) *Chgni_class* = -1		Small Positive Earnings Changes (n = 4,858) *Chgni_class* = 0		All Other Firms (n = 41,532)	
	Mean	Median	Mean	Median	Mean	Median
Total Assets	3,085.10	261.85	3,411.53	347.48	1,388.95	98.61
MVE	3,560.46	263.96	4,466.29	417.11	1,342.38	75.00
PPE	2,361.28	123.95	2,254.55	178.09	1,006.86	41.87
Sales	2,591.23	259.27	2,826.37	361.10	1,224.19	110.41
ΔAcc Rec	(13.96)	(0.79)	(27.50)	(2.06)	(10.43)	(0.39)
Accruals	(163.36)	(7.92)	(147.56)	(9.75)	(80.98)	(3.56)

Panel C - Analyst Forecast Benchmark

	Small Missed Forecast (n = 2,527) *Forecasterror_class* = -1		Meet or Just Beat Forecast (n = 6,188) *Forecasterror_class* = 0		All Other Firms (n = 16,910)	
	Mean	Median	Mean	Median	Mean	Median
Total Assets	2,025.73	280.80	2,544.46	323.52	2,277.54	261.56
MVE	2,926.43	366.30	4,082.40	463.31	2,146.49	208.61
PPE	1,347.57	129.22	1,388.98	133.77	1,683.34	123.89
Sales	1,938.73	307.50	2,332.35	358.11	1,991.05	281.65
ΔAcc Rec	(19.71)	(2.60)	(21.66)	(3.36)	(15.03)	(1.17)
Accruals	(100.73)	(8.53)	(122.52)	(9.91)	(129.93)	(10.72)

Total Assets = Compustat Data 6
MVE = Market Value of Equity = Compustat Data 99 * Compustat Data 25.
PPE = Gross Property, Plant, and Equipment = Compustat Data 7.

Sales = Net Sales = Compustat Data 12.
ΔAcc Rec = Change in Accounts Receivable as reported on the Statement of Cash Flows = Compustat Data 302.
Accruals = Difference between operating cash flows and income before extraordinary items = Compustat Data 308 – Compustat Data 123.

Net income classes = *ni_class*. The range of each *ni_class* is 0.01, for example *ni_class* –15 includes all firm-years where -0.15 ≤ Net Income < -0.14. In this way, small profit firms, *ni_class* 0, includes all firm-years where 0 ≤ Net Income < 0.01.

Change-in-net-income classes = *chgni_class*. The range of each *chgni_class* is 0.01, for example *chgni_class* –15 includes all firm-years where -0.15 ≤ Change-in-net-income < -0.14. In this way, firms with small positive earnings changes, *chgni_class* 0, includes all firm-years where 0 ≤ Change-in-net-income < 0.01.

Analyst forecast error classes = *forecasterror_class*. The range of each *forecasterror_class* is 2 cents, for example *forecasterror_class* -15 includes all firm-years where -0.30 ≤ Forecast Error < -0.28. In this way, firms that meet or just beat an analyst forecast, *forecasterror_class* 0, includes all firm-years where 0 ≤ Forecast Error < 0.02.

TABLE 2.2
Discretionary Accrual comparison of firms with small positive earnings to all other firms and firms with small negative earnings (loss avoidance benchmark)

Panel A: Modified Cross-Sectional Jones Model

	Ni_class 0 (1)	*All other Firms* (2)	*t-value*[b] *p-value* (1) vs (2)	*Ni_class -1* (3)	*t-value*[b] *p-value* (1) vs (3)
Discretionary Accruals (DA)					
n	1,663	47,987		838	
mean	0.03502	0.00530	11.75 [a]	0.03168	0.82 [a]
median	0.03372	0.01713	0.0001	0.02972	0.4146
Std. Dev.	0.10023	0.13171		0.09455	

Panel B: Forward-Looking Model

	Ni_class 0 (1)	*All other Firms* (2)	*t-value*[b] *p-value* (1) vs (2)	*Ni_class -1* (3)	*t-value*[b] *p-value* (1) vs (3)
Discretionary Accruals (DA)					
N	1,663	47,987		838	
Mean	0.02366	-0.00084	10.13 [a]	0.01712	1.63
Median	0.02222	0.00995	0.0001	0.01939	0.1028
Std. Dev.	0.09588	0.12395		0.09184	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for
1) Panel A, (1) vs. (2), results in a Z-value of 9.2442 and a t-approximation of <0.0001;
2) Panel A, (1) vs. (3), results in a Z-value of 0.7943 and a t-approximation of 0.4271;
3) Panel B, (1) vs. (2), results in a Z-value of 7.6946 and a t-approximation of <0.0001;
4) Panel B, (1) vs. (3), results in a Z-value of 1.6210 and a t-approximation of 0.1051.

Discretionary accruals used as a technique for beating the loss avoidance benchmark are considered using 49,650 firm year observations from 1988-2001 with available data on Compustat. Consistent with Dechow et al. (2003) these observations are allocated into net income classes (*ni_class*). The range of each *ni_class* is 0.01, for example *ni_class* –15 includes all firm years where –0.15 ≤ Net Income < -0.14. In this way, the benchmark beater class, *ni_class* 0, includes all firm years where 0 ≤ Net Income < 0.01.

Net Income (Compustat Data 172) in year *t* is scaled by market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-1*.

Discretionary accruals are calculated as the difference between Total Accruals and Non-discretionary accruals. Total Accruals is the difference between Net Income before extraordinary items (Compustat Data 123) and Cash Flow from Operations (Compustat Data 308), and non-discretionary accrual are estimated as a function of the level of property, plant, and equipment and the difference between the changes in revenue and changes in receivables for the Modified Cross-Sectional Jones Model:

$$ACCR_{j,t}/TA_{j,t-1} = \alpha + \beta_1 \cdot [(\Delta REV_{j,t} - \Delta REC_{j,t})/TA_{j,t-1}] + \beta_2 \cdot [PPE_{j,t}/TA_{j,t-1}] + e_{j,t} \qquad (1)$$

Non-discretionary accruals are estimated as a function of the level of property, plant, and equipment, the difference between the changes in revenue and changes in receivables (where receivables are adjusted by their expectation-*k*), lagged accruals, and future sales growth for the Forward-Looking Model:

$$ACCR_{j,t} = \alpha + \beta_1 \cdot [\Delta REV_{j,t} - (1-k)\, \Delta REC_{j,t}] + \beta_2 \cdot (PPE_{j,t}) + \beta_3 \cdot ACCR_{j,t-1} + \beta_4 \cdot GR\_Sales + e_{j,t} \qquad (2)$$

where $ACCR_{j,t}$ = total accruals for firm *j* in year *t*. (Compustat Data 123 – Compustat Data 308 or Net Income before extraordinary items – Cash Flow from Operations), $TA_{j,t-1}$ = total assets for firm *j* in year *t-1*. (Compustat Data 6), $\Delta REV_{j,t}$ = change in net revenue (Compustat Data 12), $\Delta REC_{j,t}$ = change in accounts receivable (Compustat Data 302), $PPE_{j,t}$ = property, plant, and equipment (Compustat Data 8), $ACCR_{j,t-1}$ = total accruals for firm *j* in year *t-1*, *GR_Sales* = the change in sales for firm *j* from year *t* to *t+1*, scaled by year *t* sales, and *k* = the slope coefficient from a regression of *ΔREC on ΔREV.*

Firms in financial institutions (SIC 6000 to 6999) and observations where total accruals or any of the independent variables that are in the extreme 1% of their respective distributions are excluded from the final sample.

TABLE 2.3
Discretionary Accrual comparison of firms with small positive earnings changes to all other firms and firms with small negative earnings changes (earnings improvement benchmark)

Panel A: Modified Cross-Sectional Jones Model

	Chgni_class 0 (1)	*All other Firms* (2)	*t-value*[b] *p-value* (1) vs. (2)	*Chgni_class -1* (3)	*t-value*[b] *p-value* (1) vs. (3)
Discretionary Accruals (DA)					
n	4,858	44,792		3,260	
mean	0.02566	0.00420	16.41 [a]	0.02411	0.78 [a]
median	0.02414	0.01662	0.0001	0.02376	0.4350
Std. Dev.	0.07960	0.13512		0.09232	

Panel B: Forward-Looking Model

	Chgni_class 0 (1)	*All other Firms* (2)	*t-value*[b] *p-value* (1) vs. (2)	*Chgni_class -1* (3)	*t-value*[b] *p-value* (1) vs. (3)
Discretionary Accruals (DA)					
n	4,858	44,792		3,260	
mean	0.01613	-0.00177	14.96[a]	0.01474	0.76 [a]
median	0.01580	0.00949	0.0001	0.01549	0.4445
Std. Dev.	0.07208	0.12738		0.08577	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for
1) Panel A, (1) vs. (2), results in a Z-value of 10.0617 and a t-approximation of <0.0001;
2) Panel A, (1) vs. (3), results in a Z-value of 0.5986 and a t-approximation of 0.5495;
3) Panel B, (1) vs. (2), results in a Z-value of 8.6181 and a t-approximation of <0.0001;
4) Panel B, (1) vs. (3), results in a Z-value of 0.5110 and a t-approximation of 0.6094.

Discretionary accruals used as a technique for beating the earnings improvement benchmark are considered using 49,650 firm year observations from 1988-2001 with available data on Compustat. These observations are allocated into change in net income classes (*chgni_class*). The range of each *chgni_class* is 0.01, for example *chgni_class* –15 includes all firm years where –0.15 ≤ Change in Net Income < -0.14. In this way, the earning change benchmark beater class, *chgni_class* 0, includes all firm years where 0 ≤ Change in Net Income < 0.01.

A firm's current change in earnings is calculated by subtracting net income (Compustat Data 172) in year *t-1* from net income in year *t* and scaling that amount by the market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-2*. I place firms in change-in-net-income classes (*chgni_class*).

Discretionary accruals measures are consistent with Table 2.2.

TABLE 2.4
Discretionary Accrual comparison of firms that either met or beat analysts' forecasts by one cent to all other firms and firms that missed analysts' forecasts by one or two cents. (analyst forecast benchmark)

Panel A: Modified Cross-Sectional Jones Model

	Forecasterror_class 0 (1)	*All other Firms* (2)	*t-value*[b] *p-value* (1) vs. (2)	*Forecasterror_class -1* (3)	*t-value*[b] *p-value* (1) vs. (3)
Discretionary Accruals (DA)					
n	6,188	19,437		2,527	
mean	0.01878	0.01356	3.61 [a]	0.01923	-0.21 [a]
median	0.02139	0.01879	0.0003	0.02152	0.8355
Std. Dev.	0.09719	0.10394		0.08900	

Panel B: Forward-Looking Model

	Forecasterror_class 0 (1)	*All other Firms* (2)	*t-value*[b] *p-value* (1) vs. (2)	*Forecasterror_class -1* (3)	*t-value*[b] *p-value* (1) vs. (3)
Discretionary Accruals (DA)					
n	6,188	19,437		2,527	
mean	0.00884	0.00535	2.56 [a]	0.01001	-0.57 [a]
median	0.01313	0.01080	0.0105	0.01206	0.5667
Std. Dev.	0.09141	0.09915		0.08501	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for
1) Panel A, (1) vs. (2), results in a Z-value of 3.3164 and a t-approximation of 0.0009;
2) Panel A, (1) vs. (3), results in a Z-value of -0.2276 and a t-approximation of 0.8199;
3) Panel B, (1) vs. (2), results in a Z-value of 2.0471 and a t-approximation of 0.0407;
4) Panel B, (1) vs. (3), results in a Z-value of -0.1318 and a t-approximation of 0.8952.

Discretionary accruals used as a technique for beating the analyst forecast benchmark are considered using 25,625 firm-year observations from 1988-2001 with available data on Compustat. These observations are allocated into forecast error classes (*forecasterror_class*). The range of each *forecasterror_class* is 2 cents, for example *forecasterror_class* -15 includes all firm-years where -0.30 ≤ Forecast Error < -0.28. In this way, firms that meet or just beat an analyst forecast, *forecasterror_class* 0, includes all firm-years where 0 ≤ Forecast Error < 0.02.

A firm's analyst forecast error is calculated by subtracting the most recent median I/B/E/S forecast of annual earnings per share for the current year from actual earnings per share for the current year (also obtained from I/B/E/S).

Discretionary accruals measures are consistent with Table 2.2.

TABLE 2.5
Discretionary Accrual comparison of firms with small positive earnings to firms with small negative earnings (loss avoidance benchmark)

Panel A: Forward-Looking Model. Selected results from Table 2.2, Panel B presented for comparative purposes. No alternative incentives deleted.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value* *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	1,663	838	
mean	0.02366	0.01712	1.63
median	0.02222	0.01939	0.1028
Std. Dev.	0.09588	0.09184	

Panel B: Forward-Looking Model. 55 Firms with c*hgni_class* = 0 are deleted from the *ni_class* = -1 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	1,663	783	
mean	0.02366	0.01725	1.56
median	0.02222	0.01935	0.1182
Std. Dev.	0.09588	0.09187	

Panel C: Forward-Looking Model. 264 Firms with c*hgni_class* ≥ 0 are deleted from the *ni_class* = -1 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	1,663	574	
mean	0.02366	0.00633	3.99[a]
median	0.02222	0.01431	0.0001
Std. Dev.	0.09588	0.08732	

Panel D: Forward-Looking Model. 107 firms with *forecasterror_class* = 0 are deleted from the *ni_class* = -1 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	1,663	731	
mean	0.02366	0.01954	1.02[a]
median	0.02222	0.02054	0.3074
Std. Dev.	0.09588	0.08843	

Panel E: Forward-Looking Model. 240 Firms with firms with *forecasterror_class* ≥ 0 are deleted from the *ni_class* = -1 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	1,663	598	
mean	0.02366	0.02082	0.66[a]
median	0.02222	0.02105	0.5091
Std. Dev.	0.09588	0.08793	

Panel F: Forward-Looking Model. 48 Firms with c*hgni_class* = 0, 100 firms with *forecasterror_class* = 0, and 7 firms with both c*hgni_class* = 0 & *forecasterror_class* = 0 are deleted from the *ni_class* = -1 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	1,663	683	
mean	0.02366	0.01927	1.06 [a]
median	0.02222	0.02054	0.2890
Std. Dev.	0.09588	0.08891	

Panel G: Forward-Looking Model. 211 Firms with c*hgni_class* ≥ 0, 187 firms with *forecasterror_class* ≥ 0, and 53 firms with both c*hgni_class* ≥ 0 & *forecasterror_class* ≥ 0 are deleted from the *ni_class* = -1 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	1,663	387	
mean	0.02366	0.01152	2.48 [a]
median	0.02222	0.01530	0.0133
Std. Dev.	0.09588	0.08424	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for:
Panel B results in a Z-value of 1.6205 and a t-approximation of 0.1053;
Panel C results in a Z-value of 3.7097 and a t-approximation of 0.0002;
Panel D results in a Z-value of 1.1731 and a t-approximation of 0.2409;
Panel E results in a Z-value of 0.7640 and a t-approximation of 0.4449;
Panel F results in a Z-value of 1.2108 and a t-approximation of 0.2261;
Panel G results in a Z-value of 2.4244 and a t-approximation of 0.0154.

Discretionary accruals used as a technique for beating the loss avoidance benchmark are considered using 2,446 firm-year observations in Panel B, 2,237 firm-year observations in Panel C, 2,394 firm-year observations in Panel D, 2,261 firm-year observations in Panel E, and 2,346 firm-year observations in Panel F, 2,050 firm-year observations in Panel G from 1988-2001 with available data on Compustat.

Measures of *ni_class, chgni_class, forecasterror_class* are consistent with Table 2.2, Table 2.3, and Table 2.4. Discretionary accruals measures are consistent with Table 2.2.

TABLE 2.6
Discretionary Accrual comparison of firms with small positive earnings changes to firms with small negative earnings changes (earnings improvement benchmark)

Panel A: Forward-Looking Model. Selected results from Table 2.3, Panel B presented for comparative purposes. No alternative incentives deleted.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value* *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	4,858	3,260	
mean	0.01613	0.01474	0.76
median	0.01580	0.01549	0.4445
Std. Dev.	0.07208	0.08577	

Panel B: Forward-Looking Model. 136 Firms with *ni_class* = 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	4,858	3,124	
mean	0.01613	0.01385	1.24[a]
median	0.01580	0.01474	0.2146
Std. Dev.	0.07208	0.08472	

Panel C: Forward-Looking Model. 2,657 Firms with *ni_class* ≥ 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	4,858	603	
mean	0.01613	-0.00992	4.50[a]
median	0.01580	0.00793	0.0001
Std. Dev.	0.07208	0.13986	

Panel D: Forward-Looking Model. 555 Firms with *forecasterror_class* = 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	4,858	2,705	
mean	0.01613	0.01327	1.44[a]
median	0.01580	0.01465	0.1510
Std. Dev.	0.07208	0.08869	

Panel E: Forward-Looking Model. 1,176 Firms with *forecasterror_class* ≥ 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	4,858	2,084	
mean	0.01613	0.01213	1.72[a]
median	0.01580	0.01574	0.0854
Std. Dev.	0.07208	0.09518	

Panel F: Forward-Looking Model. 115 Firms with *ni_class* = 0, 534 firms with *forecasterror_class* = 0, and 21 firms with both *ni_class* = 0 & *forecasterror_class* = 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	4,858	2,590	
mean	0.01613	0.01218	1.97 [a]
median	0.01580	0.01325	0.0493
Std. Dev.	0.07208	0.08756	

Panel G: Forward-Looking Model. 1,593 Firms with *ni_class* ≥ 0, 112 firms with *forecasterror_class* ≥ 0, and 1,064 firms with both *ni_class* ≥ 0 & *forecasterror_class* ≥ 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	4,858	491	
mean	0.01613	-0.01550	4.70[a]
median	0.01580	0.00609	0.0001
Std. Dev.	0.07208	0.14739	

Panel H: Forward-Looking Model. 103 firms with *ni_class* = 0, 1,143 firms with *forecasterror_class* ≥ 0, and 33 firms with both *ni_class* = 0 & *forecasterror_class* ≥ 0 are deleted from the *chgni_class* = -1 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
N	4,858	1,981	
Mean	0.01613	0.01062	2.34 [a]
median	0.01580	0.01426	0.0195
Std. Dev.	0.07208	0.09421	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for:
Panel B results in a Z-value of 0.9880 and a t-approximation of 0.3232;
Panel C results in a Z-value of 3.9308 and a t-approximation of <.0001;
Panel D results in a Z-value of 1.2549 and a t-approximation of 0.2096;
Panel E results in a Z-value of 0.9596 and a t-approximation of 0.3373;
Panel F results in a Z-value of 1.8148 and a t-approximation of 0.0696;
Panel G results in a Z-value of 4.5053 and a t-approximation of <.0001;
Panel H results in a Z-value of 1.6515 and a t-approximation of 0.0987.

Discretionary accruals used as a technique for beating the earnings improvement benchmark are considered using 7,982 firm-year observations in Panel B, 5,461 firm-year observations in Panel C, 7,563 firm-year observations in Panel D, 6,942 firm-year observations in Panel E, 7,448 firm-year observations in Panel F, 5,349 firm-year observations in Panel G, and 6,839 firm-year observations in Panel H from 1988-2001 with available data on Compustat.

Measures of *ni_class, chgni_class, forecasterror_class* are consistent with Table 2.2, Table 2.3, and Table 2.4. Discretionary accruals measures are consistent with Table 2.2.

TABLE 2.7
Discretionary Accrual comparison of firms that either met or beat analysts' forecasts by one cent to firms that missed analysts' forecasts by one or two cents. (analyst forecast benchmark)

Panel A: Forward-Looking Model. Selected results from Table 2.4, Panel B presented for comparative purposes. No alternative incentives deleted.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	2,527	
mean	0.00884	0.01001	-0.57 [a]
median	0.01313	0.01206	0.5667
Std. Dev.	0.09141	0.08501	

Panel B: Forward-Looking Model. 80 Firms with *ni_class* = 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	2,447	
mean	0.00884	0.00978	-0.45 [a]
median	0.01313	0.01178	0.6494
Std. Dev.	0.09141	0.08473	

Panel C: Forward-Looking Model. 2,104 Firms with *ni_class* ≥ 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	423	
mean	0.00884	-0.02490	5.28[a]
median	0.01313	-0.00207	0.0001
Std. Dev.	0.09141	0.12919	

Panel D: Forward-Looking Model. 449 firms with *chgni_class* = 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	2,078	
mean	0.00884	0.00807	0.33
median	0.01313	0.01120	0.7378
Std. Dev.	0.09141	0.08995	

Panel E: Forward-Looking Model. 1,548 firms with *chgni_class* ≥ 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	979	
mean	0.00884	-0.00250	3.35[a]
median	0.01313	0.00876	0.0009
Std. Dev.	0.09141	0.09962	

Panel F: Forward-Looking Model. 73 firms with *ni_class* = 0, 442 firms with *chgni_class* = 0, and 7 firms with both *chgni_class* = 0 & *ni_class* = 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	2,005	
mean	0.00884	0.00770	0.49
median	0.01313	0.01105	0.6249
Std. Dev.	0.09141	0.08989	

Panel G: Forward-Looking Model. 631 firms with *ni_class* ≥ 0, 75 firms with *chgni_class* ≥ 0, and 1,473 firms with both *ni_class* ≥ 0 & chg*ni_class* ≥ 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	348	
mean	0.00884	-0.03472	5.94[a]
median	0.01313	-0.01205	0.0001
Std. Dev.	0.09141	0.13499	

Panel H: Forward-Looking Model. 55 firms with *ni_class* = 0, 1,523 firms with *chgni_class* ≥ 0, and 25 firms with both *ni_class* = 0 & *chgni_class* ≥ 0 are deleted from the *forecasterror_class* = -1 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	6,188	924	
mean	0.00884	-0.00319	3.44[a]
median	0.01313	0.00868	0.0006
Std. Dev.	0.09141	0.10016	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for:
Panel B results in a Z-value of -0.0199 and a t-approximation of 0.9841;
Panel C results in a Z-value of 5.0292 and a t-approximation of <.0001;
Panel D results in a Z-value of 0.6890 and a t-approximation of 0.4909;
Panel E results in a Z-value of 2.7344 and a t-approximation of 0.0063;
Panel F results in a Z-value of 0.8292 and a t-approximation of 0.4070;
Panel G results in a Z-value of 6.1609 and a t-approximation of <.0001;
Panel H results in a Z-value of 2.8190 and a t-approximation of 0.0048.

Discretionary accruals used as a technique for beating the analyst forecast benchmark are considered using 8,635 firm-year observations in Panel B, 6,611 firm-year observations in Panel C, 8,266 firm-year observations in Panel D, 7,167 firm-year observations in Panel E, 8,193 firm-year observations in Panel F, 6,536 firm-year observations in Panel G, and 7,112 firm-year observations in Panel H from 1988-2001 with available data on Compustat.

Measures of *ni_class, chgni_class, forecasterror_class* are consistent with Table 2.2, Table 2.3, and Table 2.4. Discretionary accruals measures are consistent with Table 2.2.

TABLE 2.8
Discretionary Accrual comparison of firms above and below all three benchmarks where firms with alternative incentives are deleted from above and below the benchmark

Panel A: Loss Avoidance Benchmark. Firms deleted from the *ni_class* -1 sample are consistent with Table 2.5, Panel F. 99 firms with c*hgni_class* = 0, 187 firms with *forecasterror_class* = 0, and 24 firms with both c*hgni_class* = 0 & *forecasterror_class* = 0 are deleted from the *ni_class* = 0 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	1,353	683	
mean	0.02822	0.01927	2.07
median	0.02353	0.02054	0.0385
Std. Dev.	0.09368	0.08891	

Panel B: Loss Avoidance Benchmark. Firms deleted from the *ni_class* -1 sample are consistent with Table 2.5, Panel G. 487 firms with c*hgni_class* ≥ 0, 305 firms with *forecasterror_class* ≥ 0, and 145 firms with both c*hgni_class* ≥ 0 & *forecasterror_class* ≥ 0 are deleted from the *ni_class* = 0 sample.

	Ni_class *0* (1)	*Ni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	726	387	
mean	0.02147	0.01152	1.82 [a]
median	0.01891	0.01530	0.0687
Std. Dev.	0.09099	0.08424	

Panel C: Earnings Improvement Benchmark. Firms deleted from the c*hgni_class* = -1 sample are consistent with Table 2.6, Panel F. 99 firms with *ni_class* = 0, 1,017 firms with *forecasterror_class* = 0, and 24 firms with both *ni_class* = 0 & *forecasterror_class* = 0 are deleted from the *chgni_class* = sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs (2)
Discretionary Accruals (DA)			
n	3,718	2,590	
mean	0.01608	0.01218	1.86 [a]
median	0.01519	0.01325	0.0629
Std. Dev.	0.07315	0.08756	

Panel D: Earnings Improvement Benchmark. Firms deleted from the c*hgni_class* = -1 sample are consistent with Table 2.6, Panel H. 85 firms with *ni_class* = 0, 1,932 firms with *forecasterror_class* ≥ 0, and 38 firms with both *ni_class* = 0 & *forecasterror_class* ≥ 0 are deleted from the *chgni_class* = 0 sample.

	Chgni_class *0* (1)	*Chgni_class* *-1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
N	2,803	1,981	
Mean	0.01535	0.01062	1.85 [a]
median	0.01519	0.01426	0.0650
Std. Dev.	0.07657	0.09421	

Panel E: Analyst Forecast Benchmark. Firms deleted from the *forecasterror_class* = -1 sample are consistent with Table 2.7, Panel F. 187 firms with *ni_class* = 0, 1,017 firms with *ni_class* = 0, and 24 firms with both *chgni_class* = 0 & *ni_class* = 0 are deleted from the *forecasterror_class* = 0 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	4,960	2,005	
mean	0.00766	0.00770	-0.02[a]
median	0.01207	0.01105	0.9840
Std. Dev.	0.09515	0.08989	

Panel F: Analyst Forecast Benchmark. Firms deleted from the *forecasterror_class* = -1 sample are consistent with Table 2.7, Panel H. 144 firms with *ni_class* = 0, 3,969 firms with *chgni_class* ≥ 0, and 67 firms with both *ni_class* = 0 & *chgni_class* ≥ 0 are deleted from the *forecasterror_class* = 0 sample.

	Forecasterror_ class 0 (1)	*Forecasterror_ class -1* (2)	*t-value*[b] *p-value* (1) vs. (2)
Discretionary Accruals (DA)			
n	2,008	924	
mean	-0.00532	-0.00319	-0.52[a]
median	0.00761	0.00868	0.5999
Std. Dev.	0.10552	0.10016	

T-tests are used to test the difference between means (p-values are also presented).

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

b – The Shapiro-Wilk Test for normality is rejected. The Wilcoxon Two Sample Test for:
Panel A results in a Z-value of 2.0064 and a t-approximation of 0.0449;
Panel B results in a Z-value of 1.7772 and a t-approximation of 0.0758;
Panel C results in a Z-value of 1.7495 and a t-approximation of 0.0802;
Panel D results in a Z-value of 1.5180 and a t-approximation of 0.1291;
Panel E results in a Z-value of 0.3155 and a t-approximation of 0.7524;
Panel F results in a Z-value of –0.3295and a t-approximation of 0.7418.

Measures of *ni_class, chgni_class, forecasterror_class* are consistent with Table 2.2, Table 2.3, and Table 2.4. Discretionary accruals measures are consistent with Table 2.2.

CHAPTER 3

WHY SMALL LOSS FIRMS? EARNINGS MANAGEMENT CONSTRAINTS AND MARKET SENSITIVITY TO EARNINGS

I. INTRODUCTION

Hayn (1995) shows that there is a 'point of discontinuity' in the cross-sectional distribution of earnings around zero. Burgstahler and Dichev (1997) also document that there is a break in the distribution of earnings around zero earnings. They show that there is an unusually low concentration of firms just below zero and an unusually high concentration of firms just above zero earnings (earnings level threshold). They perform the same analysis for earnings changes and find a similar break in the distribution for small positive and small negative earnings changes (earnings changes threshold). They provide the breaks in the distributions as circumstantial evidence that earnings are managed to beat these thresholds. Degeorge, Patel, and Zeckhauser (1999) find similar results for the cross sectional distribution of analyst forecast errors (analyst forecast threshold).

Firms have incentives to beat thresholds. Brown and Caylor (2004) find that firms have positive cumulative abnormal returns around earnings announcements when they have met at least one or any combination of the three thresholds (earnings levels, earnings changes, and meeting or beating analysts' forecasts). If firms have incentives to beat a threshold, then why do so many firms miss a threshold? What prevents firms just below a threshold from managing earnings to beat a threshold? I examine the characteristics that differentiate firms just above and firms just below thresholds. I focus on two specific characteristics—market sensitivity to earnings announcements and a firm's flexibility to manage earnings.

I posit that prior to annual earnings announcements, firms just below a threshold decide whether to manage earnings to beat a threshold. First the firms' management decide whether they have the flexibility to manage earnings. Second, if management does have the flexibility to manage earnings, then the management would have to decide whether managing earnings would benefit the firm. Barton and Simko (2002) find that a firm's ability to manage earnings is negatively related to the firm's beginning-of-the-year level of net operating assets (NOA). In other words, the balance sheet constrains the amount by which firms can manage earnings. Kasznik (1999) uses change in total accruals in the prior year as a measure of flexibility and finds that firms with more flexibility are more likely to manage earnings to meet a management earnings forecast. I operationalize the first decision by using firm's beginning-of-the-year NOA and change in total accruals as proxies for a firm's flexibility to manage earnings. Firms with high levels of NOA or large changes in total accruals would not have flexibility to manage earnings to beat the threshold. I hypothesize that firms below a threshold will have higher levels NOA or higher change in total accruals than firms above a threshold (Flexibility Hypothesis).

I operationalize the second decision by using firm-specific ERCs and analysts stock recommendations prior to the earnings management decision. Firms with high ERCs and overall buy recommendations would receive more benefits from beating the benchmark. I hypothesize that firms below a threshold will have lower levels of ERCs or analyst stock recommendation than firms above a threshold (Market Sensitivity Hypothesis). Firms that have flexibility (low NOAs or change in total accruals) and would benefit from beating the threshold (high ERCs or overall buy recommendations) would be candidates for earnings management.

To test my research question I use probit regression to calculate the probability that beginning-of-the-year levels of NOA and change in total accruals will affect a firm's ability to meet or beat a threshold. I expect the coefficients on NOA and change in total accruals will be negative. I also use probit regression to calculate the probability that ERCs and analyst stock recommendations will affect a firm's incentives to meet or beat a threshold. I expect the coefficients on ERCs and analyst stock recommendations to be positive. Results consistent with my expectations provide an explanation to why there is not more of a gap just below a threshold.

One concern with comparing the full sample of firms below a benchmark to the full sample of firms above is that the sample above a benchmark contains firm-year observations that arrive there through normal operations. In additional tests I limit my sample firms above a benchmark to firms that potentially managed earnings—sample firms in the top quartile of discretionary accruals—and compare my earnings management sample above to the full sample below a benchmark.

Earnings management to meet or beat thresholds is a concern to the SEC (Donaldson 2003). Regulators and academic researchers can benefit from understanding the characteristics of firms that are manipulating earnings to meet or beat thresholds. For regulators, these characteristics can operate as red flags for investigation. For researchers, the characteristics can add variables to the tool kit used in detecting earnings management.

Results support the flexibility hypothesis. When I limit my sample firms above a threshold to potential earnings managers, the probability of meeting or beating the earnings change and analyst forecast threshold is negatively associated with the level of NOAs. Results also support the market sensitivity hypothesis. The probability of meeting or beating the earnings change and analyst forecast threshold is positively associated with the analyst stock recommendation, regardless of whether firms above a threshold are limited to potential earnings managers.

The next section discusses my hypothesis development, Section III describes the research design, Section IV presents the results, and Section V concludes and summarizes the paper.

II. HYPOTHESIS DEVELOPMENT

Barton and Simko (2002) state that the balance sheet accumulates accounting decisions that firms make. They use firm NOAs at the beginning of the quarter scaled by sales from the prior quarter as their measure of a firm's prior accounting choices. They hypothesize that if NOA of a firm is relatively high then it is less likely the firm will be able to positively bias their earnings. They focus on the analyst forecast threshold, and expect firms that beat the analyst forecast threshold to have lower NOAs at the beginning of the year (more flexibility) than firms that just missed the analyst forecast threshold. Their results support their hypothesis. I use NOAs as my first proxy for flexibility and expect a similar result for firms just above and just below the earnings level threshold. Firms just above the threshold could have more flexibility to manage their earnings to beat a threshold. They would have NOA levels that are lower than the firms just below the earnings level threshold.

Kasznik (1999) examines whether firms that have made a voluntary earnings forecast manage earnings to meet that forecast. Kasznik tests to see if a firm's flexibility to manage earnings affects actual earnings management. He measures flexibility with change in total accruals in the year prior to the management earnings forecast. Kasznik states (p. 78) " abnormal levels of lagged accruals reduce managers' ability to manage reported earnings upward in the current period." He finds that firms that overestimate their earnings forecasts are more likely to manage earnings when they have the flexibility to do so. I use change in total accruals as my second proxy for flexibility and expect firms just above a benchmark to have smaller changes in total accruals than firms just above a benchmark.

I also expect firms just above and just below the earnings levels threshold to have different incentives to manipulate or not manipulate earnings. Kothari (2001 p. 123) defines ERCs as the "mapping of earnings' time-series properties and discount rates into changes in equity market values." Firms that have the ability to manipulate earnings may decide not to manipulate earnings because doing so would have little effect on market values. That is, firms with lower ERCs have less incentive to beat earnings thresholds because their stock price 'reward' per dollar of earnings is less than for firms with higher ERCs.

However, using the ERC to measure management's incentive to manage earnings may be problematic. Sankar (1999) theoretically shows in a one period setting that firms that are managing earnings to maximize short-term gains have ERCs that are lower than if firms did not manage earnings. DeFond and Park (2001) hypothesize that for firms that report good news, income-increasing abnormal working capital accruals overstates the good news and will lead to lower ERCs. Good news firms with income-decreasing abnormal working capital accruals understate good news and will have higher ERCs. Their results support their hypotheses. The findings of Sankar (1999) and DeFond and Park (2001) show that firms that have a history of managing earnings may have lower ERCs, suggesting that the ERC may be a poor measure of the incentive to manage earnings.

As an alternative measure, I also use analysts' stock recommendations (Abarbanell and Lehavy 2003) as a measure of market sensitivity to earnings. Abarbanell and Lehavy (2003) find that firms with buy recommendations are more likely to manage earnings to meet or beat an analyst's earnings forecast. Abarbanell and Lehavy (2003, p. 10) state that they use stock recommendations rather than ERCs as a measure of market sensitivity because "this approach leads to potential staleness in the measure of sensitivity. It also introduces a potential endogeneity problem if earnings management embedded in prior earnings surprises affected the prior response to earnings news." I use analyst stock recommendations as my second proxy for a firm's ability to affect market prices through reported earnings.

To summarize, my hypotheses, stated in the alternative form, are:

Hypothesis 1: Small loss firms have higher NOAs and/or change in total accruals than small profit firms.

Hypothesis 2: Small loss firms have lower ERCs and/or lower stock recommendations than small profit firms.

I also examine difference in ERCs, analyst stock recommendations, change in total accruals, and NOAs between firms just above and firms just below the earnings change and analyst forecast error thresholds. I hypothesize that the results will be similar to the earnings level threshold.

III. EMPIRICAL DESIGN

A – Sample Selection

The sample includes all small loss, small profit, small positive earnings changes, small negative earnings change, just missed analysts' forecast, and just meet or beat analysts' forecast firm year observations in the Compustat 2002 quarterly database, April 2003 CRSP daily stock return files, and the 2003 I/B/E/S Summary History and Recommendations Detail files with data to compute NOAs, change in total accruals, ERCs and analyst stock recommendations. To estimate individual firm ERCs, I require firms to have 15 quarters of positive earnings announcements out of the 24 quarters prior to being placed in the categories around a threshold.

For additional tests my sample consists of firms with the necessary data to compute discretionary accruals. Computing discretionary accruals for financial institutions (SIC 6000 to 6999) can be problematic (DeFond and Subramanyam 1998) so I exclude these firms from the sample. Measuring accruals using changes in a series of balance sheet accounts adds measurement error in accrual estimates (Hribar and Collins 2002). I avoid this potential for measurement error by restricting the sample to the period beginning in fiscal 1988 when FAS 95 took effect. FAS 95 requires companies to report a statement of cash flows, so by using post 1987 data I measure accruals directly from the statement of cash flows, which maintains a consistent accruals measure.

B – Earnings Levels Classification

I form my small profit sample similar to Burgstahler and Dichev (1997) and Dechow et al. (2003). I scale net income (Compustat Data 172) in year *t* by market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-1*. I place firms in net income classes (*ni_class*) with the width of each *ni_class* equaling 0.01 (e.g., *ni_class -1* contains firm-years with -0.02 ≤ Scaled Net Income < 0). The small profit firms sample (*ni_class* 0) includes all firm-years where 0 ≤ Scaled Net Income < 0.02.

C – Earnings Changes Classification

Consistent with Burgstahler and Dichev (1997), I calculate a firm's current change in earnings by subtracting net income (Compustat Data 172) in year *t-1* from net income in year *t* and scaling that amount by the market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-2*. I place firms in change-in-net-income classes (*chgni_class*) with the width of each *chgni_class* equaling 0.01, similar to *ni_class* (e.g., *chgni_class* -1 contains firm-years with -0.01 ≤ Scaled Change-in-net-income < 0). The small positive earnings changes sample (*chgni_class* 0) includes all firm-years where 0 ≤ Scaled Change-in-net-income < 0.01.

D – Analyst Forecast Error Classification

I calculate a firm's analyst forecast error by subtracting the most recent median I/B/E/S forecast of annual earnings per share for the current year from actual earnings per share for the current year (also obtained from I/B/E/S). I collect the median I/B/E/S forecast of annual earnings per share from the I/B/E/S Summary History File in the month that actual earnings are reported, or in the month prior to actual earnings being reported if there is no consensus forecast in the month that actual earnings are reported. I place firms in analyst forecast error classes (*forecasterror_class*) with the width of each *forecasterror_class* equaling two cents (e.g., *forecasterror_class* -1 contains all firm-years where -0.02 ≤ Forecast Error < 0). The meet or just beat analysts' forecast sample (*forecasterror_class* 0) includes all firm-years where 0 ≤ Forecast Error < 0.02.

E – Earnings Response Coefficient Model

Lipe, Bryant, and Widener (1998, p. 195-196) state that the "relation between stock returns and accounting earnings is nonlinear, different for losses than for profits, and different across firms." They results show that "each factor is incrementally important in specifying the relation between returns and earnings." Similar to Lipe, Bryant, and Widener (1998), I estimate ERCs using the following firm specific model that takes into account nonlinearity:

$$R_{j,t} = \alpha + \beta_{1j} \cdot UNEARN_{j,t} + \beta_{2j} \cdot |UNEARN_{j,t}| * UNEARN_{j,t} + e_{j,t} \tag{1}$$

where: $R_{j,t}$ = the cumulative market-adjusted return on security *j* over the 60 day period [-58, 1] around the quarterly earnings announcement,

$UNEARN_{j,t}$ = unexpected quarterly earnings = quarterly earnings for firm *j* before extraordinary items in quarter *t* minus its earnings in quarter *t-4*, scaled by the market value of equity at the beginning of quarter *t.*

I estimate the model for each firm for the 15 to 24 quarters of positive earnings prior to the period that I include the firm in the small profit or small loss sample. When I exclude loss quarters, I avoid the dampening effect that loss firms may have on ERCs because investors believe losses are transitory (Hayn 1995). I use a seasonal random walk model for my expectation of earnings. This is consistent with ERC literature (Hayn 1995, Teets and Wasley 1996, Basu 1997, Lipe et al. 1998). Using a seasonal random walk model allows me to keep firms in the sample that do not have an analyst following. Freeman and Tse (1992) show that earnings-return relationship is nonlinear (s-shaped). I include a nonlinear term in my ERC regression. Consistent with Lipe et al. (1998), I multiply the absolute value of unexpected quarterly earnings by unexpected quarterly earnings. Similar to including the square of an independent variable, this controls for nonlinearity but retains the sign of the unexpected earnings. Lipe et al. (1998) use a 4-day return period. Similar to Kothari and Sloan (1992), I also use a 60-day return period. When I lengthen the return window, 'price leading earnings' will factor into the ERCs.

F – Accrual Model

To identify firms that are potential earnings managers, I estimate discretionary accruals using the forward-looking[4] adaptation of the Jones Model (Dechow, Richardson, and Tuna 2003; Phillips, Pincus, and Rego 2003). Nondiscretionary accruals are a function of property, plant, and equipment, the difference between change in revenue and change in receivables, lag accruals, and expected future sales estimated by the following model:

$$ACCR_{j,t}/TA_{j,t-1} = \alpha + \beta_1 \cdot [(\Delta REV_{j,t} - (1\text{-}k)\,\Delta REC_{j,t})/TA_{j,t-1}] + \beta_2 \cdot PPE_{j,t}/TA_{j,t-1} + \beta_3 \cdot ACCR_{j,t-1} + \beta_4 \cdot GR\_Sales + e_{j,t} \quad (2)$$

[4] The forward-looking discretionary accrual model has advantages over the cross-sectional Jones model. The forward-looking model makes adjustments to the modified cross-sectional Jones model. First, the model does not assume that all credit sales are discretionary and treats part of the increase in credit sales as expected. Second, the model assumes a portion of total accruals is predictable and is captured by including last year's accruals (lagged total accruals). Finally, the forward-looking model includes next year's sales growth to account for the increase in inventory that is due to future sales. Bernard and Skinner (1996) state that Jones Model improperly classifies nondiscretionary accruals as discretionary and this can lead to erroneous results. Dechow et al. (2003) show that the forward-looking model has a mean adjusted R^2 of 0.20, which is consistent with R^2s from industry-specific models (Beatty, Ke, and Petroni 2002). The higher R^2 suggests that more of the variation in total accruals is explained by the variables in the

where: $ACCR_{j,t}$ = total accruals for firm *j* in year *t*. (Compustat Data 123 – Compustat Data 308 or Income before extraordinary items – Cash Flow from Operations),

$TA_{j,t-1}$ = total assets for firm *j* in year *t-1*. (Compustat Data 6),

$\Delta REV_{j,t}$ = change in net revenue (Compustat Data 12),

$\Delta REC_{j,t}$ = change in accounts receivable (Compustat Data 302),

$PPE_{j,t}$ = property, plant, and equipment (Compustat Data 8),

$ACCR_{j,t-1}$ = total accruals for firm *j* in year *t-1*, scaled by total assets for firm *j* in year *t-2*,

GR_Sales = the change in sales for firm *j* from year *t* to *t+1*, scaled by year *t* sales, and

k = the slope coefficient from a regression of ΔREC *on* ΔREV.

I estimate the model separately for each two-digit SIC code and calendar year. I drop from the sample any combination of two-digit SIC code and calendar year with less than ten firms. I define nondiscretionary accruals as the fitted value from Eq. (1) and discretionary accruals as the residual. Similar to Dechow et al. (2003), I exclude observations from the sample where total accruals or any of the independent variables are in the extreme 1% of their respective distributions.

G – Analyst Stock Recommendations

I use analyst stock recommendations provided by I/B/E/S. The I/B/E/S Recommendations Detail file assigns a number to each recommendation between 1 and 5. A 1 recommendation indicates a strong buy; 2 a buy; 3 a hold; 4 an underperform; and 5 a sell. For ease of interpretation, I reverse the numbering so that a 5 indicates a strong buy, 4 a buy, 3, a hold, 2 an underperform, 1 a sell. This allows higher numbers to mean

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model. In other words, the residual of the regression contains smaller amounts of more market sensitivity. Similar to Abarbanell and Lehavy (2003, p. 11) I create an average recommendation for each firm-year observation. I take the three most recent recommendations prior to year-end.

H – Research Design – Initial Tests

To test my hypotheses, I use probit regression to estimate the following pooled cross-sectional equation:

$$BEAT_{j,t} = \alpha + \beta_1 \cdot NOA_{j,t} + \beta_2 \cdot \Delta TACC_{j,t} + \beta_3 \cdot ERC_{j,t} + e_{j,t} \quad (3)$$ [5]

or

$$BEAT_{j,t} = \alpha + \beta_1 \cdot NOA_{j,t} + \beta_2 \cdot \Delta TACC_{j,t} + \beta_3 \cdot ERC_{j,t} + \beta_2 \cdot STOCKREC_{j,t} + e_{j,t}$$

where:

$BEAT_{j,t}$ = 0 if *ni_class, chgni_class, forecasterror_class* is equal to -1 and 1 if *ni_class, chgni_class, forecasterror_class* is equal to 0,

$NOA_{j,t}$ = net operating assets [Total Shareholder's Equity (Compustat Data 216) – Cash and Short Term Investments (Compustat Data 1) + Total Debt (Compustat Data 9 + Data 44)] for firm *j* at the beginning of year *t* scaled by sales (Compustat Data 12) for the year *t-1*,

$\Delta TACC_{j,t}$ = change in total accruals (Compustat Data 123 – Compustat Data 308 or Income before extraordinary items – Cash Flow from Operations) for firm *j* at the beginning of year *t* [(total accruals for year t-1) – (total accruals for year t-2)] scaled by total assets (Compustat Data 6) for the year *t-3*,

ERC_j = earnings response coefficient calculated for firm *j* over the 15 to 24 quarters of positive earnings prior to the period of being included as one of the firms just above or just below a threshold (Equation 1),

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nondiscretionary accruals.

[5] Phillips et al. 2003 test to see the usefulness of deferred tax expense and discretionary accruals in determining whether a firm meets or beats an earning threshold. These two variables measure means of making thresholds, while *NOA* and *ΔTACC* measures availability of means to make a threshold. I do not control for discretionary accruals and deferred tax expense because they may control away the effects of interest (e.g. discretionary accruals that the firm actually uses must have been available so controlling for use will take away part of the effect of availability).

STOCKREC$_{j,t}$ = the average of the three most recent analyst stock recommendations for firm *j* prior to the end of year *t*.

BEAT equals 1 (0) if firms just made (missed) the earnings level threshold. I predict that the probability of just making a threshold will decrease with the level of *NOA* and the level of change in total accrual, so *NOA* and *ΔTACC* will have a negative coefficient. I predict that the probability of just making a threshold will increase with the ERC, so I expect *ERC* to have a positive coefficient. Finally, I predict the probability of just making a threshold will increase with the analyst stock recommendation; therefore I expect *STOCKREC* will have a positive coefficient. Including analyst stock recommendations severely restricts the sample size, so I present results with and without analyst stock recommendations.

I – Research Design – Additional Tests

I expect that many firms just above a threshold arrive there through normal operations. In examining the earnings level threshold, Dechow et al. (2003, pages 363, 365) estimate the slope between the region just above and the region just below their small profit firms and use a linear and exponential approximation to see how many firms they should expect to be in their small profit category. They find that they should expect 90% (85%) of the observations to be in the small profit category by chance using the linear (exponential) method and 10% (15%) of the observations have potentially managed earnings to avoid a loss. The non-earnings-managing firms above a threshold may have levels of NOA, change in total accruals, ERCs, and analysts' stock recommendations that are consistent with firms just below a threshold. These non-earnings-managing firms could confound my hypotheses. To alleviate this concern, I compare firms below a threshold with the firms above the threshold that are potential earnings managers.

I offer discretionary or abnormal accruals as one measure of earnings management. If firms use discretionary accruals to meet thresholds, then firms above a threshold should have higher discretionary accruals than firms just below the threshold. Indeed, Hansen (2004) finds that firms with small positive earnings have higher discretionary accruals than firms with small losses, after controlling for other threshold incentives. I assume that firms just above the three earnings thresholds with high discretionary accruals are candidates for earnings management because of the large literature that shows when firms have incentives to manage earnings upwards (downward), discretionary accruals are positive (negative) and significantly related to the incentive firms as compared to the non-incentive firms (e.g. Heninger 2001, Pincus and Rajgopal 2002, Matsumoto 2002)

I identify the small profit firms subsample that are potential earnings managers by partitioning my small profit firms into quartiles based upon discretionary accruals. I use the quartile with the highest levels of discretionary accruals to proxy for firms that have managed earnings to avoid a loss. Similarly, I also partition firms above the earnings changes and analyst forecast benchmark into discretionary accrual quartiles. I recalculate the probit regressions and examine whether using potential earnings management firms above a threshold, rather than the full sample of firms above a threshold, affect the results.

IV. RESULTS

A – Initial Tests

Table 3.1 contains market value of equity (MVE), sales, and total asset descriptive statistics for firms above and below the thresholds. Skinner and Sloan (2002) show that firms with high price-to-earnings and market-to-book ratios are very sensitive to small negative earnings surprises. Abarbanell and Lehavy (2003, p. 9) state that the favorableness of analyst stock recommendations increases with the price-to-earnings and market-to-book ratios and decreases with debt-to-equity ratios. I include these variables in the descriptive statistics to give some initial evidence to whether firms are sensitive to earnings news.

Panel A presents results for the full sample around thresholds and Panel B presents results where only firm-year observations above a threshold that are potential earnings managers (high discretionary accruals) are compared to the full sample of firm-year observations just below the threshold. Panel A reports that firms above each threshold have a higher market value of equity than the firms below. Panel B shows that the MVE declines for the potential earnings manager subsample and there is no significant difference for firms above and below the thresholds. Panel B also shows that firms above the earnings levels threshold that are potential earnings managers have much lower sales and total assets than the firms below. These statistics suggest that firms that are potential earnings managers do not have the same market value as non-earnings managers. Also potential earnings managers above the earnings levels threshold do not perform as well as firms that did not beat a benchmark in terms of assets and sales. Panel A and B report that firms above the earning changes and analyst forecast threshold have higher market-to-book ratios than the firms below. This is consistent with these same firms having high analyst stock recommendations.

Table 3.2 contains univariate tests of differences in NOA, change in total accruals, ERCs, analysts' stock recommendations, and discretionary accruals for firms above and below each of the three thresholds. Panel A reports that for the full sample, none of the constraint variables are significant with the predicted sign. The incentive variable (market sensitivity to earnings announcements) ERC is not significant. I expect the average analyst stock recommendation to be higher for the firms just above each benchmark as compared to the firms just below. Results for the firms above the earnings change and analyst forecast threshold confirm this expectation.

The univariate statistics for the full sample show that firms lack of market sensitivity to earnings announcements, which I measure using analyst stock recommendations, may be a reason why firms just below the earnings changes and analyst forecast threshold are not managing earnings to beat these benchmarks.

Table 3.3 contains correlation coefficients for variables I include in the probit regressions. Table 3.4 contains probit regressions for the full sample of firms. Panel A presents results without analyst stock recommendations and Panel B present results with. Panel A and Panel B report that neither of the flexibility measures are significant. Panel B reports that analyst stock recommendations are positive and significant for the earnings changes and analyst forecast threshold.

In summary, for the full sample both univariate tests and probit regressions show that firms just below the earnings changes and analyst forecast benchmark may not be managing earnings to move above the threshold because they do not get the same market reaction from their earnings announcements, as measured by analyst stock recommendations.

B – Additional Tests

In additional analysis I focus on the firms above thresholds that are potential earnings managers. Table 3.2, Panel B and Table 3.5 present univariate and multivariate results, respectively. Only firms above a threshold that are considered to be earnings managers (high discretionary accruals) are compared to the full sample of firms just below the threshold. Table 3.2, Panel B reports that change in total accruals are significantly lower for firms above the earnings level threshold and analyst forecast threshold than for the firms just below. Similar to the full sample, the average analyst stock recommendation is significantly lower for the firms above the earnings changes and analyst forecast threshold.

Table 3.5, Panel A reports that the coefficient for NOA is negative and significant for the earnings changes and the analyst forecast threshold when analyst stock recommendations are not included in the probit regressions. Panel B also reports that the coefficient on NOA is negative and significant when analyst stock recommendations are included in the regression. These results support the flexibility hypothesis and suggest that firms above the earnings changes and analyst forecast threshold that were potential earnings managers had more flexibility, as measured by NOA, to manage earnings than firms below these thresholds.

Panel B shows that change in total accruals coefficient is negative and significant for the earnings level threshold when analyst stock recommendations are included in the probit regression. Panel B also reports that the ERC coefficient for the earnings level threshold is positive and significant. Although significant, I refrain from drawing conclusions about these coefficients around the earnings levels threshold because of the data restrictions that are caused by adding analyst stock recommendations to the regression.

In regards to incentives, Panel A and Panel B show that the coefficients for analyst stock recommendation are positive and significant for the earnings changes and analyst forecast thresholds. Consistent with the market sensitivity hypothesis, firms just below the earnings changes and analyst forecast thresholds do not appear to have the same market sensitivity to earnings announcements, measured by analyst stock recommendation, as do firms above thresholds and this may keep them from managing earnings.

V. CONCLUSION AND SUMMARY

Firms have incentives to beat earnings thresholds (earnings levels, earnings changes, and forecast error). With these incentives, it is mystery why there are not less firms just below thresholds. I hypothesize that firms just below a threshold are constrained by their ability to manage earnings. I measure this constraint using net operating assets (NOAs) and change in total accruals (ΔTACC) both measured at the beginning of the year. I also hypothesize that firms above thresholds have higher market sensitivity to earnings announcements. I measure this sensitivity using earnings response coefficients (ERCs) and average analyst stock recommendations.

To test my research question, I perform probit regressions with ERC, average analyst stock recommendation, NOA, and ΔTACC as independent variables and a dichotomous measure of whether firms are just above or just below a threshold as my dependent variable. I also perform additional probit regressions for firms just below a threshold and firms just above a threshold that are potential earnings management candidates—firms in the highest quartile of discretionary accruals.

Results using the full sample of firms just around the thresholds suggest that firms below the earnings changes and analyst forecast thresholds may not manage earnings to beat the threshold because they do not receive the same market reaction to earnings announcements (measured by analyst stock recommendations) as do firms above the threshold. Additional tests where I compare firms just above the threshold, with high levels of discretionary accruals, to firms just below the threshold suggest that flexibility to manage earnings, as measured by NOA, constrain firm management from managing earnings.

Results provide regulators and academic researchers with additional variables when they examine firms that are managing earnings to beat a threshold. The results provide additional evidence that firms have natural constraints (NOAs) that deter earnings management. Finally, firms that have low market sensitivity to earnings announcement (unfavorable analyst stock recommendations) do not have strong incentives to manage earnings.

Table 3.1
Descriptive Statistics

Panel A: Full Sample

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above
MVE	n = 922	n = 1,985	n = 2,153	n = 3,445	n = 2,026	n = 5,149
mean	2519.14	3895.03*	4389.30	5416.31*	3459.65	4639.91*
median	263.79	258.49	437.08	625.79*	497.54	604.96*
Tot. Assets	n = 922	n = 1,985	n = 2,153	n = 3,445	n = 2,026	n = 5,149
mean	2376.89	2551.03	3355.26	3792.32	2272.69	2831.23*
median	253.56	261.39	414.58	501.15*	384.28	401.70
Sales	n = 922	n = 1,985	n = 2,153	n = 3,445	n = 2,026	n = 5,149
mean	1692.46	2063.51	2754.07	3050.12	2189.22	2569.27*
median	225.79	248.54	430.31	514.40*	418.02	460.60*
Debt-to-equity	n = 918	n = 1,979	n = 2,147	n = 3,437	n = 2,020	n = 5,132
mean	2.331	1.348	1.275	1.268	1.107	1.257
median	0.785	0.872*	0.979	0.933	0.893(*)	0.819
Market-to-book	n = 922	n = 1,985	n = 2,153	n = 3,445	n = 2,026	n = 5,149
mean	3.531	3.228	2.684	3.297*	3.169	3.852*
median	1.811	1.761	1.859	2.210*	2.366	2.605*
Price-earnings		n = 1,984	n = 1,930	n = 3,275	n = 1,765	n = 4,588
mean		264.61	43.68(*)	28.63	42.60	47.99
median		86.59	16.41	16.50	18.87	19.75*
Analyst Stock Rec.	n = 606	n = 1,203	n = 1,244	n = 1,949	n = 1,135	n = 3,548
mean	3.698	3.740	3.748	3.800*	3.839	3.904*
median	3.667	3.667	3.667	4.000*	4.000	4.000*

Panel B: High Discretionary Accruals (Earnings Managers) for Firms Just Above Threshold

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above
MVE	n = 922	N = 496	N = 2,153	n = 861	n = 2,026	n = 1,287
Mean	2519.14	2843.13	4389.30	5053.65	3459.65	3928.98
median	263.79(*)	147.65	437.08	415.10	497.54	466.17
Tot. Assets	n = 922	N = 496	N = 2,153	n = 861	n = 2,026	n = 1,287
mean	2376.89(*)	1367.78	3355.26	3608.34	2272.69	2627.05
median	253.56(*)	126.56	414.58(*)	282.36	384.28(*)	280.05
Sales	n = 922	N = 496	N = 2,153	n = 861	n = 2,026	n = 1,287
mean	1692.46(*)	954.70	2754.07	2555.92	2189.22	1902.89
median	225.79(*)	113.11	430.31(*)	295.63	418.02(*)	301.76
Debt-to-equity	n = 918	N = 493	N = 2,147	n = 860	n = 2,020	n = 1,284
mean	2.331	1.265	1.275	1.125	1.107	1.028
median	0.785(*)	0.682	0.979(*)	0.671	0.893(*)	0.653
Market-to-book	n = 922	N = 496	N = 2,153	n = 861	n = 2,026	n = 1,287
mean	3.531	3.440	2.684	3.549*	3.169	3.674*
median	1.811	1.811	1.859	2.324*	2.366	2.640*
Price-earnings		N = 496	N = 1,930	n = 801	n = 1,765	n = 1,171
mean		279.63	43.68	38.17	42.60	56.40
median		89.38	16.41	16.68	18.87	20.28*
Analyst Stock Rec.	n = 606	N = 306	N = 1,244	n = 488	n = 1,135	n = 912
mean	3.698	3.734	3.748	3.851*	3.839	3.950*
median	3.667	3.667	3.667	4.000*	4.000	4.000*

* - means or medians for firms just above (below) the threshold are significantly higher than the firms below (above) the threshold.

Sales = Compustat Data 12.
Total Assets = Compustat Data 6.
MVE = Market value of equity = Compustat Data 25 * Compustat Data 199.
Market-to-book = MVE / Compustat Data 216.
Price-earnings = MVE / Compustat Data172 (calculated for firms where Data 172 > 0).
Debt-to-equity = Compustat Data 181 / Compustat Data 216.

Analyst Stock Rec. = Average analyst stock recommendation for each firm-year observation taken from the three most recent recommendations prior to year end. The I/B/E/S Recommendations Detail file assigns a number to each recommendation between 1 and 5. For ease of interpretation I reverse the I/B/E/S order. A 5 recommendation indicates a strong buy; 4 a buy; 3 a hold; 2 an underperform; and 1 a sell.

Earnings Levels Threshold: I scale net income (Compustat Data 172) in year *t* by market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-1*. I place firms in net income classes (*ni_class*) with the width of each *ni_class* equaling 0.01 (e.g., *ni_class -1* contains firm-years with -0.02 ≤ Scaled Net Income < 0). The small profit firms sample (*ni_class* 0) includes all firm-years where 0 ≤ Scaled Net Income < 0.02.

Earnings Changes Threshold: I calculate a firm's current change in earnings by subtracting net income (Compustat Data 172) in year *t-1* from net income in year *t* and scaling that amount by the market value of equity (Compustat Data 25 * Compustat Data 199) in year *t-2*. I place firms in change-in-net-income classes (*chgni_class*) with the width of each *chgni_class* equaling 0.01, similar to *ni_class* (e.g., *chgni_class* -1 contains firm-years with -0.01 ≤ Scaled Change-in-net-income < 0). The small positive earnings changes sample (*chgni_class* 0) includes all firm-years where 0 ≤ Scaled Change-in-net-income < 0.01.

Analyst Forecast Error Threshold: I calculate a firm's analyst forecast error by subtracting the most recent median I/B/E/S forecast of annual earnings per share for the current year from actual earnings per share for the current year (also obtained from I/B/E/S). I collect the median I/B/E/S forecast of annual earnings per share from the I/B/E/S Summary History File in the month that actual earnings are reported, or in the month prior to actual earnings being reported if there is no consensus forecast in the month that actual earnings are reported. I place firms in analyst forecast error classes (*forecasterror_class*) with the width of each *forecasterror_class* equaling two cents (e.g., *forecasterror_class* -1 contains all firm-years where -0.02 ≤ Forecast Error < 0). The meet or just beat analysts' forecast sample (*forecasterror_class* 0) includes all firm-years where 0 ≤ Forecast Error < 0.02.

Table 3.2
Univariate Tests for Three Earnings Benchmarks

Panel A: Full Sample

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above
	n = 902	n = 1,933	n = 2,097	n = 3,364	n = 1,982	n = 5,015
NOA	0.7809	0.7982	1.9138	0.8621	0.73753	0.75008
t-value(p-value)	0.27 (0.7912)		-1.20[a] (0.2314)		0.12[a] (0.9079)	
	n = 821	n = 1,769	n = 1,920	n = 3,128	n = 1,822	n = 4,644
ΔTACC	-0.0032	-0.0143	-0.0154	-0.0066	-0.01254	-0.01243
t-value(p-value)	-1.27[a] (0.7942)		2.44[a] (0.0149)		0.02[a] (0.9823)	
	n = 555	n = 1,353	n = 1,669	n = 2,757	n = 1,631	n = 3,728
ERC	1.0915	0.9778	1.1263	0.8891	1.0321	0.9545
t-value(p-value)	-0.64[a] (0.5224)		-2.20[a] (0.0282)		-0.60[a] (0.5455)	
	n = 606	n = 1,203	n = 1,244	n = 1,949	n = 1,135	n = 3,548
Analyst Stock Rec.	3.698	3.740	3.748	3.800	3.839	3.904
t-value(p-value)	1.29 (0.1973)		2.42 (0.0156)		3.24 (0.0012)	
	n = 922	n = 1,985	n = 2,153	n = 3,445	n = 2,026	n = 5,149
Discretionary Accrual	0.0098	0.0168	0.0176	0.0197	0.01243	0.01101
t-value(p-value)	1.90[a] (0.0582)		1.15[a] (0.2510)		-0.69[a] (0.4896)	

Panel B: High Discretionary Accruals (Earnings Managers) for Firms Just Above Threshold, Full Sample Just Below.

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above	Firms Just Below	Firms Just Above
	n = 902	n = 482	n = 2,097	n = 838	n = 1,982	n = 1,261
NOA	0.7809	0.7654	1.9138	0.6811	0.73753	0.62329
t-value(p-value)	0.19[a] (0.8512)		-1.41[a] (0.1594)		-1.30[a] (0.1950)	
	n = 821	n = 427	n = 1,920	n = 779	n = 1,822	n = 1,134
ΔTACC	-0.0032	-0.0452	-0.0154	-0.0104	-0.01254	-0.02905
t-value(p-value)	-3.32 (0.0009)		-0.88 (0.3819)		-2.62[a] (0.0088)	
	n = 555	n = 311	n = 1,669	n = 651	n = 1,631	N = 867
ERC	1.0915	1.3233	1.1263	1.2355	1.0321	1.1576
t-value(p-value)	1.05[a] (0.2953)		0.50[a] (0.6207)		0.60[a] (0.5499)	
	n = 606	n = 306	n = 1,244	n = 488	n = 1,135	3.950
Analyst Stock Rec.	3.698	3.734	3.748	3.851	3.839	4.000
t-value(p-value)	0.82 (0.4145)		3.30 (0.0010)		4.21 (<0.0001)	
	n = 922	n = 496	n = 2,153	n = 861	n = 2,026	n = 1,287
Discretionary Accrual	0.0098	0.1175	0.0176	0.0933	0.01243	0.10517
t-value(p-value)	26.94[a] (0.0001)		35.37[a] (0.0001)		41.07[a] (0.0001)	

The column headings 'firms just below' and 'firms just above' is referring to firm-year observations.

a – Due to unequal variance, the Cochran and Cox (1950) approximation of the probability level of the approximate *t* statistic is used for the t-value.

NOA = net operating assets [Total Shareholder's Equity (Compustat Data 216) – Cash and Short Term Investments (Compustat Data 1) + Total Debt (Compustat Data 9 + Data 44)] for firm j at the beginning of year t scaled by sales (Compustat Data 12) for the year t-1,

ΔTACC = change in total accruals (Compustat Data 123 – Compustat Data 308 or Income before extraordinary items – Cash Flow from Operations) for firm j at the beginning of year t [(total accruals for year t-1) – (total accruals for year t-2)] scaled by total assets (Compustat Data 6) for the year t-3,

ERC = earnings response coefficient calculated for firm *j* over the 15 to 24 quarters of positive earnings prior to the period of being included as one of the firms just above or just below a threshold. I use the following firm specific model that takes into account nonlinearity:

$$R_{j,t} = \alpha + \beta_{1j} \cdot UNEARN_{j,t} + \beta_{2j} \cdot |UNEARN_{j,t}| * UNEARN_{j,t} + e_{j,t} \quad (1)$$

where: $R_{j,t}$ = the cumulative market-adjusted return on security *j* over the 60 day period [-58, 1] around the quarterly earnings announcement,

$UNEARN_{j,t}$ = unexpected quarterly earnings = quarterly earnings for firm *j* before extraordinary items in quarter *t* minus its earnings in quarter *t-4*, scaled by the market value of equity at the beginning of quarter *t.*

Analyst Stock Recommendations and threshold definitions are consistent with Table 3.1.

Discretionary Accruals = Discretionary accruals are calculated as the difference between Total Accruals and Non-discretionary accruals. Total Accruals is the difference between Net Income before extraordinary items (Compustat Data 123) and Cash Flow from Operations (Compustat Data 308), and non-discretionary accrual are estimated as a function of the level of property, plant, and equipment, the difference between the changes in revenue and changes in receivables (where receivables are adjusted by their expectation-*k*), lagged accruals, and future sales growth:

$$ACCR_{j,t} = \alpha + \beta_1 \cdot [\Delta REV_{j,t} - (1\text{-}k)\, \Delta REC_{j,t}] + \beta_2 \cdot (PPE_{j,t}) + \beta_3 \cdot ACCR_{j,t-1} + \beta_4 \cdot GR\_Sales + e_{j,t} \qquad (2)$$

where $ACCR_{j,t}$ = total accruals for firm *j* in year *t*. (Compustat Data 123 – Compustat Data 308 or Net Income before extraordinary items – Cash Flow from Operations), $TA_{j,t-1}$ = total assets for firm *j* in year *t-1*. (Compustat Data 6), $\Delta REV_{j,t}$ = change in net revenue (Compustat Data 12), $\Delta REC_{j,t}$ = change in accounts receivable (Compustat Data 302), $PPE_{j,t}$ = property, plant, and equipment (Compustat Data 8), $ACCR_{j,t-1}$ = total accruals for firm *j* in year *t-1*, *GR_Sales* = the change in sales for firm *j* from year *t* to *t+1*, scaled by year *t* sales, and *k* = the slope coefficient from a regression of *ΔREC on ΔREV*.

Table 3.3
Correlation Coefficients
Prob > |r| under H_o: Rho = 0
Number of observations

	NOA	ΔTACC	ERC	Analyst Stock Rec.	Discretionary Accruals
NOA		-0.00788 0.4085 11,016	-0.01046 0.3140 9,263	-0.00314 0.7898 7,202	-0.01381 0.1267 12,231
ΔTACC	-0.01419 0.1364 11,016		-0.01012 0.3360 9,035	0.04363 0.0004 6,604	-0.03645 0.0001 11,282
ERC	-0.15302 <0.0001 9,263	-0.00589 0.5754 9,035		0.04495 0.0030 4,368	0.03292 0.0013 9,480
Analyst Stock Rec.	-0.04078 0.0005 7,202	0.00153 0.9009 6,604	0.01665 0.2713 4,368		-0.00251 0.8294 7,398
Discretionary Accruals	-0.02435 0.0071 12,231	-0.08334 <0.0001 11,282	0.02650 0.0099 9,480	0.01413 0.2243 7,398	

Pearson (Spearman) correlation coefficients are located above (below) the diagonal. Variable definitions are consistent with Table 3.1 and Table 3.2.

Table 3.4
Probit Regression Results for Full Sample around Three Earnings Benchmarks.

Panel A: Full sample without analyst stock recommendation included in the model.

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Estimate	Pr > χ^2	Estimate	Pr > χ^2	Estimate	*Pr >* χ^2
	n = 1,794		n = 4,086		n = 5,012	
Intercept	0.53430	<0.0001	0.32939	<0.0001	0.52416	*<0.0001*
NOA	0.02805	0.3180	-0.01070	0.4983	0.00311	*0.6360*
ΔTACC	0.17579	0.4575	0.31605	0.1363	0.10678	*0.5322*
ERC	-0.00765	0.4637	-0.00989	0.0749	-0.00216	*0.6397*
Log Likelihood	-1,084.290		-2,705.826		-3,062.374	
Pr > χ^2	<0.0001		<0.0001		<0.0001	

Panel B: Full sample with analyst stock recommendation included in the model.

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Estimate	Pr > χ^2	Estimate	Pr > χ^2	Estimate	*Pr >* χ^2
	n = 787		n = 1,972		n = 2,779	
Intercept	0.36097	0.1843	-0.07987	0.6704	0.18289	*0.2904*
NOA	-0.02832	0.6754	0.03096	0.5415	-0.05857	*0.2890*
ΔTACC	0.18915	0.5955	0.40009	0.1835	0.10016	*0.6680*
ERC	0.01674	0.5790	-0.01386	0.1730	0.00815	*0.2704*
Analyst Stock Rec.	0.05469	0.4548	0.10353	0.0324	0.12859	*0.0034*
Log Likelihood	-474.742		-1,300.014		-1,583.084	
Pr > χ^2	<0.0001		<0.0001		<0.0001	

Threshold definitions are consistent with Table 3.1. The following probit regression is used for Table 3.4:

$$BEAT_{j,t} = \alpha + \beta_1 \cdot NOA_{j,t} + \beta_2 \cdot \Delta TACC_{j,t} + \beta_3 \cdot ERC_{j,t} + e_{j,t} \qquad (3)$$

or

$$BEAT_{j,t} = \alpha + \beta_1 \cdot NOA_{j,t} + \beta_2 \cdot \Delta TACC_{j,t} + \beta_3 \cdot ERC_{j,t} + \beta_2 \cdot STOCKREC_{j,t} + e_{j,t}$$

where:

$BEAT_{j,t}$ = 0 if *ni_class, chgni_class, forecasterror_class* is equal to -1 and 1 if *ni_class, chgni_class, forecasterror_class* is equal to 0, for firm *j* in year *t*.

$NOA_{j,t}$, $\Delta TACC_{j,t}$, and ERC_j are consistent with Table 3.2.

${}_iSTOCKREC_{j,t}$ = the average of the three most recent analyst stock recommendations for firm *j* prior to the end of year *t*. Opposite of I/B/E/S, a 5 recommendation indicates a strong buy; 4 a buy; 3 a hold; 2 an underperform; and 1 a sell.

Table 3.5

Probit Regression Results for Potential Earning Managers (High Discretionary Accruals) above the Three Earnings Thresholds and full sample below.

Panel A: Sample without analyst stock recommendation included in the model.

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Estimate	$Pr > \chi^2$	Estimate	$Pr > \chi^2$	Estimate	$Pr > \chi^2$
	n = 811		n = 2,142		n = 2,328	
Intercept	-0.40138	<0.0001	-0.52224	<0.0001	-0.27524	<0.0001
NOA	0.00007	0.9985	-0.12850	0.0009	-0.18605	0.0015
ΔTACC	-0.46647	0.1235	-0.22365	0.4081	-0.36726	0.1148
ERC	0.00997	0.4079	0.01075	0.1733	0.00503	0.3896
Log Likelihood	-524.231		-1,256.861		-1,505.448	
$Pr > \chi^2$	<0.0001		<0.0001		<0.0001	

Panel B: Sample with analyst stock recommendation included in the model.

	Earning Level Threshold		Earnings Changes Threshold		Analyst Forecast Threshold	
	Estimate	$Pr > \chi^2$	Estimate	$Pr > \chi^2$	Estimate	$Pr > \chi^2$
	n = 345		n = 1,008		n = 1,185	
Intercept	-0.81609	0.0495	-1.43661	<0.0001	-0.88440	0.0005
NOA	-0.02164	0.8252	-0.18196	0.0308	-0.14745	0.0710
ΔTACC	-1.06043	0.0346	0.00515	0.9899	-0.26878	0.4208
ERC	0.10727	0.0332	-0.00763	0.6479	0.01510	0.1228
Analyst Stock Rec.	0.08410	0.4523	0.24841	0.0008	0.17879	0.0052
Log Likelihood	-215.111		-576.462		-787.036	
$Pr > \chi^2$	0.0006		0.0006		<0.0001	

Threshold, model, and variable definitions are consistent with Tables 3.2 and 3.4.

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