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Do Significant Stock Price Drops Signal Red Flag for Financial Statement Fraud?

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Introduction

Stock price drops are regular occurrences in capital markets. However, when such drops are significant or occur more frequently, they can be of great concern to management. The significance and frequency of such drops, however, could signal potential problems. How management reacts to the prevention of such stock price drops is particularly important to a number of stakeholders, especially if these firms fit the description of firms that engage in financial statement fraud. The Statement on Auditing Standards No. 99 define financial statement fraud: *Consideration of Fraud in a Financial Statement Audit* (SAS 99), as an intentional act that results in a material misstatement in financial statements. There are two types of fraud considered in this definition: misstatements arising from fraudulent financial reporting (e.g., falsification of accounting records) and misstatements arising from misappropriation of assets (e.g., theft of assets or fraudulent expenditures). Often, management do feel some pressure to manipulate the company's accounting practices and, consequently, its financial reports to meet these expectations and keep the company's stock price up and from dropping in the future. While there are several reasons companies experience stock price drops, an earnings announcement that falls short of expectations is a good example. As stakeholder expectations do reflect firms' earnings expectations, management may adopt a more aggressive earnings management style in reaction to stock price drops in order to prevent future drops. While earnings management may not necessarily be fraudulent, aggressive or excessive earnings management has the potential to be considered fraudulent rather than simply an earnings management. Earnings management is where management carefully applies selected accounting choices and estimates, within the confines of the U.S. Generally Accepted Accounting Principles (GAAP), towards a desired outcome. That is, when firms use earnings management to smooth out fluctuations in earnings and/or to meet stock analysts' earnings projections, is not considered illegal or fraudulent. However, a deliberate, intentional, or reckless conduct by management in applying excessive or aggressive GAAP rules in order to mislead or deceive investors through financial misstatement is illegal and therefore fraudulent.

The purpose of this study therefore is to determine whether firms' recovery strategy following significant stock price drops is fraudulent or simply an earnings management. One of the motivating methods used in this study is utilizing Enron's known distinctive Fraud Detection Indices model (FDI) in which we matched with our sample firms. The noble intuition in performing this matching is that it gives the reader the chance to look back at the results ex post. Further, the study is motivated by exploring the limited attention paid to daily stock price drops, which many take for granted as normal occurrences of doing business. Management possibly might be applying measures necessary to maintain financial market competitiveness, which translates into fraudulent financial reporting.

There are several appealing incentives that managers may capitalize on to engage in financial misstatement. For example, Erickson, Hanlon, and Maydew (2006) found increasing accounting fraud with stock-based executive compensation, financial performance, financial distress, firm size, and where management wants to obtain external financing. In addition, price declines cause greater losses for managerial stockholdings than for option holdings because of differences in payoff convexity. Therefore, managers have greater incentives to commit fraud when they anticipate large stock price declines and when they perceive the likelihood of detection to be low (Johnson, Ryan, and Tian, 2009). Also, other studies show that stock option fraud is stronger in firms with higher outside blockholder and higher institutional ownership (Denis, Hanouna, and Sarin, 2006).

Other prior research suggests that there is a correlation between share price risk premiums and earnings variability (Ball, Kothari, and Watts 1993). Yet others suggest executive equity incentives and equity holdings as good drivers for financial statement fraud (Hanlon, Rajgopal, and Shevlin, 2003; Rajgopal and Shevlin, 2002; Meulbroek, 2001; Core and Guay, 1999; Himmelberg, Hubbard, and Palia, 1999). However, others noted some stark contrast to these assertions by

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policy makers that incentives from stock-based compensation and the resulting equity holdings increase the likelihood of financial statement fraud (Goldman and Slezak, 2006; Bar-Gill and Bebchuk, 2003; Jensen, 2003; Bebchuk, Fried, and Walker, 2002; Hall and Murphy, 2002; Jenter, 2001). Similarly, pressure to meet analysts' earnings expectations is considered as key incentive (Barton, 2002; Frankel, Johnson, and Nelson, 2002). Therefore, if firms that experience significant drop in stock prices share the same characteristics as firms that engaged in financial statement fraud, then investors would be in a better proactive position to make timely informed decision regarding their investment in such firms.

The organization of the paper is as follows. The next section reviews extant literature, followed by research questions, sample selection, and firm characteristics. The following section discussed the research methodology used in conducting our analyses and presents the results. The final section provides the conclusions of the study.

Review of Prior Literature and Research Questions

A number of regulatory agencies have been in the forefront of fighting organizational fraud. For example, the extended responsibility placed on management by section 404 of the Sarbanes-Oxley Act of 2002 is intended to restore stakeholder trust, while due diligence and professional skepticism should be the guiding principle of the auditor. In furtherance of the auditor responsibilities, the Auditing Standard No. 2 of the Public Company Accounting Oversight Board (PCAOB) made it clear that preventing and/or detecting fraud must be the focus of the audit process. This responsibility is spelled out in SAS No. 99, which requires auditors to consider the results of analytical procedures in identifying the risks of material misstatement due to fraud (AICPA, 2002). Irregularities resulting from fraudulent activities that materially misstate financial reports are of particular interest to investors and auditors as they are to managers. Auditors and managers have legal responsibilities for detecting and reporting such irregularities.

Assessment of the reliability of financial information of publicly traded companies by all stakeholders is vital. However, GAAP allows certain discretions in making choices and estimates in determining accruals basis accounting. It has long been the recommendation of the Treadway Commission to the Auditing Standards Board (Wheeler and Pany, 1996) to employ due diligence in utilizing analytical testing procedures as one important task for substantive reviews to facilitate detection of any malpractice or fraudulent financial reporting.

We applied the FDI model established in Beneish's 1999 study to 8,345 firms encountering 23,056 daily stock price falls more than ten percent. Our objective is to determine whether the characteristics of the FDI in our sample firms mirror those of fraud firms. While the focus of our study is not to identify whether these sample firms are fraudulent, but rather whether they fit the characteristics of financial statement fraud firms to the level that they may be considered as red flags or potentially fraudulent. It is also possible to see these firms as potential for financial distress. Consistent with other studies (Wohar and Rapach, 2005) that utilized price-dividend and earnings per share ratios as indicators in predicting stock price drops, we incorporate indices that cater for both areas. However, the application of Beneish's eight detection based model suggests a stronger correlation than the conventional ratios.

The result of this study is expected to be of particular interest to investors for making timely informed decisions and to independent auditors as tools for analytical procedures towards fulfilling SAS No. 99 and section 404 of the Sarbanes-Oxley Act requirements. In addition, regulators, government, internal auditors, audit committees, and consultant Certified Public Accountants (CPAs) serving as de-facto Chief Financial Officers (CFOs) of small businesses would benefit from this study. Further, two main incremental contributions of this study are identified. First, unlike earlier related analytical procedure studies which used conventional ratios to compare fraud and healthy firms, our study utilizes indices of financial variables that measure changes. Second, this study is proactive rather than reactive in nature. It serves as a preventive measure (warning about the likelihood of stock price drops or financial distress firms), rather than as a detective measure (distressed or fraud firms). We anticipate that our study would offer more benefit to stakeholders in predicting the outcome of a "healthy" firms' likelihood of stock price drops or perceived financial difficulty compared to studies that report on firms that have already been bankrupt, distressed, or fraudulent.

Initial results of our study show that all eight, except one fraud detection indices, total accruals to total assets (TATA), exhibits indices that fall in the category of firms considered to be fraudulent in prior studies, especially with Enron Company. Further robustness check was carried out to see if these results could be considered a predictor of ex-ante stock price drops. Our results suggest that all eight indices, but TATA, exhibits predictive signs of ex-ante stock price drops. Additionally, interaction analyses, controlling for firm size, industry, and the magnitude of percentage of stock price drops suggests that industries with larger mean total sales have smaller positive percentage changes between fall and recovery dates, while small to moderate mean total sales firms exhibit larger positive percentage changes. Also, as the magnitude of stock price drops intensifies (from ten to thirty percent or higher), dramatic increase in the positive percentage changes of total sales occurs.

Research Questions

Since earnings are closely associated with stock price, one wonders what the effect would be on management when faced with significant stock price drops considering the intervening circumstances such as failure to meet earnings' targets. We conducted empirical tests using fraud indices to compare firms that had significant stock price drops into three categories (ten to nineteen percent, twenty to twenty-nine percent, and thirty percent and over) for daily stock price drops. These are then matched within each industry and across industries by year. As the probability of managing earnings are higher with unusual increases in receivables, deteriorating gross margins, decreasing asset quality, sales growth, and increasing accruals (Beneish, Lee, and Tarpley, 2001; Beneish, 2001), we provide in Figure1the predictive signs and impact on earnings because of changes in indices. We provide the predictive signs to be consistent with similar studies. [see Figure I, pg 811]

Our main research question is centered on whether significant stock price drops fit Beneish's eight FDIs of the financial variables within each industry and across industries. It may be argued whether the differences in our results are contrived or a natural result of the firms' competitive positions in the industry. To determine if the differences in our results are created by managers rather than being a function of economic conditions, we compared our sample with S&P 500 abnormal excess returns within the same period. Also, we controlled for industry activity and isolate those ratios that are significantly different from the industry. Ceteris paribus, we therefore provide the following research questions:

RQ1: Do firms with significant stock price drops (SPDs) match Beneish's FDIs?

RQ2: Are firms that match Beneish's FDIs associated with firm size?

RQ3: Are the magnitude of SPDs (10%, 20% or 30%) firm driven?

RQ4: Are the magnitude of SPDs (10%, 20% or 30%) industry driven?

Our choice of variables for this study is like that of Beneish's (1999) study. We applied the eight financial index models developed by Beneish as manipulators. In addition, we controlled for Total Assets, Total Sales, and Year which events took place. We also employed all eight variables for purposes of comparison on different sample of firms and their characteristics. Appendix 1 shows how the indices are derived. [see Appendix I, pg 813]

Sample Selection

Our sample comprised of 8,345 firms from 40 industries, which encountered 23,056 daily stock price falls. Empirical tests are conducted with all firms whose CRSP and Compustat files contain all available quarterly and yearly financial data and stock returns on the NYSE and AMEX over a period of eleven years from 1995 through 2006. Financial variables used in this study comprise of earnings, accruals, and cash flows from operations. This is particularly important because it excludes non-recurring items such as extraordinary items, discontinued operations, special items, and non-operating income. Similarly, Sloan (1996) noted that the exclusion of these items from the tests allows unambiguous assessments of the persistence of the cash and accrual components of income from continuing.

We therefore analyzed annual financial data two years prior to all one-day stock price drops (SPD) exceeding ten percent. We categorized the financial variables of the firms around these two events: the date of stock price drop (falldate) and the date of recovery (recoverdate) to the original price. Firms experienced as few as a single fall event to as many as twenty-three events during our sample period.

The period of our study (1995 to 2006) is relatively unaffected by the recent U.S. financial crisis, especially in the housing market, which began in 2006. Prior to 2006, however, Moseley (2015) noted that the percentage of bank lending to households increased from thirty percent in 1970 to fifty percent in 2006, while the total value of home mortgages tripled between 1998 and 2006. If any, the period of our study signifies one of the best of economic times. Notice that the ratio of household debt to disposable income increased substantially from sixty percent in 1970 to 140 percent in 2007. The effect of this period of extraordinary increase in household debt, that would soon be known as the housing bubble had just began in 2006 (Greenspan, 2008). We believe that there is little, if any, effect of the financial crisis on this study. More so, the visible financial crisis took effect in August 2007 when the seizure in the banking system precipitated by BNP Paribas who announced that it was ceasing activity in three hedge funds that specialized in U.S. mortgage debt. It then became clear that there were tens of trillions of dollars' worth of suspect derivatives which were worth a lot less than the bankers had previously imagined.

Firm characteristics

Table 1A displays the descriptive statistics, showing summary of fall dates, days down by fall date position of all the firms and the number of falls, which ranged from one to twenty-three times. The firms with the largest frequency of stock price drops consists of one firm with twenty-three drops, four firms with twenty-one drops and one firm with twenty drops.

Table 1B presents the characteristics of the firms used in the study. It shows the S&P 500 Excess Returns by Group. To control for exogenous circumstances such as inflation and other economic factors that may have affected the market in general, we pegged the excess returns of all firms in our sample with SPDs of ten percent and higher against that of S&P clean firms' excess returns. This would help explain the difference in excess returns that are unique to the firms in our sample. Table 1B also presents the mean scores of the excess returns from both samples. The excess returns of the firms in our sample are categorized based on the magnitude of their stock price drops (group 1 = 10 -19%, group 2 = 20-29%, and group 3 = 30% and higher) and by the number of days the stock price drops have been down. The results show a mean and (standard deviation) of S&P excess fall returns of -.091 (.009) from 2,803 observations. [see Table IA and IB, pg 801–802]

When excess fall returns from group one firms with 15,671 observations are pegged against S&P excess fall returns, it shows a mean excess fall return and standard deviation of -.130 (.023). This produced a positive differential outcome, resulting into 118 firms that shifted from group one to group two, while 2,803 firms shifted from group one to a clean category (improved). Similarly, group two pegged against the S&P show 168 firms that shifted from group two to group one (an improvement), 1,528 remained in group two, while forty firms shifted from group two to group three (worst situation). However, matched group three and S&P show only thirty-nine firms shifted from group three to group two (improvement), while 2,689 remained in group three. These changes suggest that 158 firms were worst off, 3,010 were better off, while 17,199 remained unchanged. That is, a net of 2,852 firms were better off after the exogenous control.

Methods and Results

To determine information asymmetry effects relative to firm size and frequency of single day falls more than ten percent, we applied the frequency distribution model. Regression analyses were also conducted to test the significance of several frequencies, while correlations matrix was applied to asymmetric information relating to all eight FDIs.

Descriptive statistics

Table II presents the results of asymmetric information on the correlation matrix of the detection indices. The results show that only DSRI is highly correlated with SGAI, indicating a mean score of 0.896, while all the rest show no significance in correlation. Directionally, however, it is interesting to note that GMI is negatively correlated with all the other indices. Similarly, TATA is negatively correlated with all the indices, except DSRI. The high correlation between DSRI and SGAI, among other things, could suggest that management were confident in the spending of their operating activities in anticipation of realizing their DSRI. This trend is logical and consistent, because as sales increase, SGI should either remain the same or decline. However, growth in DSRI increases cash and should have a negative impact on cash portion of earnings. Therefore, accounts receivable would then translate into a rise in revenue (SGI), due to accruals concept. What is also interesting from our results is the negative correlation between SGAI and SGI (-0.032), a trend that is consistent with generally expected outcomes. This is true because, a company that intends to manipulate income would try to push SGAI down and SGI up, so this inverse relationship seems to make sense. [see Table II, pg 803]

A Comparison of FDIs Predictability

RQ1 question whether firms with significant stock price drops (SPDs) match Beneish's FDIs. Table III compares all eight fraud detection indices with that of our results. These comparisons allow us to see any similarities (or differences) in results and the likely explanation as to whether our sampled firms match those of Beneish's, which fall in the category of "manipulators." We can group all eight indices into two functions: Operational activates (Income Statement) related indices and position (Balance Sheet) related indices. The two functions are analyzed below. [see Table III, pg 804]

Firm operations related indices

These indices relate to the operating activities of the firm such as, revenues and expenses for the periods under review. These consist of Sales Growth Index (SGI), Gross Margin Index (GMI), Sales, General and Administrative Expenses Index (SGAI), and Depreciation Index (DEPI).

SGI: Beneish's FDI test results suggest that companies that manage earnings (manipulators) have their mean and median sales growth index of 1.069 and 1.411 respectively. Our results show SGI mean and median scores of 2.689 and 1.200 respectively, indicating that these firms fall within the range of manipulators. In fact, our results soared, exceeding that of Enron's SGI mean score of 1.52. This is consistent with similar studies, which suggests that growth firms are more likely to engage in financial statement fraud due to pressure in order to meet earnings forecasts. And there is a clear need for these firms to turn around the drop in their stock prices fairly quickly.

GMI: Gross margin index shows the likelihood of firms that engage in aggressive earnings. The results of Beneish's FDI relating to GMI suggest that a mean of 1.193 and a median of 1.036 are indicators of GMI manipulators. Comparatively, our results indicate a mean and median score of 1.332 and 0.889 respectively. This clearly places the firms within the range of aggressive GMI manipulators. Our mean score of 1.332 is very close to that of Enron (1.448), suggesting a more aggressive approach than the rest of the firms. Here, we see another consistent argument, that deterioration of gross margin sends a negative signal about a firm's prospect.

SGAI: There should be a linear relationship between sales and the associated costs that helped generate those sales. Therefore, it is unusual for sales to increase faster than expenses. When this happens, it signals a negative future prospect of the firm. The characteristic mean score of such firms is around 1.041 and a median of 0.960. The mean and median scores of the firms in our study indicate a good fit (1.847 and 0.984) with the manipulators as in Beneish's study. In fact, firms in our study appear to be more aggressive in the manipulation of SGAI in general compared to the mean of manipulators, and even more so, compared to Enron's median score of 0.649.

DEPI: When firms engage in lowering depreciation rates or revising the useful life of working assets upwards than comparable companies in similar industry, it indicates the likelihood of manipulating earnings. This fact is evidenced by mean DEPI greater than one, which translates into increased income. Beneish's mean and median DEPI scores of earnings manipulators (1.077 and 0.966) matches well with our results (1.125 and 0.841), showing a clear pattern of aggressive earnings to recover from the SPDs.

Firm position related indices

These indices pertain to the financial position of the firm relating to assets, liabilities, and stockholders' equity. They include Days' Sales Receivables Index (DSRI), Asset Quality Index (AQI), Leverage Index (LVGI), and Total Accruals to Total Assets (TATA).

AQI: This index is one of the most important comprehensive assessments of a company's current and future viability. Thus, an increase in asset realization risk leads to the propensity of increased capitalization, and therefore, deferred costs. Therefore, an AQI greater than one signals that the company is potentially postponing or deferring its costs so as to improve its bottom line. Other firms do so through capitalizing rather than expensing those items that should have been expensed. That is, companies found to be manipulating earnings have their AQI mean value at 1.254 and a median of one. Our results show an AQI mean and median scores of 0.660 and 0.770, both lower than the mean and median thresholds of manipulators. Thus, our firms are showing signs of improvements in asset quality. Enron, for example had a mean AQI of 1.308. In this case, none of our firms appear to be aggressive manipulators.

DSRI: We expect bigger increases in DSRI to be a result of poor receivables management or deteriorating sales or both. The impact is a negative return on earnings and therefore negative impact on stock returns. Firms that fall within this category as per Beneish's study had their mean and median DSRI of 1.465 and 1.281. Our results show a higher mean score of 2.760 and a median score of 0.995. The mean reflects a significant negative impact on cash earnings, which should have a deteriorating effect on stock prices.

LVGI: Firms faced with debt covenants often use the variables in the LVGI to manage earnings. That is, such changes are associated with the stock market effect of technical default. Therefore, when LVGI score is greater than one, it suggests an increase in leverage, which portrays the firm as riskier. Our results put the firms in this study squarely in the category of manipulators, showing mean LVGI greater than one (1.160), but with a relatively lower median score of 0.778. This is consistent with the mean and median scores of Beneish's results of manipulating firms (1.111 and 1.030 respectively.

TATA: We noticed in prior research that managers make discretionary accounting choices to alter earnings by using either total accruals or partition of total accruals. Therefore, one can expect to see higher positive accruals (less cash) to be associated with a higher likelihood of earnings manipulation. Beneish's study of manipulating firms did not show higher positive accruals to suggest any wrongdoing. The mean and median accruals were marginally positive (0.031 and 0.034). The firms in our study, however, both showed marginally negative mean (-0.010) and negative median (-0.003). This did not indicate any sign of manipulation either.

Considering all eight indices together for both studies, there has been a consistent similarity between the results, except for TATA and AQI. That is, we see similar pattern of manipulation by the firms. There is, therefore, the possibility for one to suggest that these indices can be a predictor of stock price performance. That is, when firms show such trends in their financial variables, could signal stock price drops. This is consistent with the category of firms used in this study, firms that had at least a ten percent drop in stock price. Therefore, our results seem to point to the direction that fraud detection indices could predict stock performance as per RQ1.

Size and Likelihood of SPDs

RQ2 and 3 seeks to determine any association between FDIs and firm size and the magnitude of SPDs with firm size and industry respectively. Table IV presents a comparative breakdown of total sales by industry at fall and recovery dates. This is categorized into three groups based on the magnitude of stock price drops. Groups one, two, and three shows the descriptive statistics of the percentage changes of the mean total sales of the top five and least five industries that had stock price drops of ten, twenty, and thirty percent respectively. The total sales are measured at two different dates, fall date and recovery date, from where the percentage changes are computed. Table IV also indicate that irrespective of the magnitude of SPDs, the largest percentage changes in SPDs are more likely to be seen among firms in the healthcare industries and oil and gas industries, while firms that experience the least percentage changes, irrespective of the magnitude of SPDs are more likely to be from cosmetics industries and tobacco industries. [see Table IV, pg 805]

Referring to RQ3, Table V displays the top five largest and least percentage changes in SPDs based on firm size (total asset). Firms in the software industry are more likely than others to experience the largest percentage changes in SPDs, while firms in the agricultural industry and tobacco industry experience the least percentage changes, irrespective of the magnitude of the SPDs. Considering all forty industries by size of total assets to determine likelihood of patterns among the firms, we find that on average, larger firms have lower percentage changes in total assets between fall and recovery dates. This observation holds in all three groups. In fact, as the degree of percent stock price drops increases (from ten to twenty to thirty percent), the percentage change in total assets by industry also increases. For example, the cosmetics industry (small size) has a percentage change in total assets of two percent in group one, 24.3 percent in group two, and 123% in group three. Another example is the investment and commodity dealers industry number (large size) has a percentage change in total assets of seven percent in group one, 60.7 percent in group two, and 104 percent in group three. Figure II also shows the graphical presentation of the relationship between firm size and SPDs, which suggests that smaller firms are less likely to withstand periods of financial distress, especially when they are faced with SPDs.

The significance of our findings with regards to size is an interesting one. It helps us understand the internal control implications as it relates to fraud prevention/detection framework in firm size. That is, since larger firms are more likely to withstand periods of financial distress, fewer frequency of stock price drops, and faster recover period from a stock price drop than smaller firms, it lends itself to the possibility that larger firms exhibit traits of stronger internal controls and good governance than smaller firms. In addition, this finding draws attention to corporate governance issues, which is central to fraud examiners, auditors, and audit committees' scope of engagement. [see Table V and Figure II, pg 805 and 812]

Summary Statistics by Category (t1 and t2)

Table VI Panel A tests the significance of the fraud detection indices of all the firms two years prior to failure and one year following the fall date. Similarly, Table VI Panel B tests the significance of the fraud detection indices of all the firms one year prior to the recovery date and two years following the recovery date. The t-tests in Panel A shows GMI (p-value 0.049) and TATA (p-value 0.027) as the only indices that are significant when two years prior to fall date is compared with one year prior to fall date at the five percent level.

When comparing the fall date and one year prior to the fall date, the t-test shows only DSRI (p-value 0.036) and SGAI (p-value 0.034) as significant at the five percent level. However, the tests between the fall date and one year after the fall, indicates three indices as significant. AQI (p-value 0.057) and DEPI (p-value 0.135) are both significant at the ten percent level, while TATA (p-value 0.006) is significant at the one percent level. It can be observed in Panel A that the mean values for DSRI has been disproportionately increasing (1.402, 1.695, 2.760) in relation to SGI (5.340, 3.056, 2.689) and GMI (1.086, 1.842, 1.332) for each of the respective panels. We noticed that a similar pattern applies to depreciation expense during the same period where DEPI has been decreasing (1.183, 1.129, 1.125) relative to increasing receivables. This pattern suggests improving earnings. When there is disproportionate increase in receivables relative to sales, this fact could be an indication of revenue inflation. Also, it is unusual for sales to increase faster than expenses. Thus, our tests suggest that there is a disproportionate increase in sales relative to the expenses that helped generate those revenues, which could mean earnings manipulation. For example, SGI mean increased from 2.689 during fall date to 2.703 during one year after, but expenses (SGAI) decreased from 1.847 to 1.205 during the same period. This might have resulted in the higher leverage in the same period (from 1.160 to 1.231) to salvage the shortfall. [see Table VI Panel A, pg 809]

Table VI Panel B shows a significant difference in all three SGI tests with p-values of 0.022, 0.001, and 0.043 respectively from one year prior to recovery to two years' post recovery periods. Similarly, there are significant differences in the tests between the recovery date and one year prior for all, but two indices (AQI and TATA). DSRI, SGI, SGAI, and LVGI are all significant at the five percent level; GMI at the ten percent level and DEPI at the one percent level.

Panel B suggests a more disproportionate increase in receivables relative to sales growth and expenses than in Panel A. For example, a consistent increase in DSRI from recovery date to two years following (1.392, 1.820, 2.530) does not translate into increased sales growth, but rather a consistent decrease in SGI during the same period (2.760, 1.668, and 1.473). It is also inconsistent to observe a declining SGI and still end up with increasing gross margin index for the same period. GMI has been increasing for the three years from the recovery date of 0.760, 0.918, and 1.202. Again, we see an increasing leverage (LVGI) during the same period (1.237, 1.283, and 1.334), perhaps to take care of insufficient operating cash flows during this period of financial distress. [see Table VI Panel B, pg 810]

Conclusion

This study investigates whether significant stock price drops from healthy firms share similar characteristics with known fraud firms like Enron. We applied Beneish's (1999) fraud detection indices as a proxy for financial statement fraud and or distress on 8,345 firms encountering 23,056 daily stock price drops in excess of ten percent from 1995–2006. A match in indices between our sample firms and that of Beneish's results suggested that our firms do, indeed, show signs of red flag for potential financial statement fraud. In analyzing the nature and extent of stock price drops from our sample, we see interesting results. For example, the number of SPDs ranged from one to twenty-three times across all firms. The firms with the largest frequency of stock price drops consists of one firm with twenty-three drops, four firms with twenty-one drops and one firm with twenty drops. We find information asymmetry effects relative to firm size and frequency of single day falls in excess of ten percent and the magnitude of SPDs. Our study suggests that smaller firms are more likely than larger ones to experience the largest frequency of stock price drops. That is, smaller firms are less likely to withstand periods of financial distress. There are two plausible explanations that can be attributed to this. First, that smaller organizations tend to suffer disproportionately large losses due to occupational fraud and secondly, that the specific fraud risks faced by small businesses differ from those faced by larger organizations, with certain categories of fraud being much more prominent at small entities than at larger firms. In addition, smaller firms are more susceptible to weak internal control systems and poor governance mechanisms.

We found significant correlation between the growth of Days Sales in Receivables Index (DSRI) and Selling and Administration Index (SGAI). We also found significance of sales growth in predicting stock price reactions. We, however, observed some disproportionate (inverse) relationship between Sales Growth Index (SGI) and Gross Margin

Index (GMI), which occurred in all three years, thereby showing an increasing leverage index for the same period. FDIs, therefore is an important model in identifying and predicting the likelihood of firms in financial distress. When the FDIs of firms in our sample are matched with fraud firms, as in Beneish's study, we found compelling consistencies in all, but two indices. This consistency suggests that when firms experience significant and/or frequent stock price drops, there is a likelihood of fraudulent activities (red flags) being perpetrated by management.

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Table IA: This table displays the descriptive statistics, showing Summary of Days Down by Fall Date Position of all the firms. The number of drops ranged from one time to twenty-three times. The firms with the largest frequency of stock price drops consists of one firm with twenty-three drops, four firms with twenty-one drops and one firm with twenty drops. The results indicate that failed firms have the highest mean number of drops in relation to other firm status.

tag2	**N**	**mean**	**sd**	**p50**
1	3672	249.2	451.0	50
2	1768	243.5	421.2	52
3	1063	207.2	380.0	43
4	579	183.0	325.2	34
5	417	134.4	276.7	2
6	280	133.3	254.8	34
7	157	106.4	207.5	22
8	97	102.4	207.2	20
9	110	78.3	143.8	16
10	55	93.5	293.2	16
11	44	60.8	120.0	13
12	26	50.2	101.3	9
13	25	61.3	127.5	16
14	13	181.9	352.4	29
15	11	38.5	40.2	29
16	8	65.8	135.3	6
17	6	405.2	800.2	72
18	4	119.5	221.7	10
19	4	5.3	5.3	4
20	1	275.0		275
21	4	2.5	2.4	2
23	1	1.0		1
Total	8345	217.8	405.0	42

Table IB: This Table reports the descriptive statistics comparing stock price Fall Returns and Excess Fall Returns of S&P by group. It also shows a summary of firm size by group. We used Total Assets and Total Sales as the sizes of the firms in each industry. Group one indicates firms with stock price falls of ten percent or less. Group two represents stock price falls greater than ten percent up to nineteen percent, and Group three represents firms with stock price falls of thirty percent and higher. The summary of the firm sizes are further classified into two categories, fall date and recovery date.

	Raw			Days Down				Fall Return				Excess Fall Return			
	Raw	Ex. Fall Return	Obs.	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Group	1	0	2803	73.2	193.6	1	2047	-.106	.007	-.157	-.100	-.091	.009	-.100	-.034
	1	1	15671	102.3	237.6	1	2351	-.129	.023	-.200	-.100	-.130	.023	-.200	-.100
	1	2	118	174.1	303.9	1	1493	-.189	.011	-.200	-.147	-.207	.007	-.236	-.200
	2	1	168	126.9	274.9	1	2050	-.205	.008	-.256	-.200	-.191	.008	-.200	-.151
	2	2	1528	207.1	326.8	1	2478	-.240	.028	-.300	-.200	-.241	.028	-.300	-.200
	2	3	40	327.7	376.3	13	1748	-.295	.006	-.300	-.267	-.306	.006	-.327	-.300
	3	2	39	332.1	479.4	1	2301	-.308	.007	-.327	-.300	-.291	.011	-.300	-.249
	3	3	2689	563.7	569.2	1	2508	-.487	.153	-.998	-.300	-.488	.154	-.998	-.300
Total															

Summary of Firm Size
(In Millions)

	Group 1		Group 2		Group 3	
	Total Assets	**Total Sales**	**Total Assets**	**Total Sales**	**Total Assets**	**Total Sales**
Fall date	$67,972	$34,510	$51,149	$31,366	$145,511	$67,950
Recovery date	$77,567	$38,890	$60,056	$36,156	$151,176	$79,582

Table II: This Table shows the Correlation Matrix of the fraud detection indices. It presents the results of asymmetric information on the correlation matrix of all the eight detection indices. The result suggests DSRI as highly correlated with SGAI, indicating a mean score of 0.896, while all the rest show no significance in correlation. Directionally, GMI and TATA are negatively correlated with all the other indices, except for DSRI when matched with TATA.

	DSRI	SGI	SGAI	GMI	AQI	DEPI	LVGI	TATA
DSRI	1.000							
SGI	-0.001	1.000						
SGAI	0.896	-0.032	1.000					
GMI	-0.00	-0.205	0.002	1.000				
AQI	0.002	0.005	-0.001	-0.001	1.0000			
DEPI	0.030	0.031	0.0157	-0.008	0.0058	1.000		
LVGI	-0.004	0.085	0.020	-0.002	-0.0025	-0.004	1.000	
TATA	0.014	-0.015	-0.034	-0.002	-0.0010	-0.007	-0.188	1.000

Table III: This Table presents a Comparative Analysis of all eight Fraud Detection Indices of our results and that of Beneish. These are all firms with at least ten percent stock price drops. The descriptive indicators are the means and medians. The comparisons allow for similarities (or differences) to be easily observed and likely indication of stock price failure. Consistent similarity exists between the two results, except for AQI. When firm results are similar to Beneish's, it suggests manipulation of financial variables, which influences stock price changes.

Indices	Description	Beneish's Results		Our Results	
		Mean	Median	Mean	Median
SGI	This index suggests that companies that manage earnings have a mean SGI of 1.069 and a median of 1.411. Enron's SGI, for example, was computed at 1.52, thereby placing it within the range of the average manipulator.	1.069	1.411	2.689	1.200
GMI	This test results indicated that a mean of 1.193 and a median of 1.036 are indications of GMI manipulators. Enron's GMI soared into the upper ranges with 1.448, showing clear aggressiveness in earnings.	1.193	1.036	1.332	0.889
AQI	Companies found to be manipulating earnings have their AQI mean value at 1.254 and a median of 1. Citing Enron's 1997 cost deferrals landed its mean AQI at 1.308, another clear evidence of aggressive earnings manipulations. We posit a positive relationship between AQI and the probability of earnings manipulation.	1.254	1.000	0.660	0.770
DSRI	Companies that overstated their revenues had a mean DSRI of 1.465 and a median of 1.281. In the case of Enron, a lower median figure of 0.625 surfaced, falling into the non-manipulating category. A rather high DSRI and other figures for Comptronix, one of the firms tested using Beneish was later found by its board of directors to be perpetrating fraud by three officers for overstating earnings.	1.465	1.281	2.760	0.995
SGAI	Manipulators of this index had their mean scores around 1.041 and a median score of 0.960. Enron's position was at the lower end of the median (0.649). The final score of the model suggests that Enron's SGAI score of -1.89 factored prominently, which is much higher even compared with the standard score of the five core ratios of -2.22 that was used to determine the level and degree of earnings manipulation.	1.041	0.960	1.847	0.984
DEPI	Companies that manage earnings using this model do so by lowering depreciation rates than comparable companies in similar industry. Thus, a DEPI greater than 1 indicates that assets are being depreciated at a slower rate, thereby raising the possibility that the company has revised the estimates of the assets' useful life upwards. In other words, the company's new method of depreciation increases its income.	1.077	0.966	1.125	0.841
LVGI	When LVGI is greater than 1, it means that there is an increase in leverage. Beneish indicated that the variables in this index are used to capture the company's debt covenants for earnings manipulation and that such changes are associated with the stock market effect of technical default.	1.111	1.030	1.160	0.778
TATA	Research show that managers make discretionary accounting choices to alter earnings by using either total accruals or partition of total accruals in prior work (Jones, 1991; Healy, 1985; Beneish, 1999). In this computation, Beneish used TATA to proxy for the extent to which cash underlay reported earnings. Therefore, one can expect to see higher positive accruals (less cash) to be associated with a higher likelihood of earnings manipulation. Therefore, TATA is expected to have a negative coefficient.	0.031	0.034	-0.010	-0.003

Table IV: This Table presents the descriptive results of Total Sales on the Fall Date (t1=0) and the Recovery Date (t2=0) in millions of dollars by industry. It is categorized into three groups. Group one representing firms with stock price drops up to 10%. Group 2 shows firms with stock price drops between 10% and 19%, while Group 3 indicates firms with stock price drops of 30% or higher. The Table also presents only the top and least five percentage changes between the two periods (fall date and recovery date). As the magnitude of stock price drops intensifies, from 10%to 30% or higher, we see a dramatic increase in the positive percentage changes of total sales. Also, as the magnitude of the stock price drops rises, so also is the degree of the positive percentage changes.

Group 1	**Fall Date (T1 = 0)**			**Recover Date (T2 = 0)**				
Ind.Code	N	Mean	Median	N	Mean	Median	Diff	%Chg
HEALT	429	407.0	66.8	381	654.3	80.6	247.3	60.8%
LESMS	107	144.6	37.0	102	228.1	50.2	83.6	57.8%
OILGA	621	704.0	56.7	586	1000.5	71.7	296.5	42.1%
REALE	145	198.2	59.4	133	264.4	92.2	66.2	33.4%
CONST	168	568.8	229.9	159	737.6	282.9	168.9	29.7%
EGWDS	226	1841.7	65.7	209	1919.6	79.6	77.9	4.2%
TOBAC	12	7251.6	1780.7	12	7534.6	2419.9	283.0	3.9%
FOODK	211	1222.2	161.0	198	1265.5	172.2	43.4	3.5%
LEATH	101	358.0	129.3	96	369.3	133.4	11.3	3.1%
COSME	42	253.3	20.1	39	251.8	20.9	-1.5	-0.6%
Group 2								
HEALT	33	562.6	31.5	31	1053.7	70.7	491.1	87.3%
MOTIO	16	58.2	37.7	16	100.9	62.4	42.7	73.4%
TRANS	23	555.8	57.6	21	918.6	95.4	362.8	65.3%
CHEMI	23	632.9	5.2	15	1008.3	28.7	375.4	59.3%
OILGA	55	133.1	10.5	53	200.1	21.0	67.0	50.4%
COMME	104	602.9	33.6	101	552.9	45.7	-49.9	-8.3%
LESMS	7	122.1	82.6	6	104.7	106.7	-17.3	-14.2%
MEDIC	124	187.4	43.9	112	144.1	64.3	-43.4	-23.2%
MINIG	17	401.7	4.5	17	285.2	11.1	-116.5	-29.0%
CONST	10	2245.7	659.1	10	1136.1	822.7	1109.7	-49.4%
Group 3								
PERSO	5	207.8	69.6	4	728.1	317.0	520.3	250.4%
OILGA	102	1511.4	106.7	95	4889.8	328.5	3378.4	223.5%
WHOLE	87	1055.3	294.0	79	2508.3	628.0	1453.1	137.7%

RUBBR	16	163.0	83.3	14	385.9	134.2	222.9	136.7%
OFFIC	43	692.6	85.0	29	1538.8	125.9	846.3	122.2%
MOTIO	16	633.8	24.0	16	776.1	43.6	142.4	22.5%
TRANS	40	11000.0	560.2	37	12000.0	761.9	1000.0	9.1%
UNDIS	4	173.2	56.8	3	122.1	61.6	-51.1	-29.5%
TOBAC	1	26000.0	26000.0	1	16000.0	16000.0	10000.0	-38.5%
AGRIC	3	145.7	30.5	3	26.3	25.5	-119.4	-82.0%

Where: HEALT = Health; LESMS = Legal, Educational, Social; OILGA = Oil & Gas; REALE = Real Estate; CONST = Construction; EGWDA = Electricity, Gas & Water, Distribution, Sanitary; TOBAC = Tobacco; FOOD = Food & Kindred Products; LEATH = Leather; COSME = Cosmetics; MOTIO = Motion Pictures.

Table V: This Table compares the mean Total Assets of Groups one through three on the Fall Date and the mean Total Assets of Recovery Date by Industry (Fall date - T1 vs. Recovery date - T2). It shows the top and bottom five industries by percentage change in total assets from fall to recover dates for each group. All dollar amounts are in millions of USDs.

	Falldate (T1=0)			Recoverdate (T2=0)		Difference	
Industry	**N**	**Mean**	**Median**	**Mean**	**Median**	**$ mil**	**Pct Chg**
Panel A: Group 1- Stock Price Fall between 10 and 20%							
SOFTWARE	524	129.3	35.1	219.3	75.9	90.0	69.6%
ADVERTISING	2,808	210.7	45.2	328.5	82.6	117.8	55.9%
LEGAL & EDUCATION	108	148.7	35.2	224.0	81.8	75.4	50.7%
TELECOM	798	1726	370.5	2595.5	581.3	869.5	50.4%
DRUGS	1,228	194.6	38.0	283.7	64.8	89.1	45.8%
INVESTMENTS	305	7407.9	129.9	7923.1	168.0	515.1	7.0%
OFFICE EQUIPMENT	98	6682	497.2	7034.8	628.1	352.8	5.3%
LEATHER	101	241.7	69.9	249.1	71.6	7.4	3.1%
COSMETICS	42	212.9	25.3	217.1	14.7	4.2	2.0%
TOBACCO	12	10000.0	2679.1	10000.0	4525.5	0.0	0.0%
Panel B: Group 2 - Stock Price Fall between 21 and 30%							
HEALTH	34	319.4	40.1	578.4	71.0	259.0	81.1%
TRANSPORTATION	23	388.8	61.8	693.5	98.2	304.7	78.3%
MOTION PICTURE	16	63.1	38.2	108.1	45.9	45.0	71.4%
SOFTWARE	53	148.2	60.6	245.0	82.6	96.7	65.3%
INVESTMENT	45	1062.6	105.6	1707.8	169.3	645.1	60.7%
MEDICAL	124	201.3	61.4	167.5	88.1	-33.8	-16.8%
AGRICULTURE	2	1131.9	1131.9	855.1	855.1	-276.7	-24.4%
MINING	17	1526.3	20.0	1014.4	43.5	-511.8	-33.5%
CONSTRUCTION	10	2099.0	574.1	1274	588.4	-825.1	-39.3%
UNDISCLOSED	7	25.9	31.2	15.2	9.6	-10.7	-41.4%
Panel C: Group 3 - Stock Price Fall over 30%							

SOFTWARE	55	133.6	78.0	690.6	130.5	557.0	416.9%
RUBBER	16	113.7	86.0	393.7	147.6	280.0	246.2%
PERSO	5	271.8	28.2	860.9	840.3	589.2	216.8%
LEATHER	16	255.8	185.4	707.1	407.5	451.3	176.4%
OIL & GAS	102	1769.3	234.4	4371.3	490.4	2602.0	147.1%
HOTEL	6	1248.2	324.5	1218.7	473.6	-29.5	-2.4%
MOTION PICTURE	16	738.0	45.5	687.6	151.9	-50.4	-6.8%
AGRICULTURE	3	174.6	109.0	115.8	63.1	-58.8	-33.7%
UNDISCLOSED	4	76.6	34.7	48.9	62.5	-27.7	-36.2%
TOBACCO	1	70000.0	70000.0	33000.0	33000.0	37000.0	-52.9%

Where: HEALT = Health; LESMS = Legal, Educational, Social; OILGA = Oil & Gas; REALE = Real Estate; CONST = Construction; EGWDA = Electricity, Gas & Water, Distribution, Sanitary; TOBAC = Tobacco; FOOD = Food & Kindred Products; LEATH = Leather; COSME = Cosmetics; MOTIO = Motion Pictures; MOTIO = Motion Pictures; LEATH = Leather Products.

Table VI Panel A: This is a Summary Statistics of the eight fraud detection indices categorized into two panels based on the fall dates and recovery dates of stock price drops of all three magnitudes (ten, twenty, and thirty percent). This panel (Panel A), relates to the fall date (t1) period of stock prices. It shows fraud detection indices, two years prior to the stock price fall date, the fall date, and one year after the fall date. For each year, quartile results of descriptive statistics for each index are disclosed. The Table also displays results of statistical tests (t-tests and p-values) for significance between fall dates.

Year		**DSRI**	**SGI**	**SGAI**	**GMI**[c]	**AQI**	**DEPI**[c]	**LVGI**	**TATA**
-2	N	10299	10701	8876	3715	9927	5748	10004	9676
	Mean	1.402	5.340	1.092	1.086	.725	1.183	1.186	-.005
	Std. Dev.	7.526	143.279	2.535	20.864	17.810	6.199	1.422	.259
	P25	.827	1.022	.895	.899	.784	.838	.832	-.055
	P50	.996	1.172	.988	.992	.984	.975	1.001	-.000
	P75	1.172	1.441	1.081	1.080	1.163	1.131	1.208	.059
-1	N	16278	16855	13898	6460	15326	8897	15404	14860
	Mean	1.695	3.056	1.195	1.842	.837	1.129	1.167	.053
	Std. Dev.	32.972	61.976	18.096	24.399	10.314	2.237	1.279	3.619
	P25	.833	1.022	.892	.886	.769	.837	.823	-.057
	P50	.992	1.177	.985	.988	.984	.973	.992	.000
	P75	1.171	1.455	1.077	1.071	1.160	1.131	1.195	.060
	t-test: -2/-1	-1.091	1.627	-0.660	-1.654	-0.572	0.640	1.122	-1.936
	P-value	0.138	0.052*	0.255	0.049**	0.284	0.739	0.869	0.027**
0	N	18909	19607	16192	9146	17974	10439	18030	17369
	Mean	2.760	2.689	1.847	1.332	.660	1.125	1.160	-.010
	Std. Dev.	73.040	37.619	41.035	16.950	19.405	1.794	1.696	.329
	P25	.827	1.037	.885	.889	.770	.841	.778	-.059
	P50	.995	1.200	.984	.984	.988	.980	.978	-.003
	P75	1.178	1.543	1.081	1.068	1.177	1.160	1.182	.055
	t-test: -1/0	-1.802	0.672	-1.827	1.453	1.064	0.133	0.431	2.111
	P-value	0.036**	0.749	0.034**	0.073*	0.856	0.553	0.667	0.017*
1	N	14839	15353	12359	7882	13748	7851	13789	13339
	Mean	1.478	2.703	1.205	.732	1.084	1.197	1.231	-.000
	Std. Dev.	12.983	46.991	9.494	38.818	26.561	5.581	10.727	.339
	P25	.821	1.045	.881	.878	.769	.834	.739	-.057
	P50	.989	1.235	.986	.984	.988	.980	.972	-.004
	P75	1.177	1.627	1.092	1.071	1.183	1.152	1.195	.052
	t-test: 0/1	2.366	-0.032	1.925	1.270	-1.580	-1.104	-0.772	-2.521
	P-value	0.009***	0.487	0.027**	0.898	0.057*	0.135	0.220	0.006***

* = Statistically significant at the 10 percent level; ** = Statistically significant at the 5 percent level; *** = Statistically significant at 1 percent level; [C] = These are inverted: “Last Year/This Year” as opposed to “This Year/Last Year.”

Table VI Panel B: This table shows the summary statistics of category t2 (recovery date) of all firms, irrespective of the magnitude of stock price drops. Panel B also shows the quartile descriptive statistics during the recovery date and one year post the recovery date. The results also show the t-tests and the p-values respectively.

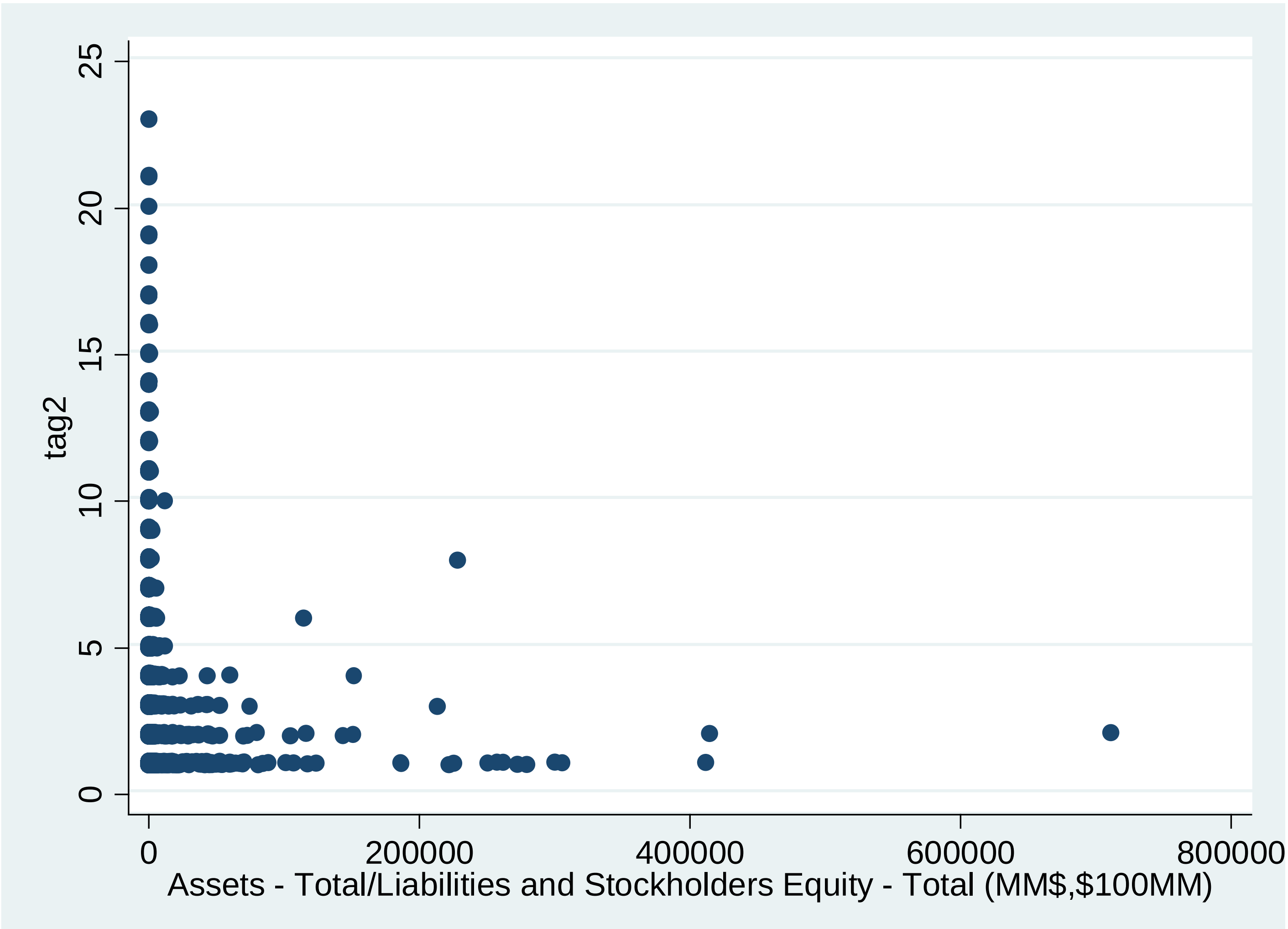
Year		DSRI	SGI	SGAI	GMI[c]	AQI	DEPI[c]	LVGI	TATA
-1	N	3274	3400	3089	1804	3265	1828	3272	3149
	Mean	7.695	1.935	4.504	1.424	.840	1.007	1.084	-.006
	Std. Dev.	158.876	14.118	85.625	9.563	10.739	1.600	1.064	.181
	P25	.8321	1.031	.912	.923	.796	.860	.801	-.058
	P50	.990	1.174	.992	.993	.994	.979	.976	-.002
	P75	1.178	1.454	1.076	1.069	1.149	1.154	1.149	.052
0	N	18864	19545	16131	11027	17714	10017	17743	17165
	Mean	1.392	2.760	1.234	.760	.939	1.114	1.237	-.009
	Std. Dev.	11.380	46.150	11.585	39.718	13.596	1.711	9.546	.354
	P25	.819	1.038	.884	.886	.766	.841	.775	-.060
	P50	.990	1.223	.988	.986	.986	.979	.978	-.005
	P75	1.182	1.598	1.094	1.070	1.176	1.148	1.191	.051
	t-test: -1/0	2.269	-2.014	2.119	1.507	-0.463	-2.594	-2.062	0.983
	P-value	0.012**	0.022**	0.017**	0.066*	0.322	0.005***	.020**	0.837
1	N	17528	18104	14969	11392	16328	9154	16326	15847
	Mean	1.820	1.668	1.433	.918	.590	1.371	1.283	-.005
	Std. Dev.	44.060	9.349	25.483	10.880	28.443	19.281	2.663	2.103
	P25	.789	.986	.910	.915	.755	.828	.879	-.070
	P50	.974	1.141	1.005	.999	.963	.968	1.017	-.010
	P75	1.150	1.426	1.127	1.094	1.106	1.121	1.279	.044
	t-test: 0/1	-1.247	3.233	-0.877	-0.401	1.429	-1.273	-0.615	-0.276
	P-value	0.106	0.001***	0.190	0.344	0.076*	0.102	0.269	0.391
2	N	15290	15855	13136	10669	14255	7961	14245	13866
	Mean	2.530	1.473	1.806	1.202	.154	1.401	1.334	.0790
	Std. Dev.	73.769	11.296	57.235	12.194	41.3917	20.877	3.681	4.067
	P25	.805	.934	.905	.916	.794	.810	.888	-.072
	P50	.976	1.091	1.001	.999	.985	.943	1.023	-.008
	P75	1.150	1.286	1.119	1.093	1.135	1.074	1.255	.049
	t-test: ½	-1.037	1.719	-0.689	-1.822	1.058	-0.097	-1.382	-2.177
	P-value	0.150	0.043**	0.245	0.034**	0.855	0.461	0.083	0.015**

* = Statistically significant at the 10 percent level; ** = Statistically significant at the 5 percent level; *** = Statistically significant at 1 percent level; [C] = These are inverted: "Last Year/This Year" as opposed to "This Year/Last Year."

Figure I: This figure presents the predictive values and impact on earnings due to changes in indices. When less than or greater than changes in indices occur, we show the likely impact that change would have on earnings, either earnings will improve or deteriorate. Also, we present the likely impact on fall returns associated with those changes.

Change in Indices	**Greater/Less than**	**Impact on Earnings**	**Sign**	**Fall Return**
ΔSGAI	>1	deteriorated	-	more negative
ΔSGAI	<1	improved	+	less negative
ΔGMI	>1	deteriorated	-	more negative
ΔGMI	<1	improved	+	less negative
ΔSGI	>1	improved	+	less negative
ΔSGI	<1	deteriorated	-	more negative
ΔSDRI	>1	deteriorated	-	more negative
ΔSDRI	<1	improved	+	less negative
ΔDEPI	>1	improved	+	less negative
ΔDEPI	<1	deteriorated	-	more negative
ΔLVGI	>1	deteriorated	-	more negative
ΔLVGI	<1	improved	+	less negative
ΔAQI	<1	improved	+	less negative
ΔAQI	>1	deteriorated	-	more negative
ΔTATA	>1	improved	+	less negative
ΔTATA	<1	deteriorated	-	more negative

Figure II: This figure shows the relative comparison between the numbers of stock price falls vs. firm Total Assets. Smaller firms are more susceptible to higher number of stock price falls than larger firms. This fact suggests that smaller firms are more likely to experience future stock price falls than larger firms and less likely to withstand periods of financial distress than larger firms.



Appendix I: This Appendix lists and presents the computations for all eight of Bebeish's Fraud Detection Indices used in this study.

1. Sales Growth Index (SGI):

   SGI = Sales Current Year/Sales Prior Year.

2. Gross Margin Index (GMI):

   GMI = [(Sales Prior Year – Cost of Goods Sold Prior Year)/(Sales Prior Year)]/
   [(Sales Current Year – Cost of Goods Sold Current Year)/(Sales Current Year)].

3. Asset Quality Index (AQI):

   AQI = 1 – [(Current Assets Current Year + PP&E)]/Total Assets Current Year]/
   1 – [(Current Assets Prior Year + PP&E)]/Total Assets Prior Year].

4. Days' Sales Receivables Index (DSRI):

   DSRI = (Receivables Current Year / Sales Current Year) /
   (Receivables Prior Year / Sales Prior Year).

5. Sales, General and Administrative Expenses Index (SGAI):

   SGAI = (Sales, General and Admin. Expenses Current Year/Sales Current Year)/
   (Sales, General and admin. Expenses Prior Year/Sales Prior Year).

6. Depreciation Index (DEPI):

   DEPI = Depreciation Prior Year / (Depreciation Prior Year + PP&E Prior Year)/
   Depr. Current Year / (Depreciation Current Year + PP&E Current Year).

7. Leverage Index (LVGI):

   LVGI = (LTD Current Yr + Current Liab. Current Yr)/Total Assets Current Yr)/
   (LTD Prior Yr + Current Liabilities Prior Yr)/Total Assets Prior Year.

8. Total Accruals to Total Assets (TATA):

   TATA = (ΔCurrent Assets -Δ Cash - ΔCurrent Liabilities - ΔCurrent Maturities of
   LTD -Δ Income Tax Payable – Depr and Amortization)/Total Assets.