Revenue Manipulation and Restatements by Loss Firms

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Abstract

This paper investigates the relation between the extent of the firm's past and expected future losses and the ex ante probability that it will manipulate revenues. When a firm has a string of losses and/or negative cash flows, traditional valuation models do not yield reliable estimates of firm value, and traditional price-earnings ratios are not meaningful. Generalizing from the literature on Internet firms, we conjecture that market participants tend to value loss firms on the basis of the level of and the growth in revenues rather than earnings, thereby motivating these firms to overstate revenue, and, consequently, accounts receivable. Consistent with this conjecture, we find empirically that the revenues of loss firms are value relevant whereas their earnings are not value relevant. Furthermore, the empirical results indicate that there is a positive relation between the number of years that firms exhibit and/or anticipate losses and investment in receivables after controlling for credit policy. We further show that the *ex ante* likelihood that firms manipulate revenue in violation of GAAP is positively associated with the history of past and expected losses as well as with the investment in accounts receivable (adjusted for credit policy). While intuition suggests that relatively new firms with a relatively high number of years of negative earnings are candidates for revenue manipulation, we find that a history of negative earnings is likely to yield revenue manipulation even after controlling for firm age, size and growth in sales.

Key Words: revenue manipulation, earnings management, restatements

Data Availability: Data used in this study are available from public sources.

1. Introduction

In their review of the earnings management literature, Healy and Wahlen (1999) conclude that the evidence concerning the specific accruals that firms use to manage earnings is rather sparse. Typically, researchers tend to rely upon total accruals or an estimate of discretionary accruals such as the Jones model (Jones 1991) or the modified Jones model (Dechow et al. 1995) to detect earnings management. Since these methods fail to identify the specific accruals used for manipulation, researchers introduce noise into the estimation process of earnings manipulation (Subramanyam 1996). Bernard and Skinner (1996) suggest that in order to better model accounting choices, one should analyze the informativeness of different categories of accruals separately based on priors about managers' incentives and abilities to manipulate specific accruals. In the same vein, Marquardt and Wiedman (2004) note that reliance on a broad measure of earnings management such as discretionary accruals does not provide much insight into *how* earnings management is achieved, in particular given that many companies are faced with multiple, often conflicting, incentives to manage earnings. The key to making a valuable contribution to the earnings management literature would seem to lie in isolating a sample of firms for which there is a single *dominating* reason for manipulation, combined with a *single* income statement item (and related balance sheet item) that managers manipulate to achieve their aims.

The purpose of this study is to show that the greater a firm's string of past and expected future losses, the more likely it is to violate GAAP by overstating revenues and accounts receivable. The linkage between loss firms and revenue manipulation has its logical genesis in the popular press and the accounting literature on Internet firms. Both

of these sources maintain that, absent a sufficient time series of positive earnings and cash flows, traditional valuation models such as the discounted cash flow and discounted residual earnings models do not yield reliable estimates of firm value. Furthermore, price-earnings ratios are not meaningful for the typical Internet firm, so analysts tend to follow the price to sales ratio instead [e.g., Demers and Lev (2000)]. In addition, although revenues are not the only source of value relevant information, a number of academic studies have shown that the market views revenues and revenue growth as highly important in valuing Internet firms [Hand (2000), Trueman et al. (2000, 2001), Bagnoli et al. (2001), Campbell and Sefcik (2001), Davis (2002), Bowen et al. (2002)]. This study extends the argument to loss firms in general. If the market substitutes revenues and revenue growth for earnings and earnings growth in valuing Internet firms because negative earnings (and cash flows) do not provide much if any value relevant information, then the same argument applies almost as forcefully for firms with strings of past and expected future losses (and negative cash flows).

The relative importance of revenues in determining the market capitalization of loss firms provides an incentive for loss firms to manipulate revenues in order to achieve greater market capitalization.[1] For the same reason, loss firms are less interested in manipulating expenses because earnings are not particularly value relevant. Firms for which earnings are value relevant may also attempt to manipulate revenues but, in contrast to loss firms, the former are just as likely to manipulate expenses (e.g., Enron).

[1] Obviously, some firms may manipulate revenues in order to avoid losses. However, to the extent that they succeed in showing profits, they are not part of our sample of "loss firms" The essential motivation of loss firms to manipulate revenues, we contend, is not loss avoidance, since many of these firms are unable to avoid losses but rather to influence their revenue-based market values.

Therefore, loss firms are likely to yield a less "noisy" sample of revenue manipulators by comparison to other firms.[2]

In contrast to most studies in the earnings management literature, we investigate earnings manipulation by loss firms through the prism of revenue restatements. In most studies of earnings management, the researcher uses a proxy for earnings management and, therefore, cannot be certain that earnings have in fact been manipulated (for a discussion of this issue see Marquardt and Wiedman 2004). Exceptions are precisely those studies that are based on restatement data (e.g., Richardson et al. 2003). We use restatement data to infer the *ex ante* likelihood that a firm will manipulate revenues. Restatements arising out of accounting errors involving revenue overstatements are fairly strong indicators of revenue manipulation, and are not necessarily a result of enforcement actions.[3]

In what follows, we first show that revenues are value relevant in explaining the market value of loss firms whereas, in contrast, earnings are not significantly associated with the market value of these firms. We then document a positive relation between the number of years that a firm exhibits and/or anticipates losses and its investment in receivables, after controlling for credit policy. This result is consistent with loss firms being more likely to manipulate revenues than profitable firms. Finally, we provide evidence that there is a positive relation between the ex-ante probability of revenue

[2] Arguably, an Internet sample of firms might yield a cleaner sample yet. However, the universe of Internet firms that restated revenues is too small to yield a meaningful sample.

[3] The SEC perceives young growth firms to have a higher likelihood of financial statement fraud and financial distress (Feroz et al. 1991; Beneish 1997). If the SEC also targets losing firms for filing review (a possibility, although without empirical support), we would find a higher proportion of losing firms among restaters and a potential spurious correlation between losses and earnings management as gauged by a restatement. Although the SEC was involved in approximately 55% of the revenue restatements during the time period covered by this study, only a portion of these were initiated by the SEC. In most restatements

manipulation and (i) the number of years that a firm exhibits and/or anticipates losses or negative cash flows, and (ii) the level of accounts receivable after controlling for the credit policy of the firm. While intuition suggests that small young firms with a relatively long string of losses are candidates for revenue manipulation, our results indicate that a history of negative earnings is associated with revenue manipulation *even* after controlling for firm age, size and growth.

This paper is organized as follows. Section 2 reviews the literature on revenue manipulation and develops the hypotheses. Section 3 outlines the research design, Section 4 details the data selection criteria and Section 5 presents the results. Section 6 concludes.

2. Literature Review and Hypotheses Development

Recent pronouncements by the Securities Exchange Commission (SEC) and the Financial Accounting Standards Board (FASB) indicate substantial concern about the tendency of internet and technology firms to report misleading levels of revenue (see SAB 101, EITF 99-17). Furthermore, regional offices of the SEC, the Federal Bureau of Investigation and the United States general attorney's office, responding to widespread concerns that investors did not receive reliable financial information in recent periods of frenetic revenue growth, are cooperating in a legal crackdown of accounting violations related to revenue recognition (New York Times, August 19, 2001). Indeed, the total number of restatements due to revenue related errors has increased substantially in recent years. The number of revenue related restatement cases from 1997 to 1999 is almost

cases, the SEC launched an investigation subsequent to a voluntary restatement by the company. This finding is also supported by Anderson and Yohn (2002) and Palmrose et al. (2004).

twice as many as the number of cases in the period from 1988 to 1996 (Callen et al. (2002)).

The literature on earnings management through revenue manipulation is fairly recent. Dechow, Sloan and Sweeney (1996) show that SEC enforcement actions are likely to involve revenue recognition issues. Nelson, Elliott and Tarpley (2002, 2003) provide survey data confirming that income-increasing earnings management involving revenue recognition are common occurrences. Plummer and Mest (2001) provide empirical evidence concerning the incentives firms have to "meet or beat" analysts' expectations through revenue manipulation while Bagnoli et al. (2001) find that capital markets respond to revenue surprises. Although these papers provide evidence of revenue manipulation, they do not analyze the relation between loss firms and revenue manipulation

A second stream of research concentrates on revenue manipulation by young firms. Rangan (1998), Teoh et al. (1999), and Shivakumar (2000) document that firms manage earnings upwards in periods prior to issuing equity in an attempt to increase share value. Marquardt and Wiedman (2004) argue that firms issuing equity prefer to manage earnings through a mechanism that suggests to the market that the reported earnings level will persist into the future in order to maximize the proceeds from the share issuance. Consequently, relatively new firms refrain from managing income through non-recurring items but instead use their discretion over sales revenue or operating expenses to achieve their earnings objectives. In addition, life cycle theory suggests that a growth maximization strategy is most cost-beneficial when firms are

relatively young.[4] Therefore, signaling growth through aggressive revenue recognition methods may result in a positive stock price reaction. Indeed, Anthony and Ramesh (1992) show that the stock price response coefficient on unexpected sales growth is significantly larger for young firms.

A relatively new stream of literature investigates the importance of revenues for Internet firms. Since most Internet firms report losses and negative cash flows, traditional valuation models cannot be applied and price-to-earnings ratios cannot be meaningfully calculated and compared. This in turn leads to an increase in the importance of revenues as Internet firms are likely to be valued based on their revenues. Demers and Lev (2001) show that analysts report and follow price-to-sales ratios for internet companies. Hand (2000), Campbell and Sefcik (2002), Davis and Monahan (2002) and Bowen et al. (2002) provide empirical evidence that the market impounds reported revenues in the stock prices of Internet firms, and Bagnoli et al. (2001) and Davis and Monahan (2002) demonstrate that the market responds to revenue surprises. Furthermore, Bowen et al. (2002) show that revenue levels are strongly associated with the market's valuation of internet firms. Taken as a whole, there is convincing evidence that internet firms have economic incentives to manipulate reported revenues in the presence of multiple years of negative reported earnings.

Overall, the literature indicates that young firms with negative earnings have economic incentives to report artificially high levels of revenue. The key reasons for revenue manipulation seem to be the incentive to capture high market capitalization and

[4] See Porter (1980) for a more complete discussion of life cycle theory.

to create positive expectations of future growth through sales.[5] We provide the actual link between losses, revenue manipulation and market capitalization. Specifically, we show that revenues are value relevant for loss firms in general regardless of industry classification, and that the probability of revenue manipulation is increasing with the firm's string of losses.[6]

Generally, firms manipulate revenues either through accounts receivable or unearned revenues, depending on the reason for the manipulation and the timing of cash collection. Some firms may manipulate revenues in order to smooth growth, whereas other firms may understate revenues to avoid regulatory sanctions or to minimize taxes (see Healy and Wahlen 1999). In these latter cases, revenue manipulation is achieved primarily through manipulation of the "unearned revenue" account. In contrast, manipulation to overstate revenues is usually achieved by recording fraudulent sales and/or by the premature recognition of legitimate sales. These forms of manipulation generally flow through accounts receivable. Given this conjecture, we expect that the investment in accounts receivable by loss firms would be higher than non-loss firms after controlling for credit policy.[7]

This discussion leads us to the following three hypotheses expressed in the alternative form:

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[5] Additional incentives to influence stock prices through revenue manipulation include managerial stock option compensation plans and firm access to equity capital (see Bowen et al. (1995)). These additional incentives are consistent with the arguments in this paper.

[6] Clearly the sample of loss firms includes firms that are headed towards bankruptcy. Although these firms may also have incentives to manipulate revenues, it is reasonable to assume that the incentives for doing so are not related to market capitalization since these firms are likely to be valued by their liquidation value. Hence, the inclusion of financially distressed companies probably biases the analysis against finding evidence that relates revenues to market capitalization. In the sensitivity analysis section we report the results of the analysis excluding financially distressed companies.

H1: There is positive relation between the extent of a firm's past and anticipated future losses and its ratio of accounts receivable to sales..

H2: There is positive relation between the extent of a firm's past and anticipated future losses and the ex ante likelihood of revenue manipulation in contravention of GAAP.

H3: There is positive relation between the accounts receivables to sales ratio (adjusted for credit policy) and the ex ante likelihood of revenue manipulation in contravention of GAAP.

3. Research Design

3.1 Research Design to Test H1

We conjecture that the decision to manipulate revenues in order to increase market capitalization is dependant upon the expectation of future losses. If managers (and investors) do not anticipate future losses, then managers will expect the market to value the firm with traditional methods that focus primarily on earnings and cash flows rather than sales revenue. If the market capitalizes firm value using earnings, then managers may have an incentive to manipulate bottom-line earnings through expense manipulation rather than through the overstatement of revenues. Revenue manipulation is often more costly than expense manipulation since the average decrease in market value once the manipulation is discovered is much higher if the manipulation involves revenues rather than expenses (see Callen et al. (2002), Anderson and Yohn (2002), and Palmrose et al. (2004),). In other words, the incentive to rely *solely* on revenue manipulation is attenuated once managers expect their firm to become profitable.

We define "loss" firms with respect to a "loss ratio", where the loss ratio for year t is computed as the proportion of years in which the firm reported negative net income

[7] Note that the assumption that all revenue manipulation cases are accompanied by overstatement of accounts receivable biases that analysis against finding positive association between revenue manipulation

for the period starting from the first year of available data until year t+3 inclusive. For example, if the firm has earnings data for the period 1988-1995, the loss ratio for 1990 is computed as the proportion of loss years in the period 1988 to 1993 inclusive. The implicit assumption here is that managers have perfect foresight regarding the *sign* of net income in the three-year period following year t.[8] This assumption is not as restrictive as it might appear since we know that analysts, who have less information about the firm than managers, routinely provide estimates of expected income. Although one may argue that analysts' estimates are far from perfect, their errors are mostly related to the level of earnings rather than the *sign* of the earnings. Furthermore, it is reasonable to assume that managers on average know roughly if their firm will be profitable or not in the foreseeable future.[9]

To examine whether loss firms have higher accounts receivable than profitable firms, we need to control for the credit policy of the firm, since extending trade credit is one of the tools used to maintain and increase competitiveness and market share.[10] Petersen and Rajan (1997) provide a comprehensive overview (and empirical evidence) of the current theories of trade credit. Consistent with their analysis of the determinants of accounts receivable, we surmise that a firm's investment in receivables is a function of the financial strength of the firm in general, its operational performance relative to its industry competitors, and its stage in the business cycle. The discussion that follows briefly addresses each of these factors.

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and the level of account receivables.

[8] In the sensitivity analysis discussed below we relax the assumption of perfect foresight.

[9] For many firms in our sample analysts forecast data is not available or there are very few analysts that cover the firm. In addition, IBES provides only one-year ahead forecasts for the majority of their sample firms. Finally, IBES does not provide analysts forecasts of future cash flows for most firms.

[10] Nonetheless, credit sales are generally costly for two main reasons: first, there is the risk of non-collection, and second, credit sales typically entail an implicit discount.

Financially strong firms are able to extend generous credit terms in order to attract and retain customers, but, because of their wealth, are not constrained do so. Conversely, financially weak firms may be forced to invest in accounts receivable in order to survive, but simultaneously may be constrained by their need for cash inflow. Following Petersen and Rajan (1997), we assume that large firms tend to be financially strong and proxy financial strength by firm size as measured by the natural log of total assets (LSIZE),.

We proxy for the operational performance of the firm relative to its industry competitors using the 4-digit SIC median adjusted growth rate in sales (GRS_P if positive, GRS_N if negative), and the 4-digit SIC median adjusted gross profit scaled by total sales (GRM). GRS_P (GRS_N) is computed as the difference between the firm's growth rate in sales and the median growth rate in the firm's 4-digit SIC industry if positive (negative) and zero otherwise. GRM is computed as the difference between the firm's gross profit margin and the median gross profit margin in the firm's 4-digit SIC industry. Following Petersen and Rajan (1997) we also include the square of GRM (GRM_SQ) in order to control for the potential non-linear relation between accounts receivable and the gross margin.[11]

The firm's stage in the business cycle is also related to its' credit policy. Young firms are more likely to extend better credit terms to their customers in order to capture greater market share and to generate superior growth rates in sales. The firm's stage in the business cycle can be proxied by (the log of) age (LAGE) and size (LSIZE). To be consistent with Petersen and Rajan (1997), we also include the square of age (LAGE_SQ)

[11] Petersen and Rajan (1997) estimate the credit policy model with (and without) age and gross margin squared. The rational for the inclusion of the squared variables is that credit policy is probably a concave function of age and gross margin. Specifically, we expect that AR will be positively related to gross margin. However, the slope should be decreasing.

in our analysis. Following Petersen and Rajan (1997), we predict that accounts receivable is positively associated with LSIZE, LAGE, GRS_P and GRM, and negatively associated with GRS_N, LAGE_SQ and GRM_SQ. [12]

We test H1 by regressing the firm's industry adjusted accounts receivable to sales ratio (ARS) on its loss ratio and on proxies for the firm's credit policy, and determine whether the coefficient of the loss ratio is positive and significant. We use two proxies for the loss ratio, NI_RAT and CF_RAT. NI_RAT (CF_RAT) for year t is computed as the proportion of years prior to and including year t+3 in which the company reported losses (negative cash flows from operations). We perform separate regressions with NI_RAT and CF_RAT because of the high correlation (0.72) between these two variables. Formally, we estimate the following model:

$$ARS_{it} = \alpha_0 + \alpha_1 LOSS_t + \alpha_2 LSIZE_{it} + \alpha_3 LAGE_{it} + \alpha_4 LAGE\_SQ_{it} + \alpha_5 GRS\_P_{it} + \alpha_6 GRS\_N_{it} + \alpha_7 GRM_{it} + \alpha_8 GRM\_SQ_{it} + \text{year dummies} + \xi_{it} \quad (1)$$

where i denotes the firm, t is a time index and the β are parameters to be estimated. The variables in equation (1) are defined as follows:

ARS_{it} = the 4-digit SIC median adjusted ratio of accounts receivable to sales at time t;

α_j = parameters to be estimated;

$LOSS_{it}$ = the proportion of years in which the firm reported negative net income before extraordinary items prior to and including year t+3;

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[12] Because of the detailed nature of their data from the National Survey of Small Business Finances, Petersen and Rajan (1997) are able to include in their analysis two additional variables that potentially affect credit policy, namely, whether the firm operates in a urban or a rural environment and the maximum amount that can be drawn on a line of credit.

$LSIZE_{it}$ = the firm's size measured as the natural log of total assets;

$LAGE_{it}$ = the natural log of the firm's age, where age is the number of years since the company became public;

$LAGE\_SQ_{it}$ = the square of LAGE;

GRS_P_{it} = the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the industry median growth rate in sales if *positive* and zero otherwise;

GRS_N_{it} = the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the industry median growth rate in sales if *negative* and zero otherwise;

GRM_{it} = the 4-digit SIC median adjusted gross profit scaled by sales, computed as the difference between the firm's gross profit margin and the median gross profit margin in the industry;

GRM_SQ_{it} = the square of GRM;

year dummies = a dummy variable indicating the year of the data observation;

ξ_{it} = white noise innovation term.

We reject H1 if the estimated coefficient of NI_RAT or CF_RAT (α_1) is less than or equal to 0.

3.2 Research Design to Test H2 and H3

To determine if loss firms manipulate revenues through the overstatement of accounts receivable, we examine whether the *ex ante* probability of revenue manipulation is positively associated with the loss ratio and the level of accounts receivable, after controlling for factors that affect the credit policy of the firm. Since the probability of

manipulation is unobservable, we utilize error restatement data to estimate the probability of manipulation using the two-stage sequential "partial observability" probit model of Poirier (1980) and Abowd and Farber (1982).[13] We use this model because the manipulation of revenues and the discovery of the manipulation take place at two sequential points in time (the manipulation at time t and the discovery of the manipulation and the need to restate at time t+x, x>0). For example, consider a firm that was discovered in year 2002 to have overstated year 2000 revenues and, as a consequence, is required to restate year 2000 revenues. From the perspective of an external observer, the restatement of year 2000 revenues is a two-stage process. In the first stage, management decides to manipulate revenues in year 2000. In the second stage, the manipulation remains dormant until it is discovered in year 2002.

In probabilistic terms, the probability of a restatement can be expressed as the joint probability of these two stages. Let P(.) denote the probability of an event and P(. /.) the conditional probability. Furthermore, let

R_{it} = the event of a restatement in year t by firm i

M_{it} = the event of revenue manipulation in year t by firm i

$UM_{i,t+x}$ = the event that revenue manipulation by firm i remains undiscovered until year t+x, x>0.

We can write the probability of a restatement due to revenue manipulation in year t as the product of the probability that the firm manipulates revenues in year t and the probability that the manipulation remains undiscovered until year t+x, x>0, conditional on revenue manipulation in year t:

[13] This model is also discussed by Madalla (1983, p.279). Poirier (1980) first developed the two stage "partial observability" probit model in a simultaneous events context. Abowd and Farber (1982) further

$$P(R_{it}) = P(M_{it} \text{ and } UM_{i,t+x}) = P(M_{it}) * P(UM_{i,t+x} / M_{it}) \quad (2)$$

Assuming that the probability that the firm manipulates its revenues in year t is a positive linear function of a vector of the firm's observed characteristics X_i and a white noise innovation term ξ_i, we can express $P(M_{it})$ as:

$$P(M_{it}) = P(X_{it}\beta + \xi_{it} > 0) \quad (3)$$

where β is the vector of parameters to be estimated. Similarly, assuming that the probability that the revenue manipulation remains undiscovered until year t+x given that the firm manipulated revenues in year t is a positive linear function of a vector of the firm's observed characteristics Z_{it} and a white noise innovation term ψ_{it}, we can express $P(UM_{i,t+x} / M_t)$ as:

$$P(UM_{i,t+x} / M_t) = P(Z_{it}\delta + \psi_{it} > 0) \quad (4)$$

where δ is the vector of parameters to be estimated. It follows from equations (3) and (4) that the unconditional probability of a restatement can be written as:

$$P(R_{it}) = P(X_{it}\beta + \xi_{it} > 0) * P(Z_{it}\delta + \psi_{it} > 0) \quad (5)$$

Estimating equation (5) by maximum likelihood yields consistent estimates of the parameter vectors β and δ.

We conjecture that the ex ante probability of revenue manipulation [$P(M_t) = P(X_{it}\beta + \xi_i > 0)$] is a function of the loss ratio and the ratio of accounts receivable to sales, after controlling for the credit policy of the firm,. We include the accounts receivable to sales ratio because of our conjecture that revenue manipulation flows through accounts receivable. We control for the credit policy of the firm on accounts receivables by incorporating the residual (ARS_RES) from the credit policy model [Equation (1)] as a

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extended the model to a sequential events context.

regressor, instead of the raw accounts receivable to sales ratio. The residual reflects the excess accounts receivable to sales ratio after controlling for growth in sales, size, age and profitability.[14,15] More formally,

$$P(M_{it}) = P(\beta_0 + \beta_1 LR_{it} + \beta_2 ARS\_RES_{it} + \xi_{it}) \quad (6)$$

The probability that revenue manipulation remains undiscovered until year t+x, given revenue manipulation in year t $P(UM_{i,t+x} / M_t) = P(Z_{it}\ \delta + \psi_{it} > 0)$ is assumed to be a function of the auditor type, the auditor's expertise in the industry, firm size as measured by (the log of) market value, and a number of "red flag" variables including the firm's growth in sales, the level of accounts receivable scaled by total assets, the ratio of inventory to total assets the likelihood of financial distress and the variability of stock returns. Stice (1991), and Pratt and Stice (1994), show that these variables are significantly associated with lawsuits against auditors and, therefore, are likely to be correlated with the probability that revenue manipulation remains undiscovered. More specifically, the conditional probability that revenue manipulation remains undiscovered until some later period (given manipulation) is likely to be smaller both if the auditor is from the "Big 8" and if the auditor has more industry expertise. In addition, big firms are scrutinized more closely by auditors and therefore the probability that the manipulation remains undiscovered is negatively associated with size. The growth in sales, accounts receivable to total assets, inventory to total assets, financial distress and the variability in stock returns are "red flag" variables that induce the auditor to scrutinize the firm more

[14] Note that the credit policy model was estimated without including the loss ratio among the independent variables.

[15] In a sensitivity analysis we estimate the model by including all the variables of the credit policy model along with the ratio of accounts receivable to sales among the independent variables. In a separate analysis, we also estimate the model replacing ARS_RES with the actual accounts receivable to sales ratio. The results obtained for both analyses are similar to those reported.

carefully and, thus, reduce the probability that the revenue manipulation will remain undiscovered.

In addition, excess sales growth has been shown to be associated with fraud (Beasley 1996, Bell et al. 1991, Loebbecke et al. 1989). Excess accounts receivable increases audit risk (SFAS 47, Audit Risk and Materiality in Conducting and Audit) because of the judgment involved in estimating uncollectible accounts. Likelihood of fraud is positively associated with the risk of bankruptcy and financial distress (Bell et al. 1991, Loebbecke et al. 1989).

We compute the variables that have not yet been formally defined as follows:

AUD = 1 if the auditor is one of the "Big 8" and 0 otherwise;

EXPR = the log of the number of contemporaneous audit clients in the same 4 - digit SIC code that employ the same auditor;

LGMV = natural log of market value;

GR_SAL = growth rate in sales;

AR_AS =the ratio of accounts receivable to total assets;

INV =the ratio of inventory to total assets ratio;

VARAR =the variance of abnormal stock returns. VARAR is the standard deviation of the residuals of the regression of daily stock returns on the value weighted market return in the fiscal year;

ALT_Z =Altman's Z score. We use ALT_Z as the proxy for the risk of bankruptcy and financial distress.

From the above discussion it follows that:

$$P(UM_{t+x} / M_t) = P(\delta_0 + \delta_1 AUD_{it} + \delta_2 EXPR_{it} + \delta_3 GR\_SAL_{it} + \delta_4 ALT\_Z_{it}$$

$$+ \delta_5 INV_{it} + \delta_6 AR\_AS_{it} + \delta_7 VARAR_{it} + \delta_8 LGMV_{it} + \psi_{it}) \qquad (7)$$

We predict that, with the exception of the intercept, all coefficients in equation (7) have negative signs.

Focusing on equation (6), we reject hypothesis H2 if the estimated coefficient of the loss ratio (β_1) is less than or equal to 0. Similarly, we reject hypothesis H3 if the estimated coefficient of the accounts receivable to sales ratio (β_2) is less than or equal to 0.

4. Data

Financial statement and price data are collected from the annual Compustat and the monthly CRSP databases, respectively. We begin by identifying all firms included in Compustat from 1987-2002 with non-missing net income before extraordinary items (DATA18) and cash flow from operations (DATA 308) (109,001 firm-year observations). Using this sample, we compute the loss-ratio. We then eliminate observations with missing values of sales (DATA12), growth in sales, accounts receivable (DATA2), inventory (DATA3) or Altman's Z score and restrict the sample period to the years from 1990 to 1999. This last restriction is necessary since the data include very few cases of financial statement restatements before 1990 or after 1999. These restrictions reduce the sample size to 46,380 observations. In addition, we eliminate industries which have no revenue related restatement cases, bringing the sample size to 18,412 firm-years.

We also impose restrictions related to stock returns and market values. We

compute annual stock returns from monthly CRSP data adjusted for dividends. Returns are computed over a period starting nine months before and ending three months after the fiscal year end. If the firm was delisted we use the delisted return. We also require valid market values of equity three months after the fiscal year end. These restrictions reduce the sample size to 11,040 firm-years. Finally, we remove 4-digit SIC codes with fewer than four firms. The final sample consists of 10,892 (1,954) firm-years (firms).[16] Visual inspection of our sample firms shows them to be distributed widely across 4-digit SIC groups with no unusually large concentrations in any specific industry sector.

The restatement sample was obtained by downloading from Lexis all 10K reports for the years 1990 to 1999 where the word "restatement" appears within three words of "financ" (short version of financial, finance, etc.). The sample was then limited to include only companies that restated their annual financial statements due to accounting errors. We define revenue related restatement errors as all errors that involve the restatement of revenues for any reason, such as premature revenue recognition and fraudulent recognition of revenues.[17] Matching the restatement data with the original sample yields 139 years of restated financial statements.

Table 1 provides descriptive statistics for the sample firms. Panel A of Table 1 shows that the sample firms are generally of medium size; the median market value of equity is about $68 million and median total assets is $58 million. The mean loss ratio computed based on net income is 0.36, whereas the mean loss ratio computed based on cash flows from operations is 0.35. These loss ratios indicate that the average firm in the sample reports losses or negative cash flows from operations in about one third of the

[16] Throughout the analyses we further eliminate the top and bottom one percent of each of the variables in the different regressions.

years since it became public. The sample firms are also relatively young (median age is 8) and grow faster than their peers (the mean industry adjusted growth rate is 14%).

Panel B of Table 1 shows summary statistics ranked by the loss ratio. We divide the sample firms into deciles based on the size of the loss ratio – firms with a loss ratio less than 10%, firms with a loss ratio greater or equal to 10% but less than 20%, and so on. Of the total number of observations, 7,262 firm-years had a loss ratio less than 50% and the remaining 3,630 had a loss ratio greater than 50%, of which 821 observations have loss ratio greater then 90%. The table indicates that the median market value of equity and the median total assets decrease with the loss ratio; the median market value of firms (total assets) with loss ratio less than 10% is $229 ($182) million whereas the median market value of firms (total assets) with loss ratio greater than 90% is $45 ($17) million. Although there is no discernable pattern in the market-to-book and price-to-sales ratios, the medians of these ratios are the highest for firms with highest loss ratio. Finally, the table shows no pattern in the ratio of accounts receivable to sales – the median ratio is 0.19 across most loss ratio groups.

5. Empirical Results

5.1 The Value Relevance of Revenues

Bowen et al. (2002) investigate whether revenues are value relevant for Internet firms by regressing the market value of equity on earnings and revenues. They report that the coefficient on revenue for loss firm-quarters is positive and significant, indicating that revenues are still value relevant after controlling for earnings in explaining market

[17] A company that restated revenues and expenses is considered to be a revenue related restatement case.

values. Following, Bowen et al. (2002) we regress earnings and revenues on the market value of equity (total assets are included in the regression to control for size):[18]

$$MVE_{it} = \omega_0 + \omega_1 Assets_{it} + \omega_2 BVE_{it} + \omega_3 Earnings_{it} + \omega_4 L\_Earnings_{it}$$
$$+ \omega_5 Revenue_{it} + \omega_6 L\_Revenue_{it} + \text{year dummies} + \xi_{it} \quad (8)$$

where i denotes the firm, t is a time index and the ω's are parameters to be estimated. The variables in equation (8) are defined as follows:

MVE_{it} = market value of equity measured three months after the fiscal year end;

$Assets_{it}$ = total assets (compustat item DATA6);

BVE_{it} = book value of equity (compustat item DATA60);

$Earnings_{it}$ = net income before extraordinary items (compustat item DATA18) if net income before extraordinary items is *positive* and zero otherwise;

$L\_Earnings_{it}$ = net income before extraordinary items (compustat item DATA18) if net income before extraordinary items is *negative* and zero otherwise;

$Revenue_{it}$ = total revenue (compustat item DATA 12) if net income before extraordinary items is *positive* and zero otherwise;

$L\_Revenue_{it}$ = total revenue (compustat item DATA 12) if net income before extraordinary items is *negative* and zero otherwise;

year dummies = a dummy variable indicating the year of the data observation;

ξ_{it} = white noise innovation term.

Table 2 shows the Ordinary Least Squares (OLS) estimation results. Consistent with Bowen et al. (2002) and Collins, Pincus and Xie (1999) the coefficient on book value of equity is positive and significant (t-statistic = 2, p-value<5%). For profitable firms, the coefficient on earnings ($Earnings_{it}$) is positive and highly significant (t-statistic = 9.1, p-value<1%); the coefficient on revenues ($Revenue_{it}$) is also positive but

[18] Note that our hypothesis is that loss firms manipulate revenues in order to enhance market capitalization. Hence the value relevance of revenues is examined in level space rather than return space.

marginally significant (t-statistic = 1.7, p-value=9.9%). For loss firms we find that the coefficient on earnings ($L\_Earnings_{it}$) is not significantly different from zero (t-statistic = 0.3, p-value=75.6%). This observation is also consistent with Collins, Pincus and Xie who show that the coefficient on earnings for loss firms is not significantly different from zero for most of their sample years.[19] The coefficient on loss firms' revenues ($L\_Revenue_{it}$), however, is positive and significantly different from zero (t-statistic = 2.5, p-value=1.4%), indicating that revenues, and not earnings, are the main driver of market value of equity for firms that report losses. Taken as a whole, our results indicate that revenues are value relevant over and above earnings for all firms. However, while earnings are value relevant for profitable firms, they are not value relevant for loss firms. These results demonstrate the singular importance of revenues for loss firms.[20]

5.2 Credit Policy and the Loss Ratio

Panel A of Table 3 presents the regression results from the OLS estimation of equation (1). We use two proxies for the loss ratio, one based on net income and the other based on cash flows from operations. The signs of the coefficients on the control variables are essentially consistent with Petersen and Rajan (1997). Specifically, in the regression where the loss ratio is computed based on earnings (Earnings column), the level of accounting receivables is positively associated with firm size (t-statistic = 8.3, p-value<1%) which proxies for the firm's financial strength and its ability to extend credit.

[19] Although the mean coefficient of earnings for loss firms is overall marginally significant, in 12 out of 18 years considered (1975-1992) the coefficient of earnings is not significantly different from zero.

[20] To ensure that our results are not affected by size, we repeated the analysis after scaling all the variables by the book value of equity and total assets, respectively. In both cases the coefficients are qualitatively similar in sign and significance to those reported. Most importantly, the coefficient on revenues for loss firms remains positive and significant.

In addition, the level of accounts receivable is also positively related to growth in sales. The coefficient on GRS_P (t-statistic = 6.3, p-value<1%) indicates that firms with industry adjusted positive growth in sales tend to extend more generous credit terms to their customers. However, the coefficient on the negative industry adjusted growth rate (GRS_N) (t-statistic = -0.6, p-value=96%) is not significantly different from zero. The coefficient on current period profitability, which is proxied by the gross margin ratio, is positive and significant (t-statistic = 7.7, p-value<1%) indicating that profitable firms extend more generous credit terms to their customers. The coefficient on the square of the gross margin is also positive and significant (t-statistic = 7.7, p-value<1%) indicating that the level of accounts receivable is a convex function of the current period gross margin. The coefficient on age is negative (contrary to our expectations) but only marginally significant (t-statistic = 1.7, p-value=9.8%). Although age is another proxy for the firm's ability to extend credit, a possible explanation for the negative coefficient is that firms in their early stage of the business cycle may extend better credit terms in order to capture greater market share. Most importantly, consistent with Hypothesis 1, the coefficients on the loss ratio is positive and significant (t-statistic = 5.6, p-value<1%) indicating that firms that experience a sequence of negative earnings report relatively higher ratios of accounts receivable to sales than more profitable firms. The results of the regression where we compute the loss ratio based on cash flows from operation are very similar. Specifically, the coefficients on the control variables are almost identical to those reported in the Earnings column. The coefficient on the loss ratio is also positive and significant (t-statistic = 15.3, p-value<1%), again, indicating that firms that experience a

sequence of negative operating cash flows report relatively higher ratios of accounts receivable to sales than more profitable firms.[21]

Panel B of Table 3 replicates Panel A of Table 3 for each loss ratio category from 0.5 to 0.9. The loss ratio (LRD) variable in Panel B is a dummy variable with a value of 1 if the firm's loss ratio is greater than the benchmark and zero otherwise. In order to conduct the median adjusted analysis, we eliminate 4-digit SIC codes containing fewer than three firms with loss ratios less than the benchmark ratio. Panel B of Table 3 shows that the estimated coefficients on the loss ratio dummies (LRD) are positive and statistically significant across all but one of the (0.6) loss ratio benchmarks, again indicating a positive association between the ratio of accounts receivable to sales and the incidence of losses. The coefficients on the control variables are consistent with those reported in Panel A: the coefficients on size, positive growth rate in sales, gross margin and the square of gross margin are positive and significant whereas the coefficient on negative growth rate in sales is negative and significant[22]

Overall, the findings in Table 3 indicate that the (industry-adjusted) ratio of accounts receivable to sales increases with the loss ratio after controlling for size, age, growth and current period profitability. This result is consistent with our hypothesis that loss firms overstate revenues in order to inflate their market values.[23]

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[21] In order to check the robustness of our results to different specifications, we conducted the following sensitivity analyses: (1) we estimated the regressions omitting the square variables, (2) we included Altman's Z in order to control for the risk of bankruptcy, (3) we replaced the net income margin with the ratio of cash flows from operations to total sales, (4) we eliminated firm-years with an Altman's Z ratio less than 1.8, and (5) given the potential correlation between the loss ratio and the gross income margin ratio, we omitted the gross income margin ratio and the square of the gross net income margin ratio from the independent variables. The results across all specifications are qualitatively similar to those presented in the tables.

[22] We repeated the analysis using cash flow based loss ratios. The results are similar to those reported.

[23] Loss firms are likely prone to selling receivables (or securitizations) because of their financing needs. If anything, the sale of receivables biases against our finding that loss firms over-invest in receivables.

5.3 Restatements and the Loss Ratio

Table 4 shows statistics on the number of restatements by year and on the association of revenue and expense restatements with the loss ratio. Panel A of table 4 shows that the overall number of restatements consistently increases over time from 8 in 1990 to 42 in 1997[24]. In the last two years of the sample period the number of restated years decreases to 34 in 1998 and 19 in 1999.[25] There were 139 restatements that involve revenues[26] and 81 restatement cases that do not involve revenues. As is the case with the overall total number of restatements, both the revenue related and non-revenue related restatements increase from 1990 to 1997 and decline after that. The RES_RATIO column shows the ratio of restatement cases to the total number of firms in the sample. The data suggest that the relative proportion of restated years has increased as well over the sample period. Specifically, in 1990 less than 1% of the firms restated their financial statements whereas by 1998 this proportion increased to 3%. Untabulated results show that revenue manipulators are scattered around 54 industries (based on 4 digits SIC codes), indicating that revenue manipulation is not an industry specific phenomena.

Panel B of Table 4 shows the means of the loss ratio for revenue related restatements and non-revenue related restatements by sample year and over all years. The loss ratio is computed based on net income (denoted NI_RAT) and based on operating

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COMPUSTAT does not provide data on the sale of receivables or securitizations and therefore we are unable to account for them in our analysis.

[24] It is important to note that Table 4 provides descriptive statistics for the number of restated years that meet all of our data restrictions. The actual number of total restatements over the 1990's is larger than the number reported here.

[25] The decrease in the number of restatement cases in 1998 and 1999 can be attributed to the timing of our data collection in 2000-2001, and it is possible that additional restatement cases pertaining to 1998 and 1999 were discovered after we finished our data collection.

cash flows (denoted CF_RAT). Comparing NI_RAT across the two categories of restatements, we find that with the exception of 1990 and 1999 the mean of NI_RAT is greater for revenue related restatements. In addition, the overall mean of NI_RAT across all sample years for revenue related restatements is 0.47 as compared with 0.38 for non-revenue related restatements, and the difference in these means is significant at less than the 1% significance level. The pattern for CF_RAT is similar. In particular, CF_RAT is higher for revenue related restatements from 1993 onwards, and the overall mean of CF_RAT for revenue related restatements (0.48) is significantly greater then the mean of CF_RAT for non-revenue related restatements (0.37). Overall, Table 4 indicates that the incidence of revenue related restatements (and of non-revenue related restatements) has increased over time, and that revenue-related restatements are positively associated with the loss ratio; firms that manipulate their revenues have higher loss ratio than firms that manipulate other accounts. This observation provides indirect support for our conjecture that loss firms have a greater incentive to manipulate revenues rather than expenses since loss firms are valued based primarily on their revenues rather than their earnings.

Table 4, Panel C shows the comparison of financial ratios between companies that restated their financial statements due to revenues manipulation and companies that did not restate their financial statements. The table indicates that companies that restated their revenues had a significantly higher loss ratio and industry adjusted accounts receivable to sales ratio. These findings are consistent with our assumption that revenue manipulation flows through accounts receivable and that there is a positive link between revenue manipulation and the loss ratio. In addition, companies that manipulated revenues are marginally younger and with lower Altman's Z score.

[26] Some of the revenue related restatements involve restatements of expenses as well.

Overall, Table 4 indicates that the incidents of revenue restatements have increased in the second half of the nineties, and that companies that manipulate revenues have higher loss ratio as compared with companies that did not restate their financial statement and with companies that restate their financial statements as result of expense manipulation. Below, we examine whether the probability of manipulation increases with the loss ratio after controlling for the credit policy of the firm and the likelihood of the firm being successful in concealing the manipulation.

5.4 The Probability of Revenue Manipulation and the Loss Ratio

Panel A of Table 5 shows the results of the "partial observability" two stage probit model using maximum likelihood estimation. The Earnings column shows the estimation results where the loss ratio is computed based on net income and the Cash Flows column shows the estimation results where the loss ratio is computed based on cash flow from operations. Both regressions are significant at less than the 5% level based on the Wald and Lagrange Multiplier (LM) statistics, both of which are distributed Chi-squared.

The parameters in the Stage 1 probability model, which estimates the probability of revenue manipulation, are broadly consistent with our predictions. Specifically, when computing the loss ratio based on income before extraordinary items we find that the coefficient on the loss ratio is positive and significant, (t-statistic = 3.6, p-value<1%) indicating a positive association between the probability of revenue manipulation and the extent of past and future losses. The coefficient on ARS_RES, the residual from the estimation of the credit policy model, is also positive and significant (t-statistic = 1.9, p-

value=5.8%). This indicates that the probability of revenue manipulation is also increasing with the ratio of accounts receivable to sales after controlling for the credit policy of the firm. The estimated probability that revenue manipulation will remain undiscovered until time t+x, conditional on manipulation having taken place at time t (stage 2), is consistent with the findings of the literature. Specifically, the conditional probability of the manipulation not being discovered given that revenues are manipulated is negatively associated with the auditor's experience in the industry (EXPR) (t-statistic = -3.3, p-value<1%) and with the likelihood of distress (ALT_Z) (t-statistic = -2.7, p-value<1%). Contrary to expectations, the coefficient on log market value of equity (LGMV) is positive and significant (t-statistic = 3.6, p-value<1%) and the coefficient on the ratio of inventory to total assets (INV) is positive and significant (t-statistic = 2.4, p-value<1%).

Unlike the results of the net income model, the results of the cash flow model are fairly weak. Although the signs of the estimated coefficients are essentially the same as the signs of the net income model, with the exception of EXPR, none of the variables are significant at conventional levels. This result is surprising given the high correlation between the two loss ratio measures. To examine whether the latter results are attributable to the two stage methodology and as a sensitivity analysis, we estimate a single stage probit model that includes all of the independent variables from both stages of the two stage probit model. The results are presented in Panel B of Table 5. Overall, both the net income and cash flow loss ratio metrics yield similar results in the one stage model. Moreover, in terms of the signs and significance of the estimated coefficients, the results of the one stage model are similar to those of the two stage sequential model when

the loss ratio is defined as the net income metric.[27] Specifically, the probability of a revenue related restated year in the one stage model is positively and significantly associated with LOSS (cash flow metric t-statistic = 5.3, net income metric t-statistic = 5.2, p-values<1%) and ARS_RES (cash flow metric t-statistic = 2.8, net income metric t-statistic = 3.3, p-values<1%). The estimated coefficients of the control variables in the one stage model are also consistent with expectations. Specifically, the coefficients on auditor experience are negative and significant (cash flow metric t-statistic = -3.2, net income metric t-statistic = 3.3, p-values<1%) . Similarly, the estimated Altman's Z score coefficients are negative and significant, (cash flow metric t-statistic = -3.3, net income metric t-statistic = 3.0, p-values<1%). The coefficient on log market value of equity is positive and significant (cash flow metric t-statistic = 3.4, net income metric t-statistic = 3.5, p-values<1%).

Overall, the results of the probit analyses confirm our hypotheses. The probability of revenue manipulation is positively associated with the loss ratio. Firms that report a longer string of negative earnings or cash flows are more likely to manipulate revenues. In addition, given our conjecture that revenue manipulation flow through accounts receivable, we find that the probability of revenue manipulation is positively related to the ratio of accounts receivable to total sales – firms with high accounts receivable to sales ratio are more likely to manipulate revenues than firms with low accounts receivable to sales ratio.

5.5 Sensitivity Analyses

[27] However, the coefficients of the variables in the first stage of the sequential model are significantly larger than the coefficients of these same variables in the one stage model.

To examine whether our results are sensitive to the implicit assumption of perfect foresight of the sign on earnings and cash flows, we repeat our analysis using loss ratios (earnings and cash flows) computed with historical information only. The credit policy analysis indicates that accounts receivable are significantly higher for firms that reported a consistent stream of negative earnings and for firms that reported negative cash flows, hence the credit policy results are insensitive to the perfect foresight assumption. Similarly, the results of the univariate analysis of the association between revenue related restatements and the loss ratio are unaffected by this assumption; revenue related restatements are associated with higher loss ratio than non-revenue related restatements, even when the loss ratio is computed based on historical information only. The results of the both the two stage and single stage probit models are also unaffected by the perfect foresight assumption. Scpecifically, in the two stage model the loss ratio based on historical net income (cash flows) is positive and significant (not significant) and positive and significant in the one stage model irrespective of the loss ratio definition..

Arguably the loss ratio depends to a large extent on the age of the firm. For older firms past years are dominant, whereas for young firms recent years and future years are dominant in the calculation of the loss ratio. In order to examine whether the results are affected by this potential bias we repeat the analysis and restrict our sample of "loss" firms to include only firms that are younger than the median age of our sample (i.e., 8 years old or less). The results obtained are qualitatively similar – loss firms report higher accounts receivable and the probability of revenue manipulation is positively associated with the loss ratio and the ratio of accounts receivable to sales.

To eliminate the possibility that our results are driven by firms in financial distress, we repeated the 2-stage probit analysis after excluding all firm-years with an Altman's Z ratio less than 1.8. The results for the earnings based loss ratio are virtually identical to those reported above. The results for the cash flows based loss ratio are stronger than those reported. Specifically, the coefficients on the loss ratio and ARS_RES are positive and significant. In addition, the coefficients on the variables in the second stage are consistent with those reported for the earnings based loss ratio regression.

6. Conclusion

The purpose of this paper is to examine whether firms reporting a string of negative earnings and/or negative cash flows overstate revenues in order to induce a higher market valuation. Traditional valuation models, such as the Discounted Cash Flows model, cannot be applied to firms that report a consistent string of losses or negative cash flows. Hence, analysts and investors are likely resort to revenue based valuation models just as they do when valuing Internet firms. Indeed, we show that revenues are value relevant in explaining market value of equity whereas earnings are not significant in explaining the market value of equity for firms reporting negative earnings. This result is consistent with the findings of Bowen et al. (2002) who report similar findings for Internet firms.

Given our assumption that revenue manipulation flows through accounts receivable, we show that firms with a more extensive string of past and anticipated losses report higher accounts receivable to sales ratio, after controlling for the firm's credit policy (where the credit policy model is consistent with Petersen and Rajan (1997)).

Furthermore, the result that loss firms report a higher ratio of accounts receivable to sales is robust to various specifications of the credit policy model.

Using restatement data, we show that firms that manipulate revenues have higher loss ratios than firms that manipulate non-revenue accounts. This finding is consistent with the conjecture that revenues are more important than expenses to loss firms simply because the market value of a loss firm is more likely to be based on revenues than on earnings. Finally, using a two-stage probit model, we show that the likelihood of revenue manipulation is increasing with the loss ratio and with the ratio of accounts receivable to sales, after controlling for the probability that the manipulation is not detected until a later stage.

Our findings have potential policy implications. Empirical evidence on equity market reactions to restatement announcements strongly suggests that the market is frequently surprised by revenue restatements. Our findings suggest that candidates for revenue related restatements are likely to be companies with a significant number of years of negative earnings and high level of accounts receivable relative to sales. This suggests a relatively cost efficient method for regulators to identify possible candidates for investigation of revenue reporting practices.

References

Abowd, J.M. and H.S. Farber. 1982. Job Queues And The Union Status Of Workers. *Industrial and Labor Relations Review* 35: 354-367.

Anderson, K. L. and T. L. Yohn, 2002. The Effect of 10-K Restatements on Firm Value, Information Assymetries and Investor's Reliance on Reported Earnings. Working paper, Georgetown University

Anthony, J.H. and K. Ramesh. 1992. Association Between Accounting Performance Measures and Stock Prices: A Test of the Life Cycle Hypothesis. *Journal of Accounting and Economics* 15: 203-227.

Bagnoli, M., M. Penno and S. G. Watts. 2001. "Auditing In The Presence Of Outside Sources Of Information," *Journal of Accounting Research*, 39: 435-447.

Beasley, M. S. 1996. An Empirical Analysis Of The Relation Between The Board Of Director Composition And Financial Statement Fraud, *Accounting Review*, 71: 443-465.

Bell, T. B. and R. H. Tabor. 1991. Empirical Analysis Of Audit Uncertainty Qualifications, *Journal of Accounting Research*, 29:350-370.

Beneish, M. D. 1997. Detecting GAAP Violation: Implications for Assessing Earnings Management Among Firms With Extreme Financial Performance. *Journal of Accounting and Public Policy* 16 : 271-309.

Bernard, V. and D. Skinner. 1996. What Motivates Managers' Choice of Discretionary Accruals? *Journal of Accounting and Economics* 22: 313-325.

Bowen, R., L. Ducharme, and D. Shores. 1995. Stakeholders' Implicit Claims and Accounting Method Choice. *Journal of Accounting and Economics* 20: 255-295.

Bowen, R.M., A. Davis, and S. Rajgopal. 2002. Determinants of Revenue-Reporting Practices for Internet Firms. *Contemporary Accounting Research* 19: 523-562.

Callen, J. L., Livnat J., and Segal D. 2002. Accounting Restatements: Are They Always Bad News for Investors? Working Paper, University of Toronto and New York University.

Campbell, K. and S. Sefcik. 2002. Virtual Sales: Barter and Revenue Management in Internet Firms. Working Paper, University of Connecticut and University of Washington.

Collins, D. W., M. Pincus and H. Xie, 1999. Equity Valuation and Negative Earnings: The Role of Book Value of Equity. *Accounting Review* 74: 29-61.

Davis, A. K. and S. J. Monahan. 2002. The Value of Relevance of Revenue for Internet Firms: Does Reporting Grossed-Up Or Barter Revenue Make A Difference? *Journal of Accounting Research*, 40: 445-484.

Dechow, P., R. Sloan, and A. Sweeney. 1995. Detecting Earnings Management. *Accounting Review* 70: 193-226.

Dechow, P., R. Sloan, and A. Sweeney. 1996. Causes and Consequences of Earnings Manipulation: An Analysis of Firms Subject to Enforcement Actions by the SEC. *Contemporary Accounting Research* 13: 1-36.

Demers, E. and B. Lev. 2001. A Rude Awakening: Internet Shakeout in 2000. *Review of Accounting Studies* 6: 331-359.

Feroz, E. H., K. Park and V. S. Pastena. 1991. The Financial and Market Effects of the SEC's Accounting and Auditing Enforcement Releases. *Journal of Accounting Research* 29 (Supp.): 107-148.

Hand, J. 2000. Profits, Losses and the Non-linear Pricing of Internet Stocks. Working paper, University of North Carolina, Chapel Hill.

Hand, John R. M., 2001. Discussion: Earnings, Book Values, And Dividends In Equity Valuation: An Empirical Perspective, *Contemporary Accounting Research*, 18: 121-130.

Healy, P. and J. Wahlen. 1999. A Review of the Earnings Management Literature and Its Implications for Standard Setting. *Accounting Horizons* 13: 365-383.

Jones, J. 1991. Earnings Management During Import Relief Investigations. *Journal of Accounting Research* 29: 193-228.

Loebbecke, J. K., M. M. Eining and J. J. Willingham. 1989. Auditors' Experience With Material Irregularities: Frequency, Nature, And Detectability, *Auditing: A Journal of Practice and Theory*, 9: 1-28.

Marquardt, C.A. and C.I. Wiedman. 2004. How are Earnings Managed? An Examination of Specific Accruals. *Contemporary Accounting Research* 21: 461-491.

.

Nelson, M., J. Elliott, and R. Tarpley. 2002. Evidence from Auditors about Managers' and Auditors' Earnings-Management Decisions. *Accounting Review* 77 (Supp.): 175-202.

Nelson, M., J. Elliott, and R. Tarpley. 2003. How are Earnings Managed?,Evidence from Auditors. *Accounting Horizons* 17 (Supp.): 17-35.

New York Times. August 19, 2001.

Palmrose, Z-V, V. J. Anderson, and S. Scholz. 2004. Determinants of Market Reactions to Restatements Announcements. *Journal of Accounting and Economics* 37 (1): 1-32

Peterson, M. A and R. G. Rajan, 1997. Trade Credit: Theories and Evidence. *Review of Financial Studies* 10: 661-691

Plummer, E. and D. Mest. 2001. Evidence On The Management Of Earnings Components, *Journal of Accounting, Auditing and Finance*, 16: 301-323.

Poirier, D. J. 1980. Partial Observability in Bivariate Probit Models. *Journal of Econometrics* 12: 209-218.

Porter, M.E. 1980. *Competitive Strategy: Techniques for Analyzing Industries and Competitors* (Free Press, New York, NY).

Pratt, J. and J. D. Stice. 1994. The Effects of Client Characteristics on Auditor Litigation Risk Judgments, Required Audit Evidence, and Recommended Audit Fees. *Accounting Review* 69: 639-656.

Rangan, S. 1998. Earnings Management and the Performance of Seasoned Equity Offerings. *Journal of Financial Economics* 50: 101-122.

Richardson, S. A., A. Tuna, and M. Wu. 2003. Predicting Earnings Management: The Case of Earnings Restatements. Working paper, University of Pennsylvania.

Securities and Exchange Commission, Staff Accounting Bulletin No. 101, Revenue Recognition in Financial Statements. December 11, 2000.

Shivakumar, L. 2000. Do Firms Mislead Investors By Overstating Earnings Before Seasoned Equity Offerings, *Journal of Accounting and Economics,* 29: 339-371.

Stice, J. D. 1991. Using Financial and Market Information to Identify Pre-Engagement Factors Associated with Lawsuits Against Auditors. *Accounting Review* 66: 516-533.

Subramanyam, K.R. 1996. The Pricing of Discretionary Accruals. *Journal of Accounting and Economics* 22 : 249-281.

Teoh, S., T. Wong, and G. Rao. 1999. Are Accruals During Initial Public Offerings Opportunistic? *Review of Accounting Studies* 4: 175-208

Trueman, B., M. H. F. Wong and X. Zhang. 2001. Back to Basics: Forecasting the Revenues of Internet Firms. *Review of Accounting Studies* 6: 305-329.

Trueman, B., M.H.F. Wong and X. Zhang. 2000. The Eyeballs Have It: Searching for the Value in Internet Stocks. *Journal of Accounting Research* 38(Supp): 137-162.

Table 1 – Descriptive Statistics

Panel A: Summary Statistics

	MEAN	STD	Q1	MEDIAN	Q3
MVE ($M)	1233	8265	21	68	266
ASSETS ($M)	814	3971	19	58	224
NI_RAT	0.36	0.31	0.09	0.30	0.57
CF_RAT	0.35	0.32	0.00	0.29	0.60
EX_ARS	0.02	0.11	-0.04	0.00	0.05
EX_GR	0.14	1.06	-0.13	0.00	0.18
AGE	11	12	4	8	15
GRM	-0.04	0.48	-0.09	0.00	0.09
INV	0.19	0.14	0.08	0.16	0.27
VAR_AR	0.003	0.010	0.001	0.002	0.003
EXPER	13	15	4	8	16

Notes:

1. MVE market value of equity measured three months after fiscal year end.
2. ASSETS is total assets (DATA 6).
3. NI_RAT (CF_RAT) in year t is the proportion of years in which the firm reports negative net income before extraordinary items (operating cash flows) prior to and including year t+3.
4. EX_ARS is the 4-digit SIC median adjusted ratio of accounts receivable to sales at time t.
5. EX_GR is the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the median growth rate in the industry.
6. AGE is the firm's age in years.
7. GRM is the 4-digit SIC median adjusted gross profit scaled by total sales, computed as the difference between the firm's gross profit margin and the median gross profit margin in the industry.
8. INV is the ratio of inventory to total assets.
9. VAR-AR is the variance of abnormal returns.
10. EXPER is the number of firms that are in the same 4-digit SIC and that employ the same auditor as the firm observation.

Panel B: Median Statistics by Loss Ratio

NI_RAT	N	MVE	ASSETS	BM	PS	AGE	ARS
0%	2793	229	182	0.41	1.10	11.00	0.17
10%	1350	101	104	0.50	0.91	8.00	0.19
20%	1273	80	81	0.51	0.89	8.00	0.19
30%	999	54	62	0.56	0.68	8.00	0.18
40%	847	48	46	0.52	0.84	8.00	0.19
50%	1046	31	33	0.57	0.75	8.00	0.19
60%	689	26	24	0.46	0.89	6.00	0.19
70%	485	29	21	0.36	1.21	8.00	0.19
80%	589	25	16	0.28	1.86	5.00	0.19
>=90%	821	45	17	0.23	4.84	4.00	0.19
SAMPLE	10892	68	58	0.44	1.02	8	0.18

Notes:

1. NI_RAT in year t is the proportion of years in which the firm reports negative net income before extraordinary items prior to and including year t+3.
2. N is the number of firm-year observations in each loss ratio.
3. MVE is market value of equity ($M) .
4. ASSETS is total assets ($M).
5. BM is the book to market ratio, computed as book value of equity divided by the market value of equity three months after fiscal year-end.
6. PS is the price to sales ratio, computed as the market value of equity three months after fiscal year-end divided by total sales.
7. AGE is the firm age in years.
8. ARS is the ratio of accounts receivable to sales.

Table 2 – Value Relevance Analysis - (Standard Errors in Parentheses)

$$MVE_{it} = \omega_0 + \omega_1 Assets_{it} + \omega_2 BVE_{it} + \omega_3 Earnings_{it} + \omega_4 L\_Earnings_{it} + \omega_5 Revenue_{it} + \omega_6 L\_Revenue_{it} + year\ dummies + \xi_{it}$$

Variable	Predicted Sign	Estimate
Intercept	+/-	1347* (342)
Assets	+/-	-0.99* (0.25)
BVE	+	2.05* (1.02)
Earnings	+	22.99* (2.53)
L_Earnings	-	1.21 (3.90)
Revenue	+	0.30** (0.18)
L_Revenue	+	1.32* (0.53)
Adj. R^2		0.55
N		10500

Notes:

1. i (t) is the firm (time) index.
2. Assets is total assets (DATA 6).
3. BVE is book value of equity (DATA 60).
4. Earnings equals to net income before extraordinary items (DATA18) if net income before extraordinary items is *positive* and zero otherwise.
5. L_Earnings Earnings equals to net income before extraordinary items (DATA18) if net income before extraordinary items is *negative* and zero otherwise.
6. Revenue equals to total revenue (DATA 12) if net income before extraordinary items is *positive* and zero otherwise.
7. L_Revenue equals to total revenue (DATA 12) if net income before extraordinary items is *negative* and zero otherwise.
8. MVEit is market value of equity measured three months after fiscal year end
9. The standard errors are adjusted for White's (1980) heteroscedasticity correction.
10. * (**) indicates significance at the 5% (10%) level.

Table 3 – The Determinants of Accounts Receivable (Standard Errors in Parentheses)

Panel A: Loss Ratio as Continuous Variable

$$ARS_{it} = \alpha_0 + \alpha_1 LOSS_{it} + \alpha_2 LSIZE_{it} + \alpha_3 LAGE_{it} + \alpha_4 LAGE\_SQ_{it} + \alpha_5 GRS\_P_{it} + \alpha_6 GRS\_N_{it} + \alpha_7 GRM_{it} + \alpha_8 GRM\_SQ_{it} + year\ dummies + \xi_{it}$$

Variable	Predicted Sign	Earnings	Cash Flows
Intercept	+/-	-0.01 (0.006)	-0.04* (0.006)
LOSS	+	0.023* (0.004)	0.06* (0.004)
LSIZE	+	0.005* (0.0006)	0.008* (0.0006)
LAGE	+	-0.005** (0.004)	-0.004 (0.003)
LAGE_SQ	-	-0.0002 (0.0009)	-0.0003 (0.0008)
GRS_P	+	0.019* (0.003)	0.013* (0.003)
GRS_N	-	-0.005 (0.008)	0.0004 (0.008)
GRM	+	0.054* (0.007)	0.066* (0.007)
GRM_SQ	-	0.054* (0.007)	0.053* (0.007)
N		10500	10500
ADJ_R^2		0.024	0.042

Notes:

1. i (t) is the firm (time) index.
2. ARS is the 4-digit SIC median adjusted ratio of accounts receivable to sales.
3. LOSS in year t is the proportion of years in which the firm reports negative net income before extraordinary items (cash flows from operations) prior to and including year t+3.
4. LSIZE is the natural log of total assets.
5. LAGE is the natural log of the firm's age.
6. LAGE_SQ is the square of AGE.
7. GRS_P is the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the median growth rate in the industry if *positive* and zero otherwise.
8. GRS_N is the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the median growth rate in the industry if *negative* and zero otherwise.
9. GRM is the 4-digit SIC median adjusted gross profit scaled by total sales, computed as the difference between the firm's gross profit margin and the median gross profit margin in the industry.
10. GRM_SQ is the square of GRM.
11. The standard errors are adjusted for White's (1980) heteroscedasticity correction.
12. * (**) indicates significance at the 5% (10%) level

Panel B: Loss Ratio as a Dummy Variable

$$ARS_{it} = \alpha_0 + \alpha_1 LRD_{it} + \alpha_2 LSIZE_{it} + \alpha_3 LAGE_{it} + \alpha_4 LAGE\_SQ_{it} + \alpha_5 GRS\_P_{it} + \alpha_6 GRS\_N_{it} + \alpha_7 GRM_{it} + \alpha_8 GRM\_SQ_{it} + year\ dummies + \xi_{it}$$

		Loss Ratio greater than or equal to:				
Variable	**Expected Sign**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Intercept	+/-	-0.006 (0.006)	-0.003 (0.006)	-0.002 (0.006)	-0.002 (0.007)	-0.001 (0.007)
LRD	+	0.011* (0.002)	0.004 (0.003)	0.007* (0.003)	0.008* (0.004)	0.01* (0.005)
LSIZE	+	0.004* (0.001)	0.004* (0.001)	0.004* (0.001)	0.003* (0.001)	0.004* (0.001)
LAGE	+	-0.004 (0.004)	-0.003 (0.004)	-0.005 (0.004)	-0.001 (0.004)	0.002 (0.004)
LAGE_SQ	-	-0.001 (0.001)	-0.001 (0.001)	0.0001 (0.001)	-0.002 (0.001)	-0.003* (0.001)
GRS_P	+	0.019* (0.003)	0.02* (0.003)	0.02* (0.003)	0.021* (0.003)	0.02* (0.004)
GRS_N	-	-0.013** (0.008)	-0.018* (0.008)	-0.016** (0.008)	-0.016** (0.008)	-0.014 (0.009)
GRM	+	0.055* (0.007)	0.052* (0.007)	0.051* (0.007)	0.052* (0.007)	0.047* (0.008)
GRM_SQ	-	0.066* (0.009)	0.068* (0.009)	0.068* (0.008)	0.068* (0.008)	0.056* (0.008)
N		10096	9810	9230	8698	7365
ADJ_R^2		0.023	0.022	0.022	0.023	0.026

Notes:

1. i (t) is the firm (time) index.
2. ARS is the 4-digit SIC median adjusted ratio of accounts receivable to sales.
3. LRD is a dummy variable with a value of 1 in year t if the proportion of years for which the company reports negative net income prior to and including year t+3 is at least as great as the given value and 0 otherwise
4. LSIZE is the natural log of total assets.
5. LAGE is the natural log of the firm's age.
6. LAGE_SQ is the square of AGE.
7. GRS_P is the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the median growth rate in the industry if *positive* and zero otherwise.
8. GRS_N is the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the median growth rate in the industry if *negative* and zero otherwise.
9. GRM is the 4-digit SIC median adjusted gross profit scaled by total sales, computed as the difference between the firm's gross profit margin and the median gross profit margin in the industry.
10. GRM_SQ is the square of GRM.
11. The standard errors are adjusted for White's (1980) heteroscedasticity correction..
12. * (**) indicates significance at the 5% (10%) level

Table 4 – Restatement Statistics

Panel A: Number of Restatement

YEAR	REV_RES	EXP_RES	ALL_RES	RES_RATIO
1990	4	4	8	0.9%
1991	7	4	11	1.2%
1992	7	5	12	1.2%
1993	13	4	17	1.6%
1994	11	6	17	1.5%
1995	17	5	22	1.8%
1996	27	11	38	3.0%
1997	23	19	42	3.3%
1998	17	17	34	3.0%
1999	13	6	19	1.8%
Overall	**139**	**81**	**220**	**2.0%**

Panel B: Revenue and Non-revenue Restatements and the Mean Loss Ratio

	REV_RES		EXP_RES	
YEAR	NI_RAT	CF_RAT	NI_RAT	CF_RAT
1990	0.22	0.29	0.54	0.30
1991	0.36	0.41	0.33	0.75
1992	0.52	0.45	0.38	0.65
1993	0.48	0.42	0.41	0.33
1994	0.33	0.41	0.23	0.16
1995	0.42	0.40	0.34	0.26
1996	0.55	0.49	0.39	0.46
1997	0.57	0.61	0.40	0.36
1998	0.46	0.58	0.35	0.30
1999	0.38	0.45	0.51	0.33
Overall	**0.47**$^{\Psi}$	**0.48** $^{\Psi}$	**0.38**	**0.37**

Panel C: Restaters Versus Non-restaters

Variable	Restaters	Non-Restaters	Diff
NI_RAT	0.466	0.355	0.111*
ARS	0.050	0.017	0.033*
GRS	0.156	0.137	0.019
AGE	10	11	-2**
MV	593	1241	-649
ALT_Z	4.0	6.4	-2.4*
VAR_AR	0.003	0.003	-0.001
N	139	10753	

Notes (Table 4):

1. REV_RES refers to restatement cases involving revenues.
2. EXP_RES refers to restatement cases *not* involving revenues.
3. RES_RATIO is the ratio of restatements to the total number of firms.
4. NI_RAT (CF_RAT) in year t is the proportion of years in which the firm reports negative net income before extraordinary items (operating cash flows) prior to and including year t+3.
5. ARS is the 4-digit SIC median adjusted ratio of accounts receivable to sales.

6. GRS is the 4-digit SIC median adjusted growth in sales, computed as the difference between the firm's growth rate in sales and the median growth rate in the industry.
7. AGE is the firm's age.
8. MV is market value of equity.
9. LAGE_SQ is the square of AGE.
10. ALT_Z is Altman's Z score.
11. VAR-AR is the variance of abnormal returns.
12. * (**) indicates significance at the 5% (10%) level

Table 5 –Probit Model of Revenue Restatement (Standard Errors in Parentheses)

Panel A: Two Stage Sequential "Partial Observability" Probit Model of Revenue Restatement (N=9910)

$$P(REV\_RES_t) = P(M_t)\, P(UM_{t+x} / M_t)$$
$$= P(X_i \gamma + \epsilon_i > 0)\, P(Z_i \delta + \eta_i > 0)$$

	Variable	Predicted Sign	Earnings	Cash Flows
STAGE 1: Manipulation $P(X_{it} \beta + \xi_{it} > 0)$	Intercept	?	-1.262** (0.222)	-1.681* (0.891)
	ARS_RES	+	3.572* (1.885)	1.911 (1.549)
	LOSS	+	4.101** (1.151)	1.123 (0.743)
STAGE 2: Discovery of Manipulation $P(UM_{t+x} / M_t) = P(Z_i \delta + \eta_i > 0)$	Intercept	?	-2.159** (0.231)	-1.28 (1.097)
	AUD	-	-0.109 (0.117)	-0.089 (0.171)
	EXPR	-	-0.135** (0.041)	-0.172* (0.104)
	GR_SAL	-	0.097 (0.083)	0.032 (0.116)
	ALT_Z	-	-0.019** (0.007)	-0.03 (0.018)
	INV	-	0.751** (0.317)	0.656 (0.67)
	AR_AS	-	0.223 (0.457)	-0.257 (0.67)
	VARAR	-	-23.323 (21.793)	-24.412 (31.569)
	LGMV	-	0.115** (0.032)	0.145 (0.097)
	WALD Statistic		76*	70*
	LM Statistic		45*	36*

Notes:

1. N= number of firm-year observations.
2. i (t) is the firm (time) index.
3. REV_RES_t is a dummy variable with 1 if the firm restated revenues in year t and 0 otherwise.
4. LOSS in year t is the proportion of years in which the company reported negative net income before extraordinary items (cash flows from operations) prior to and including year t+3.
5. ARS_RES is the residual from the credit policy regression of $ARS_{it} = \gamma_0 + \gamma_1 LSIZE_{it} + \gamma_2 LAGE_{it} + \gamma_3 LAGE\_SQ_{it} + \gamma_4 GRS\_P_{it} + \gamma_5 GRS\_N_{it} + \gamma GRM_{it} + \gamma_7 GRM\_SQ_{it} + year\ dummies + \xi_{it}$. Note that unlike equation (1), the LOSS variable is not included as a regressor. The definition of the variables in the regression is in the notes to Panel A of Table 3

6. AUD is a dummy variable that takes on the value 1 if the auditor is from the Big Eight and 0 otherwise.
7. EXPR is the log of the number of firms that are in the same 4-digit SIC that employ the same auditor as the firm observation.
8. GR-SAL is the growth in sales computed as total sales in year t divided by total sales in year t-1.
9. ALT_Z is Altman's Z score.
10. INV is the ratio of inventory to total assets.
11. AR-AS is the ratio of accounts receivable to total assets.
12. VAR-AR is the variance of abnormal returns.
13. LGMV is the natural log of MV three months after the fiscal year-end.
14. WALD is the Wald statistic distributed Chi-Squared with 12 degrees of freedom.
15. LM is the Lagrange Multiplier statistic distributed Chi-Squared with 9 degrees of freedom for testing whether $P(UM_{t+x} / M_t)=0$.
16. * (**) indicates significance at the 5% (10%) level

Panel B: One Stage Model

$$P(REV\_RES_t=1) = \pi_0 + \pi_1 ARS\_RES_{it} + \pi_2 LOSS_{it} + \pi_3 AUD_{it} + \pi_4 EXPR_{it} + \pi_5 GR\_SAL_{it} + \pi_6 ALT\_Z_{it} + \pi_7 INV_{it} + \pi_8 AR\_AS_{it} + \pi_9 VARAR_{it} + \pi_{10} LGMV_{it} + \xi_{it}$$

Variable	Predicted Sign	Earnings	Cash Flows
Intercept	?	-2.661** (0.21)	-2.515** (0.199)
ARS_RES	+	1.477** (0.453)	1.277** (0.456)
LOSS	+	0.728** (0.14)	0.683** (0.129)
AUD	-	-0.055 (0.106)	-0.049 (0.105)
EXPR	-	-0.124** (0.038)	-0.121** (0.038)
GR_SAL	?	0.097 (0.08)	0.063 (0.081)
ALT_Z	-	-0.018** (0.006)	-0.023** (0.007)
INV	-	0.757** (0.279)	0.43 (0.281)
AR_AS	-	0.042 (0.349)	-0.174 (0.341)
VARAR	-	-20.504 (16.619)	-15.709 (16.335)
LGMV	-	0.08** (0.023)	0.078** (0.023)

Notes:

1. i (t) is the firm (time) index.
2. REV_RES_t is a dummy variable with 1 if the firm restated revenues in year t and 0 otherwise.
3. LOSS in year t is the proportion of years in which the firm reports negative net income before extraordinary items (cash flows from operations) prior to and including year t+3.
4. ARS_RES is the residual from the credit policy regression of $ARS_{it} = \gamma_0 + \gamma_1 LSIZE_{it} + \gamma_2 LAGE_{it} + \gamma_3 LAGE\_SQ_{it} + \gamma_4 GRS\_P_{it} + \gamma_5 GRS\_N_{it} + \gamma GRM_{it} + \gamma_7 GRM\_SQ_{it} + year\ dummies + \xi_{it}$. Note that unlike equation (1), the LOSS variable is not included as a regressor. The definition of the variables in the regression is in the notes to Panel A of Table 3
5. AUD is a dummy variable that takes on the value 1 if the auditor is from the Big Eight and 0 otherwise.
6. EXPR is the log of the number of firms that are in the same 4-digit SIC and that employ the same auditor as the firm observation.
7. GR-SAL is the growth in sales computed as total sales in year t divided by total sales in year t-1.
8. ALT_Z is Altman's Z score.
9. INV is the ratio of inventory to total assets.
10. AR-AS is the ratio of accounts receivable to total assets.
11. VAR-AR is the variance of abnormal returns.
12. LGMV is the natural log of MV three months after the fiscal year-end.
13. * (**) indicates significance at the 5% (10%) level