EARNINGS MANAGEMENT MOTIVATIONS IN GIFT CARD BREAKAGE RECOGNITION DECISIONS

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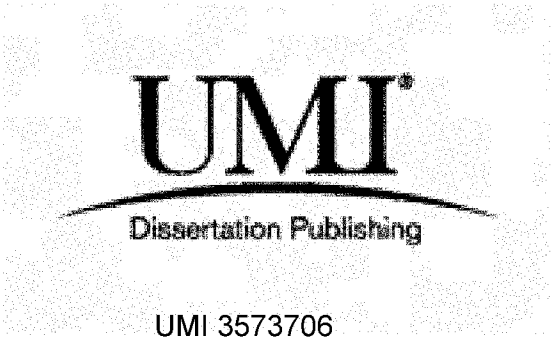

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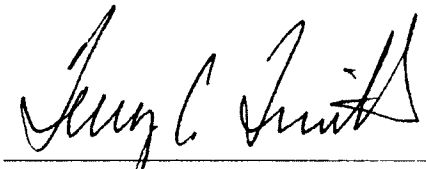

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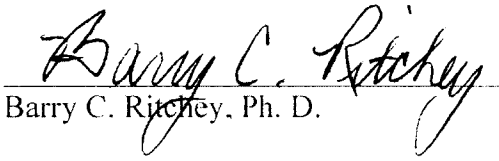

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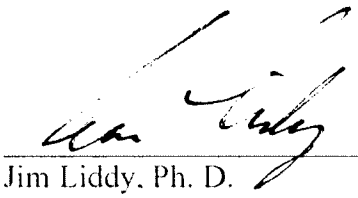

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To Jennifer whose patience, love, and support carried me through.

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ABSTRACT

Gregory G. Kaufinger

EARNINGS MANAGEMENT MOTIVATIONS IN GIFT CARD BREAKAGE RECOGNITION DECISIONS

Gift card breakage represents the unused portion of gift cards; in practice, retail firms enjoy discretion in deciding when unused gift card values are unredeemable and in reclassifying the unused portion as breakage income. This paper investigates whether three earnings management motivations currently found in earnings management literature (i.e., compensation, smoothing income, or meeting external benchmarks) influence retailers' highly discretionary decisions to recognize gift card breakage.

Quarterly breakage and supporting financial data for 58 US publicly traded retail firms for the period 2002-2011 was collected from commercial and government sources. The results suggest that retail firms use gift cards to manage earnings and that a principal motivation behind this behavior is the necessity to meet market analysts' consensus EPS forecasts. More so, the results reveal that retailers can discreetly achieve external EPS forecasts through immaterial transactions, meaning that breakage is a very useful tool to bolster earnings and EPS surreptitiously. The results also indicate that retailers exercise discretion in recognizing breakage so that senior management can benefit from performance-based compensation contracts; however, the results imply that

compensation may only be a secondary motivation, especially in the presence of a meeting benchmarks motivation. The results do not support an income-smoothing motivation. Further, the results show that breakage recognition more likely occurs in the fourth quarter. In addition, the results infer that less profitable retailers and retailers in poor financial health may benefit more from discretionary breakage decisions which suggests that weaker retailers leverage their discretion to favor the appearance of financial strength; this may be the result of an intentional, managed-choice by weaker retailers. The findings highlight the need for bright-lines rules for breakage transactions and underscore the importance of transparency and full disclosure by retailers to avoid any appearance of earnings management.

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CHAPTER 1: INTRODUCTION

1.1 Introduction and Problem Statement

The widespread use and adoption of closed-loop retail gift card programs in the late 1990s created a new, distinct, but significant derivative: *gift card breakage*. Currently estimated at $5 billion (nominal) annually (O'Connell, 2010), gift card breakage represents that "portion of gift card balances that consumers fail to redeem for merchandise" (Kile & Wall, 2008, p.76) and occurs when gift cards are lost, or when consumers elect to partially redeem or never redeem their gift cards. From a financial perspective, gift card breakage is a potentially dangerous by-product of gift card programs because it can serve as a cookie-jar reserve that can be used conveniently and effortlessly to manage earnings. It is the use of gift card breakage as an earnings management tool that is the focus of this study.

Closed-loop retail gift card programs found prominence among retailers as they moved to replace cumbersome gift certificate programs with gift cards to increase sales, decrease costs, and increase customer loyalty. Gift cards are "similar to the formerly standard paper gift certificate, but [have] the added benefit that purchases are automatically deducted and...the [cards are] entirely transferrable" (Offenberg, 2007, p. 228). Closed-loop gift card programs are structured so that the cards are sold with pre-established dollar amounts and are only redeemable at the issuing retailer (Sienkiewicz, 2007). Today, nearly all of the top 100 retailers offer gift cards of various denominations (Hitachi Consulting, 2006). The quick adoption of gift card programs by retailers was

paralleled by the quick acceptance of gift cards by consumers – the value of closed-loop gift cards sold by retailers grew from almost nil in 1997 to approximately $60 billion (nominal) in 2008 (Tower Group, n.d.). In retail accounting, values associated with unused gift cards – breakage – are income upon recognition by the retailer.

An inherent problem with breakage, however, is that it could be used to manage earnings (see e.g., Schlosser, 2005). It is widely accepted that breakage recognition occurs in an environment characterized by both non-codified breakage-related treatment guidance within generally accepted accounting principles (GAAP) and highly discretionary managerial breakage decisions. This type of environment allows retailers to determine their own breakage amounts and to time their breakage recognition activities, both which can vary significantly over time. The implication is that retailers can record breakage as often or as frequently as necessary to manage earnings. Notably, this type of earnings management is consistent with empirical literature which shows that aggressive reporting decisions increase when imprecise or ill-defined accounting standards are present (Nelson, 2003; Ng & Tan, 2003; Trompeter, 1994). The inference is that managers can undertake earnings management activity through breakage because there is little risk (e.g., audit risk or exposure risk) associated with taking a non-standard approach to measuring and reporting breakage. Unfortunately, the most serious implication of arbitrarily using breakage to manage financial results is that financial statement quality suffers (Kile, 2007; Marden & Forsyth 2007).

The intent of this study is to determine whether earnings management motivations influence retailers to recognize breakage subjectively even though financial statement quality suffers. In particular, this study addresses the question of whether compensation

motivations, smoothing income motivations, and meeting external benchmark motivations influence retailers' decisions to recognize gift card breakage arbitrarily. Here, "motivations" refer to managers' reporting incentives or reasons for action – "those conditions where managers' incentives to manage earnings are likely to be strong" (Healy & Wahlen, 1999, p.370). Based on earnings management theory, it is hypothesized that three incentives – stock-based compensation, income-smoothing actions, and meeting external Earnings Per Share (EPS) benchmark expectations – influence retailers' breakage decisions.

This study is unique in its attempt to identify multiple incentives that determine discretionary management decision-making for a new but potentially significant, revenue-related accounting transaction. The results should be useful for accounting regulators and standard setters concerned about revenue recognition because the earnings management motivations used in this study are typically found when firms present misleading financial statements (Healy & Wahlen, 1999).

1.2 Background of the Study

This section provides context for the study, including the significance of the problem, the accounting for closed-loop gift cards, and the importance of the research.

1.2.1 Significance of the Problem.

Quite often, purchased gift cards are lost or simply not used; for consumers, an unredeemed gift card is a lost opportunity and a loss of wealth. For retailers, unredeemed gift cards represent a new income element in the form of gift card breakage. Retailers have not lost sight of this fact and use breakage in an accretive manner. As evidence, Best Buy increased its pre-tax income by $29 million, or $0.04 per diluted share, in the third

quarter of fiscal 2006 due to breakage (Best Buy, 2005). More recently, Limited Brands added $47.8 million in pre-tax income, or $0.08 per share, in the fourth quarter of fiscal 2008 due to breakage (Limited Brands, 2008). Many however have expressed concern over breakage's impact on financial statements, notably on the attributes of financial statement quality like comparability and consistency (see e.g., Kile, 2007; Marden & Forsyth, 2007; Parmelee, 2006).

A retailer's ability to capitalize on breakage is facilitated by vague revenue recognition guiding principles and breakage treatment guidelines that are not codified. In fact, currently there is no generally accepted way to recognize gift card breakage because "the rapid proliferation of gift cards...caught the accounting profession flat footed" (Berner, 2005, para. 6). In the absence of authoritative rules, retailers form their own standards for handling gift card-related activities. As evidence, Feinson (2008) found no consistency in breakage recognition policies among 75 different retailers. Notably, the decision as to when unused gift card values are unredeemable and able to be recognized as income is left solely to the retailer; this determination will be different for each retailer (Sheehan, 2009) and can change over time. The implication is an environment that is highly vulnerable to discretionary actions by management. Marden and Forsyth (2007) summarized the consequence of discretionary breakage decisions:

> Being able to control when, where, and how a substantial amount of [gift card breakage] revenue can be inserted into the financial statements can be beneficial for management, but can be misleading for financial statement readers... (p.33)

Rappeport (2007) emphasized that "such subjectivity [to recognize breakage] could be dangerous as firms count on unused gift cards to pad their revenues" (para. 8).

Retailers' highly discretionary decisions to recognize breakage on their own terms impacts attributes of financial statement quality like comparability and consistency. The Financial Accounting Standards Board (FASB) describes comparability and consistency as:

> Information about a particular enterprise gains greatly in usefulness if it can be compared with similar information about other enterprises and with similar information about the same enterprise for some other period or some other point in time. Comparability between enterprises and consistency in the application of methods over time increases the informational value of comparisons of relative economic opportunities or performance. The significance of information, especially quantitative information, depends to a great extent on the user's ability to relate it to some benchmark. (Statement of Financial Accounting Concept No. 2, 2008, CON2-3)

These two qualitative characteristics, along with other attributes such as relevance, reliability, and verifiability, make financial information useful to investors and creditors. They are also "the qualities to be sought when accounting choices are made" (Statement of Financial Accounting Concept No. 2, 2008, para. 5). Intentionally violating the attributes of financial statement quality however contravenes FASB's utility objective for financial reporting:

> Financial reporting should provide information that is *useful* [emphasis added] to present and potential investors and creditors and other users in making rational investment, credit, and similar decisions. (Statement of Financial Accounting Concept No. 1, 2008, para. 34)

In short, without usefulness, there is no benefit from financial information (Statement of Financial Accounting Concept No. 2, 2008). It should be evident therefore that highly discretionary decisions – particularly those that are used to influence earnings – undermine the characteristics of financial information and weaken financial statement utility; this is a serious issue for financial reporting regulators.

More so, retailers' breakage decisions affect analysts and investors. For example, the difficulty with discretionary breakage decisions from an analyst's perspective is that comparable year-on-year retail sales are skewed by frequent changes in breakage recognition policies (Atkins, 2005). Similarly, discretionary breakage choices mask actual sales results, inhibiting investors' abilities to obtain clear pictures of retailers' operations (Gryta, 2007).

In sum, given that breakage-related decisions impact the qualitative characteristics of financial information and affect market players, an investigation into retail managements' motives for recognizing breakage is urgent and necessary. This investigation is imperative given the highly discretionary nature of breakage decisions and the ease by which breakage can be used to adjust earnings.

1.2.2 Accounting for Closed-loop Gift Cards.

From an accounting perspective, the initial sale of a gift card is recorded as a liability called deferred revenue; a company also records the corresponding receipt of cash. Income is not reported at this time. When the gift card is redeemed, the liability is removed from the balance sheet, a product or service is delivered, and a sale is recorded. Unredeemed gift cards function much the same way, except there is no impact on inventory. Unredeemed gift card balances are removed from the balance sheet by decreasing the deferred revenue liability and recognizing income on the profit and loss statement. The transaction to record income from unredeemed gift cards results in an immediate increase to a retailer's net income; in fact, aside from potential tax implications, the full value of gift card breakage falls directly to the bottom line.

Unredeemed gift cards, however, present challenges to accounting professionals and retail managers because there remains significant uncertainty regarding the redemption process. Marden and Forsyth (2007) rightly noted, "The issue [with gift cards]...is not realization, but rather estimating when the earnings process is complete" (p. 32). Conceptually, unredeemed gift cards could remain on the balance sheet as indefinite obligations. In practice however, retailers decide when unused gift card values are unredeemable and they typically do so in two phases: an initial, one-time adjustment for all prior years' unrecognized breakage (i.e., *initial breakage*), and subsequent adjustments to keep future breakage estimates current (i.e., *ongoing breakage*). Regardless of the form, retailers subjectively remove the liability and recognize breakage revenue without ever having to deliver a product or a service. The inference is that retailers' recognition decisions are highly discretionary and that breakage can be subjectively used to manage earnings at will.

The potential gains from breakage for retailers will grow as gift card popularity continues to increase. It is easy to envision retailers using breakage in highly questionable ways for some time to come. Yet surprisingly, neither the FASB or the Securities and Exchange Commission (SEC) have shown interest in tackling gift card accounting (Kile, 2007; Rappeport, 2007). It seems prudent then to undertake a study that not only explains incentives for retailers' highly discretionary breakage decisions, but also highlights the need for financial regulators to immediately address financial statement quality concerns.

1.2.3 Importance of the Research.

It is widely accepted by practitioners and academics that firms manage earnings and have many tools at their disposal to do so. However, Healy & Wahlen (1999) concluded that much of the academic research on earnings management offers little utility to standard setters and accounting regulators:

> The [earnings management] literature provides little evidence on questions of interest to standard setters, such as whether earnings management is commonplace or relatively infrequent, which accruals are managed, and effects on resource allocation decisions. As a result, there are many opportunities for future research on earnings management. (p.368)

Addressing this concern, one area where academic research on earnings management can provide utility to standard setters is on issues of revenue recognition. Without question, earnings management associated with revenue recognition is important to regulators because "revenue recognition is perhaps the single greatest problem area in US financial reporting" (Hermanson, Ivancevich, & Ivancevich, 2008, p. 40). There is, therefore, an imperative need to evaluate revenue-related instruments of earnings management, especially those items that reveal a widespread practice or articulate well the effects of earnings management decisions. The end result of such research is to bring value to standard setters and regulators who bear the responsibility of setting and enforcing accounting standards. This study addresses this need.

Equally important is the reality that within academic literature, the most popular models for detecting earnings management use an aggregated-accruals approach; this approach is neither consistent nor adequate for the standard setter or practitioner. McNichols (2000) writes:

> Earnings management measures based on [aggregated accrual models] are not sufficiently powerful or reliable to assess earnings management behavior in many contexts likely to be of interest to accounting researchers, standard letters [*sic*] and analysts. (p.337)

Primarily, aggregate accrual models are less valuable than desired because they are hard to operationalize (Dechow & Skinner, 2000). More importantly, an inherent problem with these models is that accruals will eventually reverse themselves and mask both one's ability to adequately detect earnings management or to determine whether the original accrual was a result of a discretionary action in the first place. There is, then, a need to develop alternative models for detecting earnings management that are not only useful for practitioners and regulators, but also better at identifying discretionary decisions that clearly result in earnings management actions. This study attempts to fill this gap.

1.3 Theory Base for the Research

This section provides the research question and conceptual framework for this study. Moderating variables are also examined. Figure 1 presents a high-level diagram of the proposed research model.

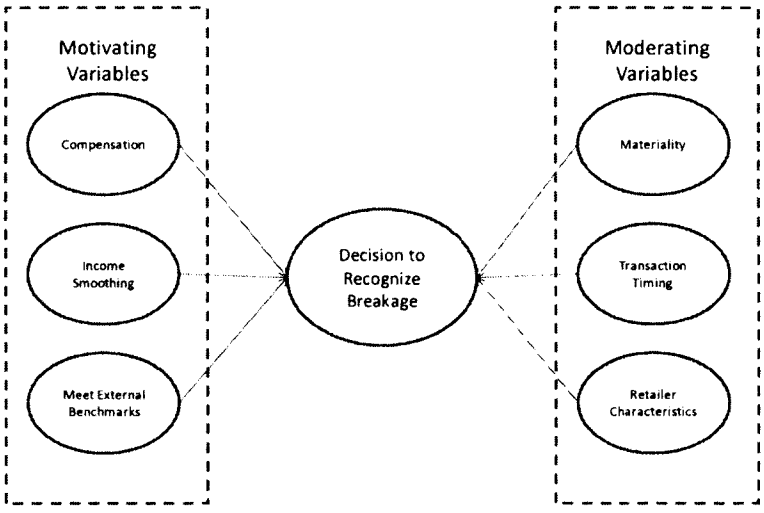


Figure 1: ***Graphical Representation of Research Model***

1.3.1 Research Question.

Do compensation motivations, smoothing income motivations, and meeting external benchmark motivations influence retailers' decisions to recognize gift card breakage arbitrarily?

1.3.2 Conceptual Framework.

The theoretical framework for this study is grounded in the conceptual framework for revenue recognition as well as earnings management theory. Revenue recognition provides the accounting context for this study; earnings management theory provides the theoretical base from which earnings management motivations can be extended to discretionary breakage revenue recognition decisions.

The aim of this research is to demonstrate that three specific motivations – compensation, smoothing income, and meeting external benchmarks – influence retailers' decisions to recognize gift card breakage at will. The idea that managers are *motivated* to influence accounting results is prevalent in earnings management literature. While there is no standard definition for the term "motivation" in the literature per se, the general understanding among academics is that the idea represents the underlying reason (Stolowy & Breton, 2004), the incentive (Healy & Wahlen, 1999), or the impetus (Fields, Lys, & Vincent, 2001) behind the decision to effect accounting results. Understanding managements' motivations are "*key* [emphasis added] to understanding the desire to engage in earning management" (Dechow & Skinner, 2000, p. 248). Clearly, therefore, the key to understanding why breakage is arbitrarily used to influence accounting results lies in understanding what motivates retail managers to engage in such highly discretionary activity.

Earnings management literature (e.g., Burgstahler & Eames, 2006; Degeorge, Patel, & Zeckhauser, 1999; Godwin, 1977; Healy, 1985; Holthausen, Larcker, & Sloan, 1995; Miller & Rock, 1985) has demonstrated that compensation, income-smoothing, and meeting benchmarks individually motivate discretionary decision-making by managements. Logically, it follows that these incentives should influence discretionary breakage decisions as well, but these motivations have not been jointly applied to discretionary revenue recognition practices or extended to individual revenue-related transactions such as breakage. In response to the gap in literature, this study constructs a motivations-based model to explain the function that these three incentives have in influencing retailers' breakage decisions. This approach is novel because it attempts to study multiple motivations on a single discretionary revenue item.

1.3.2.1 Revenue Recognition.

Recognizing unredeemed gift card values is a revenue recognition issue. Revenue recognition is the accounting term used to refer to "the recording of a sale in the formal accounting records" (Stice & Stice, 2006, p.380).

The conceptual basis for revenue recognition is guided by authoritative literature including FASB's Concept Statement No. 5 and the Securities and Exchange Commission's Staff Accounting Bulletin 104. Under this guidance, revenue recognition involves consideration of two factors: (a) being realized or realizable and (b) being earned. Realization is defined as "the process of converting noncash resources and rights into money and is most precisely used in accounting and financial reporting to refer to sales of assets for cash or claims for cash" (Statement of Financial Accounting Concept No. 6, para. 143). Clearly stated, this means that cash or a valid promise to pay has been

received. In addition, revenues are not recognized until earned. FASB Statement of Concept No. 5, paragraph 83(b) notes that "revenues are considered to have been earned when the entity has substantially accomplished what it must do to be entitled to the benefits represented by the revenues." Paragraph 84(a) notes that revenues from manufacturing and selling activities are commonly recognized at the time of sale; this typically means at delivery. The recognition of revenue must be deferred if either of these conditions is not met at the time of sale (Stice & Stice, 2006).

Despite these broad, authoritative pronouncements, it should be evident that there is no general revenue recognition *standard* per se within US GAAP (Schipper, Schrand, Shevlin, & Wilks, 2009). While some revenue-related scope and treatment exceptions exist for industry- or issue-specific items, revenue recognition remains a relatively ambiguous and discretionary activity based on events or activities that are often arbitrarily defined (Pounder, 2009; Sridharan, Summers, & McAlum, 2003). The lack of a clear revenue recognition standard permits highly-questionable management discretion in financial reports.

Consequences of poorly written revenue guidance are evident in breakage decisions. According to generally accepted accounted principles, the sale of a gift card should not be immediately recorded as revenue; instead, it should be considered both a receipt of cash and the assumption of a liability (i.e., deferred revenue). However, the problem with gift cards is not in the creation of the liability, but rather in determining when and if the liability can be removed from the balance sheet since the recognition of earned income rests on uncertain consumers' actions. As a result, the decision as to when unused gift card values are unredeemable and able to be recognized as breakage income

is left solely to the retailer. Notably, the determination of when the earnings process is complete for gift cards is different for each retailer and can change over time.

The deficiency of clearly defined standards, or bright-line rules, fosters flexible breakage policies among retailers and contributes to an environment where breakage recognition is susceptible to highly discretionary actions by management; the implication is that retailers can use breakage to influence accounting results as needed. Given that breakage is found throughout the entire retailing industry, it follows that discretionary breakage decisions by retail managements have far-reaching effects in financial markets.

Yet, an extensive review of current literature reveals that researchers do not fully understand why retail managements indiscriminately use discretionary revenue-related transactions to shape financial results. In fact, empirical studies that determine incentives for discretionary revenue recognition decisions in general are sparse and as such, only two studies are worth mentioning here. First, Bowen, Davis, and Rajgopal (2002) found that external incentives like the need for outside funding or potential marketing alliances influenced *e*-commerce managers' choices to report grossed-up and barter revenue, especially when their cash burn rates were high. Second, Altamuro, Beatty, and Weber (2005) used the adoption of Staff Accounting Bulletin (SAB) No. 101 to examine why firms accelerated revenue related to both upfront fees under license agreements and shipment of goods requiring customer acceptance. They found that for firms recording SAB No. 101 adjustments, meeting earnings benchmarks was a likely motivation for accelerating revenue in the pre-adoption/adjustment period. Neither study, however, used pervasive accounting elements which lessens their utility for standard setters and regulators in addressing revenue recognition issues. In contrast, this study examines

motivations for discretionary revenue recognition on a revenue item that is far more prevalent, widespread, and material (i.e., of significant amounts). Gift card breakage cuts across the entire retailing industry, from apparel to appliances, from discounters to department stores, and from restaurants to grocery stores. As such, breakage offers a better research environment to determine motivations for discretionary revenue recognition.

It should also be evident that existing revenue recognition literature does not provide an extensive set of incentives that can be applied to breakage decisions; therefore, it is necessary to look to other research streams for possible motives. Fortunately, potential incentives can be found in earnings management literature. Motives from this stream of literature that are pertinent to this study are reviewed next.

1.3.2.2 Earnings Management Theories.

Intentionally influencing accounting results and financial statement quality is often explained through earnings management theory. Earnings management is the intentional and strategic actions undertaken to alter financial information with the intent to mislead or influence stakeholders (Degeorge et al., 1999; Healy & Wahlen, 1999). Earnings management theory attempts to understand why managers use financial data to persuade or mislead stakeholders.

Earnings management theories grew out of research that previously focused on the determinants of accounting choice (e.g., Holthausen & Leftwich, 1983 or Watts & Zimmerman, 1978) and to some extent agency theory literature (e.g., Jensen & Meckling, 1976). The accounting choice research of the 1970s and 1980s focused mainly on contracting costs and "hard" accounting choices like inventory valuation method and

their impact on firm value or cash flow. While there were allusions to management motivation in this early research, the incorporation of management incentives (e.g., bonus plans or meeting external benchmarks) as motivators is clearly evident in earnings management research since the mid-1980s. Therefore, while the implications of accounting choice and earnings management are similar, earnings management literature focused more on intent and opportunity to mislead than did accounting choice literature.

Three broad motivations found in earnings management literature are compensation motivations, smoothing income motivations, and meeting external benchmarks motivations. A compensation motivation assumes the alteration of financial results to meet explicit and implicit management compensation contracts; a smoothing income motivation involves intentionally leveling income to influence short-term stock price; and a meeting external benchmarks motivation infers the use of discretionary accounting to achieve externally set objectives like consensus Earnings Per Share targets in order to influence investor decisions. Importantly, both researchers and practitioners acknowledge the significance of these motivations in shaping discretionary management decisions associated with earnings management. As evidence, from a survey of 253 auditors, Nelson, Elliot, and Tarpley (2002) documented that auditors believe that managers' attempts at earnings management decisions were motivated by a variety of incentives, including the need to reach targets set by compensation contracts; the need to smooth or improve income; or the need to meet analysts' estimates and influence the stock market. Likewise, the American Institute of Certified Public Accountants (AICPA) (1999) noted that management compensation tied to operating results, the desire for an

increased stock price, and the use of financial statement elements that are based on unusually subjective judgments shape earnings management decisions as well.

Without question then, compensation, smoothing income, and meeting external benchmarks motivations should be significant factors in retailers' breakage decisions. For example, retail managers' compensation is typically coupled to a financial performance objective (Gentry, 2010) which increases the likelihood that discretionary breakage will be used to manage earnings. Likewise, personal and professional pressures within retail to meet income targets (see e.g., Swain, Allen, Cottrell, & Pexton, 2002) and financial pressures from external market analysts provide motivation to both smooth earnings and meet EPS expectations. Further, retailers are clearly aware of ever-present concerns from investors about consistent year-on-year growth because the retail industry is cyclical and dependent upon consumer confidence and general economic conditions; this reality means that market-based motivations like income-smoothing become even more salient to retail managers. More importantly, the outcome of these motivations (e.g., increased compensation) can be easily obtained through breakage because the accounting transaction is effortless to implement and the current risks for recognizing inaccurate breakage are minimal to nonexistent.

In short, motivations found in earnings management literature are relevant in breakage decisions; retailers using breakage to manage earnings at the expense of the investor or financial statement quality are likely incentivized to do so because of compensation contracts, the desire to smooth income, and the need to meet financial benchmarks.

1.3.2.3 Moderating Variables.

While this review suggests that earnings management theory is appropriate for explaining retailers' decisions to recognize gift card breakage, it is necessary to consider additional variables that may serve as moderating factors in the decision-making process. This section addresses three potential moderating variables including materiality, the timing of the transaction, and retailer characteristics.

Materiality. One moderating variable is materiality, which relates to the relative size of the breakage transaction. The conceptual framework of accounting identifies materiality as an attribute of useful accounting information. FASB's Concept Statement No. 2 defines materiality as:

> The magnitude of an omission of misstatement of accounting information that, in light of surrounding circumstances, makes it probable that the judgment of a reasonable person relying on the information would have been changed or influenced by an omission or misstatement. (p. 6)

In other words, materiality deals with the question: "Is the item large enough to influence the decision of a user of the information?" (Stice, Stice, & Skousen, 2004, p.27). The SEC has indicated that "extra scrutiny should be given to [material] items that...allow a company to meet analyst earnings expectations" (Stice et al., 2004, p.27). The SEC's concern is relevant in the case of highly discretionary breakage decisions because breakage is income that can be used to meet analyst expectations.

The materiality concept likely moderates retailers' decisions because in practice, materiality is frequently determined by either "rule of thumb" calculations or materiality thresholds. For example, a financial item that exceeds 5% of income is often considered material. Within retail, a financial item that exceeds ½% of revenues is frequently judged material (Pany & Wheeler, 1989). Regardless of the actual threshold percentage,

decisions surrounding the recognition of breakage are likely subject to materiality reviews; as such, breakage transactions that are material in nature may not be recorded or the transaction may be modified to meet *de facto* materiality guidance within a retail firm. Materiality therefore has a minimizing effect which may suppress a relationship between specific motivation and recognition decision.

Timing. A second moderating variable is the timing decision, which relates to the financial period in which breakage is recognized. Literature (e.g., Collins, Hopwood, & McKeown, 1984; Jones & Bublitz, 1990; Schroff, Das, & Zhang, 2009) supports the conception that timing-related activities determine firms' financial information and that these actions are a result of a managed choice. For example, Schroff et al. (2009) observed that reversals in quarterly earnings trends tended to occur more frequently in the fourth quarter; they attributed the changes to earnings management because many of the indicators of earnings management were prevalent in the last quarter.

Given the subjective nature of breakage decisions, it should be evident that retailers have opportunity to time the recognition of breakage revenue to meet any earnings management motivation. It is likely that retailers choose to recognize breakage more frequently in particular accounting periods, such as the last fiscal quarter which is the bell-weather quarter for most retailers. It is important to recognize therefore that retailers' breakage decisions may be timed and that this timing-effect may serve as a moderator.

Retailer Characteristics. Lastly, retailers' characteristics may be a moderating factor. Literature suggests that firm characteristics such as specific line of trade or financial health frequently influence retailers' financial decisions. For example, Hayes

and Jones (2006) cited some evidence that fast fashion retailers have fewer markdowns and lower inventory costs than non-fast fashion retailers. The inference is that line of trade impacts financial decisions on inventory. Similarly, Chun, Eppli, and Shilling (2003) observed that retail firms with higher debt-asset ratios were more likely to adopt percentage lease agreements over fixed lease agreements because the former were expensed immediately. This suggests that retail managers are sensitive to their firms' financial health and make decisions accordingly. However, as is evidenced here, existing literature is not exhaustive and the relationships between financial decisions and retailer characteristics have not been fully explored.

There are a few retailer characteristics however that seem likely moderators in breakage recognition decisions. First, line of trade is a logical moderator. For example, restaurants are more likely to recognize breakage than sporting goods stores simply because of the popularity and widespread use of restaurant gift cards over sporting goods cards. Other moderators are financial in nature including net margin or overall financial health; low margin retailers, for example, most likely recognize breakage earlier and more frequently than high margin firms given that low margin firms have less financial cushion with which to operate. In short, these retailer characteristics should moderate retailers' decisions to recognize breakage.

1.3.3 Summary of the Theory Base for the Research.

In summary, motivations for discretionary breakage recognition decisions are not currently understood. However, in an environment where highly discretionary actions by managements result in misleading financial statements, determining incentives for breakage decisions is imperative. This review has demonstrated that a study using several

earning management theories should address this deficiency and advance the current body of knowledge. Specifically, this review demonstrated that three specific motives – compensation, smoothing income, and meeting benchmarks – are logical incentives shaping retailers' breakage recognition decisions. In addition, this review established that retailers' decisions can be moderated by materiality, the timing of the decision, and various retailer characteristics.

1.4 Limitations and Key Assumptions

This section distinguishes the scope of the research and identifies key assumptions underlying the analysis.

1.4.1 Limitations.

Important limitations for this study include

- This research will not address open-loop gift card programs (e.g., MasterCard®, or Visa®) which are typically operated by banks and regulated by federal banking laws, and more recently, the Credit Card Act of 2009. Likewise, other organizations running gift card programs (e.g., associations, independent sales organizations, or distributors) are also excluded.
- This study excludes the majority of retailers and possibly numerous retailers with gift card programs across many lines of trade; the actual US retail industry is comprised of nearly 2 million businesses (NAICS Association, 2009), most of which are not publicly traded.

1.4.2 Key Assumptions.

Key assumptions adopted for this research include:

- Retailers regard the impact of breakage recognition decisions as temporary in that breakage can be used as needed to manage earnings.
- State escheat laws relating to unclaimed property are irrelevant; if they were, firms would not be able to record income from unused cards. Instead, they would be required to turn over the "abandoned" funds to the relevant state.
- Consumer protection laws empowered retailers' discretionary decisions. Consumer protection laws in a majority of states outlawed expiry dates and dormancy fees; the implication is that retailers have greater uncertainty as to when the earnings process for gift cards is actually complete and therefore have more latitude in choosing when to recognize breakage.
- Breakage recognition decisions are made independent from gift card expiry dates (where present); that is, retailers maintain discretion for breakage recognition regardless of expiration date.
- Markets are efficient in the semi-strong form (Fama, 1970). This means that markets react expediently to information.

1.5 Summary

In review, the development and evolution of gift cards resulted in significant sales growth for retailers; gift cards' derivative – breakage – accrued unexpected but beneficial income as well. Unfortunately, the accounting profession's standard setters have not responded to the rapid proliferation of gift cards which means that retailers account for breakage without authoritative bright-line rules. This created an environment that is

highly susceptible to discretionary decisions by retailers and allows breakage to be used in ways that may be beneficial to retail managements but detrimental to both financial statement quality and to financial statement users. This research endeavors to discover the influence that earnings management motivations have in breakage recognition decisions, explaining why retailers use breakage in accretive, flexible, and ever-changing ways despite the negative impact on the quality of their financial statements.

CHAPTER 2: LITERATURE REVIEW

This section reviews revenue recognition and earnings management literature and highlights gaps in the literature. Research hypotheses are also developed in this section.

2.1 Revenue Recognition

Former SEC Chairman, Arthur Levitt, elevated auditors', investors', and regulators' concerns about US revenue recognition activities in his 1998 speech, *The Numbers Game.* Levitt emphatically stated:

> Companies try to boost earnings by manipulating the recognition of revenue. Think about a bottle of fine wine. You wouldn't pop the cork on that bottle before it was ready. But some companies are doing this with their revenue... (para. 35)

Since then, auditors and regulators scrutinize revenue recognition actions more closely because of the perceived/actual risk and impact on financial information. Much of the additional scrutiny is the result of new legislation or guidance. For example, in 1999, the SEC issued SAB No. 101, *Revenue Recognition in Financial Statements* (revised in SAB No. 104 in 2003) to address revenue recognition concerns. Highlighting regulators' concerns, this bulletin states:

> The [SEC] staff has become increasingly concerned with apparent increases in inappropriate earnings management activities by public companies. One of the most common earnings management tools is reporting revenue before a sales transaction has occurred or before the seller has performed under the terms of a sales contract. Improper revenue recognition is often the cause of spectacular, high-profile financial reporting problems. A March 1999 report entitled Fraudulent Financial Reporting: 1987-1997 An Analysis of U.S. Public Companies, sponsored by the Committee of Sponsoring Organizations (COSO) of the Treadway Commission, indicated that over half of financial reporting frauds in the study involved overstating revenue. A substantial portion of the

> Commission's enforcement cases involve improper revenue recognition. The Enforcement Division's Chief Accountant Walter Schuetze is often quoted that improper revenue recognition is the "recipe of choice for cooking the books." (Fact Sheet: SAB No. 101, 1999, para. 2)

That same year, the AICPA published *Audit Issues in Revenue Recognition* to highlight the auditor's role in identifying improper revenue recognition. Further, the Sarbanes-Oxley Act of 2002 influenced revenue recognition policies through strengthened internal controls and remediation guidance (Hermanson et al., 2008). Collectively, these documents underscore the accounting profession's understanding that proper revenue recognition activities are important.

In contrast to the concern expressed by practitioners and regulators, academic studies on revenue recognition practices are sparse. For example, an extensive review of current literature shows that revenue recognition has been examined mainly along two dimensions: by industry and by revenue type. Industries include the airline industry (Sharp & Taylor, 1991), the software industry (O'Connor, 2002; Sridharan et al., 2003; Zhang, 2005), and the publishing industry (Bauman, 2005) while revenue type includes deferred revenues (Bauman, 2005; Zhang, 2005), restated revenues (Callen, Robb, & Segal, 2008), and gross revenues (Bowen et al., 2002). Remarkably, academic literature has largely ignored highly discretionary revenue-related transactions even though these transactions contribute to questionable revenue-related practices. Further, empirical research has largely ignored revenue recognition practices in the broad retailing industry despite the fact that US aggregate retail sales were approximately $4 trillion in 2007 (US Census Bureau, 2009).

Not only is revenue recognition literature sparse, but specific streams of thought between studies is disjointed; in brief, the academic literature is not well developed. As

such, only two relevant studies will be cited in this review. First, Bowen et al. (2002) investigated e-commerce managers' incentives to maximize their firms' revenue; specifically, through a probit model, they examined the relationship between motives and revenue recognition decisions for grossed-up and barter revenue where grossed-up revenue is revenue before discounts and allowances (i.e., as opposed to net revenue) and barter revenue is revenue generated from the exchange of advertising space. The authors found positive associations between the choice to report grossed-up/barter revenue and several incentives including the need for external funding and the level of investor interest in the firm. Their results suggest that incentives do influence and motivate managers' to report certain types of revenue, but it should be obvious that the incentives in Bowen's study arose from the need for cash rather than for the desire to manage earnings. While cash flow incentives are important, motivations that manage earnings are more important to the standard setter.

Second, Zhang (2005) used the adoption of *Statement of Position (SOP) 91-1 on Software Revenue Recognition* to study the effects of early revenue recognition on the qualitative characteristics of reported revenue. In this study, Zhang studied 122 software firms that accrued revenue from licensing and post-contract customer support. What is striking is that prior to SOP 91-1, the software industry had diverse revenue recognition practices and no specific, authoritative revenue recognition guidance for licensing and post-contract support; that environment is very similar to the current environment surrounding breakage in the retail industry. The results are noteworthy; Zhang found that accrued revenue that was recognized early yielded more timely and relevant information but at the expense of the reliability of the information, suggesting greater uncertainty in

reported revenue. In addition, Zhang found that accrued revenue that was recognized early diminished the utility for predicting future revenue. Taken together, Zhang's findings affirm that timed discretionary revenue recognition impacts the attributes of financial statement quality and has downstream implications for analysts and other external stakeholders. His findings only strengthen the current need to address breakage recognition which has far greater bearing on the utility of financial information within the retail industry.

In sum, the lack of substantial academic research on revenue recognition activities suggests that this is a fruitful area for further study. A study on discretionary gift card breakage recognition within the retail industry fills a significant gap in the literature.

2.2 The Compensation Motivation

Despite numerous articles in the popular press that emphatically link CEO compensation to earnings management and even accounting fraud, on balance, academic literature examining the relationship between management compensation contracts and accounting earnings is mixed. Healy & Wahlen (1999) noted that while current research suggests compensation contracts induce some firms to manage earnings there is very little evidence on how widespread this behavior is and no evidence on the magnitude of such a practice. This study addresses this gap by investigating a potentially significant revenue transaction across a wide-spectrum of retail firms.

Within the compensation motivations body of literature, two strains of research have emerged that examine the relationship between compensation and accounting earnings: examination through the choice of accounting method, and examination through discretionary or total accruals. Studies using an accounting method approach

(e.g., Robbins, Turpin & Polinski, 1993; Skinner, 1993; Zmijewski & Hagerman, 1981) generally used accounting choices such as depreciation method, inventory method (e.g., FIFO), interest treatment (capitalize vs. expense), oil and gas exploration costs, or some combination of these methods. Results of these studies are mixed. For example, while Zmijewski & Hagerman (1981) found that managers choose income-increasing techniques more often in firms with accounting based compensation, Bowen et al. (1981) found that explicit management compensation packages were not a factor in the option to capitalize or expense interest costs associated with capital expenditures.

A review of more recent literature, however, suggests that the accounting method approach fell out of favor and was replaced by an accruals-based approach. Healy's (1985) seminal article was the first to adopt an accruals-based methodology where he defined accruals as "the difference between reported earnings and cash flow from operations" (p. 86). Using 94 sample companies over the period 1930 – 1980, Healy's test results suggest that the accrual policies of managers were related to income-reporting incentives in their bonus contracts. In particular, he found that managers were more likely to choose income-increasing accruals when their bonus plan upper/lower bounds were not binding. In addition, he noted that managers were more likely to defer income when their bonus cap was reached. His research was consistent with a bonus-maximization hypothesis which implies that managers make discretionary decisions to maximize their short-term bonuses.

Two important studies in the 1990s followed Healy. Holthausen et al. (1995) found results consistent with Healy – managers manipulate earnings downward when their bonuses are at a maximum, which suggests that managers "pocket" earnings to use

in the future if necessary. Likewise, Guidry, Leone and Rock (1999) found that divisional managers of a large conglomerate were likely to defer income when the earnings target in their bonus plan would not be met or when they were entitled to maximum bonuses permitted under their plan.

These foundational studies ignited inquiry into the relationship between accounting earnings and compensation with much of the literature focusing on stock option-based compensation. For example, Bartov & Mohanram (2004) found that managers inflated earnings prior to stock options exercises. Likewise, Cheng and Warfield (2005) documented that CEOs with high equity incentives (i.e., stock-based compensation) were more likely to meet or just beat analysts' forecasts and were less likely to report large positive earnings surprises; Cheng and Warfield concluded that "managers...could benefit from earnings management with the objective of keeping stock prices high and increasing the value of the shares to be sold in the future" (p. 470). Later studies by Bergstresser and Philippon (2006), Meek, Rao, and Skousen (2007), and Cohen, Dey, and Lys (2008) also found positive associations between equity incentives and managed earnings. All of these studies, however, continued Healy's accruals-based approach; while a compelling methodology, the accruals-based approach is not relevant for a study using gift card breakage because breakage is a cash flow transaction, not an accrual transaction. In addition, the accruals-based approach is not consistent or adequate for the accounting regulator.

Fortunately, research has recently begun to diversify away from the accruals-based approach; instead, a few studies have begun to use other accounting methods or specific accruals (see e.g., Harris & Bromiley, 2007 or Erickson, Hanlon, & Maydew,

2006) to investigate the influence of compensation motivations on earnings management. This suggests that researchers are broadening their approaches in their attempts to find financial items that more definitively demonstrate a link between compensation and earnings management. Plus, innovative methodologies may aid regulators better than did the previous approaches. This study contributes to this literature by examining breakage – a specific account related to revenue recognition.

In summary, investigating a compensation-earnings management link through breakage recognition not only continues the diversification of approach seen in recent literature (i.e., moving away from an accruals-based approach), but more importantly, highlights how easily discretionary revenue recognition can be used to influence earnings to improve retail managers' compensation payouts.

2.3 The Income-smoothing Motivation

Income-smoothing is "the intentional dampening of fluctuations around some level of earnings that is considered to be normal for a firm" (Beidleman, 1973, p.653). Income-smoothing related to earnings management is called artificial smoothing (Eckel, 1981). Artificial smoothing is defined as "manipulations undertaken by management to smooth income...[which] do not represent underlying economic events" (Eckel, 1981, p. 29) and differs from a naturally smooth income stream where the income generating process inherently produces a smooth stream of income. Stolowy and Breton (2003) suggested that the effects of smoothed income tend to dampen variations in earnings over time.

Managers undertake income-smoothing activities to enhance predictability of earnings (Barnea, Ronen, & Sadan, 1975; Beattie, Brown, Ewers, John, & et al., 1994), to

obtain external financing (Kanagaretnam, Lobo, & Mathieu, 2003), to improve investors' and creditors' predictions of the company's future growth (Godwin, 1977), to enhance the credibility of management's own projections in the financial press (Godwin, 1977), and to manage earnings (Matsuura, 2008; Tseng & Lai, 2007).

How income-smoothing is accomplished varies, but collectively, the body of literature suggests that revenue items and highly discretionary financial items can be used to manage earnings. For example, one stream of literature suggests that managers are likely to use revenue, contingency, and reserve accounts to smooth income (Altamuro et al., 2005; Nelson et al., 2002; Nelson, Elliott, & Tarpley, 2003; Phillips, Pincus, Rego, & Wan, 2004). Another stream suggests income-smoothing is frequently accomplished through managerial discretion (Phillips et. al, 2004) and through highly discretionary provisions like warranties, maintenance costs, and uninsured risk (Peek, 2004). However, current literature has not merged these two streams of thought; this research study combines these two literature streams by using a highly discretionary revenue item to investigate an income-smoothing hypothesis.

2.4 The Meeting External Benchmarks Motivation

Contemporary literature suggests that earnings are managed to meet stakeholders' expectations regarding simple financial benchmarks like EPS. For instance, one intriguing study by Degeorge et al. (1999) studied earnings management as a response to implicit and explicit rewards for attaining specific levels of earnings, such as positive earnings, an improvement over last year's earnings, or the market's consensus forecasts. The authors used a threshold model because they believed that financial analysts utilized thresholds as a standard for judging and rewarding executives. The model looked at three

thresholds including (a) reporting positive profits, that is, reporting earnings that are above zero; (b) sustaining recent performance, that is, making at least last year's earnings; and (c) meeting analysts' expectations, particularly the analysts' consensus earnings forecasts. Their empirical study found clear support for earnings management driven by all three thresholds. The authors concluded that executives manage earnings in predictable ways to exceed simple thresholds.

The reasons that earnings are managed to meet benchmarks vary, but one widely recognized reason is to avoid the consequences of missing a benchmark. A consequence of missing analysts' EPS forecasts, for example, is a lower stock price. Literature affirms this consequence. For example, Skinner and Sloan (2002) reported that stock prices are negatively affected by adverse earnings surprises and Barth, Elliott, and Finn (1999) also noted that market prices are sensitive to missed benchmarks. From this, it should be obvious that managers undertake actions to avoid reporting earnings lower than analysts' expectations (Burgstahler & Eames, 2006); in the case of meeting EPS forecasts, it is likely that managers minimally desire to maintain current valuations.

Important to this research is the fact that literature has demonstrated that revenue manipulation is used by managers to meet external benchmarks. For example, Stubben (2006) determined that firms prematurely recognize revenue to manage earnings to meet analysts' target forecasts. Here, premature revenue means channel stuffing sales, bill and hold sales, and sales recognized before recognition criteria are met. His model used an accruals-based approach in that he used receivables accruals as a proxy for discretionary revenue. Likewise, Caylor (2006) suggested that some firms defer more revenue when pre-managed earnings beat an earnings benchmark by a large amount and that firms defer

less revenue when pre-managed earnings miss an earnings benchmark by a large amount. Caylor also noted that a large proportion of firms use revenue manipulation to meet or beat consensus analysts' forecasts. Taken together, Caylor's findings imply that revenue manipulation to meet benchmarks is the result of a managed choice.

All told, Stubben's and Caylor's studies indicate that meeting (or just beating) analysts' forecasts are where many cases of suspected accelerated revenue recognition occur. Therefore, it seems reasonable to put forward that any revenue-related item, like breakage, should serve a similar function to meet a benchmark. The critical difference between breakage and prior studies using accruals is that breakage is a cash-based transaction and the accounting for breakage does not require multifaceted accounting procedures like recording and reversing accruals to leverage its utility in meeting earnings benchmarks. In short, it is easier for managers to use breakage to meet external benchmarks. As such, this study extends current meeting benchmarks literature through a novel, cash-based, highly discretionary revenue-related item.

2.5 Development of Research Hypotheses

This section provides background for the development of hypotheses. *All hypotheses are stated in the alternative form for clarity.*

2.5.1 Compensation Motivation.

Compensation contracts for retail managers typically include bonuses and stock options. Compensation plans are often structured to account for short- and long-term performance such that managers earn immediate benefit for short-term performance and accrue future benefit for long-term performance. For example, retail managers frequently earn stock options of various vesting dates; assuming stock price appreciation, managers

can reap short- and long-term gains based on their firms' market value. Logically, it follows that retail managers have incentive to act selfishly and influence accounting earnings because their compensation contracts are commonly tied to the value of their firms or other accounting metrics.

Literature (e.g., Bergstresser & Philippon, 2006; Cohen et al., 2008; Healy, 1985; Guidry et al., 1995; Meek et al., 2007) supports the idea that managers are motivated to influence reported results and manage earnings due to their compensation contracts. This study extends compensation motivation theory to a discretionary revenue-related transaction to identify the influence that meeting a compensation boundary has in breakage decisions. However, this study differs from previous compensation-related research in two distinct ways.

First, a unique aspect of breakage that makes it distinct from financial items used in previous compensation motivations literature is its immediate impact on earnings – recognized breakage falls immediately to the bottom-line. Prior studies used revenue-related accruals, but unlike revenue-related accruals that typically need to be offset with expense-related accruals, there is no need to offset breakage with further creative or complex accounting treatment. Conceivably, this gives managers considerable latitude to adjust or create breakage policies to meet their compensation contracts without having to worry about offsetting expenses. In the retail industry, where low margins and competition reigns, managers must covet the considerable latitude that breakage offers, especially when their bonus or stock options are tied to their firms' financial performance.

Second, breakage offers a unique environment to examine compensation motivations through a single transaction rather than through aggregate accruals. Other research (Bergstresser & Philippon, 2004; Cohen et al., 2008; Healy, 1985; Holthausen et al., 1995, Weber, 2006, etc...) used aggregated accruals where there was no distinction between revenues and expenses. Studying a single transaction rather than aggregate accruals more closely aligns to the way managers actually make accounting decisions which typically occur at the transaction level.

Therefore, consistent with a compensation motivations hypothesis, it is expected that retail managers make discretionary decisions to maximize their compensation through the recognition of gift card breakage. The assumption is that managers with compensation packages that are heavily weighted towards performance-based compensation measures will use breakage to ensure those measures are achieved. In this study, awards of stock options are used as proxy for performance-based compensation; stock options are frequently used in research as a proxy for compensation (e.g., Bergstressor & Philippon, 2004; Cheng & Warfield, 2005; Cohen et al., 2008; Harris & Bromiley, 2007; Meek et al., 2007, etc...). Stock options offer strong encouragement for managers to raise the stock price above the strike price by inflating earnings (Harris & Bromiley, 2007). In addition, CEO compensation is used as proxy in this study for all top-level managers' compensation. This approach is consistent with prior research (e.g., Burns & Kedia, 2006; Larcker, Richardson, & Tuna, 2007; Said, 2003, etc...) because CEO compensation tends to be readily available in firms' financial statements or footnotes. Thus, it is hypothesized:

H_1: The proportion of CEO pay from stock options positively influences the extent to which retailers use gift card breakage.

2.5.2 Income-smoothing Motivation.

Motivations for decisions that tend to modify income or earnings are often called income-smoothing activities. Literature (Nelson et al., 2002; Nelson et al., 2003) suggests that managers are likely to attempt income-smoothing through revenue, contingency, and reserve accounts. Without question, breakage should serve a similar role.

It should be evident that retailers are able to use breakage to smooth income because the current accounting environment is marked by fluid breakage policies and ill-defined accounting standards. Income-smoothing activities may be particularly appealing to retail managers due to the retail industry's sales profile which includes volatility, seasonality, and sales swings due to economic factors and ever-changing consumer tastes. In addition, like most income-smoothing activities, breakage decisions are highly vulnerable to discretionary actions by management. Simply stated, breakage can be modified at will to maintain stable earnings and as such, gift card breakage is another tool in the retailer's toolbox through which they can pursue income-smoothing activities. As such, in harmony with an income-smoothing hypothesis, it is expected that managers use gift card breakage revenue to smooth income. Thus, it is hypothesized:

H_2: Breakage is used by retailers to smooth earnings.

2.5.3 Meeting External Benchmarks Motivation.

Contemporary literature suggests that earnings are managed to meet stakeholders' expectations regarding simple financial benchmarks. Stolowy and Breton (2003)

suggested that the target of this form of earnings management is often the level of EPS or the variance of EPS from a prior period, respectively. Dechow and Skinner (2000) noted that the current body of literature reveals that market participants (e.g., financial analysts) respond to whether earnings meet fairly simple benchmarks and that managers appear to practice earnings management to meet these simple benchmarks. For example, Burgstahler and Dichev (1997) provide strong evidence that companies try to avoid disappointing external stakeholders like Wall Street analysts. This point is bolstered by extensive research which shows that earnings announcements below Wall Street expectations result in a drop in stock price (Stice & Stice, 2006). It is easy to infer that retailers have similar incentive to make sure that their announced results are at least equal to their expected result because of the financial and reputational implications to their organizations if they miss anticipated targets (Key, 2002).

A study using breakage will add to the literature because prior literature has not investigated whether a single, revenue-related transaction is used to meet a simple financial benchmark; previous research used proxies like accounts receivable (e.g., Stubben, 2006) or aggregate revenues (e.g., Caylor, 2006). The likelihood that breakage is used to meet financial benchmarks in the retail industry is high given the industry's low profit margins and constant market pressure from analysts to "make the number." The advantage of using a single transaction over proxies in this study is that the low-level transaction allows one to capture the specific effect of a discretionary, revenue-related decision on changes in the benchmark.

Hence, consistent with a meeting benchmarks motivation, it is assumed that retail managers use discretionary revenue changes to meet simple financial benchmarks like a

consensus earnings forecast. A consensus earnings forecast is a well-known, publicly available benchmark that is created by pooling EPS estimates from multiple financial analysts. Research has shown that analysts respond to whether actual earnings meet (miss) consensus estimates and that managers often make discretionary choices to make the consensus estimate. Therefore, it is hypothesized:

H_3: In quarters where gift card breakage occurs, breakage is used by retailers to meet analysts' consensus EPS forecasts.

2.5.4 Materiality.

Materiality was identified as a moderating factor on retailers' decisions to recognize gift card breakage. It is assumed that retailers avoid recording material breakage so as not to draw attention from external stakeholders. The inference is that immaterial breakage amounts are not construed to be misleading. Therefore, it is assumed that retailers do not intentionally recognize material breakage; as such, it is hypothesized:

H_4: Retailers are more likely to record breakage in immaterial amounts than material amounts.

2.5.5 Timing.

A second moderating factor is timing. It is assumed that the decision to recognize gift card breakage revenue is the result of a managed choice by management; as such, it is inferred that retail firms intentionally select a particular period in which to recognize their breakage revenues. Prior literature suggests that the fourth quarter (i.e., the last fiscal quarter) is frequently used to manage earnings, to "settle up" prior quarters or to record non-recurring transactions. Therefore, it is hypothesized:

H_5: Retail firms are more likely to recognize breakage in the last quarter of their fiscal year.

2.5.6 Retailer Characteristics.

The last moderating factor is retailer characteristics. Literature (e.g., Chun et al., 2003; Little, Little, & Coffee, 2009) suggests that various retailer characteristics affect financial decisions. In this study, it is assumed that retailers' breakage decisions are influenced by certain characteristics like net margin, line of trade, and overall financial health. These characteristics are broad-based and are therefore applicable to all retailers. Thus, it is hypothesized:

H_{6a}: Low margin retailers recognize more breakage than high margin retailers.

H_{6b}: The propensity to recognize breakage varies by line of trade.

H_{6c}: Retailers in poor financial health recognize more breakage than retailers in strong financial health.

2.6 Summary

In sum, current professional accounting literature gives emphasis to the need for appropriate revenue recognition policies and procedures to ensure investor confidence. Even so, the accounting academic literature has largely ignored ambiguous revenue-related practices that may contribute to market uncertainty through revenue-related earnings management. It is this lack of attention that suggests that this study fills a significant void in the literature.

Similarly, prior studies demonstrate that discretionary financial decisions are frequently influenced by earnings management motivations, including compensation contracts, income-smoothing activities, and the need to meet external benchmarks. More importantly, the literature establishes that these motivations can be applied to elective revenue decisions. In this vein, this study extends current earnings management literature by examining earnings management through a new, cash-based, highly discretionary revenue-related transaction. The critical difference between this study and prior research is that this study's subject tool for earnings management (i.e., breakage) is a single accounting transaction that does not require complex accounting maneuvers to achieve managed financial results. The action is relatively easy for managers to take and is relatively easy to detect.

CHAPTER 3: RESEARCH METHODOLOGY

The purpose of this study is to assess the influence that compensation, smoothing income, and meeting benchmarks have in retailers' decisions to recognize gift card breakage. This research is carried out through a quantitative study by examining breakage recognition activity across various lines of retail trade for the period 2002-2011[1].

3.1 Research Design

Publicly available, secondary data from commercial and government sources are used to test the hypotheses. The use of secondary data to study earnings management motivations is commonplace in literature (see e.g., Healy & Wahlen, 1999; McNichols, 2000) and is appropriate for model building research (Zikmund, 2003). Linear regression, one- and two-sample tests of hypotheses and analysis of variance (ANOVA) comprise the research design.

This study uses actual quarterly financial and non-financial data for the fiscal years 2002-2011 providing up to 40 quarterly observations for each retailer. The time period 2002-2011 is selected because of the significant growth of gift card programs that occurred in the early 2000s, and because the ten-year period ensures a sufficient sample size when testing for statistical significance.

[1] Retailers report annual results that end on dates other than December 31. Because of inherent differences in fiscal years, the actual sample includes the first quarter of 2002 through the first quarter of 2012. Adding the first quarter from 2012 ensured that the researcher had the ability to use ten years of quarterly data for all firms in the sample.

3.2 Population, Sample Frame, and Sample

The target population for this study includes current US publicly traded retailers classified as *retail trade*. The US Department of Labor (2010) defines retail trade as:

> ...establishments engaged in selling merchandise for personal or household consumption and rendering services incidental to the sale of the goods. In general, retail establishments are classified by kind of business according to the principal lines of commodities sold (groceries, hardware, etc.), or the usual trade designation (drug store, cigar store, etc.). Some of the important characteristics of retail trade establishments are: the establishment is usually a place of business and is engaged in activities to attract the general public to buy; the establishment buys or receives merchandise as well as sells; the establishment may process its products, but such processing is incidental or subordinate to selling; the establishment is considered as retail in the trade; and the establishment sells to customers for personal or household use. (para. 1)
>
> For the most part, establishments engaged in retail trade sell merchandise to the general public for personal or household consumption. (para. 2)

The sample frame, or working population, consists of those retailers within the population with formal gift card programs which were started between January 1, 1996 and December 31, 2011 within the following retail trade groups: apparel and accessories; building material, hardware, and garden supply; eating and drinking; food stores; home furniture, furnishings, and equipment; and miscellaneous retail. It is assumed that gift card usage is high within these six lines of trade and therefore, there is high potential for breakage activity. Table 1 provides the Standard Industrial Classification (SIC) definition for these lines of trade (US Dept. of Labor, 2010). The six lines of trade are widely recognized and used by both market analysts and the Security and Exchange Commission. Importantly, grouping retailers along lines of trade is consistent with prior research (see e.g., Ingene & Yu, 1982). Retailers with formalized gift card programs were identified through an internet search, resulting in a working population of 187 retailers.

Table 1: ***Standard Industrial Classification by Major Group Code***

SIC Code	SIC Name	SIC Description
52	Building Materials, Hardware, and Garden Supply	This major group includes retail establishments primarily engaged in selling lumber and other building materials; paint, glass, and wallpaper; hardware; nursery stock; lawn and garden supplies; and mobile homes.
54	Food Stores	This major group includes retail stores primarily engaged in selling food for home preparation and consumption.
56	Apparel and Accessory Stores	This major group includes retail stores primarily engaged in selling new clothing, shoes, hats, underwear, and related articles for personal wear and adornment.
57	Home Furniture, Furnishings, and Equipment Stores	This major group includes retail stores selling goods used for furnishing the home, such as furniture, floor coverings, draperies, glass and chinaware, domestic stoves, refrigerators, and other household electrical and gas appliances.
58	Eating and Drinking Places	This major group includes retail establishments selling prepared foods and drinks for consumption on the premises; and also lunch counters and refreshment stands selling prepared foods and drinks for immediate consumption.
59	Miscellaneous Retail	This major group includes retail establishments, not elsewhere classified. These establishments fall into the following categories: drug stores, liquor stores, used merchandise stores, miscellaneous shopping goods stores, non-store retailers, fuel dealers, and miscellaneous retail stores, not elsewhere classified.

In developing the sample from the working population, it is important to distinguish firm behavior regarding breakage disclosure and recognition. Table 2 summarizes the possible combinations that exist for breakage disclosure and recognition.

Table 2: ***Combinations of Disclosure, Recognition, and Breakage Amounts***

Scenario	Disclosed Breakage Recognition Policy	Recognized Breakage	Disclosed Breakage Amount
A	No	No	N/A
B	Yes	No	N/A
C	No	Yes	No
D	Yes	Yes	No
E	Yes	Yes	Yes

This study's total sample consists of firms in Scenarios *B* or *E*. Scenario *B* firms ($n = 13$) disclosed that they had formal gift card programs but that they had not recognized breakage relating to their gift card programs to date; in contrast, Scenario *E* firms ($n = 61$) disclosed both their recognition polices and the actual amount of breakage recognized by quarter. Firms with incomplete quarterly breakage data are excluded from the final sample; while this did not affect the number of Scenario *B* firms, the number of Scenario *E* firms is reduced to 45.

Finally, it should be evident that it is impossible to distinguish between firms falling into Scenarios *A* and *C* because these firms do not disclose breakage activity, even if they are recording breakage. Likewise, it should be apparent that including Scenario *D* firms is not constructive because they did not disclose dollar amounts, even though they admit to recognizing breakage. Therefore, firms in Scenarios *A*, *C*, and *D* are excluded from this study.

3.3 Data Collection

Primary data collection was accomplished by electronically searching retailers' quarterly press releases, 10-Q filings, and other public-domain publications including newspapers, wire services, and broadcast transcripts, looking for keywords such as "breakage," "gift cards," stored value cards," or "unredeemed." Generally speaking, retailers' direct press releases were readily available in PRNewswire or Business Wire via LexisNexis or ABI/Inform while other news sources such as RTTNews.com, Streetinsider.com, Seekingalpha.com, tdameritrade.com, and Morningstar.com provided valuable information such as EPS forecasts and actual EPS results. Quarterly and annual financial reports, proxy statements, and registration statements were obtained in the SEC's EDGAR database. Quarterly income statement and balance sheet figures were acquired from Thomson One. Ancillary data (e.g., line of trade, or historical prices) were compiled from EDGAR and other financial websites (e.g., finance.yahoo.com). Accuracy of the data was determined by cross-checking multiple data sources. The data was downloaded or copied from the internet into a Microsoft Excel spreadsheet to minimize data entry errors. Administrative (systematic) errors were controlled by re-checking, entry-by-entry, the database values to ensure accuracy.

The information in Table 3 summarizes the information collected for each retailer in the sample. Calculated fields derived from the downloaded data are also included.

Table 3: ***Summary of Data Fields***

Data Field	Description
	Generic Company Data
ID	Unique identifier assigned to each retailer
COMPANY	Company name
TICKER	Stock exchange ticker symbol
FY_ENDS	Ending date of fiscal year
MG	Standard Industrial Classification (SIC) major group code
MG_DESC	Description of SIC major group code
SIC	SIC code indicating a company's type of business
SIC_DESC	Description of SIC code
GCP_STRTDTE	Gift card program start date
LSTFSCLQTR	Stored binary variable where "1" indicates the last quarter in a firm's fiscal year
	Financial Data
YEAR	Financial year, e.g., 2006 (stored as YYYY)
QTR	Financial quarter reporting period, e.g., 04 (stored as Q4)
BREAKAGE	Pre-tax value of recognized breakage by quarter (nominal dollars)
EBT	Net Income before taxes by quarter
TAXPROV	Provision for income taxes by quarter
TAXRATE	Effective quarterly tax rate, calculated as TAXPROV divided by EBT
AT_BREAKAGE	After-tax value of recognized breakage by quarter calculated as BREAKAGE times (1 – TAXRATE)
OPINC	Operating Income (EBIT) by quarter (nominal dollars)

Data Field	Description
SALES	Net Sales by quarter (nominal dollars)
OPPRFTMRG	Operating profit margin, calculated as OPINC divided by SALES
OPINC_XBRKG	Operating income without breakage, calculated as OPINC less BREAKAGE
SALES_XBRKG	Net Sales without breakage, calculated as SALES less BREAKAGE
OPPM_XBRKG	Operating profit margin without breakage calculated as OPINC_XBRKG divided by SALES_XBRKG
NETOPASSETS	Net operating assets by quarter (Cash + Accounts Receivable + Inventory + Net Property, Plant, & Equipment – Accounts Payable)
ASTURN	Asset turnover, calculated as SALES divided by NETOPASSETS
ASTURN_XBRKG	Asset turnover without breakage, calculated as SALES_XBRKG divided by NETOPASSETS
RNOA	Return on net operating assets, calculated as OPPRFTMRG times ASTURN
RNOA_XBRKG	Return on net operating assets, calculated as OPINC_XBRKG times ASTURN_XBRKG
BRKG/OI%	Breakage as a percent of operating income, calculated as BREAKAGE divided by OPINC
BRKG/NOA%	Breakage as a percent of net operating assets, calculated as BREAKAGE divided by NETOPASSETS
BRKG/SALES%	Breakage as a percent of net sales calculated as BREAKAGE divided by SALES
OPTIONS	Annual stock option value – present value derived from Black-Scholes option pricing model
TCOMP	Annual CEO total compensation defined as salary + bonus + options

Data Field	Description
CEOPAYOPTNS%	Stock Options as a percent of total compensation, calculated as OPTIONS divided by TCOMP
DILSHARES	Diluted weighted average shares by quarter
RE	Actual reported EPS by quarter, excluding extraordinary items
EPS_DIFF	Change in EPS from after-tax breakage, calculated as AT_BREAKAGE divided by DILSHARES
XRE	Actual reported EPS by quarter, excluding extraordinary items and without breakage, calculated as RE less EPS_DIFF
AF	Final mean analysts' EPS forecast by quarter, excluding extraordinary items
MISSEDEPS	Stored binary variable where "1" indicates a firm would have missed AF; calculated as RE less AF
MISSEDEPS_XBRKG	Stored binary variable where "1" indicates a firm would have missed AF; calculated as XRE less AF
MATERIAL	Stored binary variable where "1" indicates BREAKAGE is greater than ½% of SALES less BREAKAGE
NETINC	Income available to common excluding extraordinary items by quarter
NTPRFTMRGN	Net profit margin, calculated as NETINC divided by SALES
NPM_XBRKG	Net profit margin without breakage, calculated as the difference between NETINC and AT_BREAKAGE divided by the difference between SALES and BREAKAGE

3.4 Empirical Model and Analysis

Specific analytical procedures for each hypothesis are outlined in this section. A regression model that combines individual hypotheses into a comprehensive empirical model is also developed and discussed in this section. Data analysis is completed through Minitab®.

3.4.1 Compensation Motivation.

This research hypothesizes that the relative size of the breakage transaction is positively related to the proportion of pay a CEO receives in stock options. Here, awards of stock options are used as proxy for performance-based compensation; in addition, CEO compensation is used as proxy for all top-level managers' compensation. Of note, because options vest at various intervals, the likelihood that retailers will recognize breakage in a particular period should be dependent upon the length of time that transpired since the grant period; following Harris & Bromiley (2007), this study controls for various vesting dates by using both total compensation and the present value of granted options from the prior year against the current year breakage activity for each retailer. Additionally, this studies assumes that compensation, including options, is spread equally throughout the year even though award dates and/or payment dates may occur infrequently (e.g., annually). This simplifying assumption is based on the reality that performance-based measures are tied to quarterly financial results and therefore it is appropriate to tie annual compensation to a particular quarter by dividing annual compensation by four.

To assess the H_1 hypothesis, *the proportion of CEO pay from stock options positively influences the extent to which retailers use gift card breakage,* this study uses ordinary least squares regression. Assuming normality of data, regression is appropriate for two reasons. One, regression explains the value of the dependent variable based on changes in the value of the independent variable, and two, both dependent and independent variables are continuous.

The null and alternative hypotheses are:

$$H_0 \quad BRKG/SALES\%_{iq} \neq f\left(\frac{\text{OPTIONS}_{i,q-1}}{TCOMP_{i,q-1}}\right)$$

$$H_A \quad BRKG/SALES\%_{iq} = f\left(\frac{OPTIONS_{i,q-1}}{TCOMP_{i,q-1}}\right)$$

where

i	Individual firm
q	Current year quarter
q-1	Prior year annual compensation allocated equally over prior year quarters; data is lagged one year
BRKG/SALES%	Dependent variable representing the relative size of BREAKAGE as a percentage of SALES.
OPTIONS	The value of OPTIONS are based on the compensation cost for financial reporting purposes for the fiscal year under SFAS 123(R) and are derived using the Black-Scholes option pricing model. For years prior to 2006, the grant date present value was determined using the Black-Scholes option pricing model. Amounts are taken from annual proxy statements (Form DEF 14A)
TCOMP	TCOMP represents base salary, bonuses, and option values from annual proxy statements

The regression equation is:

$$\frac{BRKG}{SALES}\%_{iq} = a + b_1\left(CEOPAYOPTNS\%_{i,q-1}\right)$$

where

CEOPAYOPTNS%	Independent variable calculated by dividing OPTIONS by TCOMP

The total dataset includes both firms that disclosed that they had not recognized breakage (n = 13) and firms that disclosed recognition and associated breakage amounts (n = 45). Including firms that disclosed their recognition policy but had not recognized breakage during the sample frame provides a reference point for the firms that do recognize breakage. The time period for the pooled data includes quarterly data for fiscal years 2002 through 2011. This period includes all quarters in the sample, regardless of whether breakage was recognized in a particular quarter. The critical level of significance is 0.05.

3.4.2 Modify Income Motivation.

In harmony with an income-smoothing hypothesis, it is expected that managers use gift card breakage to smooth income. For this study, Eckel's (1981) approach for determining artificial income-smoothing is used. Artificial smoothing is defined as "accounting manipulations undertaken by management to smooth income" (Eckel, 1981, p. 29). Eckel's approach is preferred because although it assumes income is a linear function of sales, it does not rely on earnings predictions, models of expected revenue, or subjective judgment. Essentially, Eckel's procedure compares a ratio of income variability to sales variability; possible income-smoothing is indicated by an index of less than 1. In essence, if the variance in income is less than the variance in sales, it can be surmised that possible income-smoothing occurred. In addition, Eckel prescribes that only those firms with an artificial smoothing index more than one standard deviation smaller than the industry average are engaging in artificial smoothing. This second step is necessary to account for the possible Scenario that a total industry is characterized by income time-series data that is less variable than its sales time-series data.

Adapting this approach, this study compares income variability to breakage variability. The period of study includes the first quarter of 2005 through the first quarter of 2012 which represents those quarters in the sample when breakage income was actually recognized by one or more firms in any given quarter. In short, the pooled dataset includes all quarters including and following initial recognition of breakage for each firm. Retailers that use breakage to smooth income should have a smoothing index less than 1 and the index should be more than one standard deviation less than the industry average; here, the firms in the sample serve as proxy for the retail industry.

Thus, to assess the H_2 hypothesis, *breakage is used by retailers to smooth earnings*, these two-step analytics are employed:

Step 1: Identification of firms where the $CV_{\Delta B} > CV_{\Delta I}$. These firms are noted as possible income smoothers.

H_0 $\left|\frac{CV_{\Delta Ii}}{CV_{\Delta Bi}}\right| \geq 1$; Non-income smoother

H_A $\left|\frac{CV_{\Delta Ii}}{CV_{\Delta Bi}}\right| < 1$; Income smoother

where

i	Individual firm
ΔI	One-period change in operating income [*OPINC*] for firm *i*
ΔB	One-period change in pre-tax breakage [*BREAKAGE*] for firm *i*
$CV_{\Delta I}$	Coefficient of variation (i.e., standard deviation divided by its mean) for the change in operating income
$CV_{\Delta B}$	Coefficient of variation for the change in breakage

Step 2: For those firms identified in step 1 as an income smoother, determine whether a firm's artificial smoothing index $|CV_{\Delta I} \div CV_{\Delta B}|$ is significantly less than the industry average.

$|CV_{\Delta I} \div CV_{\Delta B}|$ *is more than one standard deviation smaller than the industry average*

Firms that pass the dual-step filter are identified as artificial income smoothers; that is, they are using breakage income to smooth operating income.

Finally, to control for the unlikely event of a spurious relationship between operating income and breakage, this same two-step process is run for:

(1) $|CV_{\Delta I} \div CV_{\Delta S}|$ for all quarters in the sample period 2002-2011, where $CV_{\Delta S}$ is the coefficient of variation for the change in sales [SALES], and

(2) $|CV_{\Delta I} \div CV_{\Delta S}|$ for quarters prior to the initial recognition of breakage for each firm.

The first analysis follows Eckel's methodology to assess whether a retailer is, in general, an artificial income smoother over the 10-year sample period. If so, then it cannot be assumed that breakage alone is artificially smoothing income; that is, there may be other factors at work that allow retailers to smooth their income stream.

The second analysis evaluates whether a retailer is an artificial income-smoother prior to its recognition of breakage. If so, then the recognition of breakage income does not indicate changed retailer behavior and therefore one cannot infer that the firm uses breakage to smooth income. If, however, the firm is not smoothing income prior to breakage recognition, but does so after, it can be inferred that breakage is a tool to artificially smooth income.

3.4.3 Meeting Benchmarks Motivation

Consistent with a meeting benchmarks motivation, it is assumed that retail managers use discretionary breakage to meet a consensus earnings forecast. A consensus earnings forecast is a well-known, publicly available benchmark that is created by pooling EPS estimates from multiple financial analysts.

To assess H_3, *in quarters where breakage occurs, breakage is used by retailers to meet analysts' consensus EPS forecasts* this study assumes that discretionary breakage decisions minimize the forecast error arising from differences between the analysts' mean EPS projection and the actual reported results. Forecast error is calculated by taking the difference between the actual EPS result and the mean EPS analyst estimate and dividing that difference by the absolute value of the mean EPS analyst estimate. For example, if a firm reports \$1.03 against analysts' estimate of \$1.00, the forecast error is 3% ((\$1.03 - \$1.00) / |\$1.00|). To determine however whether a firm manages earnings to meet EPS estimates with breakage, it is also necessary to compute the forecast error without the impact of breakage in the actual results. The following equations represent these calculations:

$$FE\%_{iq} = \frac{RE_{iq} - \mu AF_{ip}}{ABS|\mu AF_{ip}|}$$

$$XFE\%_{iq} = \frac{XRE_{iq} - \mu AF_{ip}}{ABS|\mu AF_{ip}|}$$

where

$FE\%_{iq}$	Percent forecast error for a given firm (i) and quarter (q)
$XFE\%_{iq}$	Percent forecast error excluding after-tax breakage for a given firm (i) and quarter (q)
RE_{iq}	Actual reported diluted EPS, excluding extraordinary items
XRE_{iq}	Actual reported diluted EPS, excluding extraordinary items and after-tax breakage
μAF_{ip}	Final mean analysts' diluted EPS Forecast for the forecast period (p), excluding extraordinary items

All EPS data is corrected for extraordinary items so that earnings management employing these financial activities is excluded. Actual reported EPS is corrected for after-tax breakage income to arrive at XFE%. The period of study includes the first quarter of 2005 through the first quarter of 2012. This dataset includes all quarters including and following initial recognition of breakage for each retailer.

Differences between FE% and XFE% are calculated for each quarter by firm; these differences represent the change in forecast error due to breakage. Importantly, the resulting difference must be compared against the reality of whether a retailer would have missed the EPS projection without breakage income [MISSEDEPS_XBRKG]. This step is necessary to control for situations where either (1) breakage income is recognized but a firm would have beaten the EPS projection even without breakage income or (2) the value of breakage is nominal and does change the forecast error, but the firm would have missed the mean forecast regardless of breakage activity.

To test H_3, the null and alternative hypotheses are:

$$H_0\ (FE\%_{iq} - XFE\%_{iq}) \neq f(MISSEDEPS\_XBRKG)$$

$$H_A\ (FE\%_{iq} - XFE\%_{iq}) = f(MISSEDEPS\_XBRKG)$$

where

MISSEDEPS_XBRKG Stored dummy dichotomous variable where "1" indicates a firm would have missed μAF

An association between ($FE\%_{iq} - XFE\%_{iq}$) and MISSEDEPS_XBRKG implies that retailers are using breakage to meet estimates. No association implies that earnings management is not occurring. The approach described here is superior to the accruals-based approaches typically used in earnings management studies because of the nature of this study's transactional data.

Assuming normality, least squares regression is used to analyze the results; the critical level of significance is .05. Regression is appropriate because the dependent variable is continuous and the null hypothesis is assessing the relationship between two variables. Regression with one categorical independent variable is acceptable (see e.g., "Regression with Categorical Predictors," n.d.) even though least squares regression requires interval or ratio scale independent variables because the independent variable's scale has interval properties as explained by Nunnally and Bernstein (1994):

> ...a [categorical] scale may be regarded as an interval scale when it contains only two points. This is the basis of the analysis of variance. If the variable takes on only two values, such as gender, one level may be coded 0 and the other coded 1....The independent variable's 'scale' has interval properties, by definition, because the scale has only two points. (p. 189)

3.4.4 Materiality

Materiality was identified as a moderating factor in retailers' decisions to recognize gift card breakage. Materiality may arouse additional scrutiny by external stakeholders like regulators and investors. However, retailers can intentionally avoid recording material breakage so as not to draw attention from external stakeholders. The inference is that immaterial breakage amounts would not be construed as misleading.

Consistent with literature, it is assumed that retailers use heuristics to assess the materiality of their breakage revenue transaction; a common revenue-related heuristic within the retail industry is ½% of total revenues (Pany & Wheeler, 1989). Therefore, it is assumed that retailers will not intentionally recognize material breakage; immaterial breakage is indicated by an index of less than ½% of total revenue. As such, for hypothesis H_4, *retailers are more likely to record breakage in immaterial amounts than material amounts* the following analytics will be used:

The null and alternative hypotheses are:

$H_0 \quad \mu(Materiality\%_{iq}) \geq 0.005$

$H_A \quad \mu(Materiality\%_{iq}) < 0.005$

where

$$Materiality\%_{iq} = \frac{BREAKAGE_{iq}}{(SALES - BREAKAGE)_{iq}}$$

i = Individual firm
q = Quarter

For retailers that recognized breakage in the sample, *Materiality%* is calculated for each firm for all quarters including and following initial recognition of breakage. The

period of study includes the first quarter of 2005 through the first quarter of 2012. The mean *Materiality%* is calculated and a one-tailed t-statistic (one-sample t-test) is used to analyze the results. The one-sample t-test is appropriate because it compares the mean score of the sample to a known value. Assuming normality, the one-tailed t-distribution is suitable because the population standard deviation is not known, the number of observations is at least 30, and H_A states direction. The critical level of significance is .05.

3.4.5 Timing

A second moderating factor is timing. It is hypothesized that the decision to recognize gift card breakage revenue is the result of a managed choice by management; as such, it is inferred that retail firms intentionally select a particular period in which to recognize their breakage revenues. Retailers are faced with a choice of adjusting individual quarters or adjusting their full year results in their last fiscal quarter. Prior literature (see e.g., Collins, Hopwood, & McKeown, 1984) suggests that the fourth quarter (i.e., the last fiscal quarter) is frequently used to manage earnings, to "settle up" prior quarters or to record non-recurring transactions. Here, it is hypothesized that retailers also use their last fiscal quarter to adjust their earnings, and that they make these earnings management adjustments more frequently than they do in their other quarterly filings. Therefore, these analytics will be used to assess H_5 – *retail firms are more likely to recognize breakage in the last quarter of their fiscal year.*

The null and alternative hypotheses are:

$H_0 \quad \mu BREAKAGE_{\frac{q1}{t}i} = \mu BREAKAGE_{\frac{q2}{t}i} = \mu BREAKAGE_{\frac{q3}{t}i} = \mu BREAKAGE_{\frac{q4}{t}i}$

$H_A \quad The\ mean\ scores\ are\ not\ all\ equal$

where

i = Individual firm
q_n = Quarterly breakage ($)
t = Annual breakage ($)

For retailers that recognized breakage in the sample, quarterly breakage as a percentage of total annual breakage is calculated for each firm once breakage is recognized for the first time; this calculation provides the absolute percentage share of breakage recognized in a year by quarter. Quarterly percentages are calculated for each retailer in the period 2005-2011 as appropriate. The individual firm data is then grouped by quarter and the mean for each quarter is calculated. To evaluate this hypothesis, a one-way ANOVA test is used. The ANOVA is appropriate when comparing three or more population means to determine whether they could be equal. Here, the confidence level is 95%. If the null hypothesis is rejected ($p < .05$) a Tukey HSD *post hoc* test will determine where the significant differences occurred between quarters.

To account for fluctuations in business cycle and seasonality in timing transactions, the relative size of the breakage transaction by quarter is also considered in addition to the absolute percentage share. Here, breakage as a percent of sales provides a measure of relativeness. The null and alternative hypotheses are:

$$H_0 \quad \mu \frac{BRKG}{SALES}\%_{q1} = \mu \frac{BRKG}{SALES}\%_{q2} = \mu \frac{BRKG}{SALES}\%_{q3} = \mu \frac{BRKG}{SALES}\%_{q4}$$

$$H_A \quad \textit{The mean scores are not all equal}$$

where

q_n = Quarter

For each retailer that recognized breakage in the sample, quarterly breakage as a percent of sales is calculated for quarters once breakage is recognized for the first time. Quarterly percentages are calculated in the period 2005- 2011 as appropriate. The individual firm data is then grouped by quarter and the mean for each quarter is calculated. To evaluate this hypothesis, a one-way ANOVA test is used. The ANOVA is appropriate when comparing three or more population means to determine whether they could be equal. Here, the confidence level is 95%. If the null hypothesis is rejected ($p <$ .05), a Tukey HSD *post hoc* test will determine where the significant differences occurred between quarters.

3.4.6 Retailer Characteristics

The last moderating factor is retailer characteristics. In this study, it is assumed that retailers' breakage decisions are impacted by retailer characteristics including net margin, line of trade, and overall financial health.

To test H_{6a} *low margin retailers recognize more breakage than high margin retailers,* it is assumed that low margin retailers will benefit more from breakage recognition than high margin firms to improve financial results; that is there is more up-side potential for low-margin firms. Here, breakage as a percent of sales is a proxy for the level of breakage. To test this hypothesis, these analytics are used:

The null and alternative hypotheses are:

$$H_O \quad \mu BRKG/SALES\%_{low\ margin\ firms} \leq \mu BRKG/SALES\%_{high\ margin\ firms}$$

$$H_A \quad \mu BRKG/SALES\%_{low\ margin\ firms} > \mu BRKG/SALES\%_{high\ margin\ firms}$$

For retailers recognizing breakage in the sample (n=45), net margin is calculated by dividing quarterly net income available to common excluding extraordinary items and breakage by quarterly sales excluding breakage. To minimize the impact of year on year business fluctuations, an average net margin is calculated for each retailer over the 8-year period, 2003-2010 (32 quarters). The average net margin data is sorted, ranked, and divided into quartiles with the top quartile (top 25% of firms) considered "high" and the bottom quartile (bottom 25% of firms) considered "low." Quarterly breakage as a percent of sales for each retailer is calculated for all quarters following initial recognition of breakage, and each quarterly observation is assigned a "1" for a high margin retailer or a "4" for a low margin retailer. The mean is calculated for both groups. A one-tailed t-statistic (two-sample t-test) assesses the null hypothesis. The two-sample t-test permits comparison of two samples. Assuming normality, the one-tailed t-distribution is appropriate because the population standard deviation is not known, the quartiles are independent, and H_A states direction. The critical level of significance is .05.

Hypothesis H_{6b}, *the propensity to recognize breakage varies by line of trade,* assumes that retailers differ in their ability to benefit from gift card breakage depending on their line of trade. Lines of trade with significant gift card activity imply greater opportunity to build up unredeemed cards and to ultimately recognize breakage income. Here, breakage as a percent of sales is a substitute for the level of breakage available to individual retailers; it is expected that the average of this proxy across each line of trade will differ significantly.

The null and alternative hypotheses are:

H_O $\mu BRKG/SALES\%_1 = \mu BRKG/SALES\%_2 = \mu BRKG/SALES\%_n$

H_A *The mean scores are not all equal*

where

n = Number of lines of trade

For retailers recognizing breakage in the sample (n=45), quarterly breakage as a percent of sales is calculated for each quarter after initial recognition of breakage, and each quarterly observation is assigned a unique, SIC line of trade code (see Table 1). The period of study includes the first quarter of 2005 through the first quarter of 2012. Data is then grouped by SIC code. The mean for each SIC code is calculated. To evaluate this hypothesis, a one-way ANOVA test is used. The ANOVA is appropriate when comparing three or more population means to determine whether they could be equal. Here, the confidence level is 95%. If the null hypothesis is rejected ($p < .05$) a Tukey HSD *post hoc* test will determine where the significant differences occurred between lines of trade.

For H_{6c} *retailers in poor financial health recognize more breakage than retailers in strong financial health,* this study leverages the modified DuPont model which is widely recognized in literature (e.g., Pratt & Hirst, 2009; Soliman, 2008). The model measures the Return on Net Operating Assets (RNOA) which is the product of the operating product margin and asset turnover ratios. It differs from net margin in that it excludes the impact of taxes and includes asset efficiency. It is assumed that retailers in poor financial health will have lower RNOA than those in strong financial health and therefore will accrue greater benefits by recognizing breakage. Here, breakage as a

percent of sales is a proxy for the level of breakage. To test this hypothesis, these analytics are used:

The null and alternative hypotheses are:

$H_O \quad \mu BRKG/SALES\%_{Low\ RNOA\ firms} \leq \mu BRKG/SALES\%_{High\ RNOA\ firms}$

$H_A \quad \mu BRKG/SALES\%_{Low\ RNOA\ firms} > \mu BRKG/SALES\%_{High\ RNOA\ firms}$

For retailers recognizing breakage in the sample ($n = 45$), quarterly return on net operating assets is calculated by multiplying net operating assets by operating margin excluding breakage, where operating margin excluding breakage is operating income excluding breakage divided by sales excluding breakage. To minimize the impact of year on year business fluctuations, an average RNOA is calculated for each retailer over the 8 year period, 2003-2010 (32 quarters). The average RNOA data is sorted, ranked, and divided into quartiles with the top quartile (top 25% of firms) considered "high" and the bottom quartile (bottom 25% of firms) considered "low." Quarterly breakage as a percent of sales for each retailer is calculated for each quarter after initial recognition of breakage, and each quarterly observation is assigned a "1" for high margin retailer or a "4" for low margin retailer. The mean for both groups is calculated. A one-tailed t-statistic (two-sample t-test) assesses the null hypothesis. The two-sample t-test permits comparison between groups; assuming normality, the one-tailed t-distribution is appropriate because the population standard deviation is not known, the quartiles are independent, and H_A states direction. The critical level of significance is .05.

3.4.7 Complete Empirical Model

A complete empirical model is developed in this section to analyze and fully explain the relationship between breakage recognition and the motivation-related and moderating predictor variables noted in the individual hypotheses in this study. Multiple regression analysis is employed to measure the interaction between variables, to understand the relative contribution of the independent variables to the overall explanation, and to facilitate interpretation of the results.

The regression equation takes the form:

$$\frac{BRKG}{NOA}\%_{iq} = \alpha + b_1(CEOPAYOPTNS\%_{i,q-1}) + b_2(MISSEDEPS\_XBRKG_{iq}) + b_3(MATERIAL_{iq}) + b_4(NPM\_XBRKG_{iq}) + b_5(LSTFSCLQTR_{iq}) + b_k\,(MG_{n-1})$$

where

α	Intercept term
b	Regression coefficient
i	Individual firm
q	Quarter
Dependent Variable	
BRKG/NOA%	Represents the relative size of breakage. Calculated by dividing BREAKAGE by NETOPASSETS
Independent Variables	
CEOPAYOPTNS%	Calculated by dividing OPTIONS by TCOMP. The data is lagged by one year (*q-1*)
MISSEDEPS_XBRKG	Stored dummy dichotomous variable where "1" indicates a firm would have missed μAF

MATERIAL	Stored binary variable where "1" indicates BREAKAGE is greater than ½% of SALES less BREAKAGE
NPM_XBRKG	Net Profit Margin without breakage where net profit margin is calculated as the difference between NETINC and AT_BREAKAGE divided by the difference between SALES and BREAKAGE
LSTFSCLQTR	Stored binary variable where "1" indicates the last quarter in a firm's fiscal year
MG	Standard Industrial Classification major group code. There are $n - 1$ dummy variables added to the model. Since there are six lines of trade in the dataset, there are 5 independent variables, each coded as a 1, 0. (see Table 1)

Multiple regression is used because of its ability to analyze the relationship between a single response variable and several predictor variables. The data also fits the requirements of multiple regression well. Here, the dependent variable is continuous (metric) and the independent variables are either metric or non-metric, the latter using dummy variable coding. The critical level of significance is 0.05.

For retailers that recognized breakage in the sample ($n = 45$), quarterly data is gathered for the period 2002-2011. The data is pooled data, a combination of cross-sectional and time-series data.

In the regression model, the relative size of breakage [BRKG/NOA%] is used as a proxy for breakage. Within academic accounting literature, commons ways to standardize a dependent variable is to divide by assets or firm size; for this study, net operating assets is used as a variation on "assets" because net operating assets is a better reflection of a firm's operations.

CEOPAYOPTNS%, MISSEDEPS_XBRKG, and NPM_XBRKG are calculated as described under H_1, H_3, and H_{6a}, respectively. MATERIAL is determined by converting MATERIALITY% into a binary dummy variable, where a materiality percentage greater than 0.005 is coded as a "1." LSTFSCLQTR is determined by assigning a "1" to the fourth quarters across the sample time period. Finally, $n - 1$ dummy variables are added to the model for the six lines of trade in the dataset; five independent variables for MG are coded with a 1 if a retailer is associated with a particular line of trade. By default, if a firm is associated with the 6th line of trade, that firm has zeros across all 5 of the other line of trade independent variables.

3.5 Summary

This section developed the research methodology that assesses the influence that compensation, income-smoothing, and meeting EPS benchmarks motivations have in breakage recognition decisions. Results from these analytics are discussed in the next chapter.

CHAPTER 4: RESULTS

The purpose of this study is to determine whether compensation motivations, income-smoothing motivations, and meeting external benchmark motivations influence retailers' decisions to recognize gift card breakage arbitrarily. Chapter 4 explains the study's data, and provides the descriptive statistics and the empirical results from the sample of firms. Section 4.1 provides a high-level overview of the data and discusses issues relating to data collection, the distribution of data, missing data, and outliers. Section 4.2 presents descriptive statistics and reviews variable transformations. Section 4.3 describes the empirical results for each hypothesis, while Section 4.4 explains the results for the complete empirical model. Finally, Section 4.5 summarizes Chapter 4.

4.1 Summary of the Data

This section examines and explores the nature of the data and reviews data collection issues. In addition, this section describes each variable's shape of its distribution, addresses missing data, and discusses the process for detecting and handling outliers.

Potential US firms were identified through an internet search; 187 publicly-traded firms met an initial, two-fold criteria comprised of (a) retailers with gift card programs started between January 1, 1996 and December 31, 2011, and (b) publicly traded retailers falling within one of six lines of trade: apparel and accessories; building material, hardware, and garden supply; eating and drinking; food stores; home furniture, furnishings, and equipment; and miscellaneous retail. Of these 187 firms, 113 firms were

excluded because they either (a) did not disclose their breakage recognition policy or (b) they disclosed their breakage recognition policy and recognized breakage but did not disclose any breakage amounts. From the remaining 74 firms, an additional 16 firms were rejected because of incomplete quarterly breakage amounts (e.g., some firms reported only annual breakage values). The resulting 58 firms have combined 2010 total annual sales of roughly $200 billion and employ almost 1.4 million people. An overall profile of the final 58 firms is presented in Table 4.

Table 4: ***Retailer Characteristics***

Segment/Company Profile		
Line of Trade	Number of Firms	
Apparel and Accessory	22	38%
Building Material, Hardware, and Garden Supply	2	3%
Eating and Drinking	16	28%
Food Stores	2	3%
Home Furniture, Furnishings, and Equipment	4	7%
Miscellaneous Retail	12	21%
Total	58	100%
Geographic Region[2]		
Midwest	9	16%
Northeast	11	19%
South	21	36%
West	17	29%
Total	58	100%

[2] Geographic regions are defined by the US Census Bureau (www.census.gov). The Northeast is comprised of ME, NH, VT, MA, RI, CT, NY, PA, and NJ; the South is comprised of DE, MD, WV, VA, NC, SC, KY, TN, GA, FL, AL, MS, AR, LA, OK, and TX; the Midwest is encompasses OH, MI, IN, IL, WI, MN, IA, MO, ND, SD, NE, and KS; and the West includes MT, ID, WY, CO, NM, UT, AZ, NV, WA, OR, and CA. No firms were headquartered in Alaska or Hawaii.

Table 4: ***Retailer Characteristics (Continued)***

External Auditor		
Deloitte	13	22%
Ernst and Young	16	28%
KPMG	16	28%
PwC	8	14%
Other	5	8%
Total	58	100%

Financial Profile	
Avg. Market Capitalization (2011) ($Millions)	$2,778
Avg. Annual Sales (2010) ($ Millions)	$3,622
Avg. Annual Operating Income (2010) ($ Millions)	$242
Avg. Annual Net Profit Margin (2010)	2%
Avg. Number of Employees	23,830
Firms Disclosing & Recognizing Gift Card Breakage	45
Firms Disclosing but Recognizing $0 Gift Card Breakage	13

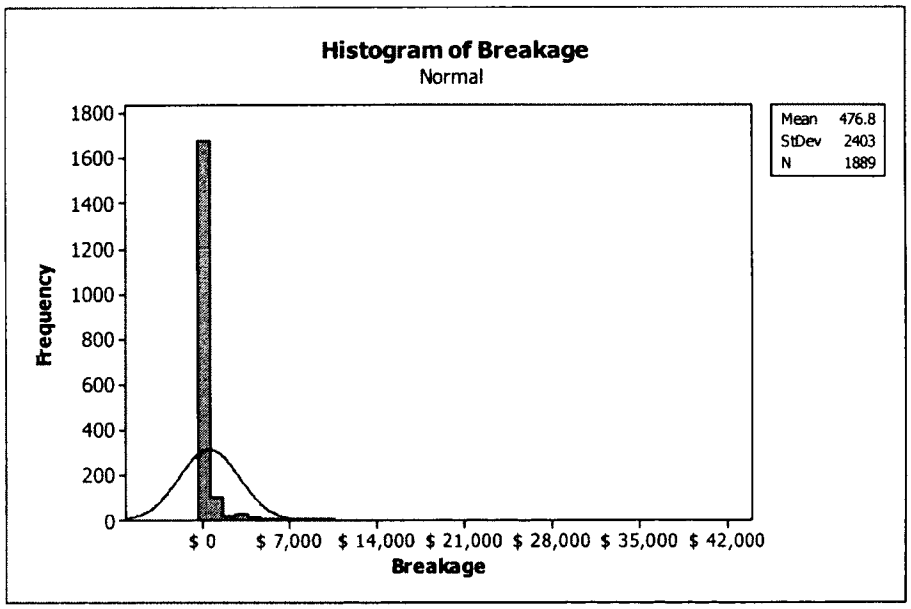
4.1.1 Gift Card Breakage.

This section examines the dependent variable BREAKAGE. Breakage amounts for the 58 firms were collected by quarter from the SEC's EDGAR database for the fiscal period 2002-2011 resulting in 1,889 quarterly observations. 10-Q and 10-K reports were queried for breakage activity by searching for key words such as "breakage," "unredeemed gift cards," "stored value cards," or "gift card." Not every firm recognized breakage every quarter; in fact, 13 firms did not recognize breakage at all and the first firm to recognize breakage in the sample did not do so until the fourth quarter of 2005. As such, only 559 quarterly observations have breakage values other than $0. The data is

ratio-level data. The histogram in Figure 2 reflects positively skewed breakage data; a high kurtosis is indicated by the peaked distribution.

The author checked for univariate outliers; 13 quarterly observations were identified as outliers within the sample because they were greater than four standard deviations from the mean (Hair, Black, Babin, Anderson, & Tatham, 2006); using four standard deviations was acceptable because of the large sample size in this study (Hair et al, 2006). Upon review, the outliers were from two firms that were the largest in the sample with annual revenues in excess of $50 billion each. While these outliers have the potential to be problematic because of their extraordinary nature, the researcher opted to retain them because they represent valid segments of the retail population; notably, they represent big box stores which have the potential for large unredeemed gift card balances. Plus, retaining the outliers ensured generalizability of the results.

Figure 2: ***Histogram of Breakage ($000)***



Total annual breakage for all firms during the sample time frame grew from nil in 2002 to $155,768,000 in 2011, with a peak amount of $194,337,000 in 2010. Average breakage recognized by any one firm in a quarter grew from nil in 2002 to $1,484,000 in 2011. The highest quarterly breakage recognized by one firm is $43,000,000; the lowest is ($281,000) which appears to be the result of one firm's correction to previously recognized breakage income. Figure 3 displays the total annual and average quarterly breakage for the 45 firms recognizing breakage in the sample.

Figure 3: ***Breakage by Year (2002-2011)***

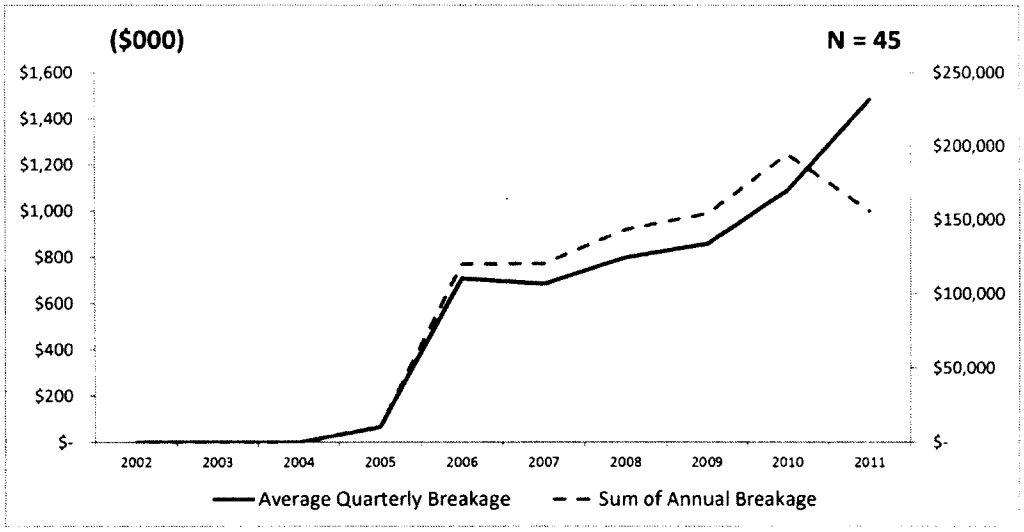


Table 5 summarizes quarterly breakage across all six retail lines of trade. The Building Material and Home Furniture/Furnishings segments have the largest mean quarterly breakage because the data includes retailers with annual sales in excess of $50 billion. The mean quarterly breakage amount is $477,000; among firms recognizing breakage, the mean quarterly breakage value is $604,000.

Table 5: *Breakage by Line of Trade*

($000)	Total Sample			Firms (N=45) Recognizing Breakage		
	*N**	*M*	*SD*	*N**	*M*	*SD*
Total – All Lines of Trade	1,889	$477	$2,403	1,492	$604	$2,690
Apparel and Accessory	706	251	912	605	293	979
Building Material, Hardware, and Garden Supply	72	3,500	6,371	72	3,500	6,371
Eating and Drinking	497	308	1,064	422	363	1,146
Food Stores	68	34	137	68	34	137
Home Furniture, Furnishings, and Equipment	146	2,033	6,275	109	2,723	7,140
Miscellaneous Retail	400	48	204	216	88	271

* *Firm quarters*

4.1.2 Other Select Variables.

This section considers independent variables and other key data that summarize the study's data well.

4.1.2.1 CEO Stock Options % of Total Compensation.

This segment examines variables related to CEO pay, including OPTIONS, TCOMP, and CEOPAYOPTNS%. Annual compensation data for each firm was collected at the CEO level for the period 2001-2011[3] resulting in 554 unique observations. The data was sourced from the SEC's EDGAR database by querying annual proxy statements (Form DEF14A), prospectuses, and registration statements (Form S-1) and searching for the compensation summary discussion and/or table. The data collected consisted of Salary, Bonus (annual and long-term incentive plans) and Stock Options. Of note, the value of options (OPTIONS) are based on the compensation cost for financial reporting

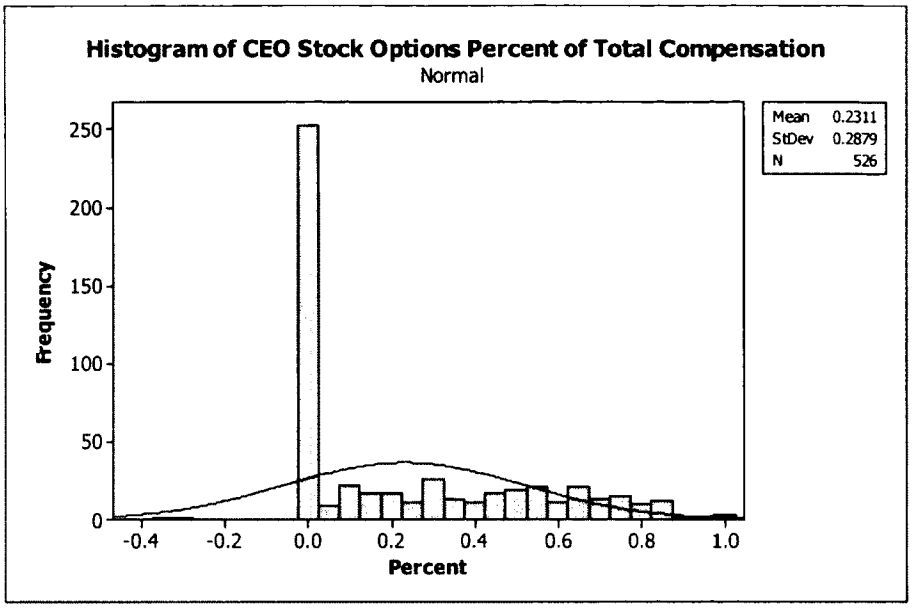
[3] Compensation data was collected for an eleven year period, starting in 2001, to accommodate lags between stock option grant and vesting dates.

purposes under SFAS 123(R); for years prior to 2006, the option value is the grant date present value as determined by the Black-Scholes option pricing model.

There were no missing values within the compensation data; however, occasionally, a change in CEO during the year or co-CEOs resulted in multiple compensation values for a firm in a year. To correct for this, the compensation amounts for each CEO were averaged and the resulting average was stored; this accommodation reduced the number of annual observations from 554 to 535.

CEO stock options as a percent of total compensation was calculated by year and stored as CEOPAYOPTNS%. Total compensation (TCOMP) represents base salary, bonuses, and option values. There were 9 instances where a CEO received no salary, bonuses, or options in a given year. These occurrences were kept in the dataset even though CEOPAYOPTNS% could not be calculated. However, this reduced the number of annual observations with a calculated value to 526. All variables described in this section are ratio-level data. The histogram in figure 4 reflects positively skewed data; a negative kurtosis is reflected by the wide distribution. A univariate identification of outliers did not reveal any values with a standard score 4.0 or greater.

Figure 4: ***Histogram of CEOPAYOPTNS%***



4.1.2.2 EPS Forecast Error Related Variables.

This section examines the variables related to EPS forecast errors, including RE, XRE, AF, FE%, XFE%, MISSEDEPS, and MISSEDEPS_XBRKG. Actual reported EPS by quarter (RE) was obtained from Thomson One for the period 2002-2011; this value was adjusted for after-tax breakage by the researcher to determine actual reported EPS by quarter without breakage (XRE). Final mean analysts' EPS forecasts were sourced from multiple locations (e.g., Thomson One, cnbc.com, RTTNews.com, tdameritrade.com, etc...), but cross-checked to ensure accuracy; adjustments for stock-splits were made as needed to align the forecasts to split-adjusted values from Thomson One. A forecast error (FE%) and a forecast error without breakage (XFE%) were determined by the author by taking the difference between the actual EPS value and the mean analyst forecast and dividing this difference by the absolute value of the mean analyst forecast.

The dataset consisted of 1,889 quarterly observations for actual reported EPS and actual reported EPS without breakage. 1,176 quarterly mean analyst EPS forecasts were obtained during the subject period; the lack of mean forecasts was primarily due to limited availability of estimates prior to 2005 or to retailers that were too small for analyst coverage. FE% and XFE% were calculated for 1,169 quarters because there were 6 instances where the mean estimate was zero, and as such no forecast error percent could be determined. Missing values were ignored because the number of cases with no missing data was sufficient for the selected analysis techniques (Hair et al., 2006). The missing analysts' forecasts therefore did not present significant issues.

A univariate inspection for outliers on FE% revealed 21 instances where the forecast error was greater than four standard deviations from the mean. Table 6 provides a profile of the identified outliers; in the majority of cases, outlying forecasts errors were generated because the mean analyst EPS forecast was small relative to the actual reported EPS. In nine of these cases, breakage was recognized by the retailer; as such, the researcher opted to retain the outlier because it was relevant to the objective of the research. The remaining outliers (12) were omitted because they occurred either before breakage recognition was initiated by an individual retailer or because the observation related to a firm that had not recognized breakage at all; therefore, the observations were not salient to the research objectives.

Table 6: ***Forecast Error (FE%) Outliers***

Observation		Mean Analyst EPS Forecast	Actual EPS	Variance	Forecast Error
1	*	0.02	0.20	0.18	900%
2	*	(0.01)	0.34	0.35	3500%
3	*	(0.05)	(0.38)	(0.33)	(660%)
4		0.01	0.12	0.11	1100%
5	*	0.03	(0.10)	(0.13)	(433%)
6	*	(0.14)	(0.75)	(0.61)	(436%)
7	*	(0.01)	(0.23)	(0.22)	(2200%)
8	*	(0.02)	(1.69)	(1.67)	(8350%)
9	*	0.01	(0.04)	(0.05)	(500%)
10		(0.01)	0.10	0.11	1100%
11		(0.05)	(0.33)	(0.28)	(560%)
12	*	(0.03)	(0.15)	(0.12)	(400%)
13		0.02	(0.20)	(0.22)	(1100%)
14		(0.04)	0.17	0.21	525%
15		0.02	0.13	0.11	550%
16		0.01	(0.05)	(0.06)	(600%)
17		0.01	(0.14)	(0.15)	(1500%)
18		(0.03)	(0.20)	(0.23)	(767%)
19		(0.01)	0.04	0.05	500%
20		(0.01)	(0.07)	(0.06)	(600%)
21		0.02	0.13	0.11	550%

** Indicates breakage recognized in the quarter; the observation was retained*

Figures 5 and 6 provide histograms of FE% and XFE%, respectively. Both variables are negatively skewed and demonstrate high kurtosis. RE, XRE, AF, FE%, and XFE% are continuous data.

Figure 5: ***Histogram of Forecast Error % (FE%)***

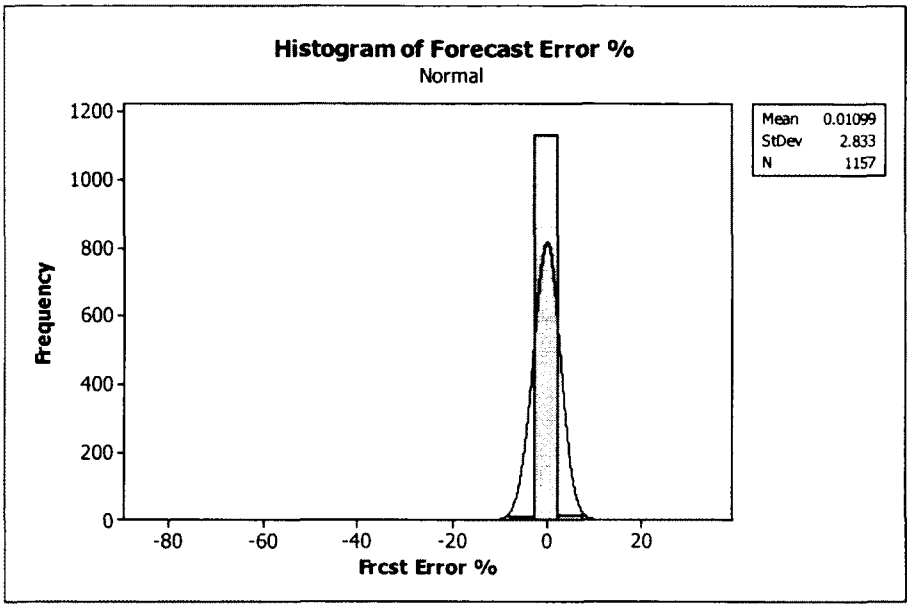
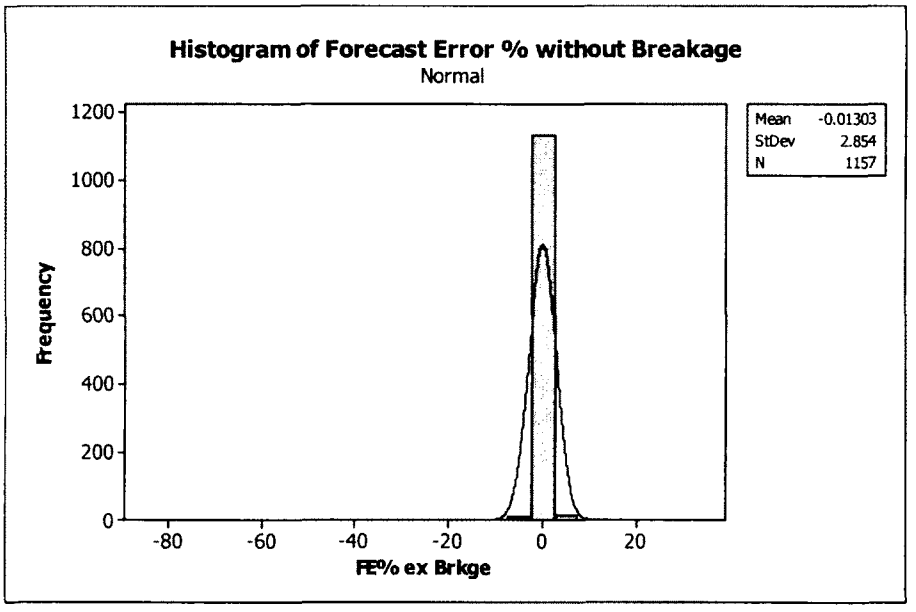


Figure 6: ***Histogram of Forecast Error without Breakage (XFE%)***



Finally, the researcher determined MISSEDEPS and MISSEDEPS_XBRKG for each quarterly observation by comparing RE to AF and by comparing XRE to AF, respectively. A "1" was assigned anytime the difference between RE and AF or XRE

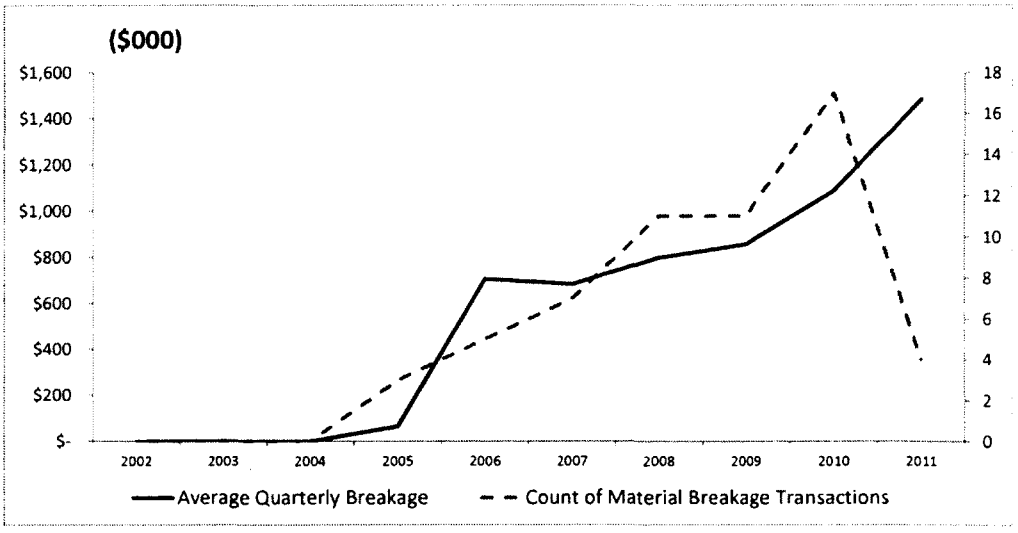
and AF was less than zero, implying that a firm would have missed the mean analyst forecast. Both MISSEDEPS and MISSEDEPS_XBRKG are dichotomous variables.

4.1.2.3 Materiality.

This section examines the variable MATERIAL. To compute the variable MATERIAL, quarterly sales values were obtained from Thomson One by firm for the period 2002-2011; the researcher computed MATERIAL by dividing breakage by the difference between sales and breakage, resulting in 1,889 quarterly observations. All values are continuous in nature.

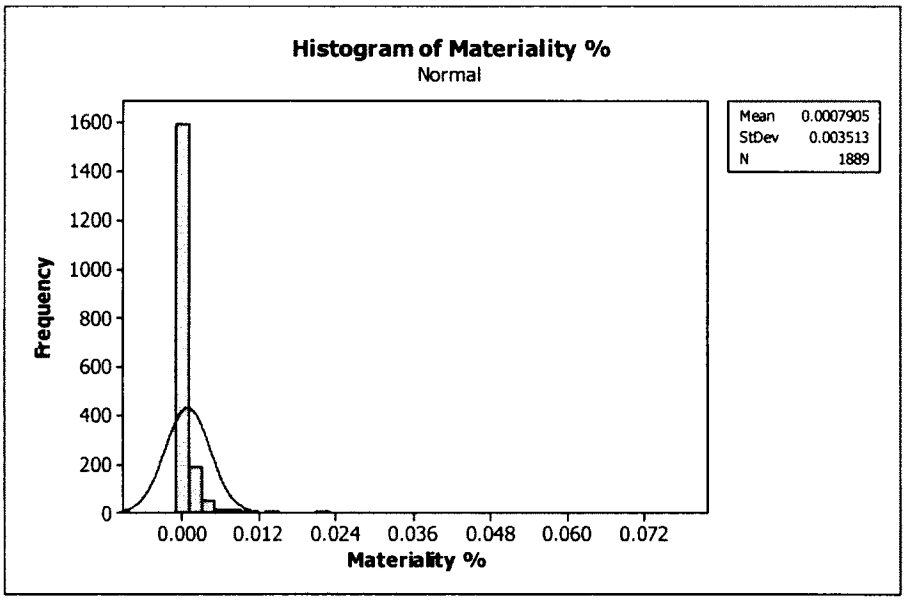
Breakage was considered material if it was greater than ½% of revenue. Of the 1,889 quarterly observations, breakage was material in 58 (3.1%) instances. More importantly, of the 559 quarters where breakage was actually recognized, breakage recognition transactions were material 10.4% of the time. Figure 7 compares average quarterly breakage against the total number of material transactions by year; there were three material transactions in 2005, rising to a high of 17 in 2010.

Figure 7: ***Breakage ($) vs. No. of Material Transactions by Year (2002-2011)***



Seventeen quarterly observations of the total 1,889 observations were identified as outliers (greater than four standard deviations). The outliers were a result of the large number of data points around 0%. Narrowing the univariate review to breakage-recognizing firms (n = 45) and to only those quarters including and following an initial breakage transaction by a firm (n = 594), 6 outliers were identified. The author maintained these outliers since large material transactions were relevant to this study's research objectives in that they represented both potential earnings management by retailers and the discretionary nature of the gift card transaction. A histogram of materiality percentage is presented in Figure 8.

Figure 8: ***Histogram of the Relative Size of the Breakage Transaction***



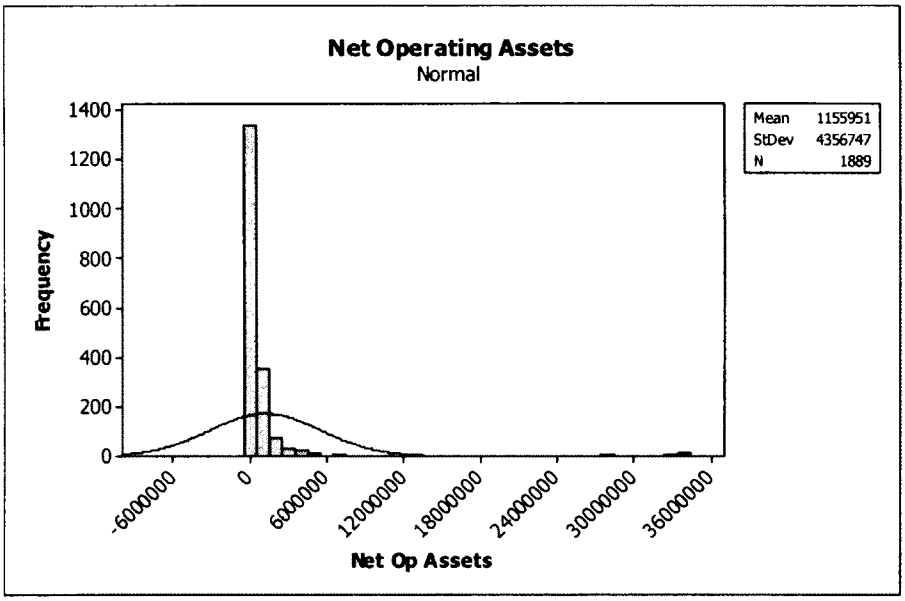
4.1.2.4 Net Operating Assets.

This section examines the variables related to net operating assets, including NETOPASSETS, RNOA, and RNOA_XBRKG. Quarterly balance sheet values by firm for the period 2002-2011 were compiled from Thomson One. Net Operating Assets for

1,889 quarters was determined by summing cash, accounts receivable (net of allowances), inventory, and property/plant/equipment (net of depreciation) and subtracting accounts payable. One quarterly observation had to be imputed by mean substitution due to incomplete quarterly data.

A histogram of Net Operating Assets is presented in Figure 9; 36 outliers, all relating to one "big-box" retailer in the sample, were maintained because of their representative nature of a segment of the population. The histogram reflects positively skewed data; a high kurtosis is indicated by a peaked distribution.

Figure 9: ***Histogram of Net Operating Assets ($000)***



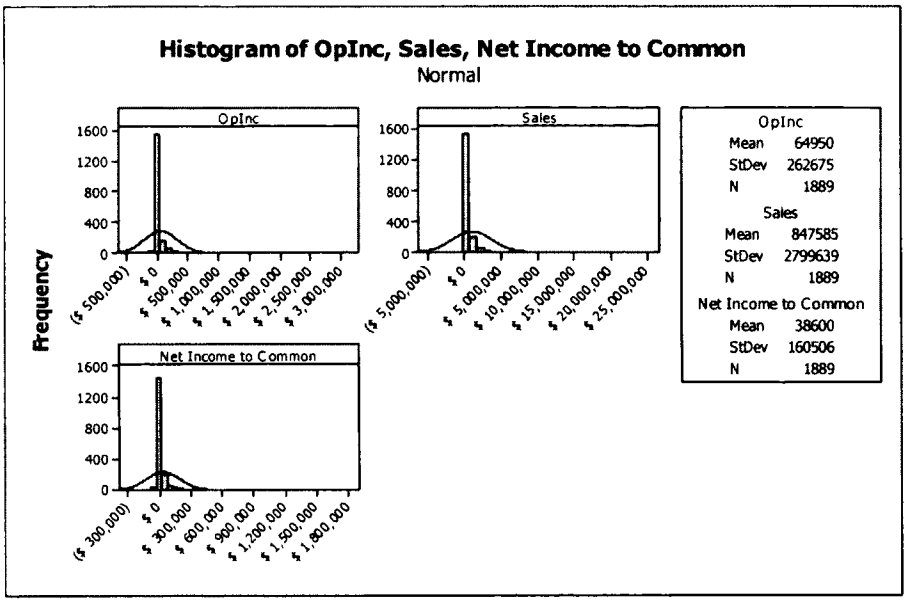
The researcher calculated quarterly returns on net operating assets (RNOA) for each retailer by multiplying operating profit margin by asset turnover. 4 quarterly observations could not be calculated due to zero sales (i.e., a divide by zero error). Three outliers (greater than four standard deviations) were retained to ensure generalizability of

the results. RNOA without breakage (RNOA_XBRKG) was also determined by the researcher. All data described in this section is ratio-level data.

4.1.2.5 Sales and Profit Margins.

This section examines the variables related to net operating assets, including SALES, OPINC, NETINC, OPPRFTMRG, SALES_XBRKG, OPINC_XBRKG, NTPRFTMRGN, and NPM_XBRKG. Quarterly sales (SALES), operating income (OPINC), and net income available to common shareholders excluding extraordinary items (NETINC) were obtained from Thomson One, resulting in 1,889 quarterly observations for each variable. There were no missing periods. Similar to BREAKAGE, outliers within SALES, OPINC, and NETINC were from the two largest firms in the sample. Again, the researcher opted to retain them because they represented valid segments of the retail population; notably, they represented "big box" stores which have the potential for large unredeemed gift card balances. The histogram in Figure 10 indicates that all three variables are positively skewed with high kurtosis.

Figure 10: ***Histograms of Operating Incomes, Sales, and Net Incomes ($000)***



The author calculated OPPRFTMRG, SALES_XBRKG, OPINC_XBRKG, NTPRFTMRGN, and NPM_XBRKG. In four instances, OPPRFTMRG and NTPRFTMRGN could not be calculated because of a zero value in SALES. NPM_XBRKG was calculated using after-tax breakage values. Finally, all variables described in this section are continuous in nature.

4.2 Descriptive Statistics.

Table 7 presents the descriptive statistics for the variables of interest for the total sample of 1,889 firm quarters over the period 2002-2011. The descriptive results are segmented by firm-type; for reference, *Scenario B Firms* (n = 13) represent those firms that disclosed their breakage recognition policy, but did not actually recognize gift card breakage. In contrast, *Scenario E Firms* (n = 45) represent those firms that not only disclosed their breakage recognition policy, but also recognized and reported quarterly breakage amounts. The descriptive results are also shown using *as reported* data and *without breakage* data, where *as reported* is actual quarterly data from financial statements while *without breakage* is calculated data that excludes the impact of breakage from a retailer's quarterly results.

Table 7: *Descriptive Statistics*

Variable	*N*	*M*	*SD*	Min. Value	Median	Max. Value	Skewness	Kurtosis
Breakage ($000)								
As Reported	1,889	$477	$2,403	$(281)	-	$43,000	10.77	147.40
Scenario B Firms	397	-	-	-	-	-	*	*
Scenario E Firms	1,492	$604	$2,690	$(281)	-	$43,000	9.58	116.58
CEO Options/Total Compensation (%)								
As Reported	1,861	23.76%	0.290	-30.34%	8.19%	100.00%	0.84	(0.65)
Scenario B Firms	389	8.53%	0.195	-30.34%	0.00%	75.15%	2.09	3.76
Scenario E Firms	1,472	27.78%	0.298	0.00%	17.84%	100.00%	0.63	(0.97)
EPS Forecast Error (%)								
As Reported	1,157	1.10%	2.834	-8350.00%	2.70%	3500.00%	(20.94)	676.66
Scenario B Firms	154	3.25%	0.535	-200.00%	2.46%	400.00%	1.71	21.92
Scenario E Firms	1,003	0.77%	3.036	-8350.00%	2.78%	3500.00%	(19.64)	592.12
Without Breakage								
Scenario E Firms	1,003	-2.00%	3.059	-8400.00%	1.61%	3300.00%	(19.74)	584.41
Operating Profit Margin (%)								
As Reported	1,885	0.83%	1.564	-6576.91%	5.41%	1375.47%	(39.06)	1,660.26
Scenario B Firms	393	-3.21%	0.288	-295.21%	3.18%	33.43%	(5.26)	37.78
Scenario E Firms	1,492	1.90%	1.753	-6576.91%	5.77%	1375.47%	(35.15)	1,334.42
Without Breakage								
Scenario E Firms	1,492	1.79%	1.754	-6576.91%	5.72%	1375.47%	(35.14)	1,333.90

Variable	*N*	*M*	*SD*	Min. Value	Median	Max. Value	Skewness	Kurtosis
Net Profit Margin (%)								
As Reported	1,885	-1.14%	1.563	-6581.24%	3.36%	1371.34%	(39.26)	1,671.73
Scenario B Firms	393	-4.05%	0.274	-295.21%	1.96%	24.67%	(5.84)	45.16
Scenario E Firms	1,492	-0.37%	1.752	-6581.24%	3.56%	1371.34%	(35.28)	1,341.47
Without Breakage								
Scenario E Firms	1,492	-0.46%	1.752	-6581.24%	3.50%	1371.34%	(35.27)	1,341.10
Return on Net Operating Assets (%)								
As Reported	1,885	-11.80%	5.462	-23329.90%	3.90%	287.30%	(41.52)	1,766.80
Scenario B Firms	393	2.29%	0.112	-48.71%	3.04%	44.51%	(0.70)	3.14
Scenario E Firms	1,492	-15.50%	6.139	-23329.90%	4.00%	287.30%	(36.94)	1,398.64
Without Breakage								
Scenario E Firms	1,492	-15.60%	6.139	-23329.90%	4.00%	287.30%	(36.94)	1,398.64
Financial Ratios (As reported, Scenario E firms)								
Breakage/Operating Income (%)								
All firm quarters	1,483	0.62%	0.076	-81.40%	0.00%	96.45%	1.05	52.82
Quarters with breakage	550	1.67%	0.125	-81.40%	1.01%	96.45%	0.40	18.10
Breakage/Sales (%)								
All firm quarters	1,492	0.10%	0.004	-0.32%	0.00%	7.42%	10.06	140.70
Quarters with breakage	559	0.26%	0.006	-0.32%	0.11%	7.42%	6.53	58.04
Breakage/Net Operating Assets (%)								
All firm quarters	1,492	0.07%	0.003	-0.20%	0.00%	5.80%	10.39	151.00
Quarters with breakage	559	0.20%	0.004	-0.20%	0.07%	5.80%	6.72	61.98

The mean level of gift card breakage among all firms is $477,000 (median, $0), while the mean level of breakage among Scenario E firms is $604,000 (median, $0). The mean and median values reflect the fact that only 30% of the study's firm quarters have breakage values other than $0. The data is not normally distributed as is evidenced by both skewness/kurtosis values and the Anderson-Darling test statistic (AD = 546.648, p < .005), but the non-normal distribution is expected due to the discretionary nature of the breakage transaction.

Mean stock option compensation as a percent of total compensation is 23.76%. Like breakage, the CEO compensation data is not normally distributed (AD = 153.590, p < .005). The mean (median) percent for Scenario B firms is 8.53% (0%) and the mean (median) percent for Scenario E firms is 27.78% (17.84%). There is a statistically significant difference in median stock option compensation percent between Scenario B firms and Scenario E firms (H = 160.75, 1 $d.f.$, p = .000). A Kruskal-Wallis non-parametric test statistic is reported here because the data is not normally distributed and data transformations are not necessary when reporting descriptive results.

The mean (median) EPS forecast error for all firms in the sample is 1.10% (2.70%), implying that on average, retailers beat analysts' EPS projections. An interesting finding is that Scenario B firms exceed analysts' forecasts by 3.25% on average while Scenario E firms top analysts' projections by only 0.77% on average. More importantly, without breakage, Scenario E firms actually miss analysts' EPS estimates by 2.00% on average. The median forecast error for Scenario E firms is 2.78% with breakage and 1.61% without breakage, suggesting that an individual breakage transaction can affect EPS. The difference in median EPS forecast error with and without breakage

for Scenario E firms is significant ($U = 529524$, $Z = 2.044$, $p = .039$, $r = .05$); the Mann-Whitney non-parametric test statistic is reported here because the data is not normally distributed (As reported: $AD = 276.017$, $p < .005$; without breakage: $AD = 273.506$, $p < .005$).

Operating profit margins for all firms averaged 0.83% over the study's time frame; the median operating profit margin is 5.41%. The data is not normally distributed as is evidenced by both skewness/kurtosis values and the Anderson-Darling test statistic ($AD = 622.921$, $p < .005$). Interestingly, the mean (median) operating margin for Scenario B firms is -3.21% (3.18%) while the mean (median) operating margin for Scenario E firms is 1.90% (5.77%). According to the Kruskal-Wallis test statistic, the difference in medians between Scenario B and E firms is statistically significant ($H = 36.02$, 1 *d.f.*, $p = .000$), which suggests that Scenario E firms are more efficient at managing operating expenses than Scenario B firms. There is, however, no statistical significance in median operating profit margins among Scenario E firms with breakage (5.77%) and without breakage (5.72%) ($U = 1120954$, $Z = .337$, $p = .737$, $r = .01$).

Net profit margins for all firms averaged -1.14%; the median net profit margin was 3.36%, affirming that margins in the retail sector are generally low. The data is not normally distributed ($AD = 640.044$, $p < .005$). The mean (median) net profit margin for Scenario B firms is -4.05% (1.96%); the mean (median) net profit margin for Scenario E firms is -0.37% (3.56%). Consistent with the findings on operating profit margin, the difference in medians among Scenario B and E firms is significant ($H = 27.17$, 1 *d.f.*, $p = .000$), but the difference in medians for Scenario E firms with breakage (3.56%) and without breakage (3.50%) is not significant ($U = 1121134$, $Z = .344$, $p = .731$, $r = .01$).

The mean return on net operating assets is -11.80%; the data is not normally distributed ($AD = 701.436, p < .005$). The mean (median) percent for Scenario B firms are 2.29% (3.04%) and the mean (median) percent for Scenario E firms are -15.50% (4.00%). There is a statistically significant difference in median return on net operating assets between Scenario B firms and Scenario E firms ($H = 5.31$, 1 *d.f.*, $p = .021$), suggesting that Scenario E firms are in better financial shape than Scenario B firms. A Kruskal-Wallis non-parametric test statistic is expressed because the data is not normally distributed.

Finally, Table 7 presents three financial ratios that are relevant descriptors for firms recognizing breakage (i.e., Scenario E firms). First, mean (median) breakage as a percent of operating income is 0.62% (0%); however, in quarters where breakage is recognized, the mean (median) percent is 1.67% (1.01%). Second, mean (median) breakage as a percent of sales is 0.10% (0%); in quarters where breakage is recognized, the mean (median) percent is 0.26% (0.11%). Third, mean (median) breakage as a percent of net operating assets is 0.07% (0%); in quarters where breakage is recognized, the mean (median) percent is 0.20% (0.07%). Collectively, these results provide insight into the relative size of breakage among retailers recognizing breakage. More importantly, for all three financial ratios, the change in the median percentage value due to breakage is statistically significant. Table 8 summarizes the Kruskal-Wallis test statistic for each financial ratio; for each ratio, the median financial ratio for quarters when breakage was recognized was compared to the respective median financial ratio (0%) for quarters when breakage was not recognized. A Kruskal-Wallis non-parametric

test is utilized because the data is not normally distributed as evidenced by the skewness/kurtosis measures.

Table 8: ***Test of Significance on Financial Ratio Medians***

Variable	*N*	Median	Kruskal-Wallis Test Statistics
Breakage/Operating Income (%)			
Quarters with breakage	550	1.01%	438.83*
Breakage/Sales (%)			
Quarters with breakage	559	0.11%	1,338.01*
Breakage/Net Operating Assets (%)			
Quarters with breakage	559	0.07%	1,338.01*

** 1 d.f., p = .000*

4.2.1 Transformations.

Because of significant violations of normality across the dependent and independent variables, the researcher attempted data transformations to improve normality. Common transformations to correct for skew and kurtosis, including the reciprocal, the log, the square root, and the square, did not significantly alter the distributions. Transformations of the data using a Johnson transformation ($p = .10$) also provided insufficient remedies. Therefore, the lack of normality of the data was accepted. Importantly, a non-normal distribution of breakage is acceptable because of the discretionary nature of the breakage recognition transaction.

4.3 Results – Individual Hypotheses

In this section, the author reports the statistical results for the eight hypotheses developed in Section 2.5. When appropriate, data complexities causing variations from the methodology outlined in Chapter 3 are discussed.

4.3.1 Hypothesis One – Compensation Motivation.

H_1 – There is no statistically significant evidence that the proportion of CEO pay from stock options influences the extent to which retailers use gift card breakage.

Preparing the data for H_1 required a three-step process. First, quarterly breakage (BREAKAGE) and sales (SALES) values were obtained from SEC's EDGAR and Thomson One, respectively, resulting in 1,889 firm quarters for each variable. Breakage as a percent of sales (BRKG/SALES%) was calculated for each firm quarter. BRKG/SALES% serves as a proxy for the level of breakage. Four firm quarters could not be determined because of zero values in SALES, which reduced the number of quarterly observations to 1,885.

Second, CEO stock options as a percent of total compensation (CEOPAYOPTNS%) was prepared and determined as described in Section 4.1.2.1. Because H_1 hypothesizes that performance-based measures are tied to quarterly financial results, the annual compensation values by firm were allocated to quarters; for example, if a CEO earned options valued at $100 and total compensation (salary + bonus + options) of $200 in a given year, a CEOPAYOPTNS% of 50% was assigned to each of the four quarters within that year. The allocation to quarters resulted in 1,861 firm quarters.

Finally, each CEOPAYOPTNS% value was matched to a BRKG/SALES% value. H_1 controls for various stock-option vesting dates by lagging CEOPAYOPTNS% one year. Therefore, prior year CEOPAYOPTNS% is matched against current year BRKG/SALES% at the firm quarter level. For example, 1Q 2010 CEOPAYOPTNS% was paired with the 1Q 2011 BRKG/SALES%.

Table 9 presents descriptive statistics for both BRKG/SALES% and CEOPAYOPTNS%. The data is presented by firm type because the hypothesis includes all firms within the sample. As a reminder, Scenario B Firms (n = 13) represent those firms that disclosed their breakage recognition policy, but did not actually recognize gift card breakage. In contrast, Scenario E Firms (n = 45) represent those firms that not only disclosed their breakage recognition policy, but also recognized and reported quarterly breakage.

Table 9: ***Descriptive Statistics for Hypothesis 1***

Variable	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
Breakage/Sales%	1,885	0.08%	0.003	-0.32%	0.00%	7.42%	11.24	176.07
Scenario B Firms	393	0.00%	0.000	0.00%	0.00%	0.00%	*	*
Scenario E Firms	1,492	0.10%	0.004	-0.32%	0.00%	7.42%	10.06	140.70
CEO Options/Total Compensation	1,861	23.76%	0.290	-30.34%	8.19%	100.00%	0.84	(0.65)
Scenario B Firms	389	8.53%	0.195	-30.34%	0.00%	75.15%	2.09	3.76
Scenario E Firms	1,472	27.78%	0.298	0.00%	17.84%	100.00%	0.63	(0.97)

* *Firm quarters*

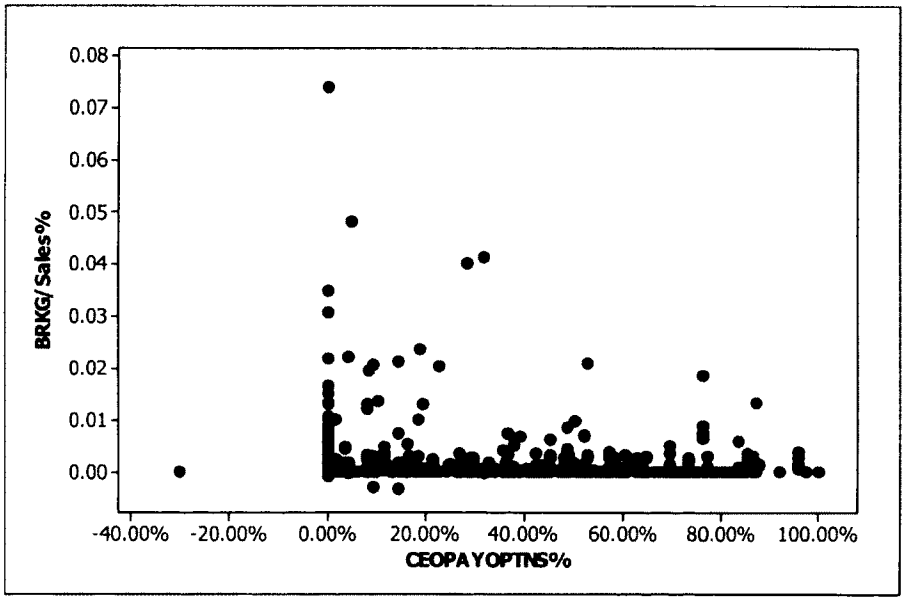
For the entire sample, mean (median) stock option compensation as a percent of total compensation is 23.76% (8.19%). The data is moderately skewed but platykurtic. The mean (median) value of CEOPAYOPTNS% for Scenario B Firms is 8.53% (0%) whereas the mean (median) value for Scenario E firms is 27.78% (17.84%). In similar

fashion, the mean (median) value of breakage as a percentage of sales for the entire sample is 0.08% (0%); for firms recognizing breakage, the mean (median) is 0.10% (0%). The BRKG/SALES% data is positively skewed and leptokurtic.

Both BRKG/SALES% ($AD = 479.03, p < .005$) and CEOPAYOPTNS% ($AD = 153.59, p < .005$) do not follow a normal distribution. Attempts at variable transformations were unsuccessful.

A requirement of ordinary least squares regression is the existence of a linear relationship between the dependent and independent variable (Hanke & Wichern, 2009). Figure 11 displays a scatterplot of BRKG/SALES% and CEOPAYOPTNS%; the plot indicates no relationship between the two variables ($r = -0.01, p = .736$). Violations of linearity of this magnitude imply that the regression model's coefficient of determination (r^2) will be zero meaning that *none* of the variability in the dependent variable above the average is explained by the independent variable (Hanke & Wichern, 2009). Therefore, the proposed regression model outlined in Section 3.4.1 was ineffectual.

Figure 11: ***Scatterplot of BRKG/SALES% and CEOPAYOPTNS%***



In response, two significant modifications of the regression model were explored to improve the model's viability in detecting a relationship between breakage and CEO compensation. First, the researcher attempted to control for vesting dates by changing the lag between the receipt of compensation and breakage recognition. Table 10 reports the Pearson correlation results of changing the lag from 1 year to 2 years and 3 years, respectively. In every instance, the results indicated no significant relationship between breakage recognition and CEO compensation. Further attempts to modify the lag were abandoned because the results continued to show no relationship between the two variables.

Table 10: ***Pearson's Coefficient (r) for Varying Lags of CEOPAYOPTNS%***

Lag of CEOPAYOPTNS%	*N**	Pearson's (r)
1-year lag	1,857	(0.008) *p* = .736
2-year lag	1,642	0.034 *p* = .166
3-year lag	1,414	0.006 *p* = .832

* *Firm quarters*

Second, the researcher attempted to control for firm type by incorporating a dummy variable into the regression model that allowed the model to parse the results between Scenario B firms and Scenario E firms. A "1" was assigned to Scenario E firms; a "0" was assigned to Scenario B firms. The results of the OLS regression are shown in Table 11; the data is presented by various lags between receipt of CEO compensation and breakage recognition. Significance ($p < .05$) of CEOPAYOPTNS% was not evident in

any of the lagged scenarios even when controlled for firm type. Complete results are shown in Appendix A.

Table 11: ***Regression Output with 'Firm Type' Control Variable***

Variable	*b*	*β*[4]	*SE b*	*t-stat*	*p-value*	
1-year lag						
Constant	.00004		.00017	0.25	0.805	
CEOPAYOPTNS%	(.00050)	(.04303)	.00028	(1.78)	0.075	
Firm Type	.00108	.13045	.00020	5.43	0.000	***
2-year lag						
Constant	.00000		.00020	0.01	0.994	
CEOPAYOPTNS%	(.00002)	(.00175)	.00031	(0.06)	0.950	
Firm Type	.00110	.13286	.00023	4.84	0.000	***
3-year lag						
Constant	.00003		.00021	0.14	0.887	
CEOPAYOPTNS%	(.00047)	(.04201)	.00033	(1.40)	0.161	
Firm Type	.00130	.15702	.00025	5.20	0.000	***

1-year lag: (Adj. R^2 = .015, $F(2,1854)$ = 14.81, p = .000);
2-year lag: (Adj. R^2 = .014, $F(2,1639)$ = 12.70, p = .000);
3-year lag: (Adj. R^2 = .017, $F(2,1411)$ = 13.52, p = .000).
*$p < .05$. **$p < .01$. ***$p < .001$.

In sum, there is no support for the hypothesis that the proportion of CEO pay from stock options influences the extent to which retailers use gift card breakage.

4.3.2 Hypothesis Two – Modifying Income Motivation.

H_2 – There is no statistically significant evidence that breakage is used by retailers to smooth earnings.

The research methodology described in Section 3.4.2 examines hypotheses two through three queries:

[4] Following Bring (1994), the standardized coefficient is calculated by multiplying the unstandardized coefficient by the ratio of the standard deviations for the independent and dependent variables.

1. Is the retailer using breakage to smooth earnings?
2. Is the retailer an income smoother, in general, over the study's 10-year time frame?
3. Was the retailer an income smoother prior to breakage recognition?

The last two questions control for the unlikely event of a spurious relationship between operating income and breakage under question one and indirectly point to whether a retailer's behavior changed upon its decision to recognize breakage.

Following Eckel (1981), the H_2 hypothesis is evaluated using annual data. Quarterly sales (SALES) and operating income (OPINC) data for all firms in the sample were obtained from Thomson One for the period 2002-2011. For both variables, the quarterly data was summed by year, resulting in 462 firm years[5]. One-period (annual) changes were calculated for both variables by subtracting a prior year from a current year ($y_n - y_{n-1}$). One-period changes were not calculated for a retailer's first firm year in the dataset (e.g., 2002) because no prior year existed; this reduced the total number of firm years for all firms to 407.

In similar fashion, quarterly breakage (BREAKAGE) data for the firms recognizing breakage in the sample was obtained from EDGAR for the period 2005-2012; no breakage was recognized prior to 2005. The data was summed by year, resulting in 167 firm years[6]. One-period (annual) changes were calculated for BREAKAGE by subtracting a prior year from a current year ($y_n - y_{n-1}$).

[5] Out of 472 firm years; 10 firm years were dropped from the analysis because of incomplete quarterly data.
[6] Out of 172 total firm years; 5 firm years were dropped from the analysis because of incomplete quarterly data. This was primarily due to the collection of 1Q 2012 breakage data as discussed in Footnote 1.

4.3.2.1 Is the retailer using breakage to smooth earnings?

One hundred sixty seven annual changes in BREAKAGE and the respective annual changes in OPINC were loaded to Minitab®. The mean and standard deviation of each variable were calculated by firm and downloaded to Excel. The coefficient of variation (CV) for the change in BREAKAGE ($CV_{\Delta B}$) and the change in OPINC ($CV_{\Delta I}$) were determined at the firm level by dividing each variable's standard deviation by its mean. In 7 instances, a CV could not be calculated because a firm's data consisted of only one annual change; these 7 firms (7 firm years) were removed from the dataset.

Next, an income-smoothing factor ($|CV_{\Delta I} \div CV_{\Delta B}|$) was calculated for each firm. In two instances, the income-smoothing factor could not be determined; these two firms (6 firm years) were deleted. The $\mu_{|CV\Delta I \div CV\Delta B|}$ and $\sigma_{|CV\Delta I \div CV\Delta B|}$ was computed for the dataset; these values served as proxies for the mean income-smoothing factor and standard deviation of the industry. Individual firms' income-smoothing factors were compared to the mean to determine outliers. Two firms were identified as outliers because their income-smoothing factor was greater than four standard deviations from the industry average (Hair et al., 2006); these 2 firms (10 firm years) were removed from the industry average because their income-smoothing factors were extraordinary observations. The final dataset consisted of 34 firms, or 144 firm years; the representative industry income-smoothing factor had a mean of 2.16.

Finally, Table 12 presents the results of the analytics employed to evaluate whether a retailer uses breakage to smooth earnings. In Step 1, twenty firms were identified as possible income smoothers; however of those twenty firms, none were identified in Step 2 as an artificial income smoother through breakage recognition as

none had an income-smoothing factor more than one standard deviation smaller than the industry average. Therefore, there is no support for the hypothesis that breakage is used to manage earnings.

Table 12: ***Income-Smoothing via Breakage***

Firm ID	$\lvert CV_{\Delta B} \rvert$	$\lvert CV_{\Delta I} \rvert$	Step 1: $CV_{\Delta B} > CV_{\Delta I}$	$\lvert CV_{\Delta I} \div CV_{\Delta B} \rvert$	Step 2: $\lvert CV_{\Delta I} \div CV_{\Delta B} \rvert > -1\sigma_{Industry}$
1	5.87	2.58	**	0.44	N/A
2	2.91	14.80		5.08	N/A
3	30.14	0.22	**	0.01	N/A
4	3.52	1.02	**	0.29	N/A
5	26.18	8.13	**	0.31	N/A
6	18.94	1.83	**	0.10	N/A
7	3.86	3.81	**	0.99	N/A
8	2.07	2.88		1.39	N/A
9	8.90	2.10	**	0.24	N/A
10	1.81	1.53	**	0.85	N/A
11	3.06	0.70	**	0.23	N/A
12	43.56	0.71	**	0.02	N/A
13	0.82	8.39		10.19	N/A
14	1.91	8.97		4.70	N/A
15	4.61	0.64	**	0.14	N/A
16	1.51	1.96		1.30	N/A
17	5.94	2.25	**	0.38	N/A
18	0.75	3.13		4.18	N/A
19	15.67	0.43	**	0.03	N/A
20	2.35	29.20		12.43	N/A
21	28.60	2.43	**	0.08	N/A
22	3.07	5.17		1.69	N/A
23	2.83	0.92	**	0.33	N/A
24	8.93	1.29	**	0.14	N/A
25	3.94	8.08		2.05	N/A
26	3.26	39.80		12.22	N/A
27	44.12	22.37	**	0.51	N/A
28	6.44	7.37		1.14	N/A
29	4.64	11.75		2.53	N/A
30	2.95	8.77		2.98	N/A
31	0.71	3.91		5.52	N/A
32	4.07	2.74	**	0.67	N/A
33	24.82	1.78	**	0.07	N/A
34	7.97	2.88	**	0.36	N/A

** *Possible income smoother (step 1)*

† *Income-smoothing behavior indicating an artificial income smoother (step 2)*

Even though no statistically significant evidence of income-smoothing through breakage was found in Section 4.3.2.1, the researcher investigated the remaining two

queries posed in the research methodology. These are discussed in Sections 4.3.2.2 and 4.3.3.2, respectively.

4.3.2.2 In general, is the retailer an income smoother?

This section examines whether a retailer is, in general, an income smoother, regardless of their breakage activity. Of note, this dataset also includes both 10 years of data and firms that disclosed their breakage recognition policies, but had not actually recognized breakage to date. This modification was made to see if there was smoothing activity across a larger pool of retailers.

Four hundred and seven annual changes in SALES and the respective annual changes in OPINC were loaded to Minitab®. The mean and standard deviation of SALES and OPINC were calculated by firm and downloaded to Excel. The coefficient of variation (CV) for the change in SALES ($CV_{\Delta S}$) and the change in OPINC ($CV_{\Delta I}$) were determined at the firm level by dividing each variable's standard deviation by its mean. In one instance, a CV could not be calculated because a firm's data consisted of only one annual change; this one firm (1 firm year) was removed from the dataset.

Next, an income-smoothing factor ($|CV_{\Delta I} \div CV_{\Delta S}|$) was calculated for each firm. The $\mu_{|CV\Delta I \div CV\Delta S|}$ and $\sigma_{|CV\Delta I \div CV\Delta S|}$ was computed for the dataset; again, these values served as proxies for the mean income-smoothing factor and standard deviation of the industry. Individual firms' income-smoothing factors were compared to the mean to determine outliers. Four firms were identified as outliers (greater than 4 standard deviations) (Hair et al., 2006); these firms (29 firm years) were removed from the industry average. The final dataset consisted of 52 firms, or 377 firm years; the representative industry income-smoothing factor had a mean of 4.94. Ten firms were

identified as possible income smoothers (Step 1), but none of these firms had an income-smoothing factor more than one standard deviation smaller than the industry average (Step 2). Therefore, there is no statistically significant evidence of income-smoothing by any firms.

4.3.2.3 Was a retailer an income smoother prior to breakage recognition?

This section examines whether a retailer was an artificial income smoother prior to its decision to recognize breakage. Here, only firms which eventually recognized breakage during the sample time frame are examined.

One hundred sixty annual changes in SALES and the respective annual changes in OPINC for years prior to the first year an individual firm recognized breakage were loaded to Minitab®. The mean and standard deviation of SALES and OPINC were calculated by firm and downloaded to Excel. The coefficient of variation (CV) for the change in SALES ($CV_{\Delta S}$) and the change in OPINC ($CV_{\Delta I}$) were calculated but in five instances, a CV could not be determined because a firm's data consisted of only one annual change; these five firms (5 firm years) were removed from the dataset.

Next, an income-smoothing factor ($|CV_{\Delta I} \div CV_{\Delta S}|$) was calculated for each firm. The $\mu_{|CV\Delta I \div CV\Delta S|}$ and $\sigma_{|CV\Delta I \div CV\Delta S|}$ was computed for the dataset; again, these values served as proxies for the mean income-smoothing factor and standard deviation of the industry. Individual firms' income-smoothing factors were compared to the mean to determine outliers. One firm was identified as an outlier (greater than 4 standard deviations) (Hair et al., 2006); this firm (7 firm years) was removed from the industry average. The final dataset consisted of 35 firms, or 148 firm years; the representative industry income-smoothing factor had a mean of 8.37. Twelve firms were identified as

possible income smoothers (Step 1), but none of these firms had an income-smoothing factor more than one standard deviation smaller than the industry average (Step 2). Therefore, once again, there is no statistically significant evidence of income-smoothing by any firms.

4.3.3 Hypothesis Three – Meeting Benchmarks Motivation.

H_3 – There is statistically significant evidence that retailers use breakage to meet analysts' consensus EPS forecasts.

For hypothesis H_3, the EPS forecast error data with breakage (FE%) and without breakage (XFE%) and the determination of whether a firm missed EPS consensus forecasts with breakage (MISSEDEPS) and without breakage (MISSEDEPS_XBRKG) was prepared and calculated as described in Section 4.1.2.2. Because hypothesis H_3 considers only those quarters when breakage was actually recognized by retailers, the dataset was limited to 559 firm quarters. Of the 559 firm quarters, a forecast error was determinable for only 529 firm quarters; the missing quarters were a result of mean estimates of zero, missing analyst EPS forecasts, or firms that were too small to receive analyst coverage. The researcher elected to take no action on the missing values because no available remedies to accommodate the missing data were applicable; in addition, the numbers of missing values were less than 10% of the total number of observations which Hair et al. (2006) suggests is acceptable for ignorable missing data. The remaining firm quarters were sufficient in number for the selected regression technique.

Table 13 provides descriptive statistics for BREAKAGE, EPS forecast error with breakage (FE%), and EPS forecast error without breakage (XFE%). The mean (median) FE% is -4.40% (2.30%) and the mean (median) XFE% is -9.70% (0.00%). The

distribution of both forecast errors is negatively skewed and leptokurtic. Attempts to improve normality through transformation failed; as such, the lack of normality of the data was therefore accepted.

Table 13: ***Descriptive Statistics for Forecast Error %***

Variable	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
Breakage ($)	559	1,611	4,209	(281)	300	43,000	5.97	44.58
Forecast Error (%)	529	-4.40%	4.15	-8350%	2.30%	3500%	-14.59	321.72
Forecast Error without Breakage (%)	529	-9.70%	4.18	-8400%	0.00%	3300%	-14.65	317.26

* *Firm quarters*

Retailers met/exceeded the mean EPS consensus forecast when recognizing breakage 75% of the time ($n = 398$); in contrast, retailers met/exceeded the EPS forecast only 63% of the time when they did not recognize breakage ($n = 337$)[7]. The difference in the proportion of meeting/exceeding the consensus forecast between the two scenarios is significant (*Fisher's exact test*, $p = .000$).

Least squares regression was used to test the null hypothesis; the linear regression model specified that the size of the difference in forecast error with and without breakage by firm and by quarter ($FE\%_{iq}$ - $XFE\%_{iq}$) was a function of whether a firm missed the consensus EPS forecast (MISSEDEPS_XBRKG). $FE\%_{iq}$ - $XFE\%_{iq}$ is a continuous variable; MISSEDEPS_XBRKG is a dichotomous variable. Regression with one categorical independent variable was an acceptable technique even though least squares

[7] These values are calculated based on 534 firm quarters. The difference in firm quarters (534 vs. 529) is a result of 5 firm quarters where the mean estimate was zero, and as such, no forecast error percent could be calculated. However, it was possible to determine whether a firm would have missed the consensus forecast in the same 5 firm quarters, and therefore, the additional firm quarters are included here.

regression typically requires interval or ratio scale independent data (see e.g., "Regression with Categorical Predictors," n.d.). Regression analysis was deemed sufficient to identify a statistically significant relationship as it was reasonable to assume that there was some positive association between differences in forecast errors and missing analysts' EPS projections.

Summarized results of the ordinary least squares regression are listed in

Table 14; complete results are shown in Appendix B. The regression equation is stated as:

$$\Delta Forecast\ Error = 0.0078 + 0.123(MISSEDEPS_{XBRKG})$$

The results of the regression indicated that the explanatory variable explained 1% of the variance in the dependent variable ($R^2 = .01$, $F(1, 527) = 6.52$, $p = .011$). MISSEDEPS_XBRKG significantly explained changes in the dependent variable, $t(528) = 2.55$, $p = .011$. The results demonstrated a significant, weak/negligible (magnitude), and positive (direction) correlation between the difference in forecast errors and missing the EPS consensus forecast ($r = .111$, $p = .011$). Based on the results, the predicted value for the difference in forecast error caused by breakage is .131 when a firm would have missed Earnings Per Share projections and the predicted value for the difference in forecast error caused by breakage is only .008 when a firm would not have missed Earnings Per Share projections.

Table 14: ***Regression Output - Hypothesis 3***

Variable	*b*	*β*[8]	*SE b*	*t-stat*	*p-value*	
Constant	0.008		0.029	0.27	0.788	
MISSEDEPS_XBRKG	0.123	0.112	0.048	2.55	0.011	**

Adj. $R^2 = .01$, $F(1, 527) = 6.52$, $p = .011$
*$p < .05$. **$p < .01$. ***$p < .001$.

The merits of the regression model were examined through an analysis of the residuals. Five observations were identified as unusual because the absolute value of the standardized residual was greater than 2; the observations affected the normal distribution of the residuals ($AD = 126.020$, $p < .005$) and ultimately any inferences that the can be made from the model. Removing the outliers improved the explanatory nature of the regression model ($R^2 = .067$, $F(1, 522) = 37.42$, $p = .000$), but the residuals continued to follow a non-normal distribution ($AD = 72.91$, $p < .005$). No autocorrelation was present ($DW = 1.96$).

Simple regression with one categorical variable is essentially a 2-sample t-test ("Regression with Categorical Predictors," n.d.); therefore, the regression results can be confirmed by comparing the mean difference in forecast error ($\mu(FE\%_{iq} - XFE\%_{iq})$) for those firm quarters where the EPS consensus forecast was missed against those firm quarters where the EPS consensus forecast was not missed. Because the original data was not normally distributed, median (*mdn*) values were compared instead of mean values through the non-parametric equivalent of the 2-sample t-test, the Mann-Whitney test. The results of the Mann-Whitney test, adjusted for ties, were consistent with the regression

[8] Following Bring (1994), the standardized coefficient is calculated by multiplying the unstandardized coefficient by the ratio of the standard deviations for the independent and dependent variables. This calculation was necessary because Minitab® does not provide β in the regression output.

results and significant at a 95% confidence level ($U = 46098$, $Z = 8.079$, $p = .000$, $r = .35$)[9], indicating that the difference in forecast error with and without breakage is greater when a firm misses analysts' EPS forecasts (*Mdn* = 3.85%, Range = 216.67%, $n = 197$) than when a firm does not miss analysts' EPS projections (*Mdn* = 0%, Range = 1357.14%, $n = 336$). Therefore, there is some statistically significant evidence that retailers use breakage to meet analysts' consensus EPS forecasts.

4.3.4 Hypothesis Four – Materiality.

H_4 – There is statistically significant evidence that retailers are more likely to record breakage in immaterial amounts that material amounts.

Preparing the data to address hypothesis H_4 required a two-step process. First, quarterly sales (SALES) for all firms were obtained from Thomson One, resulting in 1,889 firm quarters. Likewise, BREAKAGE for the 45 firms reporting and recognizing breakage was obtained from the SEC's EDGAR database. (See Sections 4.1.2.5 and 4.1.1, respectively, for a discussion on data collection and treatment of missing data and outliers for these two variables). Of interest were those firm quarters including and following a firm's initial breakage recognition transaction because the hypothesis assumed breakage recognition has occurred; as such, only 594 firm quarters were pertinent.

Second, MATERIALITY% was calculated for each of the 594 firm quarters. MATERIALITY% was determined by dividing BREAKAGE by the difference between SALES and BREAKAGE. Here, it was assumed that a material transaction was one in

[9] The researcher calculated the U and Z statistic because these test values are not part of the output of Minitab®. The U statistic is calculated as $N_1 * N_2 + ((N_1 * (N_1+1)/2) - R_1$. The Z statistic is calculated as $(U - \mu_U) / \sigma_U$.

which the materiality percentage was greater than ½% of SALES, or 0.005. Table 15 presents descriptive statistics for the MATERIALITY% variable.

Table 15: ***Descriptive Statistics for Materiality %***

	*N**	*M*	*SD*	Min	Median	Max	Skew	Kurt
MATERIALITY%	594	0.003	0.006	(0.003)	0.001	0.080	7.01	67.46

* *Firm quarters*

The research methodology prescribed a one-sample t-test (one-sided). A key assumption for a one-sample t-test (one-tailed) is a requirement of normality. Here, the assumption of normality was not met by the MATERIALITY% data as is evident from the skew test statistic (positively skewed) and peaked (leptokurtic) kurtosis test statistic; in addition, an Anderson-Darling test ($AD = 111.47, p < .005$) confirmed the sample distribution was not normally distributed. Attempts at data transformation did not improve normality; as such, a 1-sample t-test was not employed because the underlying assumption of normality was violated.

Instead, a 1-sample sign test (one-tailed), a non-parametric equivalent of a 1-sample t-test (one-tailed) was employed. The 1-sample sign test does not make any assumption about the shape of the population (Ryan, Joiner, & Cryer, 2005); that is, there is no need to justify an assumption of symmetry. A one-tailed test was still appropriate because the alternative states direction. The hypotheses associated with a 1-sample sign test mirrors those of a 1-sample t-test except that medians are used instead of means. The null and alternative hypotheses for H_4 using a 1-sample sign test are restated as:

$$H_0 \ Median_{Materiality\%} = 0.005$$

$$H_A \ Median_{Materiality\%} < 0.005$$

Complete Minitab® hypothesis test results are in Appendix C. The results are significant at a 95% confidence level ($Mdn = .001, p = .000$). Of the 594 firm quarters, 536 are below and 58 are above the hypothesized value. Therefore, based on the sample data, one can conclude that the population median is significantly less than 0.005, resulting in the rejection of the null hypothesis for H_4. The implication of a rejected null is that retailers may be able to manage earnings through immaterial entries, and therefore, not raise materiality concerns among auditors or analysts.

4.3.5 Hypothesis Five – Timing.

H_5 – There is statistically significant evidence that retailers are more likely to recognize breakage in the last quarter of their fiscal year

Hypothesis H_5 is evaluated in two ways; first, quarterly breakage as a percent of annual breakage by firm is analyzed to determine which quarter(s) accrues the largest share of annual breakage. Second, to control for fluctuations in the business cycle and seasonality, the relative size of breakage as a percentage of sales by firm by quarter was also compared. These two approaches are discussed in Sections 4.3.5.1 and 4.3.5.2, respectively.

4.3.5.1 Quarterly Breakage as a Percent of Annual Breakage.

For retailers in the sample recognizing breakage, BREAKAGE by quarter and by year was collected from the SEC's EDGAR database (see Section 4.1.1). A quarterly breakage percent was calculated by dividing a firm's quarterly breakage by its annual breakage each year, resulting in four quarterly observations per firm per year. The sum of the four quarterly observations per firm per year totaled 100%. If a firm did not recognize breakage in a particular quarter, a breakage value of $0 (0%) was used for that

quarter. Percentages for a given year were not calculated until a firm recognized breakage for the first time; the first firm to recognize breakage did so in the fourth quarter of 2005 while the last firm to recognize breakage did so in the fourth quarter of 2011. The total number of firm quarters for which a quarterly percent was calculated was 624. Table 16 provides the descriptive statistics by quarter. Mean quarterly breakage as a percent of annual breakage ranges from 16.07% in the first quarter to 49.44% in the fourth quarter.

Table 16: ***Descriptive Statistics - Quarterly Breakage % of Annual Breakage***

Quarter	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
1	156	16.07%	0.148	0.00%	17.04%	92.65%	2.06	8.72
2	156	18.41%	0.170	0.00%	18.47%	100.00%	2.10	7.06
3	156	16.08%	0.135	0.00%	16.33%	95.28%	2.32	11.58
4	156	49.44%	0.296	0.00%	40.44%	100.00%	0.53	(0.87)

* *Firm quarters*

A common statistical test used to compare three or more means is ANOVA. Assumptions for an ANOVA test require an interval or ratio dependent variable, sample independence, and a normal distribution (Lind, Marchal, & Wathen, 2005). The assumption of normality was not met by the quarterly breakage as a percent of annual breakage data ($AD = 37.73, p < .005$); attempts at data transformation did not improve normality.

Because the data described here did not follow a normal distribution, the Kruskal-Wallis test was employed as a non-parametric, but widely accepted alternative to a one-way ANOVA. The Kruskal-Wallis test relaxes the assumption of normality while maintaining assumptions for the dependent variable's level of measurement (i.e., interval or ratio), similar distribution shape (e.g. all have positive skew), and sample independence (Anderson, Sweeney, & Williams, 2011). The H_5 data met these

requirements, supporting the use of Kruskal-Wallis. The hypotheses associated with Kruskal-Wallis mirrors those of the one-way ANOVA except that medians are used instead of means (Anderson et al., 2011). The null and alternative hypotheses for H_5 using a Kruskal-Wallis are restated as:

$H_0 \quad \eta_{\frac{q1}{t}} = \eta_{\frac{q2}{t}} = \eta_{\frac{q3}{t}} = \eta_{\frac{q4}{t}}$

H_A *The medians are not all equal*

The complete output from Minitab® is in Appendix D. The results of the Kruskal-Wallis test, adjusted for ties, is significant at a 95% confidence level ($H = 187.52$, 3 *d.f.*, $p = .000$), indicating that there is at least one significant difference in medians among the factors. Therefore, the null hypothesis for H_5 is rejected.

A limitation of the Kruskal-Wallis test is that the test does not indicate between which groups the treatment differs (Dytham, 2011). Like ANOVA, the Kruskal-Wallis test requires a *post hoc* test when the null hypothesis is rejected. Since there is no equivalent Kruskal-Wallis *post hoc* test that is equivalent to an ANOVA *post hoc* test, Dytham (2011) recommends using pairwise Mann-Whitney tests to analyze individual differences between factors.

Therefore, pairwise comparisons for each possible combination of factors were conducted using a Mann-Whitney two-tailed test. Following Chiang, Englebrecht, Phillips, & Wang (2008), a Bonferroni adjustment technique was employed to adjust the significance level necessary to reject the null hypothesis by dividing the alpha level by the number of comparisons. This avoided "increased risk of Type I Error that comes with multiple comparisons" (Vogt & Johnson, 2011, p.35). First, the total number of comparisons was given by $0.5s(s-1) = 6$, where s is the number of factors. The adjusted

alpha, a, was (0.05/6)*100 = 0.833; therefore, 6 Mann-Whitney tests were run at a = 0.00833 (99.167%) confidence level. Summarized output for the 6 comparison tests, adjusted for ties, is in Table 17; see Appendix D for complete results. The results of these *post hoc* tests indicated significant differences in medians at the 99.167% confidence level between the fourth quarter and all three other quarters.

Table 17: *Post Hoc Mann-Whitney Pairwise Comparisons - Breakage by Quarter*

Quarter	1	2	3	4
1	---			
2	U = 12931 Z = 0.958 p = .336	---		
3	U = 12257 Z = 0.112 p = .908	U = 12845 Z = 0.850 p = .395	---	
4	U = 21163 Z = 11.290 **p = .000**	U = 20590 Z = 10.571 **p = .000**	U = 21310 Z = 11.475 **p = .000**	---

4.3.5.2 Breakage as Percent of Sales.

For retailers in the sample recognizing breakage, BRKG/SALES% was calculated by dividing BREAKAGE by SALES for each of the 624 firm quarters described in Section 4.3.5.1; the same numbers of firm quarters identified in Section 4.3.5.1 were used in this section to ensure that results were determined and reported over comparable time periods. BRKG/SALES% serves as a proxy for the relative size of the breakage transaction and controls for seasonality of retailers' operations. Table 18 presents descriptive statistics for breakage as a percent of sales by quarter.

Table 18: ***Descriptive Statistics of BRKG/SALES% by Quarter***

Quarter	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
1	156	0.11%	0.002	0.00%	0.05%	1.37%	3.91	23.16
2	156	0.15%	0.003	0.00%	0.06%	3.52%	7.92	78.73
3	156	0.14%	0.004	0.00%	0.06%	4.05%	9.04	96.09
4	156	0.44%	0.008	0.00%	0.17%	7.42%	5.15	34.94

* *Firm quarters*

Like the data in Section 4.3.5.1, the BRKG/SALES% did not follow a normal distribution ($AD = 113.66, p < .005$). Attempts to normalize the data through transformation failed. Once again, the ANOVA requirement of a normal distribution was violated.

The BRKG/SALES% data conformed to the assumptions behind ANOVA's non-parametric equivalent, the Kruskal-Wallis test. The data was ratio data, independent, shared similar distribution shapes as seen by the skewness/kurtosis test statistics, and was not normally distributed.

The null and alternative hypotheses for H_5 using a Kruskal-Wallis non-parametric test are restated as:

$$H_0 \quad \eta \frac{BRKG}{SALES}\%_{q1} = \eta \frac{BRKG}{SALES}\%_{q2} = \eta \frac{BRKG}{SALES}\%_{q3} = \eta \frac{BRKG}{SALES}\%_{q4}$$

$$H_A \quad \textit{The median scores are not all equal}$$

The full results from Minitab® are in Appendix D. The results of the Kruskal-Wallis test, adjusted for ties, is significant at a 95% confidence level ($H = 73.40$, 3 *d.f.*, $p = .000$), indicating that there is at least one significant difference in median among the quarters. Consistent with the results in Section 4.3.5.1, the null hypothesis for H_5 is rejected.

Post hoc, pairwise comparisons with two-tailed Mann-Whitney tests determined which medians differed among quarters; the Bonferroni technique adjusted the required confidence level to reject the null hypothesis to 99.167%[10].

Summarized output for the 6 comparison tests, adjusted for ties, is in Table 19; see Appendix D for complete results. The results of these *post hoc* tests indicated significant differences in medians at the 99.167% confidence level between the fourth quarter and all three other quarters.

Table 19: *Post-Hoc Mann-Whitney Pairwise Comparisons - BRKG/SALES%*

Quarter	1	2	3	4
1	---			
2	$U = 12922$ $Z = 0.946$ $p = .335$	---		
3	$U = 12490$ $Z = 0.404$ $p = .688$	$U = 12584$ $Z = 0.522$ $p = .598$	---	
4	$U = 17943$ $Z = 7.248$ **$p = .000$**	$U = 17301$ $Z = 6.443$ **$p = .000$**	$U = 17819$ $Z = 7.093$ **$p = .000$**	---

Collectively, these results seem to suggest that retailers are more likely to recognize breakage in the last quarter of their fiscal year. More so, because both fourth quarter breakage as a percent of annual breakage and fourth quarter breakage as a percent of sales differed significantly from the first three quarters, respectively, retailers' decisions may be a result of a managed choice.

[10] The total number of pairwise comparisons is 6; the adjusted alpha is (0.05/6)*100 = 0.833.

4.3.6 Hypothesis Six (a) – Net Profit Margin.

H_{6a} – There is statistically significant evidence that low margin retailers recognize more breakage than high margin retailers

Preparing the data to address hypothesis H_{6a} required a three-step process. First, quarterly sales (SALES) and net income available to common shareholders excluding extraordinary items (NETINC) for all firms were obtained from Thomson One, resulting in 1,889 firm quarters for each variable. Both SALES and NETINC were adjusted for pre-tax and post-tax breakage, respectively. Net profit margin without breakage (NPM_XBRKG) was calculated for the period 2003-2010 for the 45 retailers that recognized breakage, resulting in 1,335 firm quarters

Second, an average net profit margin without breakage over the period 2003-2010 was calculated for each retailer recognizing breakage to minimize the impact of year-on-year business fluctuations. The average net profit margin without breakage by firm was sorted high to low and divided into quartiles with the top quartile (top 25% of firms) considered "high margin firms" and the bottom quartile (bottom 25% of firms) considered "low margin firms." Eleven retailers were classified as high margin firms (M = 7.44%, SD = .041, Mdn = 7.25%); likewise, 11 retailers were classified as low margin retailers (M = -17.06%, SD = 3.711, Mdn = -0.79%). A "1" was assigned to high margin firms; a "4" was assigned to low margin firms[11]. Table 20 presents descriptive statistics for net profit margin by quartile.

[11] Second quartile firms were assigned a "2" and third quartile firms were assigned a "3".

Table 20: ***Descriptive Statistics of Net Profit Margin without Breakage***

Quartile	*N**	*M*	*SD*	Median
1	11	7.44%	0.041	7.25%
2	11	4.00%	0.029	3.84%
3	12	1.48%	0.058	2.07%
4	11	-17.06%	3.711	-0.79%

* *Number of breakage-recognizing retailers*

Third, breakage as a percentage of sales (BRKG/SALES%) was calculated for each firm quarter following initial recognition of breakage by an individual retailer, resulting in 594 firm quarters. BRKG/SALES% serves as a proxy for the level of breakage. Each BRKG/SALES% quarterly observation was mapped to a net profit margin without breakage quartile at the firm level. For example, if Firm *i* was classified as a high margin retailer, then each of its BRKG/SALES% by quarter were assigned a "1". Table 21 presents descriptive statistics of BRKG/SALES% by net profit margin without breakage quartile.

Table 21: ***Breakage % of Sales by Net Profit Margin without Breakage***

Quartile	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
1	147	0.16%	0.002	0.00%	0.10%	1.30%	2.73	9.99
2	164	0.10%	0.002	0.00%	0.05%	1.37%	5.19	31.11
3	126	0.33%	0.008	-0.32%	0.09%	4.83%	3.96	17.15
4	157	0.41%	0.008	0.00%	0.19%	7.42%	5.65	42.16

* *Firm quarters*

The BRKG/SALES% data did not follow a normal distribution as evidenced by both the positive skewness/peaked kurtosis values in Table 21 and the Anderson-Darling test statistic for the entire sample ($AD = 109.09, p < .005$). The Anderson-Darling test statistic revealed a distribution that was not normal at the high margin retailer level ($AD =$

12.24, $p < .005$) as well as the low margin retailer level ($AD = 25.34, p < .005$). Attempts at data transformation did not improve normality.

Therefore, while sample independence was inherent in the quartile date, the underlying assumption of normality required for a two-sample t-test was violated. As such, the researcher used the Mann-Whitney test as a non-parametric, but widely accepted alternative to a two-sample independent t-test. The Mann-Whitney test relaxes the assumption of normality while maintaining the assumptions of sample independence, similar data distributions, and data that is at least ordinal in nature (Black, 2010). The BRKG/SALES% data was continuous, supporting the use of Mann-Whitney. The hypotheses associated with this technique mirrors those of the two-sample t-test except that medians are used instead of means (Gardiner, 1997). The null and alternative hypotheses for $H6_a$ using a one-sided Mann-Whitney test are restated as:

H_O $There\ is\ no\ difference\ in\ the\ medians\ of\ BRKG/SALES\%_{low\ margin\ firms}\ and\ BRKG/SALES\%_{high\ margin\ firms}$

H_A $The\ median\ of\ BRKG/SALES\%_{low\ margin\ firms} > the\ median\ of\ BRKG/SALES\%_{high\ margin\ firms}$

The output from Minitab® is in Appendix E. The results of the Mann-Whitney test were in the expected direction and significant at a 95% confidence level ($U = 15039$, $Z = 4.569$, $p = .000$, $r = .26$)[12], indicating that breakage as a percentage of sales is greater for low margin retailers ($Mdn = 0.19\%$, Range = 7.40%, $n = 157$) than for high margin retailers ($Mdn = 0.10\%$, Range: 1.30%; $n = 147$). Therefore, the null hypothesis for $H6_a$ is rejected.

[12] The researcher calculated the U and Z statistic because these test values are not part of the output of Minitab®. The U statistic is calculated as $N_1 * N_2 + ((N_1 * (N_1+1)/2) - R_1$. The Z statistic is calculated as $(U - \mu_U) / \sigma_U$. The critical Z-value on a one-sided Mann-Whitney test is 1.645.

The implication of a rejected null is that profitability, as measured by net profit margin, seems to be an important indicator of the level of breakage firms will recognize; as evident here, less profitable firms recognized more breakage than more profitable firms, again hinting at potential earnings management.

4.3.7 Hypothesis Six (b) – Lines of Trade.

H_{6b} – There is statistically significant evidence that the propensity to recognize breakage varies by line of trade.

In this study, six lines of trade are considered (see Table 1). Each retailer is aligned to an SIC major group permitting analysis along line of trade.

Preparing the data to address hypothesis H_{6b} required that breakage as a percentage of sales (BRKG/SALES%) be calculated for the 45 firms recognizing breakage for each firm quarter following initial recognition of breakage by an individual retailer; 594 firm quarters were calculated. BRKG/SALES% serves as a proxy for a retailer's tendency to recognize breakage. Each BRKG/SALES% quarterly observation was mapped to a line of trade at the firm level. For example, if Firm *i* was classified as a Food Store (SIC Code = 54), then each of its quarterly BRKG/SALES% were assigned the line of trade code "54". Table 22 presents descriptive statistics of BRKG/SALES% by line of trade. The BRKG/SALES% data is ratio data.

Table 22: *Breakage as % of Sales by Line of Trade*

Line of Trade	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
52	48	0.05%	0.000	0.01%	0.05%	0.23%	3.05	11.90
54	17	0.05%	0.001	0.00%	0.01%	0.42%	3.42	12.14
56	218	0.20%	0.004	0.00%	0.09%	4.05%	5.95	41.79
57	56	0.28%	0.006	0.03%	0.19%	4.83%	7.01	51.27
58	181	0.39%	0.008	-0.32%	0.15%	7.42%	5.33	38.94
59	74	0.17%	0.003	0.00%	0.06%	1.96%	3.85	18.75

* *Firm quarters*

Assumptions for an ANOVA test require an interval or ratio dependent variable, sample independence, a normal distribution, and equal variances (Lind et al., 2005). The assumption of normality was not met by the BRKG/SALES% data ($AD = 109.09$, $p < .005$); attempts at data transformation did not improve normality.

Therefore, the Kruskal-Wallis test was employed as a non-parametric, but widely accepted alternative to a one-way ANOVA. The Kruskal-Wallis test relaxes the assumption of normality while maintaining assumptions for the dependent variable's level of measurement (i.e., interval or ratio) and sample independence (Anderson et al., 2011). The Kruskal-Wallis test also requires that the data come from populations with the same shape (e.g., both skewed right) (Anderson et al., 2011). The BRKG/SALES% data met these requirements, supporting the use of Kruskal-Wallis.

The hypotheses associated with Kruskal-Wallis mirrors those of the one-way ANOVA except that medians are used instead of means (Anderson et al., 2011). Formally, let η_{52} = the median BRKG/SALES% for building material, hardware, and garden supply stores; let η_{54} = the median BRKG/SALES% for food stores; let η_{56} = the median BRKG/SALES% for apparel and accessory stores; let η_{57} = the median BRKG/SALES% for home furniture, furnishings, and equipment stores; let η_{58} = the

median BRKG/SALES% for eating and drinking establishments; and let η_{59} = the median BRKG/SALES% for miscellaneous retailers. The null and alternative hypotheses for $H6_b$ using a Kruskal-Wallis test are restated as:

$H_0\ \eta_{52} = \eta_{54} = \eta_{56} = \eta_{57} = \eta_{58} = \eta_{59}$

H_A *The medians are not all equal*

The complete output from Minitab® is in Appendix F. The results of the Kruskal-Wallis test, adjusted for ties, is significant at a 95% confidence level (H = 88.28, 5 *d.f.*, p = .000), indicating that there is at least one significant difference in medians among the lines of trade. Therefore, the null hypothesis for H_{6b} is rejected.

A limitation of the Kruskal-Wallis test, like the one-way ANOVA, is that the test does not indicate which pair(s) of medians differ (Dytham, 2011). A one-way ANOVA requires a *post hoc* test to determine differences among pairs. Unfortunately, there is no equivalent *post hoc* test for Kruskal-Wallis. Dytham (2011) however recommends that pairwise Mann-Whitney tests should be carried out if a difference among pairs is important to the research.

Therefore, pairwise comparisons for each possible combination of factors were conducted using a Mann-Whitney two-tailed test. Following Chiang et al. (2008), a Bonferroni adjustment technique was employed to adjust the significance level necessary to reject the null hypothesis by dividing the alpha level by the number of comparisons. This avoided "increased risk of Type I Error that comes with multiple comparisons" (Vogt & Johnson, 2011, p.35). First, the total number of comparisons was given by 0.5s(s-1) = 15, where s is the number of factors. The adjusted alpha, a, was (0.05/15)*100 = 0.333; therefore, 15 Mann-Whitney tests are run at a = 0.00333

(99.667%) confidence level. Summarized output for the 15 comparison tests, adjusted for ties, is in Table 23; see Appendix F for complete results. The results of these *post hoc* tests indicated significant differences in medians at the 99.667% confidence level between 13 of the 15 pairwise combinations.

The inference of this finding is that some lines of trade seem to have greater opportunity to manage earnings with breakage than others. That is, the very line of trade in which retailers operate may afford them more latitude in their discretionary decision-making concerning breakage.

Table 23: ***Post-hoc Mann-Whitney Pairwise Comparisons – Line of Trade***

Line of Trade	52	54	56	57	58	59
52 (Bldg.)	---					
54 (Food Store)	$U = 666$ $Z = 3.851$ $p = .000$	---				
56 (Apparel)	$U = 7824$ $Z = 5.372$ $p = .000$	$U = 3148$ $Z = 4.797$ $p = .000$	---			
57 (Home)	$U = 2229$ $Z = 5.771$ $p = .000$	$U = 869$ $Z = 5.129$ $p = .000$	$U = 7883$ $Z = 3.363$ $p = .001$	---		
58 (Eat/Drink)	$U = 7207$ $Z = 7.016$ $p = .000$	$U = 2569$ $Z = 4.562$ $p = .000$	$U = 24777$ $Z = 4.402$ $p = .000$	$U = 5198$ $Z = 0.290$ $p = .773$	---	
59 (Misc.)	$U = 2318$ $Z = 2.841$ $p = .005$	$U = 946$ $Z = 3.228$ $p = .001$	$U = 7242$ $Z = 1.314$ $p = .189$	$U = 2737$ $Z = 3.124$ $p = .002$	$U = 8815$ $Z = 3.962$ $p = .000$	---

4.3.8 Hypothesis Six (c) – Financial Health.

H_{6c} – There is statistically significant evidence that retailers in poor financial health recognize more breakage than retailers in strong financial health

Preparing the data to address hypothesis H_{6c} required a three-step process. First, quarterly sales (SALES), operating income (OPINC) and net operating assets (NETOPASSETS)[13] for all firms were obtained from Thomson One, resulting in 1,889 firm quarters for each variable. SALES and OPINC were adjusted for pre-tax breakage. The return on net operating assets without breakage (RNOA_XBRKG) was calculated for the period 2003-2010 for the 45 retailers that recognized breakage, resulting in 1,335 firm quarters.

Second, an average return on net operating assets without breakage over the period 2003-2010 was calculated for each retailer that recognized breakage to minimize the impact of year-on-year business fluctuations. The average return on net operating assets without breakage was sorted high to low and partitioned into quartiles with the top quartile (top 25% of firms) considered "high RNOA firms" and the bottom quartile (bottom 25% of firms) considered "low RNOA firms." Eleven retailers were classified as high RNOA firms (M = 9.17%, SD = .015, Mdn = 8.49%); likewise, 11 retailers were classified as low RNOA firms (M = -122.35%, SD = 4.008, Mdn = -0.73%). A "1" was assigned to high RNOA firms; a "4" was assigned to low RNOA firms[14]. Table 24 presents descriptive statistics for RNOA_XBRKG by quartile.

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[13] NETOPASSETS is Cash + Accounts Receivable + Inventory + Net Property, Plant & Equipment – Accounts Payable. The values in the individual accounts were obtained from Thomson One and the researcher calculated NETOPASSETS.

[14] Second quartile firms were assigned a "2" and third quartile firms were assigned a "3".

Table 24: ***Descriptive Statistics of RNOA without Breakage by Quartile***

Quartile	*N**	*M*	*SD*	Median
1	11	9.17%	0.015	8.49%
2	11	5.79%	0.010	5.68%
3	12	2.53%	0.006	2.54%
4	11	-122.35%	4.008	-0.73%

* *Number of breakage-recognizing retailers*

Third, breakage as a percent of sales (BRKG/SALES%) was determined as described in Section 4.3.6; there were 594 firm quarters. BRKG/SALES% serves as a proxy for the level of breakage. Each BRKG/SALES% quarterly observation was mapped to a return on net operating asset without breakage quartile at the firm level. For example, if Firm *i* was classified as a high RNOA retailer, then each of its BRKG/SALES% by quarter were assigned a "1". Table 25 presents descriptive statistics of BRKG/SALES% by return on net operating asset without breakage quartile.

Table 25: ***Breakage as % of Sales by RNOA without Breakage Quartile***

Quartile	*N**	*M*	*SD*	Min	Median	Max	Skewness	Kurtosis
1	142	0.15%	0.002	0.00%	0.06%	1.30%	2.95	10.82
2	177	0.11%	0.002	0.00%	0.06%	1.36%	4.89	31.32
3	110	0.37%	0.008	-0.32%	0.12%	4.83%	3.61	14.12
4	165	0.40%	0.008	0.00%	0.19%	7.42%	5.88	45.26

* *Firm quarters*

The BRKG/SALES% data did not follow a normal distribution as evidenced by both the positive skewness/peaked kurtosis values in Table 25 and the Anderson-Darling test statistic for all 594 firm quarters ($AD = 109.09, p < .005$). In addition, the Anderson-Darling test statistic revealed a non-normal distribution at both the high RNOA retailer

level ($AD = 14.28, p < .005$) and the low RNOA retailer level ($AD = 27.38, p < .005$). Attempts at data transformation did not improve normality.

Therefore, while sample independence was inherent in the quartile date, the underlying assumption of normality required for a two-sample t-test was violated. As such, the researcher used the Mann-Whitney test as a non-parametric, but widely accepted alternative to a two-sample independent t-test. The Mann-Whitney test relaxes the assumption of normality while maintaining the assumptions of sample independence, similar data distributions, and data that is at least ordinal in nature (Black, 2010). The BRKG/SALES% data was continuous, supporting the use of Mann-Whitney. The hypotheses associated with this technique mirrors those of the two-sample t-test except that medians (*mdn*) are used instead of means (Gardiner, 1997). The null and alternative hypotheses for H_{6a} using a one-sided Mann-Whitney test which states direction are restated as:

$$H_O \quad There\ is\ no\ difference\ in\ the\ medians\ of\ BRKG/SALES\%_{low\ RNOA\ firms}\ and\ BRKG/SALES\%_{high\ RNOA\ firms}$$

$$H_A \quad The\ median\ of\ BRKG/SALES\%_{low\ RNOA\ firms} > the\ median\ of\ BRKG/SALES\%_{high\ RNOA\ firms}$$

The results from Minitab® are in Appendix G. The results of the Mann-Whitney test were in the expected direction and significant at a 95% confidence level ($U = 16588, Z = 6.283, p = .000, r = 0.36$)[15], indicating that breakage as a percentage of sales is greater for low RNOA retailers ($Mdn = 0.19\%$, Range = 7.42%, $n = 165$) than for high RNOA retailers ($Mdn = 0.06\%$, Range = 1.30%, $n = 142$). Therefore, the null hypothesis for H_{6c} is rejected.

[15] The researcher calculated the *U* and *Z* test statistics. See the footnote under section 4.3.6 for methodology.

An implication of this result is that retail managers seem to be sensitive to their firm's financial health and make financial decisions accordingly. Here, it seems clear that retailers in poor financial health, as measured by return on net operating assets, attempt to increase their financial performance by recognizing more breakage than retailers in strong financial health; these decisions are most likely the result of a managed choice and may hint at earnings management.

4.4 Results – Complete Empirical Model

The results of the complete empirical model are described in this section. The researcher employed a multiple regression model to measure the relationship between a single dependent variable and multiple independent variables, to understand the relative contribution of the independent variables to changes in the dependent variable, and to facilitate interpretation as to the influence of each independent variable. Section 4.4.1 summarizes the attempts to meet the necessary assumptions in multiple regression analysis, while Section 4.4.2 reports the results of the regression model.

4.4.1 Assumptions in the Multiple Regression Analysis.

The regression model specifies the relative size of quarterly breakage (BRKG/NOA%) for breakage-recognizing firms as a function of CEO compensation arising from stock options (CEOPAYOPTNS%) (lagged one year), whether a retailer missed its consensus EPS analysts' forecast (MISSEDEPS_XBRKG), whether the breakage transaction is material (MATERIAL), the quarter in which breakage is recognized (LSTFSCLQTR), the profitability of a retailer (NPM_XBRKG), and a retailer's line of trade (MG). BRKG/NOA%, CEOPAYOPTNS%, and NPM_XBRKG are continuous variables whereas MISSEDEPS_XBRKG, MATERIAL, LSTFSCLQTR,

and MG are dummy variables coded 0 and 1. BRKG/NOA% serves as proxy for gift card breakage.

One thousand, four hundred and ninety two firm quarters in the cross-sectional, time-series data were calculated for the dependent variable, BRKG/NOA%, by dividing gift card breakage (BREAKAGE) by net operating assets (NETOPASSETS). There were no missing values; however, a univariate inspection for outliers revealed 16 instances where an individual BRKG/NOA percent was greater than four standard deviations from the mean of the sample (Hair et al, 2006).

Table 26 offers a profile of the identified outliers. In nine of the cases, the outlier was the result of the retailer recognizing gift card breakage for the first time, and therefore each observation represents a valid element of the population and was retained. Twelve outliers represented the largest, quarterly breakage amount recognized by an individual retailer; of the twelve, nine were previously identified as initial breakage recognition quarters. Again, these outliers speak to the discretionary nature of breakage recognition decisions and were retained. The remaining four outliers were simply unique in their combination of values across the two variables; these observations were retained because no evidence discounted the outlier as an invalid member of the population.

Table 26: ***Breakage as Percent of Net Operating Assets Outliers***

Observation		Year	Quarter	BRKG/NOA%	*z*-score
1	*†	2008	Q4	2.1%	7.12
2	*†	2007	Q4	2.0%	6.55
3	*†	2006	Q3	2.2%	7.42
4	*†	2010	Q4	1.2%	4.07
5	*†	2010	Q4	5.8%	19.91
6	*†	2006	Q4	1.3%	4.40
7	†	2010	Q4	3.9%	13.26
8		2010	Q4	1.4%	4.70
9	†	2008	Q4	2.4%	8.13
10		2010	Q2	1.7%	5.52
11		2009	Q2	1.4%	4.71
12		2007	Q2	1.3%	4.31
13	†	2006	Q4	2.9%	9.72
14	*†	2011	Q2	3.2%	10.75
15	*†	2011	Q4	1.7%	5.65
16	*†	2008	Q4	1.8%	6.15

** Indicates quarter of initial recognition of gift card breakage by the retailer*
† Indicates largest quarterly breakage value for the retailer

Descriptive statistics for the dependent and independent variables are in Table 27. The mean (median) BRKG/NOA% is 0.07% (0.00%) which is a reflection of the fact that breakage was recognized in only 559 of the 1,492 firm quarters. The data is positively skewed and leptokurtic. The mean (median) value for CEOPAYOPTNS% is 27.78% (17.84%), indicating that on average approximately one-quarter of a CEO's compensation is derived from stock option. There were only 1,472 quarterly observations for CEOPAYOPTNS% because occasionally a CEO did not receive compensation and as such, a percentage could not be calculated. The data is moderately skewed, but platykurtic. The mean (median) NPM_XBRKG is -0.46% (3.50%), reflective of the low-margin retailing industry. The data is highly skewed and leptokurtic.

Table 27: ***Descriptive Statistics for the Multiple Regression Variables***

Variable	*N**	*M*	*SD*	Min	*Mdn*	Max	Skew.	Kurt.
BRKG/NOA%	1,492	0.07%	0.003	-0.20%	0.00%	5.80%	10.39	151.00
CEOPAYOPTNS%	1,472	27.78%	0.298	0.00%	17.84%	100.00%	0.63	(0.97)
MISSEDEPS_XBRKG	1,018	0.30	0.457	0.00	0.00	1.00	0.89	(1.21)
MATERIAL	1,492	0.04	0.193	0.00	0.00	1.00	4.78	20.84
LSTFSCLQTR	1,492	0.25	0.432	0.00	0.00	1.00	1.17	(0.63)
NPM_XBRKG	1,492	-0.46%	1.752	-6581%	3.50%	1371%	(35.27)	1,341.10
Lines of Trade:								
Building	1,492	0.05	0.214	0.00	0.00	1.00	4.22	15.83
Apparel	1,492	0.41	0.491	0.00	0.00	1.00	0.39	(1.85)
Home	1,492	0.07	0.260	0.00	0.00	1.00	3.28	8.80
Eating/Drinking	1,492	0.28	0.451	0.00	0.00	1.00	0.97	(1.07)
Miscellaneous	1,492	0.14	0.352	0.00	0.00	1.00	2.02	2.09

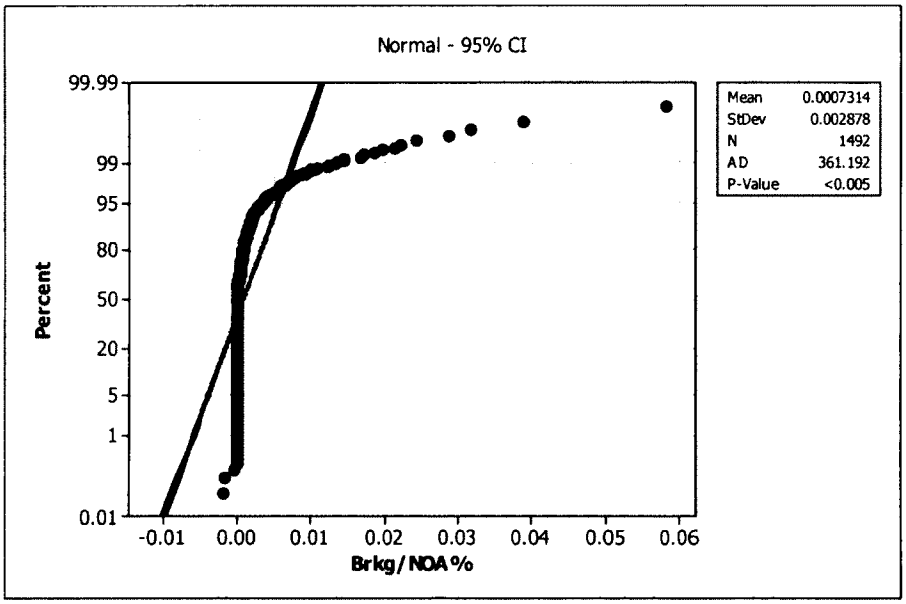
* *Firm quarters*

Regarding the dummy variables, the mean values represent the proportion of observations coded as "1." Therefore, of the 1,492 firm quarters, gift card breakage is material in 4% (n = 58) of those quarters. Likewise, the distribution of 1,492 firm quarters by lines of trade are 5% (n = 72) Building materials, Hardware, and Garden Supply; 41% (n = 605) Apparel and Accessory; 7% (n = 109) Home Furniture, Furnishings, and Equipment; 28% (n = 422) Eating and Drinking Places; 14% (n = 216) Miscellaneous Retail; and 5% (n = 68) Food Stores. As would be expected, 25% of the firm quarters represent the last fiscal quarter (fourth quarter). Finally, retailers missed consensus EPS forecasts in 30% of the 1,018 firm quarters. Of note, the lower number of firm quarters on the variable MISSEDEPS_XBRKG was a result of limited availability of analyst estimates prior to 2005 and to retailers in the sample who were too small to receive analyst coverage.

The researcher tested three regression assumptions for the individual variables including (a) normality for all metric variables, (b) constant variance (homoscedasticity)

and (c) linearity. First, Figure 12 shows the normalcy of the dependent variable, BRKG/NOA%, for breakage recognizing firms. The data did not follow a normal distribution ($AD = 361.192$, $p < .005$). Variable transformations of BRKG/NOA% through widely accepted transformation techniques, as well as transformations on the underlying variables, BREAKAGE and NETOPASSETS respectively, were unsuccessful and did not improve normality significantly. Similar issues of normalcy and the lack of remedies arise on both CEOPAYOPTNS% and NPM_XBRKG (see Figure 16 in Appendix H). The lack of the normality of the data was accepted, however, because the large sample size "[reduced] the detrimental effects of non-normality" (Hair et al., 2006, p.80).

Figure 12: ***Probability Plot of BRKG/NOA%***



Second, tests for heteroscedasticity using Levene's test for equality of variances (see Table 28) found that four variables, CEOPAYOPTNS% and the lines of trade Building, Apparel, and Miscellaneous Retail demonstrated no violation of the constant

variance assumption ($p > .05$); that is, these data did not provide enough evidence to claim that the populations have unequal variances. MISSEDEPS_XBRKG, MATERIAL, LSTFSCLQTR, and the lines of trade Home and Eating/Drinking violated the constant variance assumption; violations typically require correction action through data transformations (Hair et al., 2006). Here, however, the non-normality of the dependent variable contributed to the assumption violation, but data transformation on the dependent variable was not sufficient. Therefore, the assumption violation was accepted with the acknowledgement that the "heteroscedasticity [may] cause the predictions to be better at some levels of the independent variable than at others" (Hair et al., 2006, p.84).

Table 28: ***Statistical Test Results for Equal Variances (Homoscedasticity)***

Independent Variable	Levene Test Statistic	*p*-value
CEOPAYOPTNS%	1.06	0.273
NPM_XBRKG	N/A	N/A
MISSEDEPS_XBRKG	58.44	0.000
MATERIAL	511.54	0.000
LSTFSCLQTR	45.42	0.000
Lines of Trade:		
Building	2.61	0.107
Apparel	3.52	0.061
Home	10.28	0.001
Eating/Drinking	7.66	0.006
Miscellaneous	1.94	0.164

Finally, a Levene test statistic could not be calculated for the explanatory variable NPM_XBRKG. A scatterplot of BRKG/NOA% and NPM_XBRKG is in Appendix H. Departure from an equal dispersion is apparent by a cone-shape distribution. The heteroscedasticity was caused by the non-normality of both the dependent and predictor variable, but was accepted because neither variable was transformable.

Third, linearity was assessed through bivariate scatter plots of the dependent variable against the independent variables (see Figure 18 and Figure 19 in Appendix H), as well as through Pearson correlation coefficients[16] (see Table 29) which indicated the strength of the association between variables. An examination of the linearity among the metric variables revealed that the relationship between BRKG/NOA% and CEOPAYOPTIONS was moderately linear, while the relationship between BRKG/NOA% and NPM_XBRKG exhibited insufficient linearity. A violation of this magnitude would typically preclude the inclusion of the predictor variable NPM_XBRKG; however, consistent with the proposed hypotheses, a best subsets regression (*Mallows Cp* = 11; R^2 = 51.0) confirmed the inclusion of NPM_BRKG in the final multiple regression model as no other subset of independent variables maximized the predictability of the model. Therefore, NPM_BRKG was accepted.

Finally, the effect of sample size as it relates to both statistical power and generalizability was assessed. The regression analysis was deemed sufficient to identify a statistically significant relationship given the combination of sample size (n = 1,017), number of independent variables (n = 10), and significance level (α = .05). In addition, the ratio of observations to independent variables (102:1) met the guideline for the minimum ratio of observations to independent variables (5:1) which suggests that the model is generalizable (Hair et al, 2006).

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[16] Pearson correlation analysis requires normality among the variables analyzed (Hauke & Kossowski, 2011). However, due to violations of normality among dependent and independent variables in this study, Spearman's rank correlation, a non-parametric statistic which measures the strength of association between two variables, was also evaluated. Because Spearman and Pearson correlation coefficients did not appreciably differ across each univariate combination of variables, it is expected that non-normal distribution patterns will not have an effect on results (see e.g., Dechow & Dichev, 2002). Thus, only Pearson coefficients are presented here. See Table 34 in Appendix H for a comparison between Pearson and Spearman values.

Table 29: ***Pearson Correlation Matrix - BRKG/NOA% vs. Explanatory Variables***

	$\frac{BRKG}{NOA}$%	CEOPAYOPTNS%	MISSEDEPS w/o BRKG	MATERIAL	LSTFSCLQTR	NPM_XBRKG	MG52	MG56	MG57	MG58	MG59
$\frac{BRKG}{NOA}$%	—										
CEOPAYOPTNS%	(0.054) *	—									
MISSEDEPS w/o BRKG	0.231 ***	(0.050)	—								
MATERIAL	0.692 ***	(0.041)	0.240 ***	—							
LSTFSCLQTR	0.171 ***	0.003	0.067 *	0.198 ***	—						
NPM_XBRKG	(0.004)	0.023	(0.209) ***	(0.008)	0.011	—					
MG52 (Bldg.)	(0.037)	0.178 ***	(0.048)	(0.045)	0.001	0.006	—				
MG56 (Apparel)	(0.047)	0.012	(0.178) ***	(0.046)	(0.002)	0.021	(0.186) ***	—			
MG57 (Home)	0.084 ***	0.013	0.081 **	(0.043)	0.000	0.002	(0.063) *	(0.232) ***	—		
MG58 (Eat/Drink)	0.068 **	0.033	0.151 ***	0.128 ***	0.002	(0.030)	(0.141) ***	(0.519) ***	(0.176) ***	—	
MG59 (Misc.)	(0.035)	(0.055) *	0.000	(0.014)	(0.002)	0.001	(0.093) ***	(0.340) ***	(0.116) ***	(0.258) ***	—

*$p < .05$. **$p < .01$. ***$p < .001$.

4.4.2 Assessing Overall Model Fit and Interpretation of Results

The results of the regression indicated that the explanatory variables jointly explain 51% of the variance in the dependent variable ($R^2 = .51$, $F(10, 1006) = 104.64$, $p = .000$). Summarized results of the OLS regression model are listed in Table 32; complete results are shown in Appendix H.

4.4.2.1 Discussion of Regression Issues.

In this section, common regression diagnostics including collinearity, autocorrelation, and residual analysis are discussed.

Multicollinearity was assessed by reviewing the correlation matrix in Table 29 and the tolerance/variance inflation factor (VIF) of each independent variable. First, the correlation matrix revealed moderate correlation between several of the explanatory variables, particularly among the various lines of trades. A common rule of thumb is that correlations among the independent variables between -.70 and .70 generally do not cause difficulties (Lind et al., 2005), but the lack of any high correlation values does not ensure a lack of collinearity (Hair et al., 2006). Therefore, a better assessment of multicollinearity is a direct measure like tolerance, and its inverse, the variation inflation factor (Hair et al., 2006). Table 30 shows the tolerance and VIF collinearity statistics for each explanatory variable (in the *pre-modification* columns). Moderate collinearity existed among the lines of trade ($VIF_i > 2$), with Apparel exhibiting a high degree of collinearity ($VIF_i > 10$); high levels of multicollinearity can interfere with the ability to interpret regression results (Hanke & Wichern, 2009). Because dummy variables are typically a source of multicollinearity (Wissman, Toutenberg, & Shalabh, 2007), the researcher accommodated the multicollinearity by substituting the offending line of trade

(Apparel) for the line of trade that was originally excluded from the model (Food Stores) in satisfying the $k - 1$ requirement on dummy variables. Updated collinearity statistics are in Table 30 (in the *post-modification* columns); after the modification, collinearity diagnostic tests of VIF and tolerance were in normal ranges. This change did not impact the coefficient of determination or the F-stat and p-value of the overall model, nor did it improve or impair the heteroscedasticity issues.

Table 30: *Collinearity Statistics*

	Pre-Modification		*Post-Modification*	
Variable	Tolerance	*VIF*	Tolerance	*VIF*
CEOPAYOPTNS%	0.907	1.102	0.907	1.102
MISSEDEPS_XBRKG	0.882	1.134	0.882	1.134
MATERIAL	0.861	1.162	0.861	1.162
LSTFSCLQTR	0.955	1.047	0.955	1.047
NPM_XBRKG	0.917	1.091	0.917	1.091
Lines of Trade:				
Building	0.290	3.453	0.891	1.122
Apparel	0.089	11.291	---	---
Home	0.232	4.307	0.889	1.125
Eating/Drinking	0.103	9.696	0.796	1.256
Miscellaneous	0.178	5.622	0.858	1.165
Food Stores	---	---	0.939	1.065

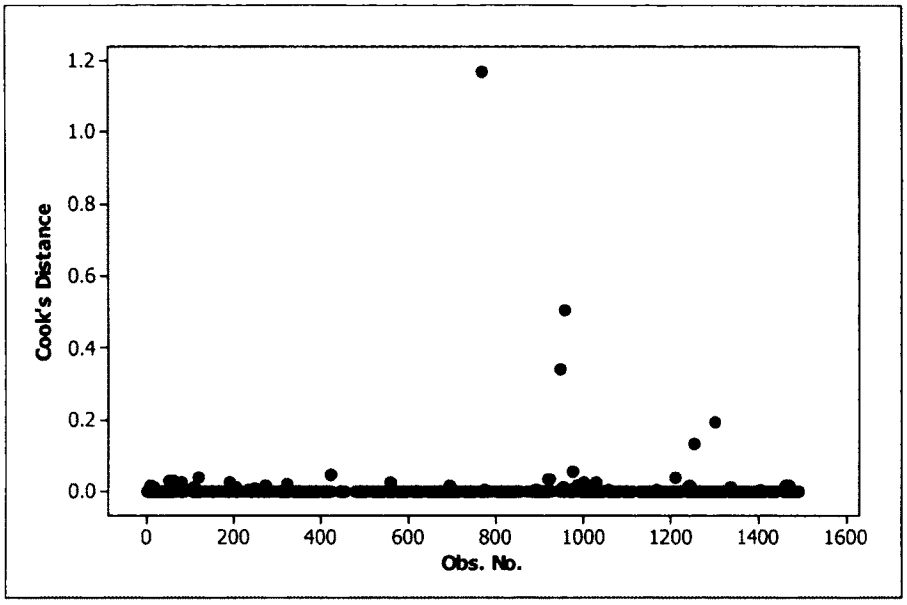
In addition to collinearity, an examination of residuals is paramount in assessing model adequacy (Hanke & Wichern, 2009). Residual analysis is used to determine serial correlation (autocorrelation), to spot outliers, to identify issues of nonlinearity, to assess normality, and to detect heteroscedasticity.

Autocorrelation was not present ($DW = 1.939$). Generally speaking, a value around 2 indicates that no autocorrelation is present (Anderson et al., 2011). More exactly, the DW test statistic must be compared to upper and lower critical values; here,

the test statistic was greater than the upper critical value and not less than the lower critical value indicating no positive or negative autocorrelation, respectively.

Outliers, or observations "that [have] a substantial difference between the actual value for the dependent variable and the predicted value" (Hair et al., 2006), can also be detected through residual analysis. Minitab® identifies these unusual observations as observations exerting high leverage or having large standardized residuals. Leverage communicates whether an observation has unusual predictors, where as a standardized residual reveals whether an observation has an unusual response (Hanke & Wichern, 2009). Leverage and large residuals can be combined into one overall measure of influence known as *Cook's Distance,* or D_i. Cook's Distance is a "weighted sum of squares of the differences between individual elements of the coefficient vectors" (Fox & Weisberg, 2011). Detecting influential outliers can be done so through a scatter plot of the Cook's Distance test statistic, or by examining values of D_i greater than $4/(N-k-1)$, where N is sample size and k is the number of independents (Fox, 1991). The bivariate scatter plot of Cook's Distance against observation number (see Figure 13) clearly indicates the presence of influential cases.

Figure 13: ***Scatter Plot of Cook's Distance (D_i)***



Employing Fox's (1991) rule of thumb identified 45 instances where D_i was greater than $4/(N - k - 1)$. Each outlier was reviewed by the researcher. A profile of the outliers is in

Table 31. In the majority of cases, the outlier represented a vital aspect of the research; that is, the outlier reflected well the discretionary nature of the breakage recognition decision in that it represented either the first time breakage was recorded by an individual retailer or simply a significantly large value of breakage (in comparison to other breakage amounts recognized by any given retailer). These outliers were retained because they met the objective of the research.

Table 31: ***Outlier Identification and Cook's Distance (D_i)***

Explanation	No. of Observations[17]	Average Breakage ($000)	Average Net Operating Assets ($000)	Average Cook's Distance (D_i)
First time breakage recognition by an individual retailer	18	$5,087	$650,722	0.0961
The largest ($) breakage value recognized by an individual retailer	22	5,225	620,977	0.1038
A significant breakage amount (in all cases, the 2nd largest ($) breakage value recognized by an individual retailer)	6	2,543	370,044	0.0169
Unknown (N/A)	13	740	117,283	0.0474

In contrast, no explanation behind the 13 outliers was identified; these appeared to be unique observations. Eliminating these 13 cases improved the model's R^2 by 0.7%; however, there was no good justification for their removal. Hair et al. (2006) suggest that the researcher "should retain the observation unless specific evidence is available that discounts the outlier as a valid member of the population" (p. 74). Absent definitive information, these 13 cases were retained.

A negative consequence of accepting outlying residuals can be a violation of linearity. Figure 20 in Appendix H shows a scatter plot of the standardized residuals versus the predicted (or, fitted) dependent values; the bivariate plot appeared to demonstrate event-based dependence (Hair et al., 2006), that is, a non-linear relationship that may have implications on any inferences made from the regressed results. However, further investigation revealed that the (x, y) points on the graph to the right of 0.006 on

[17] Column adds to more than 45 observations because some observations fell into more than one category

the *x*-axis were the direct result of the outliers mentioned earlier. This insight indicated a direct link between the identified outliers and non-linearity in the regressed results. It is the opinion of the researcher, therefore, that the apparent non-linearity is the result of extreme observations and not necessarily due to non-linearity inherent in the data.

Further, and as expected, a normal probability plot of the standardized residuals revealed that the error term does not follow a normal distribution ($AD = 149.883, p < .005$). Because a non-normal distribution of errors is "robust" to violation (Osborne & Waters, 2002), the normality issue was not a concern.

Finally, reviews of the residual plots revealed a uniform pattern which may suggest the presence of unequal variances (heteroscedasticity). Most likely, the patterns were the result of violations in other assumptions caused by the inclusion of outliers. However, the patterns were reflective of only moderate heteroscedasticity. Because the heteroscedasticity was not pronounced, the significance tests were essentially unaffected and ordinary least squares was used without concern of serious distortion (Berry & Feldman, 1985).

4.4.2.2 Interpreting the Regression Results.

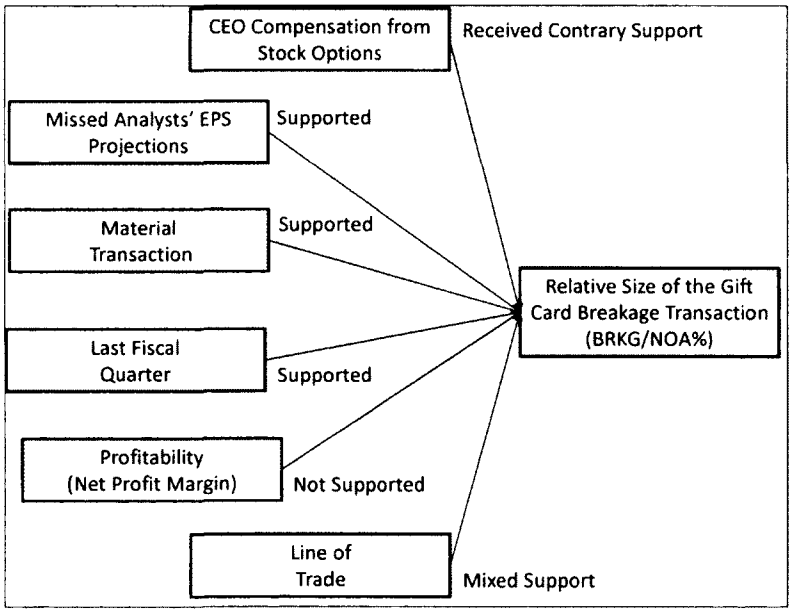
The regression results suggested that CEOPAYOPTNS% significantly explained variations in the dependent variable, $t(1,016) = -2.13, p = .03$, as did MISSEDEPS_XBRKG, $t(1,016) = 2.53, p = .01$, MATERIAL, $t(1,016) = 28.80, p = .00$, LSTFSCLQTR, $t(1,016) = 1.93, p = .05$, and the line of trade, Home Furniture & Furnishings, $t(1,016) = 5.11, p = .00$. Table 32 and Figure 14 provide a quick overview of these findings as they relate to each independent variable.

Table 32: ***Multiple Regression Results for BRKG/NOA%***

Variable	*b*	β[18]	*SE b*	*t-stat*	*p-value*	
Constant	0.0003		0.0002	1.41	0.16	
CEOPAYOPTNS%	(0.0006)	(0.0601)	0.0003	(2.13)	0.03	*
MISSEDEPS_XBRKG	0.0004	0.0707	0.0002	2.53	0.01	**
MATERIAL	0.0106	0.7140	0.0004	28.80	0.00	***
LSTFSCLQTR	0.0003	0.0506	0.0002	1.93	0.05	*
NPM_XBRKG	0.0007	0.4475	0.0006	1.25	0.21	
Lines of Trade:						
Building	0.0001	0.0051	0.0003	0.20	0.84	
Restaurant	(0.0001)	(0.0118)	0.0002	(0.40)	0.69	
Home	0.0015	0.1328	0.0003	5.11	0.00	***
Miscellaneous	(0.0001)	(0.0154)	0.0002	(0.52)	0.61	
Food Stores	(0.0002)	(0.0177)	0.0005	(0.48)	0.64	

Adj. $R^2 = .51$, $F(10, 1006) = 104.64$, $p = .011$
$*p < .05$. $**p < .01$. $***p < .001$.

Figure 14: ***Graphical Representation of Support for Each Predictor Variable***



A review of the standardized coefficients suggested that materiality was the most important explanatory variable, followed by line of trade (i.e., Home Furniture, Furnishings, & Equipment), whether the firm missed analysts' EPS forecasts, the

[18] See Footnote 8.

proportion of CEO compensation stemming from stock options, and the quarter the breakage was recognized, respectively.

Based on these results, the following linear function is put forth:

$$\frac{BRKG}{NOA}\%_{iq} = .0003 + (-.0006)(CEOPAYOPTNS\%_{i,q-1}) + .0004\left(MISSEDEPS_{XBRKG_{iq}}\right) + .0106\left(MATERIAL_{iq}\right) + .0003(LSTFSCLQTR_{iq}) + .0015\left(MG_{Home_{iq}}\right)$$

As an example, if an eating/drinking retailer recognizes material breakage (i.e., > ½% of revenue) in their last fiscal quarter, and its CEO earned 25% of his/her compensation in stock options in the prior year, and the retailer would have missed EPS without breakage, then according to the regression model, the expected quarterly BRKG/NOA% for that retailer would be:

$$\frac{BRKG}{NOA}\%_{iq} = .0003 + (-.0006)(25\%) + .0004(1) + .0106(1) + .0003(1) + .0015(1)$$

$$\frac{BRKG}{NOA}\%_{iq} = 1.15\%$$

As a second example, if a home furnishings retailer recognized immaterial breakage (i.e., < ½% of revenue) in their last fiscal quarter, and its CEO earned 75% of his/her compensation in stock options in the prior year, and the retailer would not have missed EPS even though it recognized breakage, then according to the regression model, the expected quarterly BRKG/NOA% for that retailer would be:

$$\frac{BRKG}{NOA}\%_{iq} = .0003 + (-.0006)(75\%) + .0004(0) + .0106(0) + .0003(1) + .0015(0)$$

$$\frac{BRKG}{NOA}\%_{iq} = 0.16\%$$

A further elaboration of the findings will be presented in Section 5.4.

4.5 Summary

The quantitative analysis carried out by this study used various non-parametric tests as well as OLS regression and comparisons of relative dispersion (CV). Table 33 provides a summary of the results by hypothesis. Importantly, the results recognized the influence of analysts' consensus EPS forecasts and to a lesser extent, compensation contracts, in retailers' breakage recognition decisions. In addition, the findings suggested that both the size (materiality) and the timing of the breakage transaction were relevant factors. Likewise, the results demonstrated different breakage recognition practices among retailers as a result of their profitability, line of trade, or overall financial health. There was no statistically significant evidence that breakage is used to smooth earnings.

Table 33: ***Summarized Results by Hypothesis***

Hypothesis	Hypothesis Description	Result
H_1	Compensation Motivation	Unsupported; no evidence
H_2	Income-smoothing Motivation	Unsupported; no evidence
H_3	Meeting External Benchmarks Motivation	Supported; statistically significant evidence
H_4	Materiality	Supported; statistically significant evidence
H_5	Timing	Supported; statistically significant evidence
$H_{6(a)}$	Profitability (Profit Margins)	Supported; statistically significant evidence
$H_{6(b)}$	Line of Trade	Supported; statistically significant evidence
$H_{6(c)}$	Financial Health	Supported; statistically significant evidence
Complete Empirical Model		Support for a Compensation Motivation (contrary support), Meeting External Benchmarks Motivation, Line of Trade (mixed support), Materiality, and Timing

In summary, the purpose of this chapter is to report and explain the findings; the next chapter discusses conclusions and their implications. In addition, Chapter 5 restates the research, the methodology, the results, the limitations, and suggests further research.

CHAPTER 5: SUMMARY AND DISCUSSION

This chapter restates the research problem and reviews the major methods used in the study. The principal sections of this chapter summarize the results and discuss conclusions and their implications. Suggestions for future research and study limitations are also highlighted.

5.1 Statement of the Problem

The use of gift card breakage as an earnings management tool is the focus of this study. The intent of the research is to determine whether three earnings management motivations including compensation, smoothing income, and meeting external benchmarks influenced retailers' decisions to recognize gift card breakage income arbitrarily. Arbitrary, discretionary financial decisions have the potential to undermine the characteristics of financial information, weaken financial statement utility, and affect market players like investors and market analysts. This dissertation also examines whether the breakage recognition decision, and inherently the motivation, is qualified by the relative size of the breakage transaction, by the financial period in which breakage is recognized, and by distinguishable characteristics of the retailer like overall financial health and line of trade. This investigation is carried out by collecting breakage data from publicly available financial reports for firms within the retail segment.

While prior literature examines the idea that managers are motivated to influence accounting results, the earnings management motivations employed in this study have not been jointly applied to discretionary revenue practices or extended to individual revenue-

related transactions such as gift card breakage. This study addresses this gap in literature. In addition, this study is the first to attempt to determine the multiple motivations that shape management decision-making for a new but easily manipulated revenue transaction. If differs from previous earnings management studies in that it uses a single, cash-based revenue transaction that is found in an environment differentiated by a high degree of managerial discretion and non-codified treatment guidelines. The results should be informative for accounting regulators and standard setters who are concerned about the use of revenue as an earnings management tool.

5.2 Review of Methodology

As explained in Chapter 3, this study is carried out through a quantitative study by examining breakage recognition activity across various lines of retail trade for the period 2002-2011. The time period was selected because of the significant growth of gift card programs that occurred in the early 2000s and because the 10-year period ensures a sufficient sample size when testing for statistical significance and generalizability of results. The quantitative analysis includes the use of various non-parametric tests as well as OLS regression and comparisons of relative dispersion (CV).

The quantitative study relies chiefly on publicly available, secondary data from commercial and government sources. US publicly traded firms were identified through an internet search; 58 retail firms met the search criteria consisting of (a) retailers with a gift card program started between January 1, 1996 and December 31, 2011 within one of six lines of trade, including apparel and accessories; building material, hardware, and garden supply; eating and drinking places; food stores; home furniture, furnishings, and equipment; and miscellaneous retail, (b) retailers with a disclosed breakage recognition

policy, (c) retailers who disclosed breakage amounts, and (d) retailers who reported complete quarterly breakage values over the study time frame.

Accuracy of the data is determined by cross-checking multiple data sources. The data was downloaded or copied from the internet into a spreadsheet to minimize data entry errors. Administrative errors are controlled by re-checking, entry-by-entry, the database values to ensure accuracy.

A total of 1,889 firm quarters were collected for the study's variables; notable exceptions were CEO compensation which was collected on an annual basis, and analysts' consensus EPS forecasts which was collected for only 1,176 firm quarters because consensus data was scant prior to 2005 or because a specific retailer was too small to receive analyst coverage. In a majority of cases, outliers (greater than 4 standard deviations from the mean) were retained because the outliers represented significant elements of the population or were representative of the discretionary nature of breakage and were therefore salient to the research objectives. Missing values were not an issue.

Due to violations of normality, non-parametric tests were used to assess hypotheses four, five, and six. OLS regression was employed to evaluate hypothesis one and three, as well as the summary empirical model. Finally, a comparison of relative dispersion was used to assess hypothesis two. The findings of these statistical analyses are elaborated in the next section.

5.3 Summary of Results

This study looks at six hypotheses (some with multiple components) and a summary regression model in an attempt to identify factors that contribute to a firm's decision to discretionarily recognize gift card breakage. In general, the results appear to recognize the influence that a meeting benchmarks motivation has in breakage recognition decisions; in addition, the findings show mixed results on the influence of the compensation motivation on breakage recognition decisions, suggesting that compensation may not be a direct motivator, but an indirect motivator based on interactions with other motivations. The results did not appear to support the modify income motivation. Importantly, the findings give the impression that both the size of the breakage transaction (materiality) and the timing of the breakage transaction are important moderating factors. Likewise, the results appear to demonstrate that different breakage recognition practices exist among retailers as a result of their profitability, line of trade, or overall financial health.

In this section, each of the individual hypotheses, along with the summary empirical model, are reviewed and evaluated based upon the results of the study. All hypotheses are stated in the alternative form for clarity.

H_1: The proportion of CEO pay from stock options positively influences the extent to which retailers use gift card breakage.

A Pearson correlation coefficient of -0.01 (p = .736) suggests no significant relationship between breakage and CEO pay from stock options; as such the proposed linear regression model was ineffectual. Attempts at modifying the regression function by toggling the length of time between grant date and breakage recognition date, and by

controlling for firm type proved insufficient; in the latter case, significance ($p < .05$) was not achieved, and as such, the regression did not find a supportable association between breakage and CEO pay from stock options. The failure to detect a relationship may have been caused by the way in which annual compensation values were allocated to quarters. As such, this hypothesis is not supported.

H_2: Breakage is used by retailers to smooth earnings.

The employed methodology failed to detect income-smoothing activity. While 20 firms were identified as possible income smoothers in that their $CV_{\Delta B} > CV_{\Delta I}$, none of the firms could be verified as artificial income smoothers as none had an income-smoothing factor more than one standard deviation smaller than the industry average. The failure to detect income-smoothing activity was most likely caused by the way the industry average income-smoothing factor was calculated from the sample itself. This hypothesis is not supported.

H_3: In quarters where gift card breakage occurs, breakage is used by retailers to meet analysts' consensus EPS forecasts.

There is statistically significant evidence that among firms that recognize breakage, gift card breakage is used by retailers to meet analysts' EPS consensus forecasts. The mean (median) forecast error with breakage (FE%) is -4.40% (2.30%) while the mean (median) forecast error without breakage (XFE%) is -9.70 (0.00%); the difference in medians is significant ($p = .006$) suggesting that a breakage transaction increases actual reported EPS and permits retailers to beat analysts' EPS consensus forecasts. This is further validated by the finding that retailers met/exceeded analysts' EPS consensus forecasts when recognizing breakage 75% of the time ($n = 398$), but

met/exceeded analysts' EPS consensus forecasts only 63% of the time when they did not recognize breakage (n = 337). The difference in the proportion of meeting/exceeding the consensus forecast between the two scenarios is significant (*Fisher's exact test*, p = .000).

The results of the regression model comparing the difference between forecast error with breakage and forecast error without breakage against whether a firm would have missed analysts' EPS consensus forecasts without breakage is significant as well (R^2 = .01, $F(1,527) = 6.52$, p = .011). The explanatory variable significantly explained changes in the dependent variable, $t(528) = 2.55$, p = .011. While the R^2 is small, explaining only 1% of the variation in the dependent variable[19], it is significant; a small R^2 may be acceptable however because this study examined a single revenue transaction against a cumulative profitability measure (EPS). Based on the results, the predicted value for the difference in forecast error caused by breakage is 13.1% when a firm would have missed EPS projections and the predicted value for the difference in forecast error caused by breakage is 0.8% when a firm would not have missed EPS projections. These results highlight the influence of breakage on the forecast error.

A final confirmation of the suggestive influence of analysts' consensus EPS forecasts on breakage recognition decisions was confirmed through the non-parametric equivalent of a 2-sample t-test, the Mann-Whitney test. The results of the Mann-Whitney test, adjusted for ties, are consistent with the regression results and significant at a 95% confidence level (U = 46098, Z = 8.079, p = .000, r = .35), indicating that the difference in forecast error with breakage and forecast error without breakage is significantly greater when a firm misses analysts' EPS forecasts (*Mdn* = 3.85%, n = 197) than when a firm does not miss analysts' EPS projections (*Mdn* = 0%, n = 336). In sum, this hypothesis is

[19] Of note, eliminating 5 outliers (standardized residual > 2) increased the R^2 to .067, or 7%.

supported. As such, the model suggests that retailers use breakage to meet analysts' consensus EPS forecasts.

H_4: Retailers are more likely to record breakage in immaterial materials than material amounts.

A 1-sample sign test ($Mdn = .001$, $p = .000$) revealed that among firms that recognize breakage, retailers are more likely to record immaterial breakage, where immaterial is defined as less than ½% of revenue. Therefore, this hypothesis is supported. These results may imply that retailers are able to use immaterial breakage entries to manage earnings and therefore not raise materiality concerns among auditors or analysts.

H_5: Retail firms are more likely to recognize breakage in the last quarter of their fiscal year.

Based on the results, there is statistically significant evidence that among firms that recognize breakage, retailers are more likely to recognize breakage in the last quarter of their fiscal year. This study examines this hypothesis from two perspectives. First, a Kruskal-Wallis test ($H = 187.52$, 3 *d.f.*, $p = .000$) combined with a pairwise Mann-Whitney *post hoc* test at a 99.167% confidence level shows that median fourth quarter breakage as a percent of annual breakage (40.44%) is significantly greater than the median percent of the first three quarters, respectively. Second, another Kruskal-Wallis test ($H = 73.40$, 3 *d.f.*, $p = .000$) combined with a pairwise Mann-Whitney *post hoc* test at a 99.167% confidence level reveales that median fourth quarter breakage as a percent of sales (0.17%) is significantly greater than median breakage as a percent of sales of the first three quarters, respectively. In short, this hypothesis is supported.

Together, the results reveal that the fourth quarter is used to record the largest breakage transaction in both absolute and relative terms. Because both fourth quarter breakage as a percent of annual breakage and fourth quarter breakage as a percent sales differed significantly from the first three quarters, respectively, the results suggest that retailers' decisions may be a result of a managed choice.

H_{6a}: Low margin retailers recognize more breakage than high margin retailers.

Using breakage as a percent of sales as a proxy for breakage, a one-sided Mann-Whitney test ($U = 15039$, $Z = 4.569$, $p = .000$, $r = .26$) found that among firms recognizing breakage, low margin retailers recognize more breakage ($Mdn = 0.19\%$, $n = 157$) than high margin retailers ($Mdn = 0.10\%$, $n = 147$). The results suggest that less profitable companies may benefit more through breakage recognition, particularly to improve their margins. This finding seems to hint at potential earnings management, particularly among low-profit firms. As such, the hypothesis is supported.

H_{6b}: The propensity to recognize breakage varies by trade.

Using breakage as a percent of sales as a proxy for breakage, a Kruskal-Wallis test ($H = 88.28$, 5 *d.f.*, $p = .000$) combined with two-tailed pairwise Mann-Whitney *post hoc* tests at the 99.667% confidence level found that among firms recognizing breakage, there are significant differences between the lines of trade in this study. Highest levels of breakage occurred in the Home Furnishings, Furniture, and Equipment; Eating and Drinking Places; and Apparel and Accessory Stores lines of trade. In contrast, Miscellaneous Retail; Building Materials, Hardware, and Garden Supply; and Food Stores saw lower levels of breakage. This finding indicates that sizable breakage activity is more likely to occur within some retail segments than others. The implication is that

retailers within some lines of trade may use more latitude in making discretionary decisions on breakage, and therefore, a larger lever in which to manage earnings. As such, the hypothesis is supported.

H_{6c}: Retailers in low financial health recognize more breakage than retailers in strong financial health.

Using breakage as a percent of sales as a proxy for breakage and return on net operating assets as an indication of financial health, a one-sided Mann-Whitney test at a 95% confidence level ($U = 16588$, $Z = 6.283$, $p = .000$, $r = .36$) found that among retailers recognizing breakage, firms in poor financial health recognize more breakage ($Mdn = 0.19\%$, $n = 165$) than firms in strong financial health ($Mdn = 0.06\%$, $n = 142$). This suggests that firms in poor financial health may look to recognize breakage to improve not only their operating margins but also their asset turnover metric. Further, it seems evident that these decisions are most likely the result of a managed choice and may hint at earnings management. In sum, the hypothesis is supported.

Complete Empirical Model

Using breakage as a percent of net operating assets as the dependent variable and as a proxy for breakage, an OLS regression indicated that the predictor variables jointly explain 51% of the variance in the response variable above its average ($R^2 = .51$, $F(10, 1006) = 104.64$, $p = .000$). Among firms recognizing breakage, the regression results suggest that the compensation motivation significantly explained variations in the dependent variable, $t(1,016) = -2.13$, $p = .03$, as did the meeting benchmarks motivation, $t(1,016) = 2.53$, $p = .01$. The results also reveal the importance and moderating effects of the size of the transaction, $t(1,016) = 28.80$, $p = .00$, the timing of the transaction,

$t(1,016) = 1.93, p = .05$, and the retailers' line of trade, specifically Home Furniture, Furnishings and Equipment, $t(1,016) = 5.11, p = .00$. A review of the standardized coefficients revealed that the most important explanatory variable is the size of the breakage transaction; notably, the results suggested that the meeting benchmarks motivation is more important than the compensation motivation.

The results of the regression model may be influenced by violations of OLS regression assumptions, including a non-normal distribution of error terms, moderate heteroscedasticity of the residuals, and non-linearity of the residuals. However, it is the opinion of the researcher that the violations are the result of accepting extreme observations as determined by the Cook's Distance test statistic. The extreme observations were retained in the model because they represented significant breakage events, specifically first time breakage recognition by an individual firm or the largest breakage value(s) recognized by an individual retailer. As such, the extreme observations represented well the discretionary nature of the breakage transaction. In sum, it is the opinion of the researcher that the significance tests are essentially unaffected and that the OLS results can be used without concern of serious bias.

5.4 Discussion of the Results

The key to understanding any decision to manage earnings lies in grasping managerial motivations for engaging in such activity (Dechow & Skinner, 2000). This study considered whether compensation contracts, income-smoothing concerns, or meeting external EPS benchmarks motivated retail managers across six retail lines of trade to use breakage arbitrarily to influence their accounting results. A critical difference between this study and prior motivation-related earnings management literature is that

this study's subject tool for earnings management – gift card breakage – is a new and highly subjective revenue-related derivative of retail closed-loop gift card programs. Another critical difference is that this study uses a single, cash-based transaction rather than aggregated accruals; the use of a single transaction more closely aligns to the way managers think and make decisions, which is typically at the transaction level (see e.g., Stice et al., 2004), and the use of a cash-based transaction avoids problems typically associated with accruals-based models (see e.g., Dechow & Skinner, 2000).

5.4.1 Earnings Management Motivations.

This section synthesizes and analyzes the results of the influence of compensation, income-smoothing, and meeting benchmarks motivations on breakage recognition decisions.

The most significant outcome of this study is the apparent influence that a meeting external benchmarks motivation has on retailers' decisions to recognize gift card breakage. Consistent with Burgstahler and Dichev (1997), this study provides evidence that companies try to avoid disappointing market analysts; here, retailers appear to avoid missing the mean quarterly consensus analysts' EPS forecast with breakage. As evidence, the results suggest that for firms recognizing breakage, the forecast error, which is the difference between actual EPS and consensus EPS, would have been on average 13% larger had they not recognized breakage in those quarters where they would have missed consensus EPS. This percentage compares to a forecast error that would have been on average only 0.8% larger had they not recognized breakage in those quarters where they would not have missed consensus EPS. Expressed on a per share basis, the average EPS miss would have been two cents larger versus zero cents larger, respectively. The

implication seems obvious: breakage allows firms to escape the negative market consequences of missing EPS forecasts, such as lower stock prices (Skinner & Sloan, 2002).

Further evidence of the influence of the meeting benchmarks motivation is seen in the result that shows that retailers met/exceeded EPS consensus forecasts 75% of the time with breakage, but only 63% of the time without breakage (*Fisher's exact test*, $p = .000$). The statistically significant difference in proportions demonstrates the potential of breakage in earnings management to meet consensus forecasts.

As such, one apparent consequence of this study should be the adoption of GAAP treatment guidelines and prescribed reporting requirements for breakage to elevate the transparency of the transaction. Financial regulators should move to adopt appropriate bright-line rules on breakage revenue recognition issues. More so, a second consequence of this study is a call for upper-level retail managers to avoid the appearance of earnings management; even if a firm is not intentionally managing earnings with breakage, the results of this study demonstrate that an appearance to manipulate exists. Managers should avoid any appearance to manipulate earnings in their role as financial stewards of company resources. To address this concern, retail managers should establish in-house policies which govern breakage recognition decisions and fully disclose these policies in their financial footnotes. Financial disclosures should state the in-house policy clearly and provide breakage amounts by quarter, an assessment of gift card redemption history, and a reconciliation of the deferred gift card liability account.

A second finding is the potential influence of CEO compensation on breakage recognition decisions. In this study, the compensation motivation hypothesis was

contrarily supported when breakage was regressed against multiple motivations and moderating variables in the complete regression model. In one sense, these results mirror existing literature which has yet to definitively show a strong relationship between compensation contracts and accounting earnings. However, the contrarian results, as demonstrated by negative regression coefficients, are counterintuitive in that it suggests that CEO pay from stock options negatively influences breakage recognition. This conflicting outcome however is most likely due to the fact that the regression model leveraged a research design where annual compensation values were interpolated to quarterly values; that is, breakage was regressed against compensation that did not vary quarter to quarter within a given year. As such, it is the researcher's opinion that the contradictory finding is the result of the nature of the research approach and not necessarily support that higher (lower) stock option compensation results in lower (higher) breakage values. More importantly, the fact that the compensation motivation is significant when regressed with other predictor variables in the complete regression model may suggest that compensation may be an important earnings management motivation, especially in the presence of other earnings management motivations like meeting external benchmarks. Since CEOs are both managing their careers in order to be seen as effective stewards of their organizations (Fama, 1980) and managing perceptions of how well their companies are performing (i.e., by sustaining company stock price), logically it follows that if retail firms maintain stock valuations by managing earnings to meet EPS forecasts, CEOs with stock option compensation still accrue intrinsic and extrinsic benefits. On one hand, they are seen as successful agents of the organization, and on the other hand, the value of their options (i.e., their compensation) does not

diminish. As rightly noted by Cheng and Warfield (2005), managers benefit from earnings management that keeps stock prices high; this study seems to support their contention.

Finally, the results do not seem to support an income-smoothing motivation. This conclusion could be interpreted in one of two ways. First, sampled retailers may not be intentionally trying to smooth their income. This interpretation is plausible in that no retailer was identified as an artificial income smoother over the study's 10-year time frame, with or without the impact of breakage. Plus, this understanding would be in harmony with Eckel's (1981) original work that found that 97% of firms were not successful income smoothers; in other words, income-smoothing may not be as prevalent as some empirical literature might suggest. An alternative, and more likely interpretation, is that the statistical model failed to find support because the industry average income-smoothing factor, to which each firm's income-smoothing factor was compared, was not actually representative of the entire retailing industry. That is, the subset of firms used to calculate the industry's income-smoothing factor was in some way atypical of the retail industry. Future research on the linkage between single revenue transactions and income-smoothing may want to find a more representative market basket of retailers in order to determine the retailing industry's overall income-smoothing factor.

5.4.2 Materiality, Timing, & Retailer Characteristics.

This section synthesizes and examines the effects of the size (materiality) and timing of the breakage transaction, as well as retailer breakage recognition practices in light of their profitability, line of trade, or overall financial health.

First, existing literature supports the notion that a financial item that exceeds ½% of revenue within the retail segment is frequently judged material (Pany & Wheeler, 1989). This study's finding that retailers are more likely to record breakage less than ½% of revenue is significant in that it implies that retailers could manage earnings through immaterial breakage accounting entries. A presupposed benefit for the retailer is that immaterial amounts will not draw attention and scrutiny from auditors, analysts, and regulators. Since auditors' materiality decisions, for example, typically follow closely conventional "rules of thumb" (Bernardi & Pincus, 1996; Chewning, Wheeler, & Chan, 1998), retailers' attempts at earnings management through breakage may go unnoticed. While key stakeholders may believe that immaterial breakage amounts are not misleading, the results of this study suggest that even non-misleading transactions can be used to manage earnings.

The results shed light on a possible connection between immaterial breakage entries and the meeting benchmark motivation. In the case of meeting EPS forecasts, for example, retailers appear to be able to increase their actual EPS through immaterial breakage entries to meet consensus forecasts. As evidence, among firms recognizing breakage, retailers met EPS projections through immaterial breakage amounts in 80% of the firm quarters[20] where they would have missed their respective consensus EPS forecast without the breakage transaction; this proportion is significant (*Fisher's exact test, p* = .000) and suggests that breakage is a very useful tool to bolster earnings surreptitiously. The discernible link between meeting an external benchmark through immaterial amounts must be attractive for retailers.

[20] Out of 197 firm quarters

Second, this study finds that retailers are more likely to recognize breakage in the last quarter of their fiscal year. One possibility for this outcome is that retailers are simply recording breakage at a predetermined point after initial sale of a gift card. For example, if most gift card sales occur in the fourth quarter, then one could surmise that breakage is simply being recognized in the same quarter, perhaps one or two years later. However, the results seem to refute this explanation in that the relative size of fourth quarter breakage was significantly larger than the other three quarters, respectively. Another possible explanation for this, which would be consistent with prior literature, is that since the fourth quarter is frequently considered a "settling-up" quarter, retailers are merely attempting to adjust their full-year results by ensuring that their balance sheets are fair representations of economic reality. A differing explanation however, also consistent with prior literature (e.g., Collins et al., 1984; Schroff et al., 2009), is that these timing related decisions are the result of a managed choice. The author believes that this latter explanation is highly plausible because an earnings management motivation, that is the meeting external benchmarks motivation, was present in the fourth quarter. Retailers may intentionally record more breakage in the fourth quarter because of earnings pressure surrounding full year results. As evidence of this, 36% of the sampled occurrences where firms potentially recognized breakage to meet EPS happened in the fourth quarter; this percent compares with 20%, 20%, and 24% among the first three quarters, respectively[21]. It seems very likely that external pressures to meet fourth quarter consensus forecasts, and indirectly full-year forecasts, propel retail managers to recognize more breakage in

[21] The difference between the fourth quarter and the other three quarters is statistically significant at a 99% confidence level.

the fourth quarter than was recognized earlier in the year when meeting quarterly results is not as vital.

Finally, the results of this study appear to suggest that breakage recognition practices differ significantly depending upon retailers' line of trade, profitability, and overall financial health. For example, the results demonstrated that among retailers recognizing breakage, low margin firms (as measured by Net Profit Margin) and firms in poor financial health (as measured by Return on Net Operating Assets) recognize more breakage as a percent of sales than high margin firms and firms in stronger financial health, respectively. This finding suggests that breakage is viewed by low-profit retailers as a means to increase profitability and key performance metrics, which may represent mere window-dressing or more likely, an intentional, managed choice to accelerate recognition of unredeemed gift cards by weaker and less profitable retailers.

One surprising outcome is the lack of relationship between breakage and profitability in the complete OLS regression model. This may imply that while a retailer's profitability profile affects decision-making on accounting earnings, it does not necessarily suggest earnings management. An investigation into the relationship between retailer profitability and earnings management motivations, e.g., meeting EPS forecasts, may be an interesting study for future research.

In similar fashion, breakage differs significantly across line of trade, suggesting that line of trade may be an important lever in a retailers' ability to recognize breakage and ultimately manage earnings. The highest levels of breakage occurred in the Home Furnishings, Furniture, and Equipment; Eating and Drinking Places; and Apparel and Accessory Stores lines of trade. These lines most likely have higher gift card usage, and

therefore, a higher probability of breakage. Firms with more breakage opportunity may be more inclined to tap their unredeemed gift card reserves, possibly even to manage earnings. One noticeable finding along this line of thinking was the significant influence of the Home Furnishings, Furniture, and Equipment line of trade in the complete OLS regression model. This line of trade consists of retailers selling both home furnishings and electronics. Interestingly, these sampled retailers recognized breakage in 54% of the firm quarters where they would have missed consensus EPS[22], which appears to hint at the use of breakage to manage earnings in this line of trade.

In sum, retailer characteristics appear to influence the relative size of the breakage transaction, and as such, may sway discretionary decisions to manage accounting earnings. Importantly, the apparent link between immaterial breakage and meeting EPS forecasts is especially revealing in the context of managed earnings.

5.5 Contributions to Knowledge

This study contributes to both revenue recognition and earnings management literature by examining a new and significant revenue transaction that could be used to manage earnings. In particular, this study addresses a fundamental gap in academic literature in that much earnings management literature offers little utility to standard setters and accounting regulators (Healy & Wahlen, 1999); in contrast, this study focuses on earnings management with revenue which can provide benefit to those who bear the responsibility of setting and enforcing accounting standards because "revenue recognition is perhaps the single greatest problem area in US financial reporting" (Hermanson et al.,

[22] This proportion is statistically significant (*Fishers exact test*, $p < .005$) versus other lines of trade, including Building, Materials, Hardware, and Garden Supply (26%); Apparel and Accessories (25%); and Miscellaneous Retail (31%). In contrast, this proportion is not statistically significant versus Eating and Drinking Places (44%) or Food Stores (47%).

2008). The results of this study seem to highlight the immediate need for clear accounting standards (i.e., bright-line rules) on breakage recognition and should prompt standard setters to craft appropriate rules quickly given the appearance of earnings management through breakage. The direct benefit of bright-line rules is that financial preparers, audit committees, and other stakeholders will be more equipped to determine when the earnings process for gift cards is actually complete; this knowledge will immediately enhance comparability and consistency of financial statements and improve financial statement quality.

Beyond addressing accounting standards concerns, this study also contributes to earnings management motivation literature because it examines joint motivations behind a cash-based transaction within the context of a highly discretionary environment; this differs from previous research that relied on single motivations tested with established models using aggregated accruals. As such, this study provides additional insights into managed choices at the transaction level. The results appear to suggest that retailer managers adopt revenue-related accounting tools like breakage to influence earnings, particularly in the context of meeting consensus EPS forecasts and to a lesser extent, to achieve compensation contract outcomes.

From a practitioner's perspective, this study informs external stakeholders of both the incentives that drive breakage recognition decisions and how those decisions impact financial statement quality. Raising awareness among key stakeholders elevates the likelihood that regulators will address discretionary breakage practices. Furthermore, this study apprises retail managers of the need to institute and disclose appropriate breakage recognition policies to minimize appearances of earnings management. Suitable policies

and quarterly/annual disclosures within financial reports will increase transparency and reduce ambiguity that financial results are being managed furtively with breakage.

5.6 Suggestions for Future Research

While this study advanced the earnings management body of literature, it also leaves some questions unanswered and opens future research possibilities. Among the most promising areas for future research are the following:

- Research which examines the market's reaction to breakage recognition seems warranted, especially in light of the appearance of earnings management through breakage. Researchers should employ a time-study methodology to assess whether there were significant changes in stock price immediately after breakage recognition, particularly if the breakage was deemed material in nature. This type of extension will advance the understanding of how the market views earnings management through a single revenue transaction.
- Natural extensions of this study could investigate other earnings management motivations, or validate the findings of this study. Alternative motivations in earnings management literature include lending contracts, additional equity offerings, or tax minimization, among others. Research that brings further clarity to compensation influences on breakage decisions will be beneficial as well.
- An interesting research study could be conducted to assess the signaling effects of breakage transactions; this type of study would be especially useful in light of this study's findings that demonstrated that retailers' profitability and overall financial health may determine alternative breakage practices. As an example, would

increases in levels of breakage signal a weakening financial condition? This appears to be a fruitful area of study.

5.7 Limitations

There are a number of limitations to the study, with the most noteworthy being the nature of data. Specifically, there are significant violations of normality across the dependent and independent variables; while non-parametric tests are employed to account for these variations in several situations, the research accepts several underlying violations of linear regression and of the variate in the complete OLS model. While it is the opinion of the researcher that the OLS significance tests are essentially unaffected because of the large sample size and the necessity to include extreme observations that correspond with the objectives of this research, the insights yielded by the regression model may be inefficient or biased.

A second limitation involves the sample selection. Because retailers *voluntarily* disclose breakage practices and policies in their financial footnotes, the research indirectly uses of a convenience sampling technique. As such, sampled firms may not be representative of the retailing industry at large. It is possible that there are unique but unidentifiable characteristics among these firms that precipitated their voluntary disclosure which might bias the findings. Therefore, the results may not be generalizable to other retailers outside the sample who recognize breakage but do not disclose such activity.

A third limitation stems from the interpolation of annual CEO compensation data to quarterly values. This simplifying assumption implies that bonus and stock related CEO compensation could conceivably be distributed equally throughout the year; yet, it

is more likely that payouts of this nature are targeted on year-end numbers. There may be no underlying reason to suspect quarterly distributions. In addition, the decision to average multiple compensation values due to CEO turnover or co-CEO relationships could be problematic if compensation contracts differed significantly between CEOs. These limiting factors may affect any inferences arising from the compensation motivation.

A final limiting factor involves the analysts' EPS consensus forecast data. Analyst coverage varied widely. Some firms in the sample were too small to receive analyst coverage; other firms had analyst coverage that started and stopped intermittently. More so, the lack of mean consensus data prior to 2005 is obtrusive. Finally, the number of analysts covering any one firm ranged from one to over twenty. Even with these variations, this study assumes that analysts' projections are void of estimation bias and are a true reflection of market expectations. Yet, literature demonstrates that analysts' projections differ significantly from actual earnings (Dreman & Berry, 1995). Given the circumspect nature of analysts' projections, inferences made in this study regarding a meeting benchmarks motivation may be impacted by the strength and reliability of the external benchmark.

5.8 Summary

Evidence from this study suggests that retail firms use gift card breakage to manage earnings. The results imply that a principal motivation behind this behavior is a desire to meet market analysts' consensus EPS forecasts; that is, retail managers appear to make highly discretionary breakage decisions as a result of real or perceived financial and reputational consequences if they miss anticipated EPS targets. More so, the results

suggest that retailers can discreetly achieve consensus forecasts through immaterial transactions. The inference is that breakage is a very useful tool to bolster earnings and EPS surreptitiously.

The results also suggest that retailers exercise discretion in recognizing breakage so that senior management can benefit from performance-based compensation contracts. The results infer that compensation may be an important, but secondary motivation, especially in the presence of a meeting benchmarks motivation. Logically, when retail firms maintain stock valuations by managing earnings to meet EPS forecasts, CEOs with stock option compensation accrue tangible benefits.

In addition, the outcomes of this study imply that less profitable retailers and retailers in poor financial health may benefit more from discretionary breakage decisions than more profitable retailers and retailers in strong financial health. An apparent implication is that financially weaker retailers leverage their discretion to recognize breakage to favor the appearance of financial strength; these results hint at an intentional, managed-choice to improve financial results.

This investigation highlights the need for bright-line rules for breakage and raises awareness on how a revenue-related transaction can be used to manage earnings. The results of this study should provide investors and stakeholders new information regarding the implications of fluid breakage recognition policies on financial statement quality. Likewise, regulators, in their efforts to improve financial statement comparability and consistency among retailers, should find the results of this study useful when developing disclosure requirements for breakage.

For retail managers, this study underscores the importance of transparency and full disclosure in financial information; specifically, retail managers should avoid any appearance to manipulate earnings in their role as financial stewards of company resources. To address this concern, retail managers should establish in-house breakage policies, fully disclose these policies in their financial footnotes, and publicly communicate both their gift card redemption history and reconciliations of their deferred gift card liability account.

In review, retail gift card breakage is a new and powerful accounting element that can be used to influence accounting results because breakage policies are not codified and are inconsistently applied. In this type of environment, breakage recognition is especially susceptible to highly discretionary actions by managements. This investigation suggests that discretionary breakage decisions may be influenced to a large extent by the need to meet analysts' EPS forecasts and to a lesser extent, to achieve compensation contract outcomes. The discernible link between meeting an external benchmark through immaterial amounts is especially revealing in the context of managed earnings. The results should be of interest to standard setters, analysts, investors, and retail managers who are concerned about actual or apparent attempts to manipulate earnings through revenue.

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APPENDIX A – TEST RESULTS FOR H_1

Results for: 1-year lagged data

Regression Analysis: BRKG/Sales% versus CEOPAYOPTNS%, FIRM_TYPE

The regression equation is
BRKG/Sales% = 0.000043 - 0.000496 CEOPAYOPTNS% + 0.00108 FIRM_TYPE

1857 cases used, 32 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	0.0000428	0.0001730	0.25	0.805
CEOPAYOPTNS%	-0.0004962	0.0002788	-1.78	0.075
FIRM_TYPE	0.0010846	0.0001997	5.43	0.000

S = 0.00336120 R-Sq = 1.6% R-Sq(adj) = 1.5%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	0.00033461	0.00016731	14.81	0.000
Residual Error	1854	0.02094582	0.00001130		
Total	1856	0.02128043			

Source	DF	Seq SS
CEOPAYOPTNS%	1	0.00000130
FIRM_TYPE	1	0.00033331

Unusual Observations

Obs	CEOPAYOPTNS%	BRKG/Sales%	Fit	SE Fit	Residual	St Resid
9	0.49	0.008612	0.000886	0.000105	0.007726	2.30R
118	0.19	0.013022	0.001031	0.000091	0.011991	3.57R
155	0.50	0.009803	0.000878	0.000108	0.008924	2.66R
191	0.08	0.012356	0.001088	0.000104	0.011268	3.35R
200	0.00	0.008532	0.001127	0.000117	0.007405	2.20R
212	0.00	0.010909	0.001127	0.000117	0.009781	2.91R
423	0.28	0.040460	0.000986	0.000088	0.039474	11.75R
647	0.08	0.019608	0.001086	0.000103	0.018522	5.51R
768	0.05	0.048319	0.001103	0.000108	0.047215	14.05R
893	0.87	0.013594	0.000694	0.000188	0.012900	3.84R
945	0.00	0.074198	0.001127	0.000117	0.073071	21.75R
946	0.00	0.013073	0.001127	0.000117	0.011946	3.56R
947	0.00	0.010314	0.001127	0.000117	0.009187	2.73R
948	0.00	0.008094	0.001127	0.000117	0.006967	2.07R
949	0.76	0.018795	0.000749	0.000161	0.018046	5.38R
950	0.76	0.009115	0.000749	0.000161	0.008366	2.49R
951	0.76	0.007622	0.000749	0.000161	0.006873	2.05R
953	0.53	0.021050	0.000865	0.000112	0.020185	6.01R
957	0.08	0.013229	0.001087	0.000103	0.012142	3.61R
967	0.00	0.016647	0.001127	0.000117	0.015519	4.62R
971	0.00	0.015321	0.001127	0.000117	0.014194	4.23R
975	0.00	0.030837	0.001127	0.000117	0.029710	8.84R
979	0.00	0.009049	0.001127	0.000117	0.007922	2.36R
996	0.00	0.013546	0.001127	0.000117	0.012419	3.70R

1000	0.18	0.010123	0.001036	0.000091	0.009087	2.70R
1167	0.10	0.013695	0.001076	0.000100	0.012619	3.76R
1238	0.00	0.021932	0.001127	0.000117	0.020804	6.19R
1242	0.14	0.021427	0.001056	0.000095	0.020371	6.06R
1246	0.09	0.020885	0.001082	0.000102	0.019803	5.89R
1250	0.04	0.022413	0.001106	0.000110	0.021307	6.34R
1252	0.32	0.041526	0.000969	0.000088	0.040557	12.07R
1298	0.00	0.035151	0.001127	0.000117	0.034023	10.13R
1333	0.19	0.023722	0.001033	0.000091	0.022688	6.75R
1463	0.02	0.010266	0.001119	0.000114	0.009147	2.72R
1469	0.23	0.020607	0.001015	0.000089	0.019592	5.83R
1538	0.66	0.000000	-0.000286	0.000235	0.000286	0.09 X
1539	0.70	0.000000	-0.000305	0.000242	0.000305	0.09 X
1540	0.70	0.000000	-0.000305	0.000242	0.000305	0.09 X
1541	0.70	0.000000	-0.000305	0.000242	0.000305	0.09 X
1542	0.70	0.000000	-0.000305	0.000242	0.000305	0.09 X
1543	0.71	0.000000	-0.000310	0.000244	0.000310	0.09 X
1544	0.71	0.000000	-0.000310	0.000244	0.000310	0.09 X
1545	0.71	0.000000	-0.000310	0.000244	0.000310	0.09 X
1546	0.71	0.000000	-0.000310	0.000244	0.000310	0.09 X
1547	0.75	0.000000	-0.000328	0.000252	0.000328	0.10 X
1548	0.75	0.000000	-0.000328	0.000252	0.000328	0.10 X
1549	0.75	0.000000	-0.000328	0.000252	0.000328	0.10 X
1550	0.75	0.000000	-0.000328	0.000252	0.000328	0.10 X
1551	0.75	0.000000	-0.000330	0.000252	0.000330	0.10 X
1552	0.75	0.000000	-0.000330	0.000252	0.000330	0.10 X
1553	0.75	0.000000	-0.000330	0.000252	0.000330	0.10 X
1554	0.75	0.000000	-0.000330	0.000252	0.000330	0.10 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Results for: 2-year lagged data

Regression Analysis: BRKG/Sales% versus CEOPAYOPTNS%, FIRM_TYPE

The regression equation is
BRKG/Sales% = 0.000002 - 0.000020 CEOPAYOPTNS% + 0.00110 FIRM_TYPE

1642 cases used, 247 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	0.0000015	0.0001957	0.01	0.994
CEOPAYOPTNS%	-0.0000195	0.0003103	-0.06	0.950
FIRM_TYPE	0.0011008	0.0002273	4.84	0.000

S = 0.00354935 R-Sq = 1.5% R-Sq(adj) = 1.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	0.00032004	0.00016002	12.70	0.000
Residual Error	1639	0.02064792	0.00001260		
Total	1641	0.02096796			

Source	DF	Seq SS
CEOPAYOPTNS%	1	0.00002452
FIRM_TYPE	1	0.00029552

Unusual Observations

Obs	CEOPAYOPTNS%	BRKG/Sales%	Fit	SE Fit	Residual	St Resid
9	0.52	0.008612	0.001092	0.000122	0.007520	2.12R
118	0.29	0.013022	0.001097	0.000098	0.011926	3.36R
155	0.00	0.009803	0.001102	0.000133	0.008700	2.45R
191	0.17	0.012356	0.001099	0.000105	0.011257	3.17R
200	0.00	0.008532	0.001102	0.000133	0.007430	2.09R
212	0.00	0.010909	0.001102	0.000133	0.009807	2.76R
423	0.57	0.040460	0.001091	0.000132	0.039369	11.10R
647	0.18	0.019608	0.001099	0.000104	0.018509	5.22R
768	0.03	0.048319	0.001102	0.000127	0.047217	13.31R
893	0.67	0.013594	0.001089	0.000154	0.012505	3.53R
945	0.76	0.074198	0.001087	0.000177	0.073111	20.62R
946	0.76	0.013073	0.001087	0.000177	0.011986	3.38R
947	0.76	0.010314	0.001087	0.000177	0.009227	2.60R
949	0.53	0.018795	0.001092	0.000123	0.017703	4.99R
950	0.53	0.009115	0.001092	0.000123	0.008023	2.26R
953	0.08	0.021050	0.001101	0.000117	0.019949	5.62R
967	0.00	0.016647	0.001102	0.000133	0.015545	4.38R
971	0.00	0.015321	0.001102	0.000133	0.014219	4.01R
975	0.00	0.030837	0.001102	0.000133	0.029735	8.38R
979	0.00	0.009049	0.001102	0.000133	0.007947	2.24R
996	0.18	0.013546	0.001099	0.000103	0.012447	3.51R
1000	0.16	0.010123	0.001099	0.000106	0.009024	2.54R
1167	0.33	0.013695	0.001096	0.000099	0.012599	3.55R
1238	0.14	0.021932	0.001100	0.000108	0.020832	5.87R
1242	0.09	0.021427	0.001101	0.000116	0.020326	5.73R
1246	0.04	0.020885	0.001101	0.000124	0.019783	5.58R
1250	0.32	0.022413	0.001096	0.000099	0.021317	6.01R
1252	0.00	0.041526	0.001102	0.000133	0.040424	11.40R
1298	0.00	0.035151	0.001102	0.000133	0.034048	9.60R
1333	0.45	0.023722	0.001094	0.000110	0.022628	6.38R
1463	0.30	0.010266	0.001097	0.000098	0.009170	2.58R
1469	0.41	0.020607	0.001094	0.000105	0.019512	5.50R
1538	0.70	0.000000	-0.000012	0.000274	0.000012	0.00 X
1539	0.71	0.000000	-0.000012	0.000276	0.000012	0.00 X
1540	0.71	0.000000	-0.000012	0.000276	0.000012	0.00 X
1541	0.71	0.000000	-0.000012	0.000276	0.000012	0.00 X
1542	0.71	0.000000	-0.000012	0.000276	0.000012	0.00 X
1543	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1544	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1545	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1546	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1547	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1548	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1549	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X
1550	0.75	0.000000	-0.000013	0.000285	0.000013	0.00 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Results for: 3-year lagged data

Regression Analysis: BRKG/Sales% versus CEOPAYOPTNS%, FIRM_TYPE

The regression equation is
BRKG/Sales% = 0.000030 - 0.000468 CEOPAYOPTNS% + 0.00130 FIRM_TYPE

1414 cases used, 475 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	0.0000304	0.0002135	0.14	0.887
CEOPAYOPTNS%	-0.0004676	0.0003331	-1.40	0.161
FIRM_TYPE	0.0012994	0.0002501	5.20	0.000

S = 0.00359233 R-Sq = 1.9% R-Sq(adj) = 1.7%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	0.00034896	0.00017448	13.52	0.000
Residual Error	1411	0.01820873	0.00001290		
Total	1413	0.01855769			

Source	DF	Seq SS
CEOPAYOPTNS%	1	0.00000059
FIRM_TYPE	1	0.00034837

Unusual Observations

Obs	CEOPAYOPTNS%	BRKG/Sales%	Fit	SE Fit	Residual	St Resid
9	0.00	0.008612	0.001330	0.000146	0.007282	2.03R
118	0.32	0.013022	0.001180	0.000107	0.011842	3.30R
155	0.00	0.009803	0.001330	0.000146	0.008473	2.36R
200	0.12	0.008532	0.001275	0.000123	0.007257	2.02R
212	0.17	0.010909	0.001252	0.000116	0.009656	2.69R
423	0.10	0.040460	0.001284	0.000126	0.039177	10.91R
647	0.30	0.019608	0.001187	0.000107	0.018420	5.13R
768	0.00	0.048319	0.001328	0.000145	0.046990	13.09R
893	0.74	0.013594	0.000983	0.000183	0.012611	3.52R
945	0.53	0.074198	0.001083	0.000132	0.073115	20.37R
946	0.53	0.013073	0.001083	0.000132	0.011990	3.34R
947	0.53	0.010314	0.001083	0.000132	0.009231	2.57R
949	0.08	0.018795	0.001292	0.000129	0.017503	4.88R
950	0.08	0.009115	0.001292	0.000129	0.007823	2.18R
967	0.00	0.016647	0.001330	0.000146	0.015317	4.27R
971	0.00	0.015321	0.001330	0.000146	0.013991	3.90R
975	0.00	0.030837	0.001330	0.000146	0.029507	8.22R
979	0.00	0.009049	0.001330	0.000146	0.007719	2.15R
996	0.16	0.013546	0.001255	0.000116	0.012291	3.42R
1000	0.00	0.010123	0.001330	0.000146	0.008793	2.45R
1167	0.28	0.013695	0.001198	0.000107	0.012497	3.48R
1238	0.09	0.021932	0.001287	0.000127	0.020645	5.75R
1242	0.04	0.021427	0.001310	0.000137	0.020116	5.60R
1246	0.32	0.020885	0.001181	0.000107	0.019704	5.49R
1250	0.00	0.022413	0.001330	0.000146	0.021084	5.87R
1298	0.64	0.035151	0.001029	0.000157	0.034122	9.51R

1333	0.20	0.023722	0.001236	0.000112	0.022486	6.26R
1463	0.23	0.010266	0.001224	0.000110	0.009042	2.52R
1469	0.00	0.020607	0.001330	0.000146	0.019277	5.37R
1538	0.71	0.000000	-0.000302	0.000302	0.000302	0.08 X
1539	0.75	0.000000	-0.000319	0.000311	0.000319	0.09 X
1540	0.75	0.000000	-0.000319	0.000311	0.000319	0.09 X
1541	0.75	0.000000	-0.000319	0.000311	0.000319	0.09 X
1542	0.75	0.000000	-0.000319	0.000311	0.000319	0.09 X
1543	0.75	0.000000	-0.000321	0.000312	0.000321	0.09 X
1544	0.75	0.000000	-0.000321	0.000312	0.000321	0.09 X
1545	0.75	0.000000	-0.000321	0.000312	0.000321	0.09 X
1546	0.75	0.000000	-0.000321	0.000312	0.000321	0.09 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

APPENDIX B – TEST RESULTS FOR H_3

Regression Analysis: Change in Forecast Error versus MissedEPS_xBrkg

The regression equation is
Change in Forecast Error = 0.0078 + 0.123 MissedEPS_xBrkg

529 cases used, 30 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.00781	0.02900	0.27	0.788	
MissedEPS_xBrkg	0.12258	0.04802	2.55	0.011	1.000

S = 0.531654 R-Sq = 1.2% R-Sq(adj) = 1.0%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	1.8420	1.8420	6.52	0.011
Residual Error	527	148.9600	0.2827		
Total	528	150.8020			

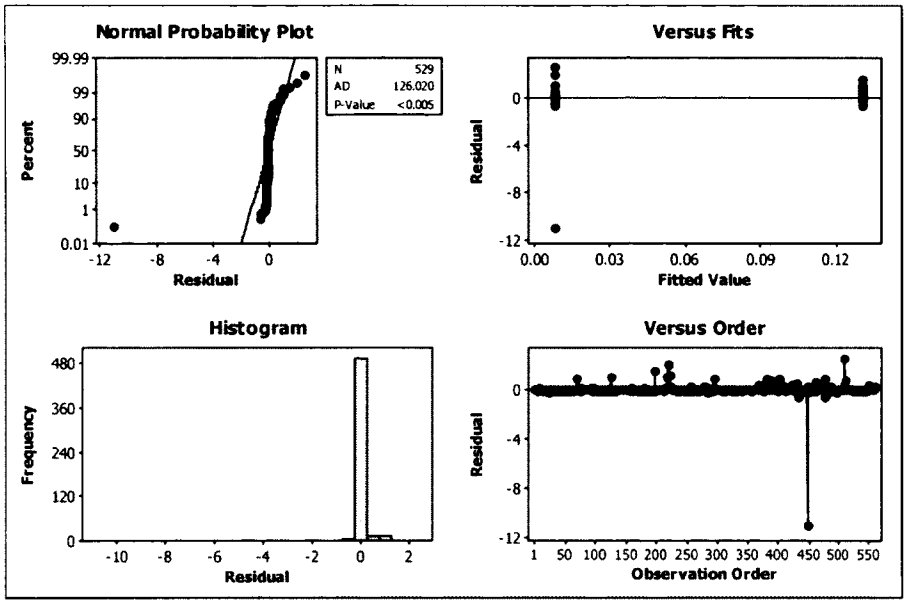
Unusual Observations

Obs	MissedEPS_xBrkg	Change in Forecast Error	Fit	SE Fit	Residual	St Resid
197	1.00	1.6667	0.1304	0.0383	1.5363	2.90R
219	0.00	2.0000	0.0078	0.0290	1.9922	3.75R
222	1.00	1.2000	0.1304	0.0383	1.0696	2.02R
447	0.00	-11.0000	0.0078	0.0290	-11.0078	-20.74R
510	0.00	2.5714	0.0078	0.0290	2.5636	4.83R

R denotes an observation with a large standardized residual.

Durbin-Watson statistic = 1.95805

Figure 15: ***Residual Plots for Change in Forecast Error***



APPENDIX C – TEST RESULTS FOR H_4

Sign Test for Median: Materiality %

```
Sign test of median =  0.00500 versus < 0.00500

                 N  Below  Equal  Above       P   Median
Materiality %  594    536      0     58  0.0000  0.00099
```

APPENDIX D – TEST RESULTS FOR H_5

Comparison of quarterly breakage recognized as percent of annual breakage recognized

Kruskal-Wallis Test: Qrtly % versus Qtr

```
Kruskal-Wallis Test on Qrtly %

Qtr        N  Median  Ave Rank      Z
Q1       156  0.1704     249.3  -5.05
Q2       156  0.1847     267.7  -3.58
Q3       156  0.1633     250.2  -4.99
Q4       156  0.4044     482.8  13.62
Overall  624             312.5

H = 186.65  DF = 3  P = 0.000
H = 187.52  DF = 3  P = 0.000  (adjusted for ties)
```

Mann-Whitney Test and CI: Q1, Q2

```
      N   Median
Q1  156  0.17038
Q2  156  0.18466


Point estimate for ETA1-ETA2 is -0.00273
99.2 Percent CI for ETA1-ETA2 is (-0.04511,0.01477)
W = 23651.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.3385
The test is significant at 0.3358 (adjusted for ties)
```

Mann-Whitney Test and CI: Q1, Q3

```
      N   Median
Q1  156  0.17038
Q3  156  0.16333


Point estimate for ETA1-ETA2 is 0.00000
99.2 Percent CI for ETA1-ETA2 is (-0.02780,0.02612)
W = 24321.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.9081
The test is significant at 0.9076 (adjusted for ties)
```

Mann-Whitney Test and CI: Q1, Q4

```
      N   Median
Q1  156  0.17038
Q4  156  0.40437


Point estimate for ETA1-ETA2 is -0.27529
99.2 Percent CI for ETA1-ETA2 is (-0.35692,-0.22691)
W = 15414.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: Q2, Q3

```
      N   Median
Q2  156  0.18466
Q3  156  0.16333


Point estimate for ETA1-ETA2 is 0.00247
99.2 Percent CI for ETA1-ETA2 is (-0.01441,0.03846)
W = 25090.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.3965
The test is significant at 0.3947 (adjusted for ties)
```

Mann-Whitney Test and CI: Q2, Q4

```
      N   Median
Q2  156  0.18466
Q4  156  0.40437


Point estimate for ETA1-ETA2 is -0.25959
99.2 Percent CI for ETA1-ETA2 is (-0.34032,-0.19987)
W = 15989.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: Q3, Q4

```
      N   Median
Q3  156  0.16333
Q4  156  0.40437


Point estimate for ETA1-ETA2 is -0.27576
99.2 Percent CI for ETA1-ETA2 is (-0.35519,-0.21668)
W = 15271.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Comparison of BRKG/SALES% by Quarter

Kruskal-Wallis Test: Brkg/Sales% versus Qtr

```
Kruskal-Wallis Test on Brkg/Sales%

Qtr         N     Median  Ave Rank      Z
Q1        156  0.0005299     268.5  -3.52
Q2        156  0.0006330     287.1  -2.03
Q3        156  0.0005727     275.6  -2.95
Q4        156  0.0017431     418.7   8.50
Overall   624                312.5

H = 73.07  DF = 3  P = 0.000
H = 73.40  DF = 3  P = 0.000  (adjusted for ties)
```

Mann-Whitney Test and CI: Q1, Q2

```
      N   Median
Q1  156  0.00053
Q2  156  0.00063


Point estimate for ETA1-ETA2 is -0.00002
99.2 Percent CI for ETA1-ETA2 is (-0.00033,0.00011)
W = 23649.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.3376
The test is significant at 0.3349 (adjusted for ties)
```

Mann-Whitney Test and CI: Q1, Q3

```
      N   Median
Q1  156  0.00053
Q3  156  0.00057


Point estimate for ETA1-ETA2 is 0.00000
99.2 Percent CI for ETA1-ETA2 is (-0.00022,0.00016)
W = 24095.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.6893
The test is significant at 0.6877 (adjusted for ties)
```

Mann-Whitney Test and CI: Q1, Q4

```
      N   Median
Q1  156  0.00053
Q4  156  0.00174


Point estimate for ETA1-ETA2 is -0.00095
99.2 Percent CI for ETA1-ETA2 is (-0.00153,-0.00055)
W = 18638.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: Q2, Q3

```
      N   Median
Q2  156  0.00063
Q3  156  0.00057


Point estimate for ETA1-ETA2 is 0.00000
99.2 Percent CI for ETA1-ETA2 is (-0.00014,0.00031)
W = 24833.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.5994
The test is significant at 0.5980 (adjusted for ties)
```

Mann-Whitney Test and CI: Q2, Q4

```
      N   Median
Q2  156  0.00063
Q4  156  0.00174


Point estimate for ETA1-ETA2 is -0.00086
99.2 Percent CI for ETA1-ETA2 is (-0.00143,-0.00048)
W = 19272.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: Q3, Q4

```
      N   Median
Q3  156  0.00057
Q4  156  0.00174


Point estimate for ETA1-ETA2 is -0.00093
99.2 Percent CI for ETA1-ETA2 is (-0.00151,-0.00053)
W = 18760.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

APPENDIX E – TEST RESULTS FOR H_{6a}

Mann-Whitney Test and CI: Low Profit Margin, High Profit Margin

```
               N   Median
Low Margin   157  0.00193
High Margin  147  0.00101


Point estimate for ETA1-ETA2 is 0.00075
95.0 Percent CI for ETA1-ETA2 is (0.00047,0.00111)
W = 27442.0
Test of ETA1 = ETA2 vs ETA1 > ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

APPENDIX F – TEST RESULTS FOR H_{6b}

Kruskal-Wallis Test: Brkg/Sales% versus LineTrade

```
Kruskal-Wallis Test on Brkg/Sales%

LineTrade     N     Median  Ave Rank      Z
52           48  0.0004634     159.5  -5.81
54           17  0.0001097     103.8  -4.72
56          218  0.0009086     287.8  -1.05
57           56  0.0019034     366.3   3.15
58          181  0.0015176     357.9   5.68
59           74  0.0005779     260.4  -1.99
Overall     594                297.5

H = 88.26  DF = 5  P = 0.000
H = 88.28  DF = 5  P = 0.000  (adjusted for ties)
```

Mann-Whitney Test and CI: LT52, LT54

```
       N   Median
LT52  48  0.00046
LT54  17  0.00011


Point estimate for ETA1-ETA2 is 0.00029
99.7 Percent CI for ETA1-ETA2 is (0.00009,0.00044)
W = 1842.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0001
```

Mann-Whitney Test and CI: LT52, LT56

```
        N   Median
LT52   48  0.00046
LT56  218  0.00091


Point estimate for ETA1-ETA2 is -0.00044
99.7 Percent CI for ETA1-ETA2 is (-0.00077,-0.00019)
W = 3816.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: LT52, LT57

```
       N   Median
LT52  48  0.00046
LT57  56  0.00190


Point estimate for ETA1-ETA2 is -0.00142
99.7 Percent CI for ETA1-ETA2 is (-0.00234,-0.00070)
W = 1635.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
```

Mann-Whitney Test and CI: LT52, LT58

```
        N   Median
LT52   48  0.00046
LT58  181  0.00152


Point estimate for ETA1-ETA2 is -0.00102
99.7 Percent CI for ETA1-ETA2 is (-0.00175,-0.00058)
W = 2657.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: LT52, LT59

```
       N   Median
LT52  48  0.00046
LT59  74  0.00058


Point estimate for ETA1-ETA2 is -0.00025
99.7 Percent CI for ETA1-ETA2 is (-0.00080,0.00001)
W = 2410.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0045
The test is significant at 0.0045 (adjusted for ties)
```

Mann-Whitney Test and CI: LT54, LT56

```
        N   Median
LT54   17  0.00011
LT56  218  0.00091


Point estimate for ETA1-ETA2 is -0.00068
99.7 Percent CI for ETA1-ETA2 is (-0.00127,-0.00030)
W = 711.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: LT54, LT57

```
       N   Median
LT54  17  0.00011
LT57  56  0.00190


Point estimate for ETA1-ETA2 is -0.00156
99.7 Percent CI for ETA1-ETA2 is (-0.00282,-0.00036)
W = 236.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
```

Mann-Whitney Test and CI: LT54, LT58

```
        N   Median
LT54   17  0.00011
LT58  181  0.00152


Point estimate for ETA1-ETA2 is -0.00120
99.7 Percent CI for ETA1-ETA2 is (-0.00265,-0.00054)
W = 661.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: LT54, LT59

```
       N   Median
LT54  17  0.00011
LT59  74  0.00058


Point estimate for ETA1-ETA2 is -0.00045
99.7 Percent CI for ETA1-ETA2 is (-0.00142,-0.00012)
W = 465.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0013
The test is significant at 0.0013 (adjusted for ties)
```

Mann-Whitney Test and CI: LT56, LT57

```
        N   Median
LT56  218  0.00091
LT57   56  0.00190


Point estimate for ETA1-ETA2 is -0.00070
99.7 Percent CI for ETA1-ETA2 is (-0.00140,-0.00007)
W = 28196.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0008
The test is significant at 0.0008 (adjusted for ties)
```

Mann-Whitney Test and CI: LT56, LT58

```
        N   Median
LT56  218  0.00091
LT58  181  0.00152


Point estimate for ETA1-ETA2 is -0.00050
99.7 Percent CI for ETA1-ETA2 is (-0.00086,-0.00016)
W = 38551.5
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

Mann-Whitney Test and CI: LT56, LT59

```
        N   Median
LT56  218  0.00091
LT59   74  0.00058


Point estimate for ETA1-ETA2 is 0.00014
99.7 Percent CI for ETA1-ETA2 is (-0.00016,0.00047)
W = 32762.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.1889
The test is significant at 0.1888 (adjusted for ties)
```

Mann-Whitney Test and CI: LT57, LT58

```
        N   Median
LT57   56  0.00190
LT58  181  0.00152


Point estimate for ETA1-ETA2 is 0.00008
99.7 Percent CI for ETA1-ETA2 is (-0.00064,0.00086)
W = 6794.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.7727
The test is significant at 0.7727 (adjusted for ties)
```

Mann-Whitney Test and CI: LT57, LT59

```
       N   Median
LT57  56  0.00190
LT59  74  0.00058


Point estimate for ETA1-ETA2 is 0.00081
99.7 Percent CI for ETA1-ETA2 is (0.00003,0.00168)
W = 4332.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0018
The test is significant at 0.0018 (adjusted for ties)
```

Mann-Whitney Test and CI: LT58, LT59

```
        N   Median
LT58  181  0.00152
LT59   74  0.00058


Point estimate for ETA1-ETA2 is 0.00063
99.7 Percent CI for ETA1-ETA2 is (0.00015,0.00121)
W = 25286.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0001
The test is significant at 0.0001 (adjusted for ties)
```

APPENDIX G – TEST RESULTS FOR H_{6c}

Mann-Whitney Test and CI: Low RNOA, High RNOA

```
             N   Median
Low RNOA   165  0.00188
High RNOA  142  0.00059


Point estimate for ETA1-ETA2 is 0.00094
95.0 Percent CI for ETA1-ETA2 is (0.00069,0.00125)
W = 30282.5
Test of ETA1 = ETA2 vs ETA1 > ETA2 is significant at 0.0000
The test is significant at 0.0000 (adjusted for ties)
```

APPENDIX H – TEST RESULTS FOR THE COMPLETE EMPIRICAL MODEL

Figure 16: ***Probability plots of CEOPAYOPTNS% and NPM_XBRKG***

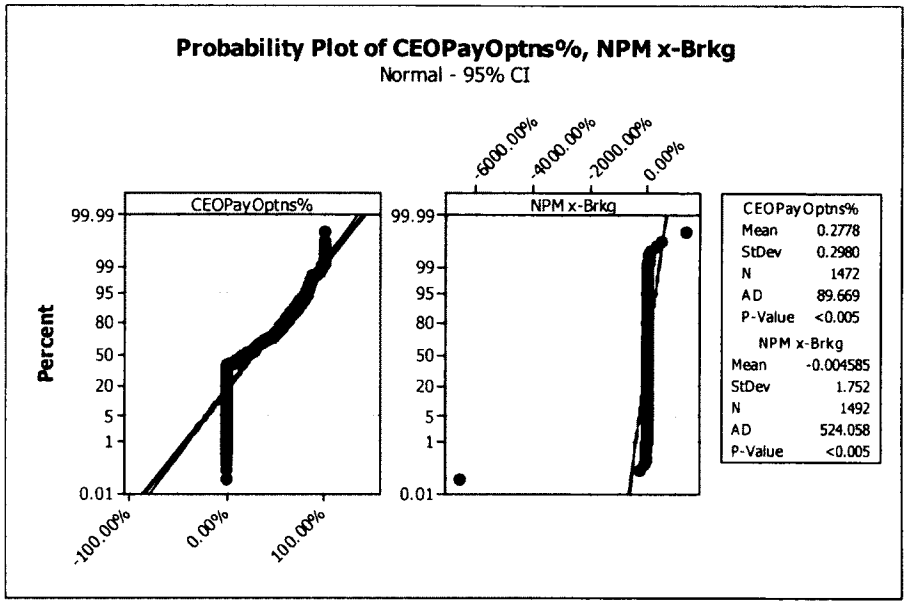


Figure 17: ***Scatterplot of BRKGNOA% and NPM_XBRKG***

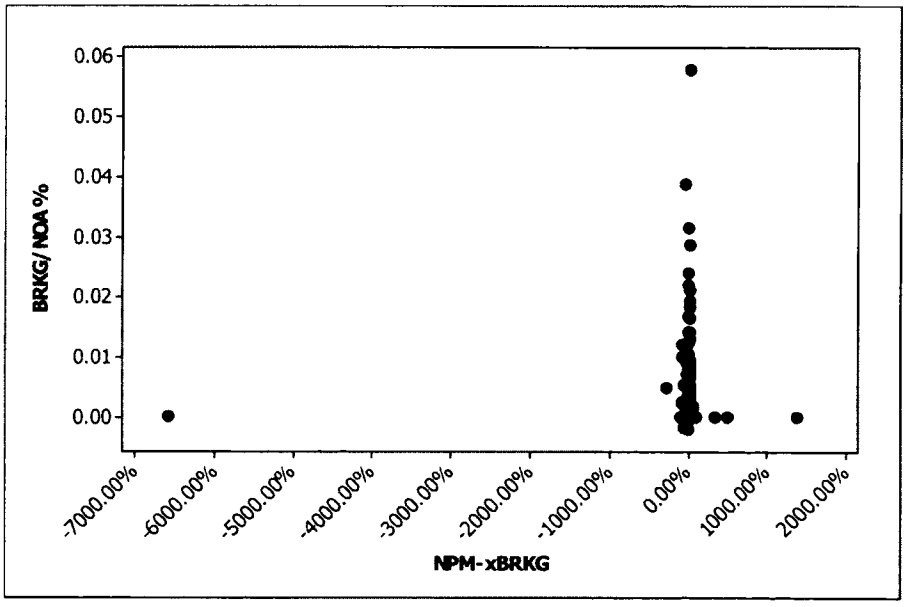


Figure 18: ***Scatterplots for Linearity Assumptions (1 of 2)***

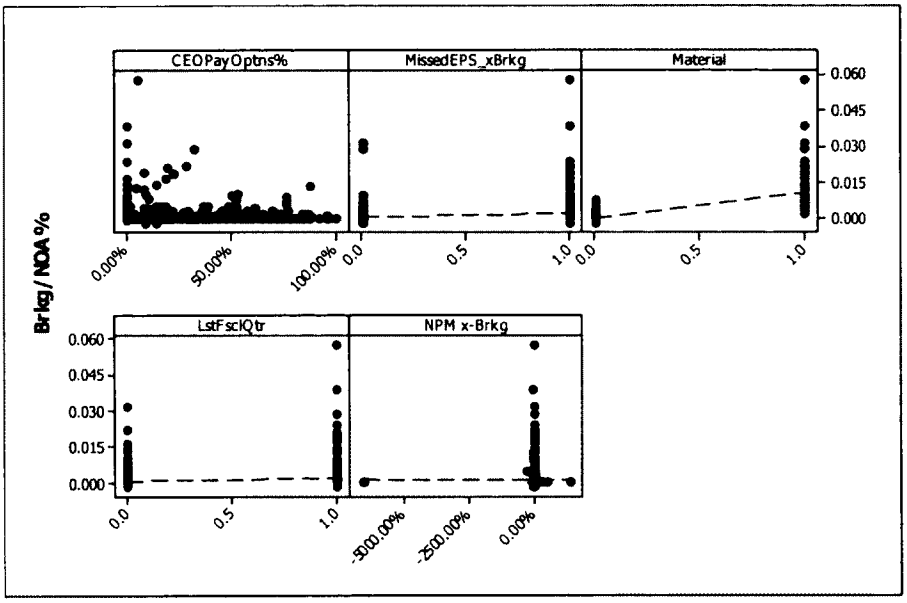
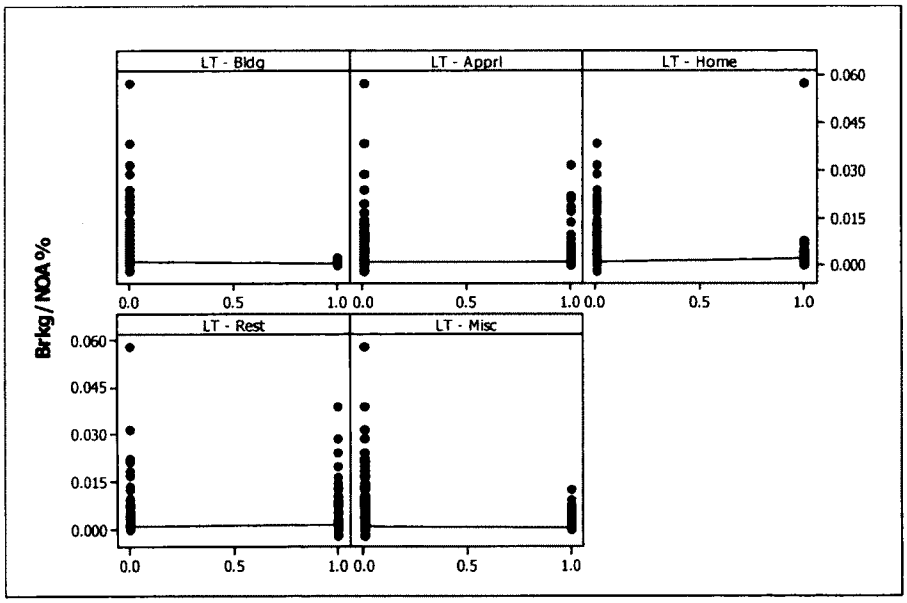


Figure 19: ***Scatterplots for Linearity Assumptions (2 of 2)***



OLS Regression Analysis: Brkg/NOA% versus Independent Variables (includes Food Stores as 5th line of trade)

The regression equation is
Brkg/NOA% = 0.000338 - 0.000581 CEOPayOptns% + 0.000445 MissedEPS_xBrkg + 0.0106 Material + 0.000338 LstFsclQtr + 0.000735 NPM x-Brkg
+ 0.000069 LT - Bldg - 0.000075 LT - Rest + 0.00147 LT - Home - 0.000126 LT - Misc - 0.000244 LT - Food

1017 cases used, 475 cases contain missing values

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.0003385	0.0001538	2.20	0.028	
CEOPayOptns%	-0.0005808	0.0002733	-2.13	0.034	1.102
MissedEPS_xBrkg	0.0004454	0.0001759	2.53	0.011	1.134
Material	0.0106267	0.0003690	28.80	0.000	1.162
LstFsclQtr	0.0003376	0.0001754	1.93	0.054	1.047
NPM x-Brkg	0.0007352	0.0005870	1.25	0.211	1.091
LT - Bldg	0.0000685	0.0003444	0.20	0.842	1.122
LT - Rest	-0.0000753	0.0001872	-0.40	0.688	1.256
LT - Home	0.0014686	0.0002874	5.11	0.000	1.125
LT - Misc	-0.0001263	0.0002453	-0.52	0.607	1.165
LT - Food	-0.0002436	0.0005127	-0.48	0.635	1.065

S = 0.00240442 R-Sq = 51.0% R-Sq(adj) = 50.5%

PRESS = 0.00620091 R-Sq(pred) = 47.74%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	10	0.00604947	0.00060495	104.64	0.000
Residual Error	1006	0.00581595	0.00000578		
Total	1016	0.01186542			

Source	DF	Seq SS
CEOPayOptns%	1	0.00006425
MissedEPS_xBrkg	1	0.00061605
Material	1	0.00515920
LstFsclQtr	1	0.00002065
NPM x-Brkg	1	0.00000826
LT - Bldg	1	0.00000011
LT - Rest	1	0.00001182
LT - Home	1	0.00016663
LT - Misc	1	0.00000121
LT - Food	1	0.00000130

Unusual Observations

Obs	CEOPayOptns%	Brkg/NOA%	Fit	SE Fit	Residual	St Resid
9	0.49	0.005580	0.011488	0.000377	-0.005909	-2.49R
15	0.52	0.005451	0.010746	0.000406	-0.005295	-2.23R
49	0.69	0.003615	0.011028	0.000417	-0.007412	-3.13R
61	0.45	0.003528	0.011595	0.000395	-0.008068	-3.40R
73	0.00	0.000079	0.000915	0.000517	-0.000836	-0.36 X
74	0.00	0.000174	0.000566	0.000502	-0.000391	-0.17 X
75	0.00	0.000167	0.000569	0.000502	-0.000403	-0.17 X

76	0.00	0.000211	0.000576	0.000502	-0.000365	-0.16 X
77	0.00	0.000172	0.000921	0.000517	-0.000749	-0.32 X
79	0.00	0.000259	0.000127	0.000499	0.000132	0.06 X
80	0.00	0.006519	0.000578	0.000502	0.005941	2.53RX
81	0.00	0.000000	0.000475	0.000515	-0.000475	-0.20 X
82	0.00	0.000000	0.000121	0.000499	-0.000121	-0.05 X
83	0.00	0.000000	0.000137	0.000499	-0.000137	-0.06 X
84	0.00	0.000000	0.000135	0.000499	-0.000135	-0.06 X
85	0.00	0.000000	0.000475	0.000515	-0.000475	-0.20 X
86	0.00	0.000000	0.000150	0.000499	-0.000150	-0.06 X
87	0.00	0.000000	0.000135	0.000499	-0.000135	-0.06 X
88	0.00	0.000000	0.000134	0.000499	-0.000134	-0.06 X
106	0.00	0.006954	0.011820	0.000385	-0.004866	-2.05R
118	0.19	0.021219	0.011711	0.000381	0.009508	4.01R
191	0.08	0.019578	0.011666	0.000365	0.007912	3.33R
204	0.00	0.006474	0.011669	0.000425	-0.005195	-2.20R
248	0.00	0.007732	0.002632	0.000323	0.005100	2.14R
272	0.00	0.004677	0.010975	0.000395	-0.006298	-2.66R
323	0.16	0.005332	0.011552	0.000418	-0.006220	-2.63R
423	0.28	0.022080	0.011236	0.000380	0.010845	4.57R
558	0.38	0.003437	0.011486	0.000362	-0.008050	-3.39R
694	0.39	0.005194	0.011132	0.000386	-0.005938	-2.50R
768	0.05	0.058034	0.013205	0.000446	0.044828	18.97RX
917	0.00	0.002019	0.011656	0.000359	-0.009637	-4.05R
921	0.38	0.002109	0.011474	0.000360	-0.009364	-3.94R
945	0.00	0.038890	0.011365	0.000395	0.027525	11.61R
951	0.76	0.005873	0.010839	0.000388	-0.004966	-2.09R
952	0.76	0.005759	0.010802	0.000387	-0.005043	-2.13R
953	0.53	0.010188	0.010799	0.000523	-0.000611	-0.26 X
955	0.53	0.002592	-0.000268	0.000564	0.002860	1.22 X
957	0.08	0.004899	0.009571	0.001609	-0.004672	-2.61RX
971	0.00	0.012279	0.011009	0.000580	0.001270	0.54 X
975	0.00	0.024143	0.011589	0.000354	0.012555	5.28R
976	0.00	0.002494	0.000102	0.000518	0.002391	1.02 X
983	0.00	0.005125	0.011270	0.000391	-0.006145	-2.59R
992	0.36	0.005524	0.011253	0.000362	-0.005729	-2.41R
1000	0.18	0.005557	0.011007	0.000513	-0.005450	-2.32RX
1026	0.00	0.003487	0.011017	0.000399	-0.007530	-3.18R
1209	0.83	0.001895	0.010413	0.000418	-0.008518	-3.60R
1236	0.00	0.005531	0.011676	0.000362	-0.006145	-2.59R
1238	0.00	0.016630	0.011362	0.000377	0.005268	2.22R
1240	0.14	0.005172	0.011116	0.000378	-0.005945	-2.50R
1252	0.32	0.028699	0.011112	0.000388	0.017588	7.41R
1298	0.00	0.031662	0.010973	0.000395	0.020689	8.72R
1333	0.19	0.016989	0.011601	0.000364	0.005388	2.27R
1425	0.00	0.000353	0.000895	0.000516	-0.000542	-0.23 X
1426	0.00	0.000179	0.000113	0.000499	0.000065	0.03 X
1427	0.00	0.000189	0.000558	0.000502	-0.000369	-0.16 X
1428	0.00	0.000204	0.000115	0.000499	0.000089	0.04 X
1429	0.00	0.001412	0.000452	0.000515	0.000960	0.41 X
1430	0.00	0.000000	0.000550	0.000502	-0.000550	-0.23 X
1431	0.00	0.000000	0.000556	0.000502	-0.000556	-0.24 X
1432	0.00	0.000000	0.000551	0.000502	-0.000551	-0.23 X
1442	0.00	0.000000	0.000114	0.000499	-0.000114	-0.05 X
1463	0.02	0.005603	0.011410	0.000386	-0.005807	-2.45R
1469	0.23	0.018444	0.011649	0.000372	0.006795	2.86R
1483	0.83	0.000000	-0.000410	0.000626	0.000410	0.18 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Durbin-Watson statistic = 1.93851

Figure 20: ***Residual Plots of BRKG/NOA%***

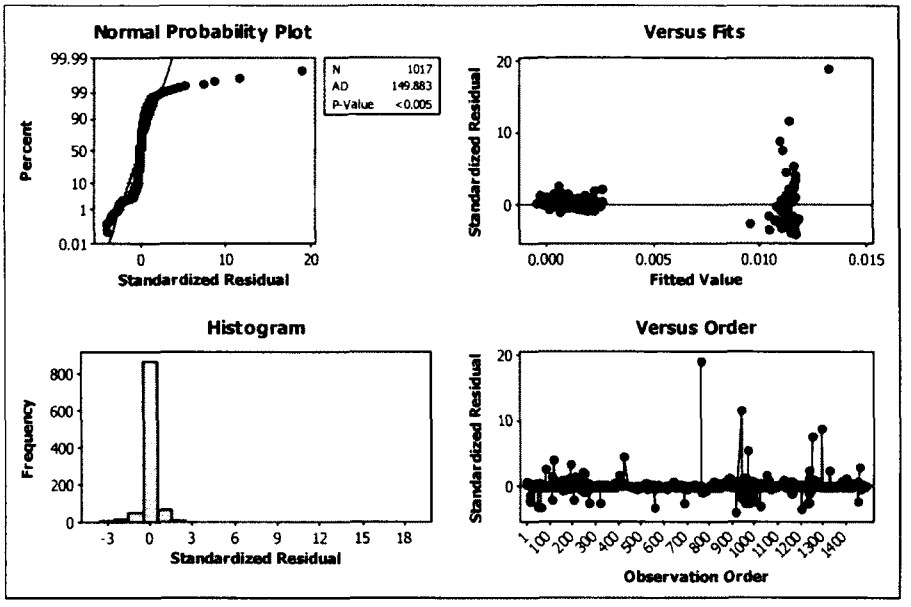


Table 34: Pearson and Spearman Correlation Coefficients

Independent Variable	Pearson r	Spearman r_s
CEOPAYOPTNS%	(0.054) *	0.018 *
MISSEDEPS w/o BRKG	0.231 ***	0.242 ***
MATERIAL	0.692 ***	0.382 ***
LSTFSCLQTR	0.171 ***	0.105 ***
NPM_XBRKG	(0.004)	(0.096) ***
Lines of Trade:		
Building	(0.037)	0.069 **
Apparel	(0.047)	(0.052) *
Home	0.084 ***	0.127 ***
Eating/Drinking	0.068 **	0.035
Miscellaneous	(0.035)	(0.061) *
Food	(0.044)	(0.081) **

VITA

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The author is the son of George Kaufinger and Loretta E. Kaufinger. He was born in October 1969 in Endicott, New York.

A graduate of Horseheads High School in Horseheads, New York, he began his higher education at Geneva College, Beaver Falls, Pennsylvania in 1987. He completed his Bachelor of Science degree in 1991 with majors in accounting and business administration. In 1991, he went to Lehigh University in Bethlehem, Pennsylvania where he earned the Masters of Business Administration degree in 1992. Doctoral studies in Business Administration at Anderson University were started in 2008.

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