The Use of Financial Ratio Models to Help Investors Predict and Interpret Significant Corporate Events*

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Abstract

A firm in steady state generates predictable income and investors can generally agree on valuation. However, when a significant corporate event occurs this creates greater uncertainty and disagreement about firm valuation and investors could prefer to avoid holding such a stock. We examine research that has developed financial ratio models to (i) predict significant corporate events; and (ii) predict future performance after significant corporate events. The events we analyze include financial distress and bankruptcy, downsizing, raising equity capital, and material earnings misstatements. We find that financial ratio models generally help investors avoid stocks that are likely to have significant corporate events. We also find that conditional on a significant event occurring, financial ratio models help investors distinguish good firms from bad. However, we find that research design choices often make it difficult to determine model predictive accuracy. We discuss the role of accounting rule changes and their impact overtime on the predictive power of models and provide suggestions for improving models based on our cross-event analysis.

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1. Introduction

Accounting research has focused much attention on understanding the usefulness of financial statement information. This is of critical importance to our profession since one of the objectives of financial reporting and regulation is to make managers accountable to investors so that there is efficient allocation of capital. The best companies should receive financing and have higher valuations than the worse companies. However, financial statements are full of numbers and determining which numbers are important and which are irrelevant is one of the difficulties in analyzing financial information and determining value. In hindsight it may seem obvious that a decline in profit margin for a particular firm was important, but how do we know whether such a signal is relevant to other firms?

In order to understand whether a particular number is relevant, the general approach in financial statement analysis is to calculate ratios that represent key underlying constructs, such as profitability, liquidity, efficiency, and leverage. The user can then analyze time-series and cross-sectional trends in the ratios. However, even after performing this analysis, the user must still determine how to weigh the information for decision-making. For example, if the user is concerned with assessing the probability of financial distress, does an increase in profitability offset a decline in liquidity? How should these signals be interpreted and what rule should the user follow? What is needed is a model that can summarize the relevant information and determine the appropriate weights to be placed on the various financial ratios.

This paper reviews models that researchers have developed to predict significant corporate events. We focus on significant corporate events rather than just predicting future performance per se, because the announcement of the event provides a clear indicator for evaluating model accuracy. In addition, the announcement provides a clear end point for a trading strategy betting one way or another on the valuation implications of the event. We focus on research that has developed models to predict four major corporate events: (i) the likelihood of bankruptcy and financial distress; (ii) the likelihood that the firm will need to downsize due to poor acquisition choices or a change in the demand for its products (goodwill impairments, restructurings, and special items); (iii) the likelihood that the firm will need to raise equity financing; and (iv) the likelihood that the firm has violated GAAP and committed financial statement fraud. These announcements at a fundamental level are not conveying good news.

Significant corporate events increase uncertainty about the true valuation of the firm and are likely to cause revisions in stock prices and create more volatility in stock returns. This can be problematic for investors that need to trade for liquidity reasons within a finite horizon (e.g., one year) and for investors that do not hold diversified portfolios. From this perspective we ask four research questions.

First, *can financial ratio models available in the literature help the investor avoid stocks that are likely to have significant corporate events?* If the answer is yes, then what is the benefit/cost from avoiding stocks where the models assign high probabilities? This is relevant because significant corporate events can be quite rare so there are likely to be many more firms assigned a high probability of the corporate event than actually have the corporate event. Thus avoiding all stocks with high probabilities could limit portfolio diversification and investment opportunities.

A second and related question is: *how much of the information in the financial ratio model is already included in price and do market-based measures or other non-financial signals subsume the financial information in the model?* There are potentially many other sources of information aside from the financial statements that could be both more timely and incrementally informative about the corporate event such as management's voluntary disclosures or news reported by the press. In addition, factors such as the state of the economy and changes in government rules and regulations could also impact the likelihood of the corporate event. Thus, even when financial statements accurately reflect the operating performance of the business, stock prices will reflect a broader set of information. If stock prices reflect the information in the financial ratio models plus more, then the investor is "price protected." In such a case, trading based on the model's recommendation is unlikely to improve the value of the investor's portfolio, except by random chance.

The third question we address is the following. *What should an investor who already owns the stock do if the firm announces a major corporate event? Can financial ratio models help the investor decide whether to continue to own or sell the stock?* That is, conditional on the corporate event occurring, can financial ratio models provide information about cross-sectional variation in future firm performance?[2]

The final question we ask is related to the ratios included in the models. *Are there any particular ratios that appear to be important and what underlying construct do they reflect? In addition, have researchers analyzed the role of accruals?* This question will

[2] We also attempted to investigate error rates. That is, if the model recommends sell, what is the likelihood that the stock will go down versus up (what is the dispersion of returns)? This is relevant even if on average the model is correct since investors do not necessarily own all the stocks engaging in the corporate event. However, few studies do this type of analysis.

help us determine whether there are any inconsistencies in ratio choice or why one ratio loads in one setting but not in another. Analyzing the role of accruals is of interest because accruals are the Doctor Jekyll and Mr. Hyde of accounting research. On the one hand, we know that accruals provide forward-looking information about future earnings and future cash flows and are relevant for valuation. But, on the other hand, much accounting research focuses on the negative role of accruals. Managers can manipulate accruals to boost earnings and so reduce the informativeness of earnings. In addition, even in the absence of manipulation, extreme accruals have different properties from average accruals and lead to less persistent, lower quality earnings. This information is not always fully reflected in prices (e.g., Sloan 1996). Therefore, it is of interest to know whether models using cash flows are superior to models using earnings or whether the decomposition into cash flows and accruals improves predictability.

Our review proceeds as follows. In the next section we provide a summary of our main findings from each corporate event. In section 3 we describe the approach we adopted to identify and classify papers. In sections 4 through 7 we review each of the corporate event literatures. Section 8 provides our conclusions.

2. Summary of Findings

Below we describe our findings for each corporate event category. For each corporate event we provide the frequency of the event over time in **Figure 1**. We provide the stock price reaction to the announcement of the event and the future stock returns following the event in **Table 1**.

Financial Distress and Bankruptcy

A great deal of research effort has been exerted in predicting financial distress and bankruptcy. Bankruptcy is a rare event with less than one-half of a percent of firms going bankrupt in a particular year. Therefore, although models are fairly accurate in identifying firms that go bankrupt they misclassify a large number of firms.[3] Our investigation of the role of stock returns indicates that early research focused exclusively on financial statement information and found that their models were useful in distinguishing firms that went bankrupt from those that did not. Later research added market-based measures and used more sophisticated statistical techniques and found that poor prior stock price performance is a strong predictor of bankruptcy. However, financial ratios still appear to have information incremental to stock returns for predicting bankruptcy at least one year ahead.

The third question asks: conditional on the model indicating the firm is financially distressed should the investor sell?[4] The answer is "yes" although there is some disagreement in the literature. Researchers such as Dichev (1998) using the Ohlson-model, find that firms with high probabilities of bankruptcy earn lower one year ahead returns consistent with investors not fully incorporating the information in the model.[5] However, later research by Vassalou and Xing (2004) using distance to default models finds that firms with higher likelihoods earn positive returns over the next month

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[3] For example, when Beaver, McNichols, and Rhie (2005) rank all firms based on their model's forecasts of probability of bankruptcy, they find that 86% of the bankrupt sample fall into top 30 percent of the ranked probability. However, 95 percent of the firms ranked in the top 30 percent, do not go bankrupt.

[4] We condition on the probability of financial distress rather than the bankruptcy event, since firms are delisted after going bankrupt and so expected returns are usually close to -100%.

[5] Dichev (1998) reports that the high probability portfolio earns raw returns of 0.6% per month and the low probability earns 1.18%. More recently, Campbell, Hilscher, and Szilagyi (2008) using a model that includes financial ratios as well as lagged market returns that buys low probability firms and sells high probability firms, reports annualized monthly hedge returns of 12%.

consistent with high probability firms being more risky.[6] However, further research that uses both financial models and distance to default models generally finds a negative relation between distress risk and one-month ahead returns. This is relevant since value firms (high book-to-market firms) are often argued to have higher future returns because some of them are "distressed" and this risk is priced (Fama and French 1995). However, direct measures of distress risk produce opposite results. Reconciling these various relations provides opportunities for future research (e.g., Griffin and Lemon 2002, Piotroski 2000). In addition, it would be interesting to analyze the importance of stock price momentum in distance to default models. Does momentum explain their superiority over the less timely financial ratio models? Is distress a driver of momentum or are distance to default models just momentum packaged in a different form?

Our final question asks which financial ratios are important. The results suggest that low income and high leverage are significant in all models examined. Liquidity measures do not appear to be as important. Why liquidity is not important is not specifically addressed in the literature. We also find that early research documented the existence of an accounting loss as an important predictor. However, the importance of a loss to model accuracy has declined in recent years coinciding with the increasing frequency of firms reporting losses. The declining importance does not appear to be due to industry composition or firm size since models usually consider these factors. One explanation is that over time accounting standards require more downward revaluations of assets to fair value. Future research could investigate whether the move to fair values has improved the balance sheet for predicting bankruptcy versus the income statement. In

[6] Vassalou and Xing (2004) find one-month ahead raw returns of 2.12% for high probability, and 1.14% for the low probability firms.

a related vein, we find models do not specifically attempt to decompose earnings into a permanent versus transitory (e.g., write-downs, impairments) component. Do these fair-value revaluations explain why income measures are losing their relevance and how have recent accounting standard changes that have made restructuring charges more persistent affected bankruptcy prediction models?

Interestingly, none of the financial ratio models that we identify decompose earnings into a cash and accrual component, suggesting that this decomposition is perhaps not important for predicting bankruptcy. However, given the accrual anomaly, one would think that this decomposition would be important in distress models predicting future returns. Another issue is whether models should consider managers' incentives to manipulate accruals to hide financial distress versus accruals providing timely forecasts of future cash flows and hence forecasting financial distress.

Downsizing: Goodwill Write-offs, Restructurings, and Special Items

When a company sheds its assets this could be good news or bad news depending on investor' priors. Announcing a restructuring indicates that radical changes are needed at the company to make it more competitive (which is bad news) but that managers are taking significant steps to change the business model (which is good news). A goodwill write-off indicates that managers paid too much for a previously purchased company (bad news). Special items such as inventory, receivable, and PP&E write-downs indicate that management overproduced inventory, provided too much credit to customers, or that assets are not as productive as previously anticipated (all bad news).

Downsizing is a less rare event than bankruptcy (around 10% to 20% of firms record special items greater than 1% of assets in a given year). Downsizing is likely to be a necessary but not a sufficient condition for financial distress. We find that financial ratio models do help predict downsizings up to one year ahead and that stock returns measured over the same time interval as the financial ratios are also incrementally informative. Interestingly, for forecasting special items in general, researchers have not specifically focused on the relative content of market-based versus financial ratio models.

Can analyzing financial ratios help predict future goodwill write-offs and does the market fully anticipate this event? The evidence suggests that an investor should examine both the size of the goodwill relative to assets and the level of earnings. If goodwill is large and earnings are low, then sell the stock to avoid a potential large decline in stock price (Li and Sloan 2012). This result holds for the post SFAS 142 time period.[7] Investors do not appear to realize that the goodwill is impaired until about six months before the goodwill impairment announcement. In contrast, the financial ratio models forecast this event 12 months in advance. Some interesting questions are: do managers delay reporting goodwill write-offs and only do so when pressure comes to bear (perhaps from the auditor) or is this delay an intention of the standard? What is the role of voluntary disclosure? Do managers hint at the impending impairment to warn investors?

Our third question asks: can financial ratio models help investors decide whether to sell the stock, conditional on the firm announcing a downsizing? The fundamental issue comes down to the relation between the charge or write-off and future earnings. Does the charge result in future earnings decreases or increases or have no predictive ability? A second question that relates to the first is: Do investors understand the relation

[7] SFAS 142 changed the rules for goodwill from amortization over a finite life to periodic impairment testing.

between the charge and future earnings? We find that the answer to these questions appears to be contingent on the accounting standard governing the downsizing and has changed over time as FASB rules have changed. For example goodwill used to be amortized but now is left on the book until impaired. Under the old rules, prices were more timely in reflecting goodwill impairments. In contrast restructuring charges under old rules were transitory and if anything set the firm up with future earnings reserves. Under the old rules prices responded to the predictable earnings increases. However, under the new rules, restructuring charges are smaller and more persistent and so future earnings are less likely to "improve" mechanically. As a consequence prices no longer appear to increase in a predictable way after restructurings.[8] It would be interesting for future research to delve more deeply into these findings and establish whether they are the consequences of the rule change, management incentives, or the time period.

The fourth question asks: what ratios are most important for predicting downsizing? Declining earnings and declining sales are important signals as is the recording of a loss. A market-to-book ratio less than one is also indicative of future write-offs consistent with the book part of the ratio reflecting over-valued assets (rather than the market being pessimistic). What is the role of accruals? Are managers who have boosted earnings in the past with accruals more likely to record accrual reversals or write-offs? The papers we reviewed did not specifically address this question.[9] However, there is some circumstantial evidence. Bens and Johnston (2009) investigate

[8] See Burgstahler, Jiambalvo, and Shevlin (2002), Dechow and Ge (2006) and Bhojraj, Sengupta, and Zhang (2009).

[9] Dechow, Ge, Larson, and Sloan (2011) show that considering the timing of accrual reversals can considerably improve the power and specification of discretionary accrual models such as Jones (1991). Thus, it would be interesting to know whether conditional on a write-off, firms on average, have high prior discretionary accruals and if so why.

whether managers use their discretion to over-accrue restructuring charges and find that high prior accruals are predictive of future discretionary restructuring charges. Interestingly, in contrast to distress models, leverage is negatively associated with future restructuring charges. Perhaps, highly levered firms are more efficient, or better monitored, and so are less likely to over-invest or use resources for projects that end up being abandoned.

Equity Issuances

Is raising equity good or bad news? It could be a bad signal when the firm is in financial distress and needs cash to sort out its problems. It could also be a bad signal if managers time equity issuances when they believe the stock is overpriced. However, it could be a good signal when the firm has a great business model and is going to be the next Starbucks/Chipotle Mexican Grill/Home Depot with a shop on every street corner (unless the firm is over-investing and is soon to hit its saturation point). On average the stock market reaction to seasoned equity offerings is negative (-2%). For IPO investment bankers attempt to price issues so that there is a positive return on the first day. The average first day return is around 14 percent.[10]

The percent of firms that do initial public offerings (IPOs) or seasoned equity offerings (SEOs) varies greatly from year to year. For example, in 2010, just 94 firms had IPOs, whereas in 1996, 675 firms had IPOs. The lowest IPO year is 2008 with just 21 firms.[11] Therefore, the state of the stock market has a significant influence on

[10] Investment bankers do not always get it right. For example, on the first day of trading Facebook closed at $38.23, just 0.6 percent above the initial public offering price — a price that represented 100 times historical earnings. The stock lost over a quarter of its value in less than a month and halved its IPO value in three months (see http://dealbook.nytimes.com/2012/05/18/facebook-opens-at-42-05-in-debut-but-falls-quickly/?hpI).

[11] See Jay Ritter's website: http://bear.warrington.ufl.edu/ritter/IPOs2012Underpricing.pdf.

whether firms raise equity and how common or rare the event is. We do not attempt to review literature on the timing and the determinants of IPOs since financials are not readily available for researchers.

We find less research attempting to predict SEOs using financial ratios. This is a potentially useful avenue for future research since (i) the announcements of an SEO can be bad news; (ii) being able to predict which firms are able to raise financing could be useful for determining which distressed-cash-burning firms will survive (relevant in bankruptcy prediction); and (iii) it could be relevant to short-sellers betting that firms with bad business models will go out of business. If a bad firm can convince investors to provide more financing, then such a firm can continue its operation and would not be a good candidate to short.

Should an investor sell the stock of a firm that issues equity via an IPO or SEO? Most of the IPO/SEO research has focused on this question. The answer is "yes." Researchers have developed models to determine which SEO/IPO stocks are most likely to go down. Early research argued that IPO/SEO firms engaging in earnings management by manipulating accruals were the most likely to perform poorly in the future. However over time the story has changed somewhat to consider the possibility that market timing plays a role. Perhaps overvalued companies are more likely to raise financing and then park the money in short-term assets. These firms could either overinvest or be less able to generate the returns that earlier projects generated. As a consequence investors are disappointed. Therefore, is it management manipulation of accruals or are accruals reflecting bad decisions? Another issue raised in the literature is: do managers always want to boost income at the time of the SEO/IPO? The answer appears to be contextual. Would a firm in the technology sector really want to cut R&D to boost earnings prior to an SEO if investors view R&D as its most valuable asset? Do firms generating losses really want to sacrifice future earnings by manipulating accruals in the SEO year? Thus the role of real earnings management around IPO/SEOs continues to be an interesting area for future research.

In the studies we examine no researchers specifically analyze financial distressed firms raising cash. For example how do firms that are highly levered and reporting special items do? Perhaps "good" financially distressed firms avoid raising equity capital because managers view their firms as underpriced? Researchers do find that SEO firms with high book-to-market ratios perform better in the future, which is perhaps, consistent with value stock (possibly financially distressed) performing better than growth stock.

<u>Material Earnings Misstatements</u>

Manipulating earnings and then getting caught is viewed as a very negative signal by the market.[12] The announcement of suspicious accounting on average leads to an 8% stock price decline. Getting caught for fraud is about as rare an event as going bankrupt, with only about 0.5% of firms being identified in a given year. Therefore, frauds tend to occur in industries that are viewed as "needing cash" that are industries having high growth potential, such as internet, software, or new technologies.

Can financial ratio models help in the detection of fraud or serious misstatements? The answer is similar to bankruptcy. Models are fairly accurate at identifying fraud firms, but there are a lot of firms that look suspicious that do not subsequently announce a fraud. Are investors price-protected? The answer is no, if anything, fraud firms have strong

[12] We do not examine discretionary accrual models in this review.

positive prior stock price performance. Keeping the stock price high could be part of the reason the firm is committing fraud in the first place.

If a firm announces a serious, suspicious, accounting misstatement and the stock price as a consequence plummets, what should an investor holding the stock do? Can ratios help predict which fraud firms will survive? This is a difficult question to answer because researchers need to decide when to measure the reputational loss effect of the accounting misstatement. We focus on research that uses financial statement fraud samples and find that there is not a great deal of evidence on this question. It appears that making governance changes can improve the chances of the firm's survival (but not necessarily get rid of its tarnished reputation). However, many fraud firms go bankrupt within three years of the announcement. This suggests that poor accounting quality could be a useful predictor of financial distress and bankruptcy.

What financial ratios are important for predicting fraud? Research suggests that fraud firms want to appear to be growth firms in need of cash, so high accruals, sales growth, growth in receivables, growth in inventory, growth in leases, etc., are all indicative of potential misstatements. In fraud research, accruals definitely play a "distortive" rather than "informative" role in predicting the future. Fraud firms tend to have high market-to-book ratios and higher prior stock returns in contrast to bankruptcy and downsizing models where market-to-book is low or insignificant and stock returns are negative.

3. Review Approach

Exhibit 1 provides a general overview of our approach to the review. There are many factors that influence the numbers reported in the financial statements. Only some of these numbers will be relevant for developing models that predict corporate events. There are many corporate events that researchers have analyzed. We focus on the shaded boxes and review literature related to bankruptcy, downsizing, equity issuances, and financial misstatements and fraud. We then examine models that have been developed to predict future outcomes. Our review focuses only on models that predict future stock returns or future earnings.

Our approach to identifying key representative papers for each corporate event is as follows. We search Google Scholar and ssrn.com, and read key papers in each area and follow up with cited research. We do not attempt to do a thorough investigation of working papers. We narrow the selection of papers in two ways: (i) papers need to perform regressions that use accounting numbers to predict the corporate event; or (ii) papers need to analyze future stock price performance or earnings subsequent to the event. Thus our search excludes papers that focus only on non-financial measures to predict the event (such as corporate governance) or that analyze other factors that are consequences of the corporate event (such as changes in analysts forecasts, or corporate governance).

For each corporate event we do the following:

(1) Create **Table A** that focuses on models to predict the corporate event. This includes: the name of the study; the number of treatment firms and non-treatment firms; the accounting ratios analyzed; the stock-based measures or other variables analyzed; and the explanatory power of the model.
(2) Create **Table B** that focuses on models predicting the performance of the firm after the corporate event. We provide a brief narrative of the main results provided by the paper.
(3) Search the literature and determined the frequency of the corporate event (see **Figure 1**); the stock price reaction to the announcement of the corporate event; and the one year ahead stock returns after the announcement of the event (summarized and reported in **Table 1**). The numbers in Table 1 are approximate since we do not have specific data on each event to do an independent analysis.
(4) Provide in **Sections 4 through 7 of the paper**, a brief summary of the literature for each corporate event.

4. Models Predicting Bankruptcy and Default Risk

Declaring bankruptcy marks the end of the corporation in its current form. It can result in the death of the company or a major restructuring and a transformation of the financial structure of a business. Shareholders are guaranteed to receive only pennies on the dollar for their investment and debtholders stand to lose a substantial portion of their investment. Clearly being able to identify and avoid firms with high bankruptcy risk is in the interest of most stakeholders. Thus it is not surprising that there is substantial early research on this topic.

The focus on the literature has changed over time. Early literature used bankruptcy as an illustrative case to show the usefulness of accounting variables. Later research developed models for predicting financial distress in a dynamic setting where models could be estimated monthly or even daily because of the use of stock returns (distance to default models). Various researchers have then compared accounting based models to the other models. Many researchers both test their ability to predict bankruptcy or delisting and determine whether their model predicts future returns. In order to avoid repetition we include early papers focused specifically on bankruptcy in the next section, and then discuss predicting distress and its consequence in section 4.2.

4.1. Models Predicting Bankruptcy Risk

Table 2A provides an overview of variables used and research design choices. We divide the table into sections based on the type of statistical model employed. Early studies include Beaver (1966) who matched 79 failed firms to non-failing firms and found significant difference in financial ratios such as cash flow to total debt and net income to total assets up to five years ahead of the event. Altman (1968) provides a more rigorous approach and his key insight was to combine different financial ratios into one single measure, known as the **Z-Score**. He uses a multiple discriminant analysis (MDA) approach, which is a technique to classify an observation into one of several a prior groupings depending upon the observation's individual characteristics. His model correctly classifies 31 out of 33 bankruptcy cases one year prior to the bankruptcy. The predictive ability of the model decreases when the forecast horizon is increased, but it still performs better than random selection.[13]

One significant shortcoming of the MDA technique is that it uses a matched sample approach to differentiate treatment firms. The matching approach limits the interpretation of the predictive ability of the model. Ohlson (1980) proposes a conditional logit model to mitigate this problem. Under this approach, an indicator variable equals one for treatment firms and zero for other observations. By including all other firms in the control group more accurate estimates of coefficients can be determined. The other innovation in his paper is the use of indicator variables. He has an indicator variable that takes the value of one when total liabilities exceeds total assets, and a second indicator variable that takes the value of one when net income is negative for the prior two years. He predicts bankruptcy within one year or two years. The coefficients on his Model 1:

[13] Following Altman's seminal work, many researchers adopted multiple discriminant analysis to predict bankruptcies. Dambolena and Khoury (1980) is another study that uses MDA as their statistical technique to predict bankruptcies. Their innovation is to consider both the level of financial ratios and the stability of those ratios as a firm approaches bankruptcy. They show that there is a substantial degree of instability in the financial ratios for firms that go bankrupt compared to those that do not and the level of instability increases as failure approaches.

bankruptcy within one year; are used to constitute the **O-Score**. The model in the study correctly predicts 96% of the bankruptcies when the cutoff probability is set to 50%.[14]

Two decades following Ohlson (1980), Shumway (2001) suggests that **hazard models** are appropriate for predicting bankruptcy. The hazard rate is the probability of going bankrupt at time t, conditional upon survival until time t. Shumway (2001) chooses firm age as the proxy for length of survival (the number of calendar years the firm has traded on NYSE or AMEX). Suppose a firm is listed on NYSE in 1981 and goes bankrupt in 1983. In 1981 and 1982 it will be assigned a "0" and in 1983 year it will be assigned a "1." A firm that never goes bankrupt will be assigned a "0" in all years. The difference between a logit model and hazard rate model is subtle since both use an indicator variable as the dependent variable. Shumway (2001, p. 123) points out that the test statistics for the hazard model can be derived from the test statistics reported by a logit program and that a hazard rate model can be viewed either as a logit model performed by year, or a discrete accelerated failure–time model.

Shumway (2001) uses both accounting and market-based variables in his hazard model. His results indicate that some of the ratios in Altman (1968): working capital to total assets, retained earnings to total assets, and sales to total assets are not statistically significant when the hazard model is used.[15] He also adds size, past stock return, and idiosyncratic return volatility as explanatory variables and shows that all of these market-based variables are strongly related to bankruptcy. The highest decile of the hazard rate

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[14] Zmijewski (1984) discusses methodological issues about the estimation techniques used in financial distress prediction models and focuses on two biases: "*choice-based sample bias*" and "*sample selection*". His results suggest that such biases exist, but in general, do not affect the statistical inferences or overall classification rates.

[15] He shows that when MDA is chosen as the estimation technique these ratios are still statistically significant.

based solely on market variables identifies 69% of actual bankruptcies in out-of-sample tests. This percentage increases to 75% when accounting variables are included.[16]

Black and Scholes (1973) and Merton (1974) show that a firm's equity can be viewed as a call option on the value of the firms' assets. Under the option pricing framework, the probability of bankruptcy is simply the probability that the market value of the assets is less than the face value of liabilities. In order to use such models researchers have to calculate the market value of assets and their volatility. These models are generally called "**Distance to Default (DD)"** and are dynamic since they can be measured on a daily basis. Intuitively, the distance to default can be thought of as:

(Market value of assets – face value of debt)/volatility of assets

The firm will have to pay off the principal amount of the debt at some point in the future and so the debt represents the strike price of the option. The formula provides an indication of the number of standard deviations the firm is from default and so high values of DD indicate lower default risk (see the notes to Table 2A for the actual formula).

Hillegeist, Keating, Cram, and Lundstedt (2004) compare the predictive ability of their distance-to-default model to Altman's Z-Score and Ohlson's O-Score. The comparisons are based on the Pseudo-R^2. They find that distance-to-default probabilities better explain bankruptcies than the accounting-based models.[17] However they do not

[16] Chava and Jarrow (2004) provide some improvements to Shumway (2001) by using a larger sample and showing the importance of industry effects. They also focus on one month ahead returns (rather than forecasting longer than one-year horizons) and find that market based measures subsume the information in accounting ratios (which is not particularly surprising since returns will be more timely in a monthly setting).

[17] Agarwal and Taffer (2008) compare the predictive ability of distance-to-default models to that of traditional simple accounting-ratio-based models for UK firms. They find based on ROC curves that a traditional Z-score outperforms distance-to-default models in terms of predicting failure. They reach a

determine whether accounting variables have incremental explanatory power. Bharath and Shumway (2008) compare the accuracy of various models and conclude that the Merton DD probability is a useful variable for forecasting default, but it is not sufficient on its own. When they add return on assets to the DD measure, the accuracy of the models in out of sample tests improves. Altman, Fargher, and Kalotay (2010) estimate the relation between default likelihood (distance-to-default) and fundamental variables. Their results show that fundamental variables explain up to 60% of the variation in default likelihood models. They also show that the out-of sample classification performance of the fundamental model that explains default likelihood is comparable to that of default likelihood models.

4.2. Financial Distress and Future Stock Returns

After the publication of Fama and French (1995) that showed that the book-to-market ratio predicted the cross-section of returns better than beta, much time has been spent justifying how book-to-market can be viewed as a "risk factor" even though unlike beta, there was no theory to motivate its empirical investigation. Fama and French (1995) suggest that value stock (high book-to-market firms that earn higher future returns) could be "distressed" and if such risk is priced by the market, then this could explain the higher future returns. Therefore, a link was made between distress risk and market-to-book and subsequent research has tried to establish whether "distress" is a priced source of risk. Unfortunately, as we will see below, the story does not hang together very well. **Table 2B** provides a summary of the key findings.

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similar conclusion to Hillegeist et al. (2004) that both accounting based models and the distance-to-default model carry unique information about firm failure and they are not sufficient on their own.

Dichev (1998) is one of the first studies to investigate the relation between distress (measured using the O-score) and future returns. He finds that investors are not rewarded for holding distressed stocks but instead such stocks earn lower future returns. His results suggest that distress risk is not a systematic priced risk and could be due to mispricing.[18] Since none of the distress models to this point in time had included book-to-market as a determinant, the question is: what is the relation between "distress" and book-to-market?

Griffin and Lemmon (2002) investigate this issue using the O-score and show that the return differential for the O-score cannot be explained by the three-factor model or by other variables linked to distress risk, such as leverage and profitability. They do find that for "growth" stocks (low book-to-market firms), there is a very large difference in the returns to high versus low distress risk stocks. They suggest that Dichev's finding of a negative relation between distress risk and future returns is largely driven by the underperformance of low book to market firms (growth firms). Note this clearly does not support "value" stocks earning higher returns due to distress.

Piotroski (2000) directly investigates the relation between distress and high book-to market (value) firms. He develops a score that gives a 1 or a 0 based on 9 financial ratios that could indicate distress – a high score means that the firm is a "winner", a low score – a "loser." Piotroski (2000) documents that firms with low scores have higher frequencies of performance related delistings. He further shows that within the category of "value" stocks, firms with low scores earn lower future returns (inconsistent with "value" firms

[18] A trading strategy that longs firms with lowest probability of bankruptcy and short firms with highest probability of bankruptcy based on O-Score earns a 12.2% hedge return.

earning higher expected returns because they are distressed). He finds that for value stocks the differential annual return between “winners” and “losers’ is over 23%.

Vassalou and Xing (2004) is the first study to use a distance to default model to measure distress risk. They investigate distress with respect to the two Fama-French factors: size and market-to-book. They find that conditioning on high distress risk, that small firms (that are distressed) earn higher future returns than large firms (that are distressed). In addition they find that high book-to-market value firms (that are distressed) earn higher returns than low book-to-market growth firms (that are distressed). They suggest that default risk is only rewarded to the extent that the firm is small or has a high book-to-market ratio. Note their result of a positive relation between default risk and future returns is opposite to the findings of other research in this area. Several authors provide explanations for these opposite results. Da and Gao (2010) show that Vassalou and Xing’s (2004) result is driven by short-term return reversals in extreme negative return stocks. Garlappi et al. (2008) find the positive relation between distress and future returns does not exist if stocks less than $2.00 are excluded from the sample.[19]

Campbell et al. (2008) estimates a dynamic panel model using a logit specification to measure the probability that a firm delists because of bankruptcy or failure. They also include all performance related delistings and D ratings issued by a leading credit agency as measures of failure. By broadening the definition of failure they capture cases where firms are distressed but manage to avoid bankruptcy. They focus on predicting distress

[19] Chava and Purnanandam (2010) argue that realized returns are too noisy to detect the true relation between distress risk and expected return and propose the use of implied cost of capital (ICC) as an alternative measure of the expected return. They use analysts forecast of EPS and long-term growth to obtain proxies for future cash flows and ICC is the rate that equates the future cash flows to current price. They find a positive relationship between default risk and ICC. They show that there is no anomalous negative relationship between risk and realized returns in the pre-1980 period, and argue that the negative relationship observed in the post-1980 period is caused by higher-than-expected bankruptcy filings and lower-than-expected earnings of high default risk stocks.

and they use a one month ahead forecast horizon. They include both accounting and market variables but scale net income and leverage by market value of assets rather than the book value of assets and include additional lags of stock returns and net income. [20] They find that corporate cash holdings, the market-to-book ratio, and a firm's price per share contribute to the explanatory power. Interestingly, they focus on firms with stock prices less than $15 (that are likely to be smaller firms) and find a negative relation between distress risk and abnormal future stock returns. A monthly trading strategy provides annualized hedge returns between 9.7% and 22.7% depending on the selection of abnormal return measure.

Taking a different approach, Correia, Richardson and Tuna (2012) explore the usefulness of accounting and market based information in explaining corporate credit spreads during the 1980-2010 period.[21] They test the predictive ability of a wide set of default forecasting models in out-of-sample tests for actual bankruptcies. The "Estimated Default Frequency" (EDF) provided by Moody's performs better than other distress risk models. Based on the predicted values of distress risk, they calculate the implied credit spreads. Then they look at the difference between (actual credit spreads less the implied credit spreads) and find that there is a positive association between this difference and future bond returns implying that the credit market does not fully incorporate the default information provided by models.

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[20] They suggest that scaling by market value increases the Pseudo-R^2 from 0.260 to 0.299.

[21] The credit spread is ($r_i - r_t$), where r_i is the yield of a bond and r_t is the yield on a Treasury bond with similar maturity. The yield on a bond is an equivalent concept to the internal rate of return for an investment. The future cash flows of a bond (interest and principal) are constant and known, so when there is distress news, the market value of the bond will decline, which will result in a negative bond return. However, when the market value declines the yield on the bond (the rate that matches the bond market value to the future cash flows) increases. Thus, credit spreads should be positively related to distress.

In summary, distress stocks earn lower future returns consistent with overvaluation, and distress risk does not explain the higher future returns to high book-to-market firms. Piotroski's (2000) results suggest that value stocks that have high returns are not distressed. Based on the evidence what is our recommendation to an investor who finds that one of his stock is distressed: "sell."

4.3. Role of Accounting Information in Distress Prediction

Beaver et al. (2005) examine whether the predictive ability of financial ratios for bankruptcy has changed over time. They find that financial ratios when used alone provide significant explanatory power for bankruptcies, but their power has slightly decreased over time. However, the explanatory power of a model that includes both financial ratios and market-based variables has not changed over time.[22] In a follow up study, Beaver, Correia, and McNichols (2012) focus on identifying the source of the decline. They include in their model, an indicator variable for losses (negative return on assets) and find that it loads significantly. They examine the association between proxies for discretion over financial reporting and the usefulness of financial ratios in predicting bankruptcy. Their proxies include the frequency of: (i) restatements; (ii) high discretionary accruals; (iii) high R&D expense; (iv) book-to-market ratios close to one; and (v) frequency of losses. They sort firms into partitions based on each criteria and show that the predictive accuracy of the models decrease with the undesired property.[23]

[22] They provide three potential explanations for the decline in the predictive ability of financial ratios for bankruptcies: FASB Standards, the increase in discretionary financial reporting behavior, and the increase in unrecognized assets and obligations. However, they do not explore which explanation is the driving factor of the decline.

[23] For example, the highest three deciles of probability of bankruptcy based on accounting variables can only predict 50% of actual bankruptcies for the restatement years while this percentage is 82.02% for the non-restatement years. For the discretionary accrual partition they show that, in the low discretionary accrual sample the highest three deciles of probability of bankruptcy based on accounting variables can

Thus their results suggest that when accounting based variables are likely to be distorted in some way, they are less useful for predicting bankruptcy and these distortions could have increased over time.

5. Modeling the Decision to Downsize

We first discuss research related to goodwill. We then discuss research related to special items and restructurings. Compustat began providing more detailed information on special items after 2000. Therefore, early research tends to provide evidence on the broad category of special items. Within each subsection we discuss both research that has forecasted the event (details provided in **Table 3A**) as well as research predicting performance after the event (**Table 3B**).

5.1 Goodwill Impairments

When a company purchases another firm and pays more than the fair value of the net assets, the company is required to record goodwill. Goodwill represents assets that cannot be recorded in the accounting system, such as customer loyalty and the future sales they will generate; or it can represent synergies between the two companies. However, goodwill can also represent overpayment. In particular, it is well known that when companies get into bidding wars, there is a winner's curse. Goodwill can also be a very fuzzy asset when firms purchase other companies using their own shares. When managers view their own stock as overvalued they can do two things: (i) issue equity and invest in new ideas; or (ii) takeover other companies with good ideas. Either option is good for the company because they can convert their overvalued currency into real assets.

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predict 76% of actual bankruptcies and this percentage becomes 82% and 68% for the medium and large discretionary accrual sample respectively, indicating a decline in the predictive ability of financial ratios in bankruptcy because of high accruals.

An overvalued company may strategically "pay too much" for another company simply because both the target and the bidder understand that the value of the bidder is inflated. In such cases "goodwill" would simply represent the wedge between the market's view of the bidder's value versus the "true" intrinsic value.[24] Such an amount should probably be immediately written off, however accounting rules do not allow immediate write-offs of goodwill and managers are unlikely to admit that their own shares are overvalued.

Can an investor distinguish "good" goodwill that represents future sales from bad goodwill that will become impaired at the time of the acquisition or at some later point? Table 3A provides relevant papers and the answer appears to be "yes." The literature in this area often makes comparisons pre and post SFAS 142 implemented in 2003. Generally, at the time of the acquisition the relevant predictors of future goodwill impairments fall into two categories: financial ratios that provide indicators about future performance and acquisition information that provides indicators of overpayment. The bottom line is that overpayment indicators are more important than financial ratios for predicting future impairments (Hayn and Hughes 2006, Gu and Lev 2008, and Li et al. 2011).[25] However, the pseudo R-squares are around 20 percent and studies generally do not perform detailed classification analysis to determine the type I and type II error rates.

What about in the years following the acquisition, when the goodwill is sitting as an asset on the books? Can an investor determine whether managers are delaying

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[24] For example, suppose the bidder has two shares worth $50 so that the market value of the company is $100 but its intrinsic value is $80. Suppose the target has a market and intrinsic value of $40. If the bidder exchanged one of its $50 shares for the target, then goodwill of $10 is recorded. However, the $10 goodwill does not represent synergies or future benefits, it simply represents the premium related to the inflated stock price. Note that the $10 is not an "overpayment" because purchasing the target has increased the bidders intrinsic valuation (the bidder's intrinsic value increases to $90 after the deal). See Lundholm and Sloan (2012) for more discussion of this issue.

[25] Hayn and Hughes (2006) compare the predictive power of performance and acquisition indicators. They find that pseudo R-squares of acquisition indicators (10%) are higher than performance indicators (6%).

recording an impairment relating to the goodwill? Li and Sloan (2012) provide a model to predict goodwill impairments. A firm is more likely to record an impairment when it has a low ROA, a high ratio of goodwill to assets, and a high book-to-market ratio. They find that their model anticipates the goodwill impairment at least one year ahead of the actual impairment. In addition, they find that forming a "high probability of impairment" portfolio three months after the fiscal year end earns future annual returns of approximately -22%. Note that investors do partially anticipate goodwill impairments. Francis et al. (1996), Li et al. (2011), and Li and Sloan (2012) all find that negative stock returns are significant predictors of goodwill impairments. However, in the post SFAS 142 period investors do not appear to fully anticipate impairments.

5.2 Restructuring Charges and Special Items

Restructuring charges represent management's estimates of costs to change the business to make it more competitive. A firm that needs to restructure is clearly not doing too well. Can an investor avoid such firms using financial ratio models or is the information in the financial ratios already reflected in stock returns? A key issue for valuation relates to the persistence of restructuring charges. Are restructuring charges transitory (and thus should get zero weight in valuation) or persistent (so should get some weight)? Or do they cause negative serial correlation in earnings? Mechanically, the more future expenses managers can bring into the current restructuring charge, the larger the negative charges and the higher future earnings. Thus there are three things to consider when observing a restructuring charge: (i) the underlying economic drivers that cause the firm to take the restructuring charge; (ii) the accounting rules and the implications the restructuring charge has for future earnings; and (iii) whether investors understand the implications of the restructuring charge for future earnings.

Several researchers attempt to address consideration (i) and predict economic drivers of restructuring charges (see Table 3A). The models are generally run by industry and researchers find that the fundamental ratios most important for predicting future restructurings include sales growth and the ratio of cost of goods sold to inventory (inventory turnover).[26] Sales growth and inventory turnover measure the popularity of a company's products, the efficiency of its operations, and the growth prospect. Thus, it makes sense that restructuring firms, which are performing poorly, will have lower sales growth and inventory turnover prior to the restructuring.

Consideration (ii) is complicated by the fact that the rules have changed over time to limit management's ability to include future expenses in the charge. Two rule changes are important. EITF NO. 94-3 (issued in 1994) states that a firm should not include costs that have future benefits in the restructuring charge. This rule is investigated by Bens and Johnston (2009) who find that the rule temporarily curtailed managers from over-accruing restructuring charges.[27] The second rule is SFAS 146 implemented in 2003. This rule mandates firms only include exit costs in restructuring charges as they are incurred, and thus forces more persistence into restructuring charges and less ability to create earnings reserves. Therefore, prior to 2003, restructuring charges are expected to be more transitory or even used to boost earnings in years after the charge is taken. After

[26] These two accounting variables have the highest number of significant coefficients across 11 (Lee 2013) or 14 (Bens and Johnston 2009) industry specific models.

[27] Bens and Johnston (2009) decompose restructuring charges into a component driven by fundamentals and a residual. The residual (which is the proxy for discretionary restructurings) is then regressed on earnings management proxies, such as the likelihood the firm is taking a bath, future restructuring reversals (that boost future earnings), and future accruals (that boost future earnings). They find that the excess reserves are smaller after rule changes (EITF NO. 94-3) that restricted management's discretion.

SFAS 146 they should be more persistent. Lee (2013) documents evidence that restructuring charges are indeed more persistent after 2003.

Consideration (iii) asks whether investors understand the implications of restructuring charges? Lee (2013) finds that after SFAS 146 investors respond more strongly to restructuring charges consistent with them understanding their greater persistence. In a related vein, Cready, Lopez, and Sisneros (2010) show that investors understand that when a firm has had a history of special items, these special items are likely to be more permanent.[28] They analyze returns at quarterly earnings announcements as well as returns over the quarter and show that investors place more weight on special items for firms with a history. They find for firms with a history, the valuation weights on special items are similar to other components of earnings.

However, these studies do not address the issue of whether the market gets it right. Do investors correctly weigh special items and restructuring charges? Burgstahler et al. (2002) investigate the implications of special items for future quarterly earnings and show that a negative special item leads to a positive earnings innovation for the next four quarters (in other words the special item creates a reserve that is leaked into earnings over the next four quarters). They investigate the role of negative special items with respect to the post earnings announcement drift.[29] They suggest that their findings indicate that investors underweigh the positive (leaking) implications of special items for future earnings. These results suggest that an investor should hold on to a stock when it

[28] For example, Kodak reported restructuring charges from downsizing for more than 12 years in a row and finally declared bankruptcy in 2012. See for example, http://www.businessweek.com/stories/2004-02-08/commentary-kodaks-fuzzy-numbers.

[29] With the post earnings announcement drift, investors underweight the implications of an earnings innovation for future earnings and so respond to predictable earnings changes. A negative special item recorded in quarter t+k is likely to result in a negative earnings surprise ($E_{t+k} – E_{t+k-4}$) but then have a positive effect on future quarterly earnings.

announces a special item since the firm should have future positive earnings surprises (at least prior to SFAS 146).

The recording of special items is also likely to lead to negative accruals (recording restructuring liabilities and writing down assets). Sloan (1996) shows that firms with negative accruals tend to have higher future stock returns. Dechow and Ge (2006) investigate whether low accruals driven by special items are important drivers of the accrual anomaly because accruals related to special items are likely to be particularly "transitory." They find that special items are a key driver of the higher returns to low accrual firms.[30] Thus their result suggests that if a firm announces a special item and at the same time the firm is recording very negative accruals, then the investor should hold on to the stock since stock returns are likely to increase in the future.

Bhojraj et al. (2009) focus specifically on restructuring charges. As noted by Lee (2013) after SFAS 146, restructuring charges are likely to be more persistent and probably do not have the "leaking" implications for future earnings innovations documented by Burgstahler et al. (2002). Consistent with SFAS 146 impacting the time-series properties of earnings and investors perceptions, in the pre-SFAS 146 period, Bhojraj et al. (2009) find that firms with large restructuring charges have positive future returns of 37% but post SFAS 146, when restructuring charges are more persistent, firms with large restructuring charges have negative returns of -7.6% (see Bhojraj et. al. 2009, Table 3). Bhojraj et al. (2009) also compare the Dechow and Ge (2006) findings in 2000-2002 (pre SFAS 146) to 2003-2006 (post SFAS 146). They find in the pre SFAS 146 restructuring charges are the major component of special items and strong evidence

[30] For the lowest decile of accruals: future returns are 17% for firms that record special items and 7.5% for firms that do not (see their Table 3).

consistent with Dechow and Ge (2006). After the introduction of SFAS 146, restructuring charges are more persistent and so low accrual firms are more likely to continue to report lower earnings. They show that the low accrual decile no longer earns positive future returns in the post SFAS 146 period.

So what should an investor do after 2003 when he or she owns a stock that announces a restructuring charge? The answer appears to be "sell." There is likely to be more restructuring charges in the future that are not fully anticipated by investors.

6. Models of Equity Issuance

6.1. Predicting Initial Public Offerings (IPOs)

Due to data limitations, few studies examine the use of financial ratios in predicting when a firm will go public. Some exceptions reported in **Table 4A** are: Pagano, Panetta, and Zingales (1998) analyzing Italian firms; Boehmer and Ljungqvist (2004) analyzing German firms; and Brau, Francis, and Kohers (2003) who analyze US firms that choose to conduct an IPO versus private firms that choose to be acquired by a public firm.

Several researchers have investigated the question of: given a firm is going public do managers window-dress the financial statements and boost earnings? Friedlan (1994) focuses on a small sample that discloses financial statement data in the prospectus and finds that total accruals, discretionary accruals, and earning changes of IPO firms are greater than those of matched non-IPO firms. Teoh, Wong, and Rao (1998) compare depreciation methods and the allowance for bad debts of IPO firms with their earnings-performance matches. They show that IPO firms use more income-increasing depreciation method and less bad debt expenses relative to receivables than their matches.

6.2. Predicting Future Performance after an IPO

A well-known anomaly is that IPO firms earn lower returns over the three years after going public (e.g., Ritter 1991). However, some firms do spectacularly: Can financial ratio models and other information help pick the good firms from the bad?

A large volume of research has investigated factors surrounding the deal (see **Table 4B**). Future returns are more negative if a firm (i) goes public in a "hot" market (high volume year); (ii) is in a "hot" industry (when more firms from the same industry go public); (iii) has a higher first day stock return; (iv) has original entrepreneurs who sell more of their ownership stake; and (v) has analysts that are forecasting high long-term growth.[31]

Can financial ratios provide additional insights? The focus of the research into this question has been on whether IPO firms that appear to engage in earnings management underperform. Teoh, Wong, and Rao (1998) find that the return on sales in the three post-IPO years relative to the IPO year declines by 16.50% for the quartile with the highest issue-year abnormal current accruals. In contrast, the IPO firms in the quartile with the lowest issue-year abnormal current accruals do not underperform in the post-issue years.[32] Ducharme, Malatesta, and Sefcik (2001) find similar results. Morsfield and Tan (2006) find that IPO-year abnormal accruals are lower in the presences of venture capitalists (VCs) and argue that VC monitoring could reduce earnings management.

Other researchers question the extent to which managers will boost earnings at the time of the IPO. Ball and Shivakumar (2008) and Venkataraman, Weber, and Willenborg

[31] See Ritter (1991), Jain and Kini (1994), and Rajan and Servaes (1997).

[32] Teoh, Welch, and Wong (1998a) document very similar results as in Teoh, Wong, and Rao (1998), and further show that the differential performance between high and low discretionary accruals is robust to test specifications that control for market capitalization, book-to-market, expected return benchmark, holding period, and cumulation method effects.

(2008) argue that firms will report more conservatively around the IPO due to increased regulatory and legal penalties for misreporting. Armstrong, Foster, and Taylor (2008) argue that research design issues need to be considered before assuming earnings management. The incentive to inflate accruals probably depends on whether the firm is reporting a profit or a loss. If the firm is reporting a loss, does it really make sense to boost accruals and make the loss smaller? We don't think so. Investors have to be valuing a loss company on a basis other than an earnings multiple so the answer probably depends on what investors view as key drivers of value. Singer, Fedyk, and Soliman (2012) use a simultaneous equations approach and suggest that different sectors (internet, technology, assets in place, and science) have different financial statement attributes that investors view as key drivers of value. They find that managers in certain sectors will actually take actions that hurt earnings so that they can report high sales growth or larger investment in R&D. They do not analyze future stock price performance based on these incentives. In addition, Allen (2012) finds that IPO firms often take full valuation allowances for deferred tax assets relating to their losses. If they only cared about earnings such actions would not make sense. Allen (2012) argues that they do not just take full valuations to be "conservative." They do so because of statutory rule related to ownership changes. In summary, managers in IPOs are obviously interested in selling their companies for a good price but "earnings" are not the only thing investors focus on, and therefore managing this number is not the only thing managers will focus on either.

6.3. Predicting Seasoned Equity Offerings (SEOs)

Several researchers have asked managers why they choose to raise equity. For example, Graham and Harvey (2001)'s survey indicates that more than two-thirds of

Chief Financial Officers assert that earnings per share dilution and recent stock price appreciation are the most important determinants of equity issuance.

Eckbo, Masulis, and Norli [(2007) Chapter 6, p. 236], list several reasons for why managers make a security offerings. They state:

> "the most common reason given for these actions (equity offerings) is to raise capital for capital expenditures and new investment projects. Other reasons explored in the literature include the need to refinance or replace existing or maturing securities, to modify firms capital structure, to exploit private information about securities intrinsic value, to exploit periods when financing costs are historically low, to finance mergers and acquisitions, to facilitate asset restructuring such as spin-offs and carve-outs, to shift wealth and risk bearing among classes of securities, to improve the liquidity of existing securities, to create more diffuse voting rights and ownership, to strengthen takeover defenses and to facilitate blockholder sales, privatizations, demutualizations and reorganizations."

That's a lot of reasons! Unfortunately Eckbo et al. (2007) do not model these choices.

Mackie-Mason (1990) examines whether a firm will issue equity or debt. The paper finds that financial statement variables such as tax loss carryforwards, R&D expenditure, earnings variance, and free cash flow are positively associated the likelihood of equity issuance, and investment tax credits, advertising expense, PP&E, and net assets are positively associated with debt issuance. Non-financial variables such as bankruptcy score, past stock return, issue price, whether firms pay dividend, and whether firms are in regulated industries are also significant determinants of equity offering decisions. This model correctly predicts 75% of the equity issues in the sample. Jung, Kim, and Stulz (1996) examine a similar model. Guo and Mech (2000) find that stock split declarations, dividend announcements, and earnings releases help investors anticipate equity issues after controlling for variables that that predict external financing and variables that predict preference for equity over debt issues if the firm uses external financing. Deng, Hrnjic, and Ong (2012) focus on the real estate investment trust industry (REIT) and find that investor sentiment and growth play a role in the decision to issue equity. However, their model has very low explanatory power.

Several researchers have investigated whether firms "time" their equity issuances when the stock is overvalued. Jindra (2000) calculates overvaluation using three earnings-based valuation approach and suggests that SEO firms appear overvalued. McLaughlin, Safieddine, and Vasidevan (1996) compare issuers with non-issuers and find no difference in the level of free cash flows (their proxy for over-valuation). They suggest that the lack of difference is inconsistent with managers "timing" issuances. However, it is not clear (at least to us) why free cash flows should be related to overvaluation. DeAngelo, DeAngelo, and Stulz (2009) examine whether the SEO decision is explained by "timing" or by the firm's life cycle (when growth opportunities exceed internally generated cash flow). They find that both timing and lifecycle proxies are significantly associated with equity issues but suggest that the lifecycle effect is stronger. Alti and Sulaeman (2012) find that high past stock returns lead to an increased likelihood of equity issue only when the firm contemporaneously faces high institutional demand. They suggest that the presence of institutions purchasing the issue reduces the concern that managers are "timing" the issue and take advantage of asymmetric information.

6.4. Predicting Future Performance after a SEO

SEO firms typically have high returns in the year before issuing, low returns around the offering announcement, and low long-run stock returns. For example, Loughran and Ritter (1995) report an average return of 72% in the year before issuing. Ritter (2003) shows the two-day average abnormal return is about -2% for U.S. firms. Rangan (1998) shows that the abnormal return in the first year after the offering is -7.4%.

Can financial variables help distinguish good SEOs from bad? We summarize key papers in **Table 5B**. Accounting researchers have focused on the story that managers manipulate earnings at the time of the SEO, and investors do not realize this, and as a consequence investors are surprised when future earnings are lower (so future returns decline). Rangan (1998) shows that high discretionary accrual issuers underperform low discretionary accrual issuers by 7% to 9% in the first year following the issuance. Teoh, Welch, and Wong (1998b) analyze four accruals measures – discretionary current accruals, discretionary long-term accruals, nondiscretionary current accruals, and nondiscretionary long-term accruals, and find that only discretionary current accruals is significantly negatively associated with future earnings and future returns. Economically, Teoh, Welch, and Wong (1998b) show that the return difference between the highest and lowest quartiles of discretionary current accruals ranges between 42% and 61% over a five-year horizon, depending on the return benchmarks. These two studies conclude that investors fail to see through the manipulation around the offering and are subsequently disappointed after the offering.[33] Further, Lim, Thong, and Ding (2008) argue that more diversified firms can engage in greater levels of earnings management. They find that diversified firms have higher discretionary accruals and their future stock price performance is particularly poor.

Cohen and Zarowin (2010) investigate whether real earnings management impacts future performance. They combine both R&D and SG&A into a single measure and

[33] However, others question whether investors can be fooled by accruals. Shivakumar (2000) argues that investors will infer earnings management and rationally undo its effects at equity offering announcements. Specifically, he shows that: (i) investors reduce their price response to unexpected earnings released after the offering announcements; and (ii) there is a negative relation between pre-announcement abnormal accruals and the stock price reaction to the offering announcement. Therefore, it appears that investors are suspicious of high accruals (although perhaps not enough - since future returns are more negative for high accrual firms).

show that SEO firms that cut these expenditures in the year of the SEO have poor future earnings performance. Kothari, Mizik, and Roychowdhury (2012) form 8 groups based on the sign of abnormal ROA, abnormal R&D, and abnormal accruals. They show that the group with the lowest future returns is the one with positive abnormal ROA, negative abnormal R&D, and positive abnormal accruals (-11.8%).[34] These results suggest that cutting R&D to boost earnings around the time of the SEO leads to poor future performance.

However, as with the IPO literature it is not clear that all firms engaging in SEOs will want to always boost earnings. For example Sun (2013) finds that SEO firms have high abnormal R&D but low abnormal SG&A, and the market responds positively to the abnormal R&D and negatively to the abnormal SG&A. This is consistent with Singer et al.'s (2012) contention that some firms do not necessarily want to cut R&D to boost earnings, when investors view R&D as a value-enhancing asset. Managers' decision on manipulating earnings upward is affected by how investors might value such as decision.

There are other factors beyond the financials that an investor should also consider. A traditional view is that managers will issue equity when they view the firm as overvalued (Myers and Majluf 1984). Some firms have greater investor recognition than others and so can be easily hyped. These firms are the ones that regular people understand what they are doing and know their products (e.g., Google, Facebook, Apple, etc.). From this perspective, one thing an investor should consider is the amount of voluntary disclosures that the firm is making. Lang and Lundholm (2000) document that

[34] They further suggest that firms that engage in real earnings management by cutting R&D have lower future returns (-10.8%) than the group of firms with positive abnormal accruals (-4.7%). Note however, that prior research generally focuses on firms in the top quartile of abnormal accruals rather than the top half, and so their tests of the impact of accruals have low power.

firms that substantially increase their disclosure activity in the six months before the offering experience larger price declines at the announcement of the offering and also in the 18 months following the announcement.

Another important factor an investor should realize is that financial analysts are not unbiased conveyers of information. Most analysts work for investment bankers who are not in business for charity reasons. The selection of firms an analyst follows is not random and considerations include investor interest and how much brokerage and investment banking business the firm has the potential to bring into the bank. For example, Dechow, Hutton, and Sloan (2000) show that the post-offering underperformance is most pronounced for firms with high growth forecasts made by affiliated analysts. After controlling for the over-optimism in earnings growth expectation, the post-offering underperformance disappears.

However, the issue is more than affiliated analysts. Dechow et al. (2000) find that unaffiliated analysts are also very optimistic for firms raising capital. More generally, Bradshaw, Richardson, and Sloan (2006) find a positive relation between external financing and analyst optimism. Specifically, they find that the more equity financing raised by a firm, the greater the analyst optimism. For equity issuances, analysts' optimism is mainly reflected in their long-term forecasts (long-term growth and target prices) and their recommendations. The over-optimism may not be intentional, it could be that the market in general is over-excited about the stock; managers of the stock are excited about their product and want to invest (which creates accruals); and analysts believe in the story. Thus, market hubris could also play a role in the overvaluation of certain SEOs.

What is our advice for an investor that owns a stock that is doing an SEO? The evidence suggests that if the firm has high accruals, is cutting R&D, and analysts have very optimistic long-term forecasts, then a prudent investor should "sell."

7. Modeling Material Earnings Misstatements

We review research that has identified misstating firms from SEC Accounting and Auditing Enforcement Releases (AAERs). There is an extensive body of research examining the consequences of firms restating earnings and that literature is not included in this review. We do not include research on restating firms mainly to reduce the scope of the review and also because material misstatements will be subject to SEC enforcement actions (and so end up in the AAER database).

7.1 Predicting Material Earnings Misstatements

Dechow, Sloan, and Sweeney (1996) find that for a sample of 92 firms subject to SEC enforcement actions, the stock prices decline by 9% on the day of the initial announcement of the alleged earnings manipulation. They further find that prices decline by 30% within four months following the announcement. Obviously, an investor would prefer not to have such stocks in their portfolio.

Which financial ratios appear to be most important for detecting material misstatements? Dechow et al. (1996) find that relative to a matched control sample, working capital accruals and discretionary accruals increase as the alleged year of earnings manipulation approaches, and then decrease significantly after the manipulation years primarily due to accruals reversals (e.g., Dechow, Hutton, Kim, and Sloan 2012).

Their evidence also suggests that misstating firms are using more income increasing accounting rules and are raising equity financing.

Beneish (1999) uses a sample of 74 firms identified by press releases or the SEC for having misstating earnings and 2,332 control firms. He calculates growth in eight key financial variables, including growth in days sales in receivable, growth in gross margin, etc (see **Table 6A** for more details). If there is no growth each ratio will equal 1 and a high value of each growth ratio is indicative of a greater likelihood of misstatement. He then investigates the type I and type II errors for his model and provides a relative cost analysis to determine how to trade-off type I and type II errors. He finds that his model is better at predicting misstatements than a naïve model.[35]

Dechow et al. (2011) develop a financial ratio model to predict material accounting misstatements. Their sample consists of 494 manipulating firm-years and over 130,000 non-manipulating firm-years. They develop three models: the first one includes only financial variables measured directly from the financial statements. This model includes total accruals, the percentage of soft assets on the balance sheet (assets that are not cash or PP&E), changes in ROA, changes in cash sales, and whether the firm is raising financing. The second model adds other non-financial information disclosed in the footnotes to the first model and includes abnormal reductions in the number of employees, and the use of operating leases. The third model adds market-based variables such as book-to-market ratio and prior year's stock return to the second model. They find that both financial and nonfinancial information are important for predicting financial misstatements. Stock-based variables do not subsume the significance of the other

[35] Beneish, Lee, and Nichols (2012) flag firms with a Beneish's M-score greater than -1.78 and show that these firms underperform by on average -7.5% (see their Table 2).

financial statement variables. The output of the model is a scaled logistic probability (they term the F-score), where values greater than one indicate a greater likelihood of a misstatement. Based on an F-score of 1, the percentage of correctly classified manipulators is 69%. The percentage of incorrectly classified non-manipulators is 36%.

Sun (2013) investigates the use of real earnings management among misstating firms. She finds that misstating firms have lower abnormal SG&A but higher abnormal R&D than their control firms in the years in which the SEC alleged that earnings are overstated. The finding of unusually high R&D is inconsistent with the prediction associated with real earnings management. However, this result is consistent with investors viewing R&D as a value-enhancing asset (e.g., Singer et al. 2012). Furthermore, managers are reluctant to cut R&D since it may hurt stock prices.

Hribar, Kravit, and Wilson (2013) develop a model of accounting quality by focusing on audit fees. They regress audit fees on various economic predictors and the residual (UAF) is their proxy of accounting quality. They show that UAF is incrementally important over measures of accounting quality such as the absolute value of discretionary accruals and the components of the F-score in predicting AAER misstatements and restatements.

Many studies have examined the role of corporate governance and incentive compensation for predicting misstatements. Dechow et al. (1996) and Beasley (1996) document that board characteristics and director characteristics such as whether the CEO is chairman of the board and the number of outsiders on the board, are important determinants of financial misstatements. Feng, Ge, Luo, and Shevlin (2011) show that CEO pay-for-performance sensitivity and CEO power are significant determinants of financial misstatements, but Chief Financial Officer (CFO) pay-for-performance sensitivity is not. They also show that CFO turnover is significantly higher within three years prior to the occurrences of accounting manipulations for AAER firms than control firms. They conclude that the involvement of the CFO in accounting manipulation is more likely due to CEO pressure rather than their personal financial incentives.

Whether top management commits fraud for compensation reasons is a controversial topic. Erickson, Hanlon, and Maydew (2006) examine the sensitivity of top five managers' stock compensation relative to stock prices, and find no consistent evidence that executive equity incentives are associated with fraud. A similar conclusion is drawn by Armstrong, Jagolinzer, and Larcker (2010) using propensity score matching. If top managers are not doing it for compensation reasons, then what is their motivation? Does it come down to ego and lack of moral upbringing? Managers don't take the risk of committing fraud for fun so what is going on? The matching procedure done in Armstrong et al. (2010) is so comprehensive, one wonders whether the managers of counter-factual firms with such similar characteristics to the fraud firms also engage in earnings management (just perhaps not as egregious). Or perhaps the managers of the counter-factual firms are getting so over-paid and taking so many other perks, that there is no need to commit fraud.

Price, Sharp, and Wood (2011) compare commercial and academic risk measures that have been used to predict accounting irregularities. The commercial risk measures include the Accounting Risk measure and the Accounting and Governance Risk measure developed by Audit Integrity, LLP. The academic measures include working capital accruals (Sloan 1996), M-score (Beneish 1999), F-score (Dechow et al. 2011), accruals quality measure (Dechow and Dichev 2002), discretionary accruals (Dechow, Sloan, and Sweeney 1995), and unexpected audit fee measure (Hirbar et al. 2013). They conclude that the commercial measures have relatively greater explanatory power. However, it is difficult from analyzing their results to directly determine how many extra fraud firms are correctly identified using the commercial measures versus the academic measures. Therefore, it is hard to know the economic significance of their conclusion. In addition, one problem with the commercial measures is that the researcher does not know the inputs or their relative weights in the model and how they have changed over time. Therefore over-fitting and hindsight bias concerns exist.

7.2 Predicting Future Performance after Material Earnings Misstatements

If an investor is unlucky enough to own a stock that is identified as engaging in earnings manipulation (by the press, the firm itself, or some other party) what should the investors do? As mentioned above, there is a negative stock price reaction when suspicious accounting is announced, but what happens in the long run? The issue of concern is that the investor wants to avoid firms on the path to an SEC investigation and subsequent fraud charges (companies like Enron) or that take large restatements. However, the investor would want to hold on to a stock that will subsequently recover from such a scandal. Such a firm is likely to be undervalued because it is being pooled with "bad" misstating/fraud firms. To our knowledge a comprehensive analysis of this type has not been done.

In **Table 6B**, we report two papers that investigate fraud firms' performance in the post-fraud period. Farber (2005) finds that his sample of 87 AAER firms have poor governance relative to a control sample in the year prior to the fraud detection year. However the AAER firms take actions to improve their governance after the detection, and show governance characteristics similar to the control firms three years after the detection year. While the improvements in governance do not significantly affect analysts, institutional investors, and short sellers' behaviors, firms that take actions to improve governance have better stock performance in the following three years. However, unfortunately there are only 34 of the 87 companies that appear to have survived over the three-year period and so it is unclear what governance changes the non-surviving firms made and whether the effect is causal.

Leng, Feroz, Gao, and Davalos (2011) investigate the long-term performance and failure risk of AAER firms. They show these firms experience significantly negative abnormal operating and stock performance up to three years following the AAER release date. This is surprising since the AAER release date can often be quite a bit later than when the manipulation occurred and so one would expect all the bad news to be in the price. Specifically, the mean 1-year, 2-year, and 3-year buy-and-hold return after the AAER month are: –12.97%, –23.68%, and –26.02%, respectively. AAER firms are also more likely to fail in the post AAER period. They find that 28% of AAER firms are either bankrupt or delisted after the enforcement actions. Note, however, that the authors did not provide a cross-sectional investigation of which firms perform poorly or go bankrupt and which one's survived. We view this as an interesting avenue for future research.

8. Conclusion

We review financial ratio models developed in the literature that (i) predict significant corporate events; and (ii) predict cross-sectional variation in earnings and stock returns after these events. The four significant corporate events we analyze are bankruptcy and distress, downsizing, equity issuances, and announcements of financial misstatements and fraud.

The research suggests that accounting models can help predict bankruptcy and that market-based measures improve predictive ability. It is interesting that market-based measures are not even more superior to accounting based measures. There are several possible explanations. First, option-pricing models impose strict assumptions that could induce measurement error. Second, financial ratios reflect firm-specific performance, whereas stock returns reflect both firm and market factors and market factors could be less relevant for predicting bankruptcy. Third, there could be a self-fulfilling prophecy with respect to accounting ratios. Debt covenants use accounting ratio to determine default and credit rating agencies use ratios as inputs to downgrade debt. If default and downgrades are important determinants of bankruptcy, then key ratios should correlate with bankruptcy.

The research on downsizing reveals that different charges have different implications for future earnings and this in turn impacts investor responsiveness. Goodwill impairments appear to be delayed by managers and investors do not perfectly anticipate the timing of goodwill impairments. In contrast, restructuring charges can lead to future restructuring changes and therefore have implications for future earnings. These implications are not always fully anticipated by investors. Determining the valuation implications of special charges continues to be an interesting area for future research.

The research on why SEOs/IPOs underperform in the future continues to expand. One explanation is that management boosts earnings at the time of the SEO, and investors are disappointed when future earnings are low. Another related explanation that does not require earning management is market "timing." When investor sentiment is strong, and the firm has shown strong past growth, the stock is more likely to be overvalued and so managers are more likely to issue equity. Investors are subsequently disappointed when future investments do not yield as high returns as they did in the past. Determining the relative importance of each explanation offers opportunities for future research.

The research on material misstatements is extensive and we limit our review to misstatements involving SEC enforcement actions. It would be interesting to better understand the relative importance of financial variables versus other variables such as opportunities created by poor governance, incentives created by compensation, and pressure from top management, in predicting misstatements.

Our review reveals that investors appear to overvalue firms prior to the revelation of a significant corporate event and face a lower return afterwards. What drives this delayed response? Could less restrictive short-selling rules improve market efficiency? We also find that return on assets is a key ratio predicting events. Could models be improved by inputting a better forecast or future earnings than lagged earnings? For example, earnings could be decomposed into cash flows and accruals, or continuing versus transitory components, or alternatively, analysts' forecasts could be used. We leave such questions for future research.

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Exhibit 1: Determinants and Consequences of Significant Corporate Events

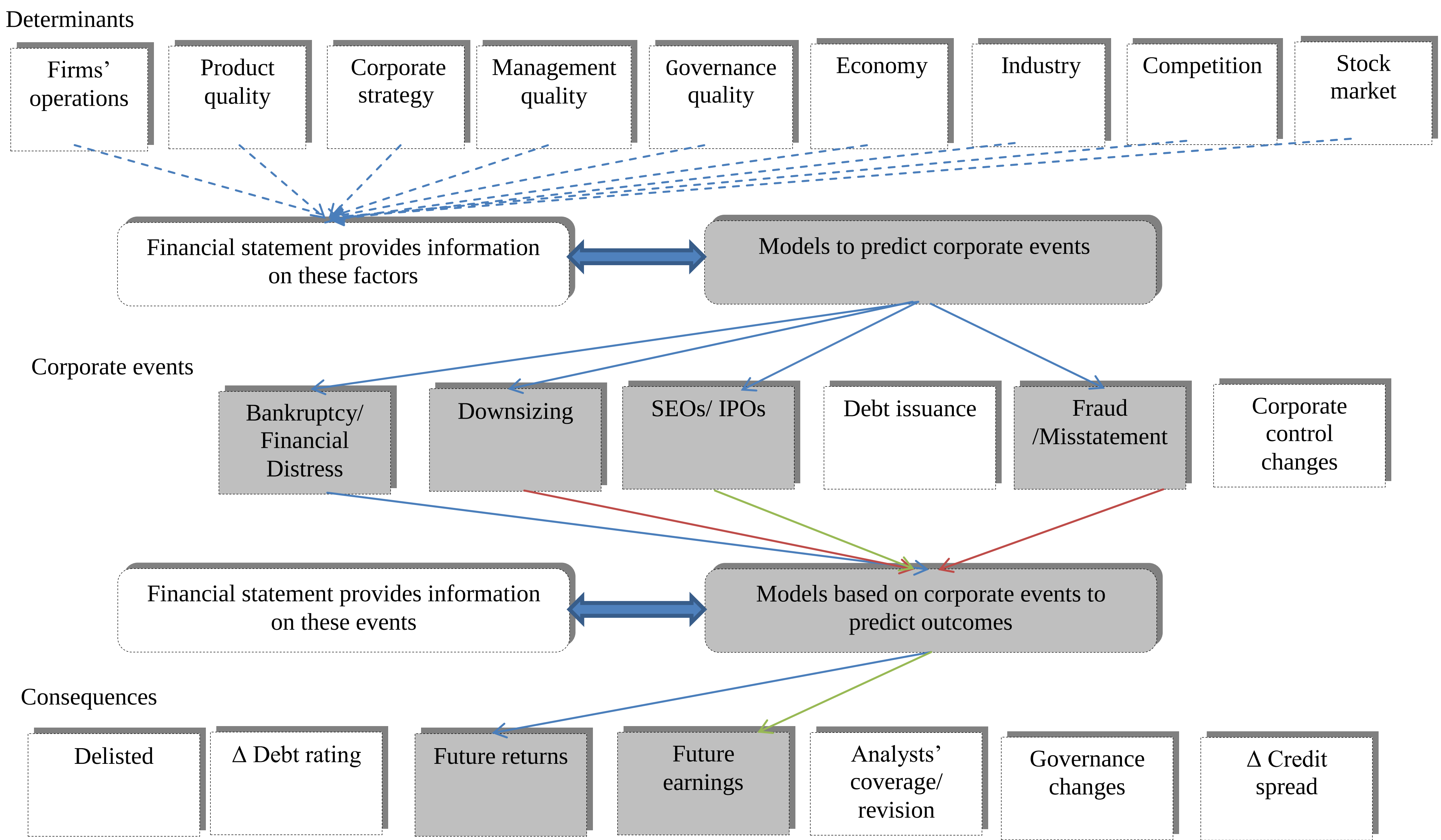
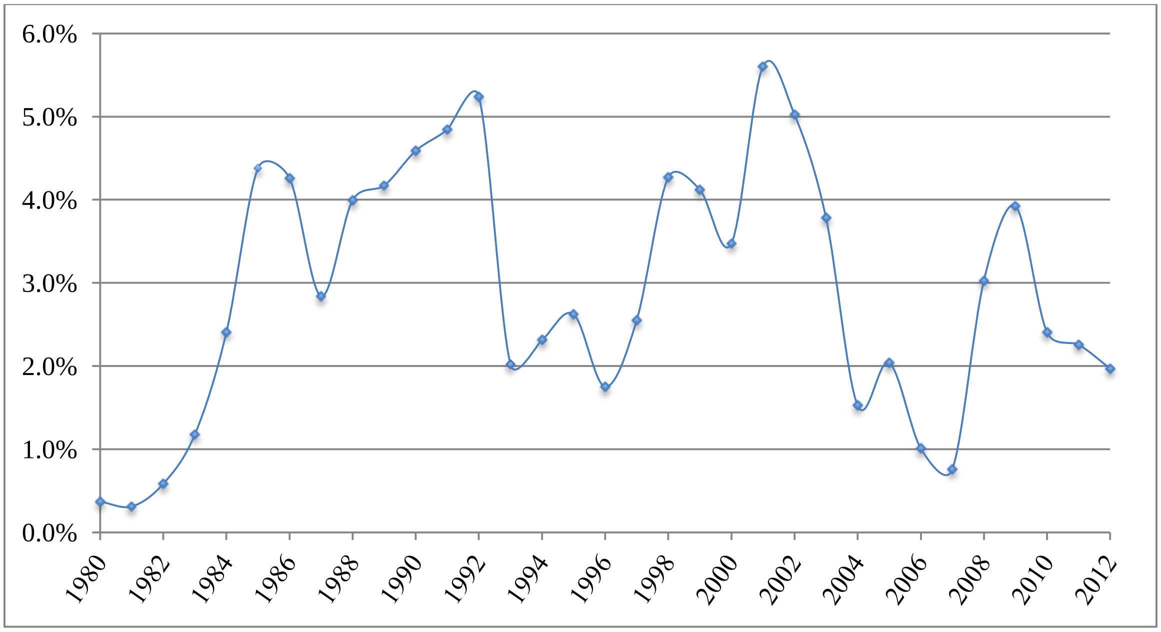
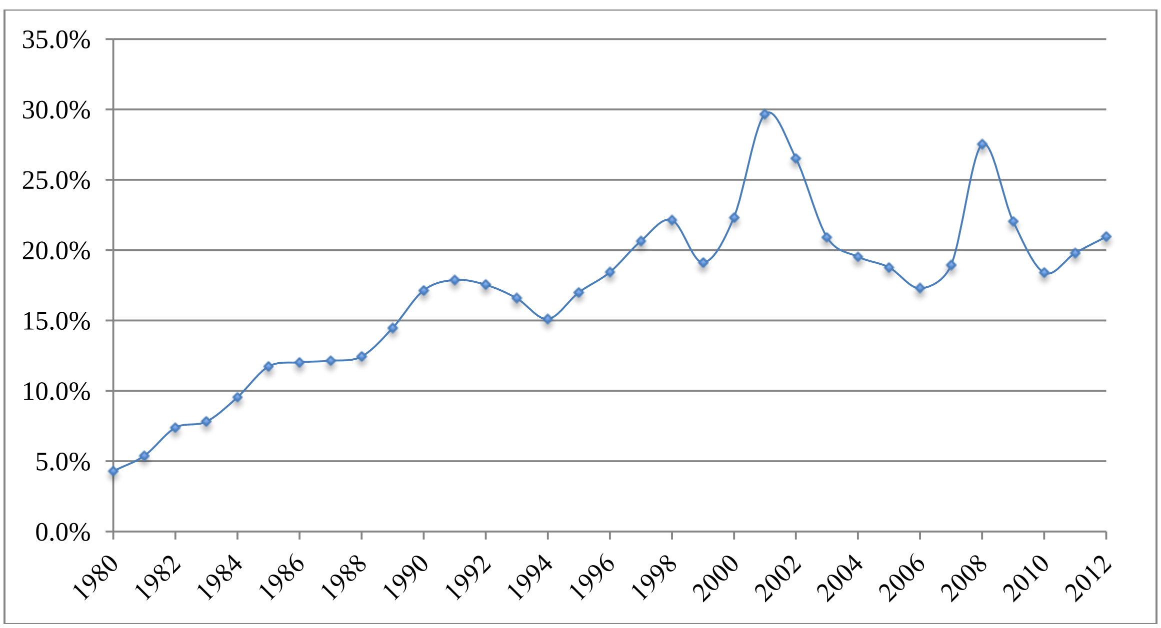


Figure 1A: Percentage of Firms with Performance Related Delistings (1980 - 2012)



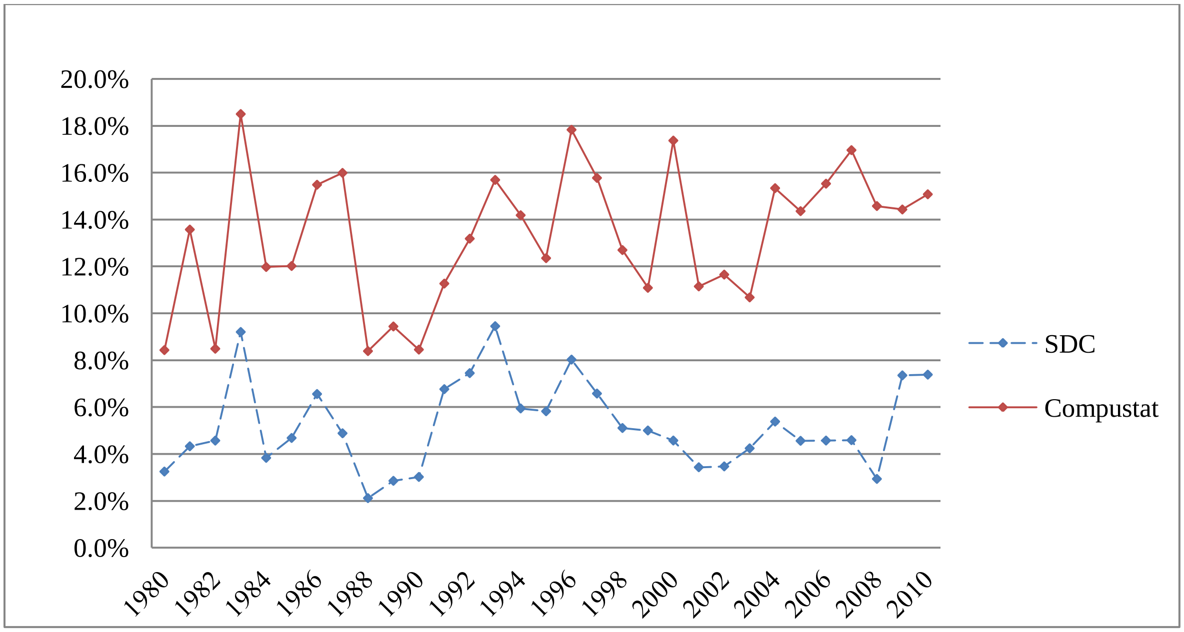
Note:
The percentage is calculated as the number of firms with performance related delistings divided by the number of firms in CRSP. Sample universe is NYSE, AMEX, and NASDAQ firms. Firms are defined as having performance related delistings if they have delisting code that is equal to 400 or between 550 and 585.

Figure 1B: Percentage of Firms with Large Negative Special Items (1980 - 2012)



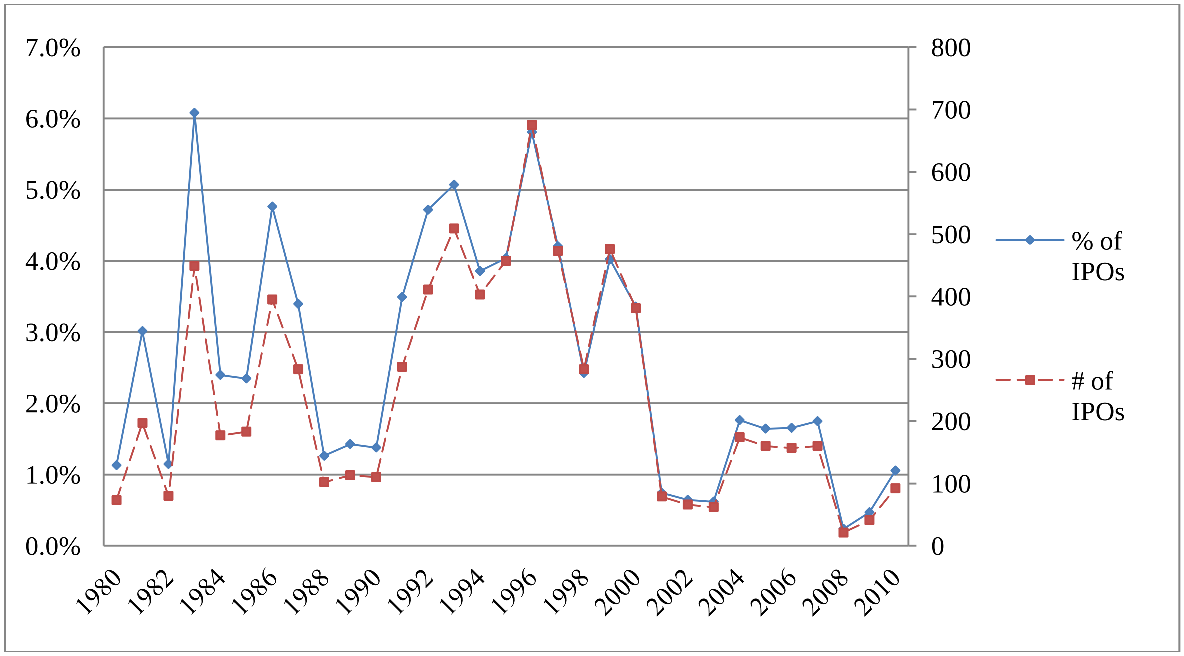
Note:
The percentage is calculated as the number of firms with negative special items in excess of 1% of total assets divided by the number of firms in Compustat.

Figure 1C: Percentage of SEOs (1980 - 2010)



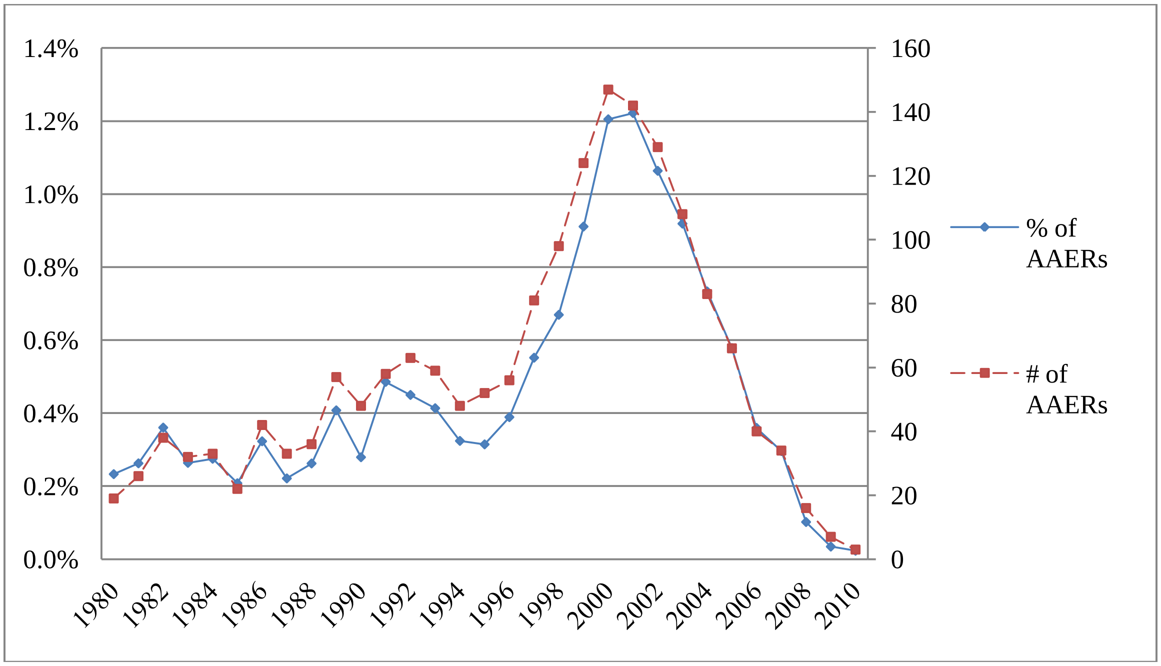
Note:
SDC: The number of SEOs in SDC database divided by the number of firms in Compustat.
Compustat: The number of firms with sstk (funds received from issuance of common and preferred stock) / market capitalization greater than 1% divided by the number of firms in Compustat.

Figure 1D: Percentage of IPOs (1980 - 2010)



Note:
The % of IPOs is calculated as the number of IPOs in Ritter (2013) divided by the number of firms in Compustat. The # of IPOs is the number of IPOs in Ritter (2013)。

Figure 1E: Percentage of Firms with Material Earnings Misstatements as Identified by the SEC's Accounting and Auditing Enforcement Releases (1980 - 2010)



Note:
The % of AAERs is calculated as the number of firms that manipulated earnings in a particular year obtained from the AAER database (see CFRM: http://groups.haas.berkeley.edu/accounting/aaer_database/) divided by the number of firms in Compustat. The # of AAERs is the number of firms in the AAER database that manipulated earnings in a particular year.

TABLE 1: Investor Response to Corporate Events

	Event	Corporate Event Short-Window Announcement Returns	Future Long-Run Returns After Corporate Event Announcements
1	Default	-3.5%	N/A
2	Bankruptcy	-21.7%	N/A
3	Predicted distress	N/A	-17.9%
4	Goodwill impairment	-1.8%	N/A
5	Predicted goodwill impairment	N/A	-21.7%
6	Restructuring charges	0.6%	-7.6%
7	Special items	-0.3%	17.0%
8	SEOs	-2.0%	-7.4%
9	IPOs	14.0%	-7.0%
10	Misstatement	-9.0%	N/A
11	Predicted material misstatement	N/A	-7.5%

Notes:
Future long run returns are measured over the annual interval.
N/A: Not applicable or not examined in this review.
The sources of each corporate event:
1. Default: Beneish and Press (1995);
2. Bankruptcy: Lang and Stulz (1992);
3. Predicted distress: Campbell, Hilscher, and Szilagyi (2008);
4. Goodwill impairments: Li and Sloan (2012), Table 5;
5. Predicted goodwill impairments: Li and Sloan (2012), Table 8, Panel B;
6. Restructuring charges announcement return: Lee (2013), Table 4, Panel B. The 0.6% is conditioned on observations in the post SFAS 146 period. Restructuring charges long-window return: Bhojraj, Sengupta, and Zhang (2009), Table 3, Panel B. The -7.6% is conditioned on firms with large restructuring charges in the post-SFAS 146 period;
7. Special items announcement return: Francis, Hanna, and Vincent (1996), Table 3. Special items (write-offs) are generally revealed at the time of earnings announcements and so the individual impact is difficult to isolate. -0.3% is our own estimate. Special items long-window return: Dechow and Ge (2006), Table 3, Panel B. The 17.00% is conditioned on firms with low accruals and large negative special items;
8. SEOs: Ritter (2003), and Rangan (1998);
9. IPOs: Lough and Ritter (2002), and Ritter (2013). The -7% is based on the finding of a -20.0% cumulative 3-year market adjusted buy-and-hold return;
10. Misstatement announcement: Dechow, Sloan, and Sweeney (1996);
11. Predicted material misstatement: Beneish, Lee, and Nichols (2012), Table 2.

TABLE 2A: Predicting Bankruptcy and Financial Distress

Study	Sample Period	#D	#ND	Accounting Variables	Market Variables	Percentage Correctly Classified
Classification Tests						
Beaver (1966)	1954-1964	79	79	CFO/TL (-) ROA (-) TL/TA (+) WC/TA (-) CA/CL (-)	N/A	1 Year - 97% 2 Years - 89% 3 Years - 89% 4 Years - 94% 5 Years - 91%
Multiple Discriminant Analysis						
Altman(1968)	1946-1965	33	33	WC/TA (+)[1] RE/TA (+) EBIT/TA (+) Sales/TA (+)	ME/TL (+)	1 Year - 94% 2 Years - 72%
Dambolena and Khoury (1980)	1969-1975	34	34	Profitability measures (5 ratios) Activity and turnover measures (4 ratios) Liquidity measures (4 ratios) Indebtedness measures (6 ratios) Standard deviation of each ratio		Not reported
Probit Models						
Zmijewski(1984)	1972-1978	81	1,600	ROA (-) TL/TA (+) CL/CA (+)		Approx. 40%
Logit Models						
Ohlson(1980)	1970-1976	105	2,058	ln (TA/GNP price-level index) (-) TL/TA (+) WC/TA (-) CL/TA (+) Neg equity (-) ROA (-) CFO/TL (-) Neg. ROA (2) (+) ΔROA (-)		1 Year - 95% 2 Years - 81%
Beaver, McNichols, and Rhie (2005)	1962-2002	544	74,823	ROA (-) TL/TA (+) EBITDA/TL (-)	Ln(ME) (-) LERET (-) LSIGMA (+)	1st decile 69% with accounting var. 1st decile 72% with market. var. 1st decile 80% with combined model
Campbell, Hilscher, and Szilagyi (2008)	1963-1998	797	1,282,853[2]	ROA (-) TL/TA (+)	NI/MTA (-)[3] TL/MTA (+) CHE/MTA (-) RSize (-) LERET (-) MTB (+) Price (-)	Not Reported
Beaver, Correia, McNichols (2012)	1962-2002	1,251	134,113	Neg. ROA (-) ROA (-) Tl/TA (+) EBITDA/LA (-) Intersections with negative ROA	Ln(ME) (-) LERET (-) LSIGMA (+) Intersections with negative ROA	1st decile 56% with accounting var. 1st decile 50% with market var. 1st decile 64% with combined model

TABLE 2A - *Continued*

Study	Sample Period	#D	#ND	Accounting Variables	Market Variables	Percentage Correctly Classified
Hazard Rate Models						
Shumway (2001)	1962-1992	229	27,997	WC/TA (-) RE/TA (-) EBIT/TA (-) Sales/TA(+) ROA (-) TL/TA (-) CA/CL (-)	ME/TL (-) Rsize (-) LERET (-) LSIGMA (+)	1st decile 69% with Market var. 1st decile 75% with combined model
Chava and Jarrow (2004)	1962-1999	404	72,184	Shumway (2001)		1st decile 72% with market var. 1st decile 74.4% with combined model 1st decile 72.8% with IE[4] 1st decile 60% all firms[5]
Distance to Default Models						
Hillegeist, Keating, Cram, and Lundstedt (2004)	1980-2000	756	77,344[6]	Distance-to-Default[7]		Not reported
Vassalou and Xing (2004)	1971-1999	93,702		Distance-to-Default[7]		Not reported
Multiple Models						
Bharath and Shumway (2008)	1980-2003	1,449	350,662	ROA (-)	Distance-to-Default [7] Ln(ME) (-) Ln(FD) (+)[8] LERET (-) 1/LSIGMA (-)	1st decile 65%[8] 1st decile 75.8%[8]
Correia, Richardson and Tuna (2012)	1980-2010	1,797	194,481	Distance-to-Default [7] Beaver et al. (2012) Bharath and Shumway (2008) Moody's EDF[10]		N/A[9]
Accounting Based Fundamental Analysis						
Piotroski (2000)[11]	1976-1996	14,043		F_ROA F_ ΔROA F_CFO F_ACCRUAL F_ΔMARGIN F_ΔTURN F_ΔLEVER F_ΔLIQUID EQ_OFFER		1.8% of high score firms (financially strong firms) gets performance related delistings while the percentage is 10.1% for low score firms (financially weak firms).

Notes:
1. Lower Z-Score indicates higher risk, and therefore the signs here are in line with other findings.
2. Monthly observations.
3. MTA is total assets adjusted: MTA = TA + 0.1(ME-BE).

TABLE 2A - *Continued*

Notes:

4. Industry effects.
5. The sample includes all firms including financial institutions.
6. Different models have different number of observations. Numbers here are based on Shumway (2001).
7. Distance-to-Default is calculated as follows:
   DD (t) = (log (V_A/D))+(r - 1/2 * σ_A^2) (T-t) / (σ_A * sqrt (T-t)), where V_A is value of the assets, σ_A is the volatility of the value of the assets, and D is the face value of debt. DD (t) is then transferred into a probability measure using the normal distribution.
8. Ln (ME) and Ln (FD) are the natural logarithms of market equity and face value of debt, respectively.
   A probability measure based on a hazard rate model that includes only DD correctly estimates 65% of the bankruptcy cases in the first decile. A probability measure that includes DD and some other market variables accurately estimates 75.8% of the bankruptcy cases in the first decile.
9. They use the "power curve" to evaluate the various default forecast models. The differences across models seem to be small and not statistically significant.
10. Moody's KMV model uses a very similar approach to calculate their Estimated Default Frequencies (EDF) measure. The major difference comes from the conversion of the calculated distance measure to the probabilities. Moody's use their own historical distribution of defaults instead of a normal distribution.
11. Piotroski (2000) focuses on high book to market firms and assigns a value of 1 to each variable if it is positive (except ΔLEVER and ΔLIQUID) so the highest score is 9.

TABLE 2B: Financial Distress and Future Performance

Study	Model Used	Outcome
Negative Relation Between Distress Risk and Future Returns		
Dichev (1998)	Z-Score O-Score	High probability of bankruptcy is not rewarded with high stock returns. Firms with high bankruptcy risk earn substantially lower than average returns.
Piotroski (2000)	Piotroski Score	Within the high book-to-market firms, a trading strategy that longs firms with high F-Score (financially strong firms) and shorts firms with low score (financially weak firms generates abnormal annual returns of 23%. Mean ROA is -7.9% and 2.7% for financially weak firms and financially strong firms, respectively.
Griffin and Lemmon (2002)	O-Score	The book-to-market anomaly is more pronounced for financially distressed firms. Negative relationship between distress risk and future returns exists within low book-to-market firms.
Campbell, Hilscher, and Szilagyi (2008)	Logit (Both accounting and market variables)	Financially distressed stocks earn lower than average returns. The distress risk measure is updated in a monthly basis and the negative relation between financial distress and future returns is reported for one-month ahead returns.
Garlappi, Shu, and Yan (2008)	Moody's EDF	Higher default probabilities are not associated with higher expected stock returns.
Correia, Richardson, and Tuna (2012)	Distance-to-Default Beaver et al. (2012) Bharath and Shumway (2008) Moody's EDF	They link the forecasting accuracy of default and bankruptcy prediction models to credit market data. They find a positive association between the differences in actual credit spreads and implied credit spreads based on default forecast models and future credit returns.
Positive Relation Between Distress Risk and Future Returns		
Vassalou and Xing (2004)	Distance-to-Default	Small firms and value stocks earn higher returns than big firms and growth stocks if risk of default is high. High-default-risk firms earn higher returns than low default risk firms, only if they are small in size and/or high BM. The raw returns to the portfolios based on default-risk show a positive relationship between one-month ahead returns and default risk.
Chava and Purnanandam (2010)	Hazard Rate Model Distance-to-Default	When implied cost of capital is used as the measure of expected return, there is a positive relation between distress risk and expected returns.

TABLE 3A: Predicting Downsizing

Study	Sample Period	Treatment	Non-treatment	Accounting Variables	Other Variables	Classification
Goodwill Impairments						
Francis, Hanna, and Vincent (1996)	1989 - 1992	93 goodwill impairments[2]	Firms matched by year[3]	**ΔBTM (-)** BTM (-) **ΔROA (-)** IND_Sales growth (+) **IND_ΔBTM (-)** **IND_ΔROA (-)** **Good (-)** Poor (-) **History (+)** **IND_History (-)** **Log(sales) (+)**	**CAR_{t-1} (-)** **CAR_{t-5} (-)** **ΔManagement (+)**	Pseudo $R^2 = 0.326$
Hayn and Hughes (2006)	1988 - 1998	180 acquiring firms	1,096 acquiring firms	**Segment-level ROA (-)** Firm-level ROA (-) **ΔSegment-level ROA (-)** **Goodwill (+)** Loss_DUM (+) Sales_Growth (-) ΔCompetition (+)	**Overpayment (+)** Other acquisition variables[4]	Pseudo $R^2 = 0.128$
Gu and Lev (2011)	1990 - 2006	417 acquiring firms	1,719 acquiring firms	**Goodwill (+)**	**Overpayment (+)** Other acquisition variables[4] **Log (MV) (-)**	Pseudo $R^2 = 0.251$
Li, Shroff, Venkataraman, and Zhang (2011)	1996 - 2006	1,584 Firms	1,584 firms matched on industry, market value and book-to-market ratio	**H_MTB prior to acquisitions (+)**	**Overpayment (+)** Other acquisition variables[4] Acquirer's Log (MV) (+) Target's Log (MV) (-)	Pseudo $R^2 = 0.226$
Li and Sloan (2012)	Pre and post SFAS 142	6,613 firm-years	42,837 firm-years	**Goodwill (+)** **ROA (-)** **BTM (+)** **IMPI (+)**	**CAR_{t-1} (-)**	Top decile 34.3%[5]

TABLE 3A - *Continued*

Study	Sample Period	Treatment	Non-treatment	Accounting Variables	Other Variables	
Write-offs / Special items						
Francis, Hanna, and Vincent (1996)	1989 - 1992	674 write-offs[2]	Firms matched by year[3]	See Panel A: Goodwill Impairments	See Panel A: Goodwill Impairments	Pseudo R^2 = 0.049
Restructuring Charges						
Francis, Hanna, and Vincent (1996)	1989 - 1992	191 restructurings[2]	Firms matched by year[3]	See Panel A: Goodwill Impairments	See Panel A: Goodwill Impairments	Pseudo R^2 = 0.125
Bens and Johnston (2009)	Pre and Post EITF No. 94-3	420 firms	3,641 firms matched by industry	<u>Predictors of REST:</u> **AR_TO (-)** **INV_COGS (-)** **PPE_TO (-)** **Sales_EMP (+)** **Loss_DUM+)** **PM (-)** **ΔROE (+)**	<u>Predictors of REST:</u> **CAR_{t-1} (-)** **ΔGDP (-)**	R^2 = 0.122
				<u>Predictors of Excess:</u> **$Bath_t$ (+)** $Smooth_t$ (-) AST_DISP[6] (+) **ACC_t[6] (+)** **Reversal[6] (+)** **Log (Assets) (-)** **Leverage (-)**	<u>Predictors of Excess:</u> **EITF No. 94-3 (-)** ΔManagement (+) ΔEMP[6] (+)	R^2 = 0.205

Notes:

1. We predict the downsizing event in year t, and all the financial and nonfinancial variables are measured at year t-1 unless there is a subscript indicating the true time period in which the variable is measured. The signs of the coefficients of each variable are reported in parentheses. (+) indicates that a higher value of the variable is more likely to result in the predicted event (goodwill write off, restructuring charge, negative special item). (-) indicates the opposite. Variables are defined in Table 3C.
2. The number of firm-year observations is not reported in Francis et al. (1996).
3. The sample size of non-treatment firms equals to the sample size of treatment firms.
4. Other acquisition variables include indicators of multiple bidders, tender offers, and termination fees, the percentage of stock transactions, the percentage of foreign acquisitions made by acquirers, acquirers' one-year abnormal return after the acquisition announcement, and acquirers' intensity in acquisition activities.
5. Top decile predicts 34.3% of sample with goodwill impairment. The percentage of firms with actual impairment is 32.7% (see Li and Sloan 2012, Table 4).
6. These variables are ex post discretionary accounting measures. They use financial/nonfinancial information after the restructuring.
7. Significant variables are bolded.

TABLE 3B: Downsizing and Future Performance

Study	Data	Findings
Goodwill Impairment		
Li, Shroff, Venkataraman, and Zhang (2011)	Quarterly	Goodwill impairment is a leading indicator of a decline in future sales growth and operating income growth. Analysts appear to incorporate these implications into their EPS forecasts.
Write-offs / Special Items		
Burgstahler, Jiambalvo, and Shevlin (2002)	Quarterly	Analyze the role of negative special items within the context of the post earnings announcement drift. They show that the negative special items lead to positive future earnings innovations. They find that investors underestimate the innovation effect.
Dechow and Ge (2006)	Annual	Show that the positive future returns for low accrual firms are mainly driven by low accrual firms with special items.
Cready, Lopez, and Sisneros (2010)	Quarterly	Show that investors respond more to negative special items for firms that have a history of reporting negative special items, consistent with investors' understanding that special items reported in the current quarter are likely to be more persistent.
Restructuring Charges		
Chaney, Hogan, and Jeter (1999)	Quarterly	Restructuring charge announcements cause analysts to revise down forecasts of future earnings although they are still too optimistic.
Atiase, Platt, and Tse (2004)	Annual	Restructuring charges are significantly positively associated with improvements in post-restructuring earnings and operating income, but this association is largely driven by firms with multiple restructurings. There is mixed evidence on the association between restructuring charges and post-restructuring improvements in cash flow from operations.
Bhojraj, Sengupta, and Zhang (2009)	Annual	They replicate Dechow and Ge (2006) and find that both the negative effect of restructuring charges on future earnings and the market overreaction to restructuring charges are smaller subsequent to SFAS 146. Thus restructuring firms with low accruals do not generate higher future stock returns in the post SFAS 146 period.
Lee (2013)	Annual	Restructuring charges become more persistent after SFAS 146. Investors place a higher valuation multiple on restructuring charges, consistent with them understanding the greater persistence of restructuring charges.

TABLE 3C: Variables

Variables		Definitions
ACC	=	Firm level accrual / Assets - Industry level accrual / Assets (accrual = change in current assets - change in cash - change in current liability+ change in short-term debt - depreciation);
AR_TO	=	Sales / Trade receivables;
AST_DISP	=	Sum of proceeds from asset disposals in year t+1 and t+2 / Total assets;
Bath	=	1 if there are incentives to take a big bath, 0 otherwise;
BTM	=	Book-to-market ratio;
CAR	=	Cumulative abnormal return;
ΔCompetition	=	Change in the level of industry competition;
EITF No. 94-3	=	1 if it is the post-EITF No. 94-3 period, 0 otherwise;
ΔEMP	=	Change in number of employees from the year before to two years after restructurings / Sales;
Excess	=	Abnormal restructuring charges / Market value;
ΔGDP	=	Annual percentage change in real U.S. GDP;
Good	=	1 if a firm has a positive earnings surprise, 0 otherwise;
Goodwill	=	Goodwill / Total assets;
H_MTB	=	1 if the acquirer's MTB prior to the acquisition falls in the top quartile of its distribution, 0 otherwise;
IMPI	=	1 if the firm has goodwill in the top decile and ROA in the bottom decile, 0 otherwise, -1 if a firm's goodwill falls below the annual median and ROA falls above the annual median, and 0 otherwise;
IND_ΔBTM	=	Industry level ΔBTM;
IND_ΔROA	=	Industry level ΔROA;
IND_History	=	Industry-level history of reporting negative special items;
IND_Sales growth	=	Industry level sales growth;
INV_COGS	=	Cost of goods sold / Inventory;
Leverage	=	Debt / Total assets;
Loss_DUM	=	1 if a firm reports operating loss or net loss, 0 otherwise;
ΔManagement	=	1 if a firm experiences a change in CEO or top management, 0 otherwise;
MTB	=	Market-to-book ratio;
Overpayment	=	Overpayment for the target;
PM	=	Profit margin;
Poor	=	1 if a firm has a negative earnings surprise, 0 otherwise;
PPE_TO	=	Sales / PP&E;
REST	=	Restructuring charges / Market value;
Reversal	=	Sum of reversals of restructuring charges in year t+1, t+2, t+3/ $REST_t$;
ROA	=	Return on assets;
ROE	=	Return on equity;
Sales_EMP	=	Sales / Number of employees;
Sales_Growth	=	Percentage change in sales;
SFAS142	=	1 if it is the post-SFAS 142 period, 0 otherwise;
SFAS146	=	1 if It is the post-SFAS 146 period, 0 otherwise;
Smooth	=	1 if there are incentives to smooth earnings, 0 otherwise;
Transition SFAS142	=	1 if it is the transition period of SFAS 142, 0 otherwise;

TABLE 4A: Predicting Initial Public Offerings (IPOs)

Study	Period	Treatment	Non-treatment	Accounting Variables	Other Variables	Classification
Friedlan (1994)	1981-1984	155 US firms	Firms matched by industry/year or industry/year/sales growth	**Disc. acc. (+)** **ΔAcc./sales (+)** **ΔNI/sales (+)** ΔCF/sales (+)	N/A	N/A
Pagano, Panetta, and Zingales (1998)	1982-1992	69 Italian firms	12,391 observations	**Log sales (+)** **Sales growth (+)** CAPX/PPE (+) Debt/AT (-) **ROA (+)**	Bank rate (+) Herfindahl index (-) **Industry MTB (+)**	Pseudo R^2 = 10%
Teoh, Wong, and Rao (1998)	1980-1990	1,682 US firms	Firms matched by performance	**Income increasing. Dep. policy (-)** **Bad debt/receivables (-)**	N/A	N/A
Brau, Francis, and Kohers (2003)	1984-1998	3,147 US firms	2,691 target firms	N/A	**Herfindahl index (+)** **Industry** **Industry debt/assets (-)** Industry MTB (-) **IPO volume (+)** Market return (-) **3-month T-bill rate (+)** **No. of secondary shares/total shares (-)** **Transaction value (+)**	Not reported
Boehmer and Ljungqvist (2004)	1984-1995	207 Germany firms	123 firms	**Ind-adj. earnings growth (+)** **Ind-adj. Δreturn on sales (+)** **Ind-adj. sales growth (+)**	**Dum for intention to sell secondary shares (-)** Industry MTB (+) **Industry index return (+)** Age (+) Industry index return volatility (+) **Family firms (-)** **Consumer confidence index (+)** Corporate bond yield premium (-) 4-quarter IPO initial return (+) **Number of IPOs (-)**	N/A
Brau and Fawcett (2006)	2000-2002	124 IPOs	212 non-IPOs	N/A	Survey variables	N/A

TABLE 4B: IPOs and Future Performance

Study	Period	Sample	Findings
Ritter (1991)	1975-1984	1,526 firms	IPO firms that are younger, go public in high volume years, and are underpriced on the day of the issuance show poor long-term future stock performance.
Jain and Kini (1994)	1976-1988	2,126 firms	The post-issue underperformane of IPO firms is positively and significantly associated with equity retention by the original entrepreneurs.
Rajan and Servaes (1997)	1975-1987	2,725 firms	IPO firms have poor future stock performance when analysts are optimistic about a firm’s long-term prospects. When firms are divided into quartiles according to their long-term growth projections, the hedge return between the highest and the lowest projected growth quartiles is more than 100%.
Teoh, Welch, and Wong (1998a)	1980-1992	1,649 firms	IPO firms with high discretionary accruals show poor stock return performance in the three years thereafter. Issuers in the highest quartile of accruals have a three-year aftermarket stock return of approximately 20% less than issuers in the lowest quartile.
Teoh, Wong, and Rao (1998)	1980-1990	1,682 firms	IPO firms with high discretionary accruals experience poor post-issue earnings and stock performance. Return on sales in the three post-IPO years relative to the IPO year declines by 16.50% for the quartile with the highest discretionary accruals. Over the 36-month holding period, the difference of market-adjusted return between the highest and lowest quartile is around 30%.
DuCharme, Malatesta, and Sefcik (2001)	1982-1987	171 firms	IPO firms with high discretionary accruals in the year prior to the IPO or in the year of the IPO show poor future earnings and stock returns.
Teoh and Wong (2002)	1975-1990	1,395 IPOS 1,260 SEOs	Analysts are more optimistic for SEO firms reporting high accruals. Predicted analysts forecast errors from accruals significantly explain SEOs' long-term underperforamnce.
Morsfield and Tan (2006)	1983-2001	2,630 IPOs	IPO firms have lower discretionary accruals when they are backed by venture capitalists (VCs). VC-backed IPO firms experience better long-run stock performance than non-VC-backed IPOs over a three-year window.

TABLE 5A: Predicting Seasoned Equity Offerings (SEOs)

Paper	Period	Treatment	Non-treatment	Accounting Variables	Other Variables	Classification
McLaughlin, Safieddine, and Vasidevan (1996)	1980-1991	900 SEOs	900 matched firms	FCF/AT (+) ΔInd-adj CF/AT (+) **Dummy for Tobin Q >1 (+)** Tax/AT (-) **Debt/AT (+)** LogAT (+)		N/A
Guo and Mech (2000)	1980-1994	892 SEOs	5,696 non-SEOs	**CF (-)** **Diff. between debt and target debt (+)** **Log mkt cap (+)**	MTB (+) **Return (+)** Return volatility (-) Market return volatility (-) **Stock split ann. (+)** **No. of days since earnings release (-)** Dividend ann. (+) **No. Of days since dividend ann. (-)**	Pseudo R^2 = 13.44% 86.40% correct prediction
Jindra (2000)	1980-1995	2,141 SEOs	All non-SEO firms (30,862) or a matched sample (2,141 obs.)	**Leverage (+)** **ROA (-)** **RD/Sales (+)** **LogAT (+)**	**Misvaluation (+)** **Prior 6-month raw return (+)** **Tobin Q (-)** **IPO dummy (+)**	Pseudo R^2 = 25%
DeAngelo, DeAngelo, and Stulz (2009)	1975-2001	4,291 SEOs	Non-SEOs		**MTB (+)** **Prior three years return (+)** **Future three years return (-)** **No. of years listed (-)**	N/A

Alti and Sulaeman (2012)				**Log AT (+)** **ROA (-)** **CAPX/AT (+)** **RD/AT (+)** **Debt/AT (+)**	**Institutional demand (+)** Institutional ownership (+) **Previous quarter return (+)** **Prior six months return (+)** MTB (+) **No. of quarters listed (-)** **Return volatility (-)** **IPO dummy (+)** Share trading vol. (-)	Pseudo R^2 = 12.7%
Deng, Hrnjic, and Ong (2012)	1986-2009	994 SEOs made by REITs firms	29,312 non-SEOs	AT (+) Debt/AT (+) ROA (+)	**Investor sentiment (+)** **Growth (+)** **Risk premium (+)** CAR around Earn. Ann. (+) **Age (-)** NASDAQ (+) Equity REIT (-) Mortgage REIT (+)	Pseudo R^2 = 2%
Jung, Kim, and Stulz (1996)	1977-1984	192 equity issues	276 bond issues	**Tax/AT (-)** LT debts/AT (+) CF/AT (+) Liquid assets/AT (+) **AT (-)**	**MTB (+)** **RET volatility (+)** **Economy leading indicators (+)** **RET_{t-1} (+)** **Gross proceeds (-)** RET $_{t+1,\ t+5}$ (-)	77% correct prediction
Mackie-Mason (1990)	1977-1987	1,747 SEOs/debt issues		**Tax loss carry forwards/sales (+)** **Investment tax credit/sales (-)** **RD/sales (+)** **Advertising/sales (-)** **Earnings variance (+)** **PPE/equity (-)** **FCF/sales (+)** **Net assets (-)** Debt/AT (+) ΔDebt/AT (+)	**Bankruptcy (+)** **Issue value/Mcap (-)** **ΔStock price (+)** **Paying dividend (-)** **Regulated firms (+)**	75% correct equity prediction

Note:
Significant variables are bolded.

TABLE 5B: SEOs and Future Performance

Study	Period	Treatment	Findings
McLaughlin, Safieddine, and Vasudevan (1996)	1980 - 1991	1,296 SEOs	SEO firms experience a significant decrease in profitability following the offering. The decline is greater for firms that have higher free cash flow, and is smaller for firms that invest in fixed assets.
Rangan (1998)	1987 - 1990	230 SEOs	SEO firms with high discretionary working capital accruals during the year of the offering experience poor future earnings and stock performance. High discretionary accruals issuers underperform low discretionary accrual issuers by 7% to 9% in the first year following the issuance.
Teoh, Welch, and Wong (1998b)	1970 - 1989	1,265 firms	SEO firms with high discretionary working capital accruals show poorer long-term earnings and stock price performance. The return difference between the highest and lowest quartiles of discretionary accruals ranges between 42% and 61% over a five-year horizon.
Dechow, Hutton, and Sloan (2000)	1981 - 1990	1,179 SEOs	Sell-side analysts make overly optimistic long-term growth forecasts for firms issuing equity. Analysts employed by lead managers of the offering make the most optimistic growth forecasts. The post-offering underperformance is most pronounced for firms with high growth forecasts made by affiliated analysts.
Shivakumar (2000)	1983 - 1992	1,222 SEOs	SEO firms with high discretionary accruals have lower stock price reaction to the offering announcement. Investors also reduce their price response to unexpected earnings released after offering announcements. These findings suggest that investors infer earnings management and rationally undo its effects at equity offering announcements.
Lang and Lundholm (2000)	1992	41 firms	SEO firms that substantially increase their disclosure activity in the six months before the offering experience larger price declines at the announcement of offering and also in the 18 months following the announcement.

TABLE 5B - *Continued*

Study	Period	Treatment	Findings
Bradshaw, Richardson, and Sloan (2006)	1971 - 2000	99,329 obs. with external financing data	There is a significant and negative relation between corporate external financing activities and future profitability and stock returns. This result is consistent with firms timing financing activities to exploit the temporary misvaluation since external financing is shown to be positively related to overoptimism in analysts' forecasts.
Lim, Ding, and Thong (2006)	1991 - 2001	940 SEOs	Firm diversification contributes to the poor post-issue stock performance. Diversified issuers (proxied by the number of segments) with high discretionary accruals underperform other SEO firms over a 3-year holding period.
Cohen and Zarowin (2010)	1987 - 2006	1,151 SEOs	Using real earnings management proxies developed in Roychowdhury (2006), they find that the decline in post-SEO operating performance (ROA) is more attributable to real earnings management than accruals management.
Kothari, Mizik, and Roychowdhury (2012)	1970 - 2001	3,754 SEOs	Partitioning SEO firms based on the sign of abnormal ROA, abnormal R&D, and abnormal accruals, they show that real earnings management is an important driver of negative future stock return.

TABLE 6A: Predicting Material Earnings Misstatements (Samples based on the SEC Accounting and Auditing Enforcement Releases (AAERs))

Paper	Period	#T	#NT	Accounting variables	Other variables	Classification
Dechow, Sloan and Sweeney (1996)	1982-1992	92 firms	85 firms	**Accruals** **Accounting principles** **External financing**	**Board char.**[1] **Director char.** **Covenant default**	Not reported
Beasley (1996)	1980-1991	75 firms	75 firms	Growth in assets (+) Indicator for persistent loss (+)	**Board char.** **Director char.**	15%
Beneish (1999)[2]	1982-1992	74 firms	2,332 firms	**RECT/SALE growth (+)** **Gross margin growth (+)** **NCA/AT (+)** **Sales growth (-)** Dep growth (+) SGA growth (-) Debt/AT growth (-) **Accruals/AT (+)**		Pseudo R^2=37% 58% correctly classified[3]
Erickson, Hanlon, and Maydew (2006)	1996 - 2003	50 firms	100 firms	Firms' desire for external financing (+) **Debt/AT (+)** BTM (-) P/E (+) ROA (-) **Sales growth (+)** Altman's Z (-)	CEO pay sensitivity (+) MV (+) Board char. Director char. Age of firm (-) M&A (+) **Stock volatility (+)**	Not reported
Dechow, Ge, Larson, and Sloan (2011)	1982-2005	494 obs.	132,967 obs.	**RSST accruals (+)** **ΔRECT (+)** **ΔINVT (+)** **%Soft assets (+)** **ΔCash sales (+)** **ΔROA (-)**	**Issuance (+)** Δemp (-) **ΔOplease (+)** **Ret (+)** **Lag_Ret (+)**	69% correctly classified[4]
Feng, Ge, Luo, and Shevlin (2011)	1982-2005	116 obs.	219 obs.	F-score variables	**CEO pay sensitivity (+)** CFO pay sensitivity **CEO paysclice (+)** **Director char.**	Not reported
Price, Sharp and Wood (2011)	1995-2008	444 obs.	48,376 obs.	WC accruals (+) M-score (+) **F-score (+)** Accruals quality (+) Disc. acc. (+) **Residual audit fees (+)**	**Audit integrity's accounting and governance risk score (+)**	Pseudo R^2=12%

TABLE 6A - *Continued*

Paper	Period	#T	#NT	Accounting variables	Other variables	Classification
Hribar, Kravit and Wilson (2013)	2000-2007	140 obs.	140 obs.	**Residual audit fees (+)** Accrual quality (-) **Abs_Disc. acc. (-)** Smooth (-) Std. Dev. of CFO (+) F-score variables	BTM (+)	Pseudo R^2=11%

Notes:

1. Board char.: board of directors characteristics. Director char.: director characteristics.
2. M-Score = -4.840 + 0.920*DSRI + 0.528*GMI + 0.404*AQ + 0.892*SGI + 0.115*DEPI - 0.172*SGAI - 0.327*LVGI + 4.697*TATA.
   F-Score = -7.893 +0.790*rsst_acc + 2.518*ch_rec + 1.191*ch_inv + 1.979*soft_assets + 0.171*ch_cs -0.932*ch_roa + 1.029*issue
3. Based on the M-Score, the percentage of correctly classified manipulators ranges from 58% to 76%. The percentage of incorrectly classified nonmanipulators ranges from 7.6% to 17.5%.
4. Based on the F-Score, the percentage of correctly classified manipulators is 69%. The percentage of incorrectly classified nonmanipulators is 36%.
5. Significant variables are bolded.

TABLE 6B: Future Performance after the Announcement of Material Earnings Misstatements (Samples based on the SEC Accounting and Auditing Enforcement Releases (AAERs))

Paper	Sample Period	Treatment	Findings
Farber (2005)	1982 - 2000	87 firms	AAER firms with improved governance after fraud detection do not show an increase in analyst following or institutional holdings, but have superior stock price performance in the following three years.
Leng, Feroz, Cao and Davalos (2011)	1982 - 2004	229 firms	AAER firms experience significantly negative abnormal operating and stock performance up to three years following the AAER announcement. They are also more likely to fail in the post-AAER period. 28% of AAER firms either go bankrupt or are delisted after the enforcement actions.