To Catch a Thief: Can forensic accounting help predict stock returns?

Messod D. Beneish, Charles M.C. Lee, D. Craig Nichols**

August 15, 2011

Abstract

An earnings manipulation detection model based on forensic accounting principles (Beneish 1999) has substantial out-of-sample ability to predict cross-sectional returns. We show that the model correctly identified, ahead of time, 12 of the 17 highest profile fraud cases in the period 1998-2002. Moreover, the probability of manipulation estimated from this model (PROBM) consistently predicts returns over 1993-2007, even after controlling for size, book-to-market, momentum, accruals and the level of open short interest. Separating high PROBM from low PROBM firms within each of these characteristic deciles greatly improves long/short hedge returns. Further analyses show that PROBM also helps predict future earnings because of its ability to anticipate the persistence of current years' reported accruals. Overall, our findings offer significant empirical support for the investment approach advocated by forensic accountants.

Comments Welcome
Please do not quote without permission

** Beneish (dbeneish@indiana.edu) is Sam Frumer Professor of Accounting at Indiana University, Lee (clee8@stanford.edu) is Joseph McDonald Professor of Accounting at Stanford University, and Nichols (dcnichol@syr.edu) is Assistant Professor of Accounting at Syracuse University. An earlier version of this paper was presented at the June 2007 Corporate Ethics and Investing Conference of the Society of Quantitative Analysts, the May 2008 LSV-Penn State Conference, and workshops at Cornell University, Indiana University, the University of Maryland and Notre Dame University. The authors would like to thank the participants at these workshops, as well as C. Harvey, P. Hribar, J. Salamon, and C. Trzincka, S. Bhojraj, D. Givoly, J. Lakonishok, M. Lang, A. Leone, R. Morton, B. Swaminathan, P. von Hippel, N. Yehuda, and X. Zhang, for helpful discussions and comments. We also thank M. Drake, L. Rees, and E. Swanson, for kindly sharing their short-selling data with us.

1. Introduction

In an ideal world, companies' financial statements always convey a concise, but representatively faithful, portrait of the corporation's state of financial affairs. Unfortunately, due either to limitations inherent in the language of accounting, or divergent incentives between a firm's managers and its capital providers, published financial statements often fall short of this ideal. Sometimes one must look deeper into a firm's financial reports to extract important elements of its true economic conditions.

In recent years, the term "Forensic Accounting" has acquired currency as a moniker for the art and science of carefully investigating company financial records with a view toward forecasting its future prospects. Closely related to the "Quality of Earnings" analysis popularized by O'Glove (1987), Kellogg and. Kellogg (1991) and Siegel (1991), forensic accountants pour over company's financial statements looking for inconsistencies, irregularities, and other signs of trouble. While these efforts have resulted in individual success stories (see Schilit (2002) for a number of case studies), the evidence to date has been largely anecdotal.

In this study, we provide new evidence on the overall efficacy of "forensic accounting" in detecting corporate fraud and predicting stock returns. Our focus is on a statistical model built by Beneish (1999) that relies on financial statement information to detect accounting manipulation. This model was estimated using data from the period 1982-1988 and its holdout sample performance was assessed in the period 1989-1992. Since the publication of the original study, this model has attracted attention after flagging Enron well in advance of its eventual demise.[1] It has been featured in financial statement analysis textbooks (e.g., Fridson 2002, Stickney et al. 2003) and in articles directed at auditors, certified fraud examiners, and investment professionals (e.g., Cieselski 1998, Merrill Lynch 2000, Wells 2001, DKW 2003, Harrington 2005). However, direct evidence of its out-of-sample performance is, once again, ad hoc and anecdotal.

[1] The model gained widespread recognition when a group of MBA students at Cornell University posted the earliest warning about Enron's accounting manipulation score using the Beneish (1999) model a full year before the first professional analyst reports (Morris 2009). This episode in American financial history is preserved in the Enron exhibit at Museum of American Finance, New York (www.moaf.org) and is also recounted in Gladwell (2009).

In this analysis, we show that the Beneish (1999) model performs quite well in detecting accounting fraud among a sample of the most famous cases in recent years. We use a list of "highest profile" fraud cases as identified by www.auditintegrity.com (see Table 1 for details). Using the exact model published in the *Financial Analyst Journal* in 1999 we find that 12 out of the 17 best known non-financial fraud cases during 1998-2002 were flagged by the model using financial information available well in advance of the public disclosure of their accounting problems. On average, the Beneish (1999) model flags 14.5% of all firms as potential manipulators; therefore, the "hit rate" of 71% (12 out of 17) among these large fraud cases is highly statistically significant.[2]

We also extend the literature on forensic accounting by examining the ability of the Beneish (1999) model to predict stock returns. While relatively few firms are actually indicted for accounting fraud, the probability of manipulation generated by the model may well be indicative of a firm's future prospects. Specifically, we conjecture that firms which share common attributes with known earnings manipulators (i.e. those who "look like thieves"), also have other problems (either lower earnings quality or more challenging economic conditions) that are not yet fully transparent to the market. Although the accounting games they engage in might not result in future indictments, on average these firms will earn lower future returns.[3]

Our evidence shows that the Beneish (1999) model, exactly as originally published, exhibits a strong ability to predict stock returns out-of-sample. Between 1993 and 2007 (a 15-year period that is subsequent to the model's estimation and holdout samples), firms that were flagged as potential earnings manipulators by the model returned 9.7% lower annualized size-adjusted returns than firms that were not flagged. A strategy that shorts flagged firms (approximately 15% of all firms) and buys all the other firms earns positive returns in 13 out of 15 years.

[2] Collectively, these firms lost over $180 billion in market capitalization upon public disclosure of their accounting problems, suggesting these results are also economically significant.

[3] We are aware of no prior study that focuses on this hypothesis. The focus of Beneish (1999) and Dechow et al. (2011) is on fraud detection and neither provides evidence on the efficacy of the model as an out-of-sample forecaster of stock returns. Testing an earlier prototype model, Beneish (1997) provided limited evidence of return predictability in a small sample with only 468 firm-years in the pre-1993 period (i.e. prior to the start of our sample).

The probability of manipulation produced by the model (PROBM) seems particularly effective when used in conjunction with other known predictors of cross-sectional returns. In a multivariate Fama-MacBeth framework, PROBM has incremental predictive power for cross-sectional returns after controlling for the book-to-market ratio (BTM), firm size (MVE), total accruals (Accruals), price momentum (Momentum), and the level of open short interest (SIRatio). In fact, PROBM is associated with the second largest long/short extreme-decile hedge return and has the highest t-statistic among these six variables in a multivariate regression framework.

The predictive power of PROBM is also quite robust across multiple sub-populations. Sorting firms first into deciles by each of the other five firm characteristics (Momentum, MVE, BTM, SIRatio, or Accruals), we find that firms identified by PROBM as potential manipulators (flagged firms) systematically underperform non-flagged firms in virtually every decile of every sort variable. For example, a momentum strategy's one-year-ahead size-adjusted return of 9.2% is more than doubled (to 23.5% per year) when PROBM is used to select potential manipulators from within momentum losers and to select non-manipulators from within momentum winners.

Because of its relatively high correlation with the Accruals variable, we conduct an extensive analysis of the joint ability of Accruals and PROBM to predict returns. We show that when firms are sorted on these two variables independently, PROBM is particularly effective in predicting returns among low Accruals firms (i.e. firms that have "high earnings quality" according to their accrual ranking). Among firms in the lowest Accrual quintile, the spread in size-adjusted returns between high PROBM firms and low PROBM firms is -15.7% over the next 12 months. Among firms in the second lowest Accrual quintile, the spread is -9.2% per year. In contrast, Accruals has no significant ability to predict returns within any PROBM quintile.

One problem with the independent sort for highly correlated variables is the uneven number of observations within each resulting group. We address this limitation using nested sorts. The dominance of the PROBM variable over Accruals is striking when the two variables are sorted sequentially. When firms are first sorted by PROBM and then allocated evenly by Accruals, PROBM shows strong predictive power for returns in all five Accrual quintiles, while Accruals has little or no power to predict returns in any of the PROBM quintiles. Conversely, when firms are first sorted by Accruals, then sorted into quintiles by PROBM, we find that PROBM is effective as a predictor of returns in all but the middle Accrual quintile.

To shed further light on the source of PROBM's predictive power, we examine its incremental ability to predict the persistence of firms' earnings. Prior studies have demonstrated that the cash flow component of earnings is more persistent than the accruals component (for example, see Sloan (1996) and Richardson et al. (2005)). We extend this analysis by exploring the differential persistence of one-year-ahead accruals for high and low PROBM firms. In other words, we examine the information content of PROBM in forecasting next year's earnings, and in particular the accrual component of earnings. If the forensic accounting principles that underpin this model are useful in separating firms with relatively high/low quality earnings, this fact should be evidenced in a difference in the persistence of future accounting accruals.

Our analysis reveals two striking findings. First, the one-year-ahead persistence of *income-increasing* accruals is significantly lower for high PROBM firms. Specifically, firms in the lowest PROBM decile have an average income-increasing accrual persistence of 0.810 (which is comparable to the persistence of cash flows in magnitude), while firms in the highest PROBM decile have an average accrual persistence parameter of only 0.433 (almost half as large, and statistically significantly different). In other words, for firms reporting income-increasing accruals, PROBM is highly effective in discriminating between those whose accruals will reverse next year, and those whose accruals will persist.

We also observe a symmetric result among firms reporting *income-decreasing* accruals in the current year. Among firms with income-decreasing accruals, those in the highest PROBM decile have an average accrual persistence of 0.628, while those in the lowest PROBM decile have an average persistence of 0.350. In other words, any income-decreasing accrual reported in the current year is much more likely to persist for high PROBM firms than for low PROBM firms. Once again, this result shows that PROBM is useful in predicting future earnings because of its ability to anticipate the persistence of current years' reported accruals.

Overall, our analyses provide significant support for use of forensic accounting in equity investing. We show the Beneish (1999) model is effective in detecting accounting fraud in a sample of some of the most famous cases in recent years. We also show that this model has incremental ability to predict stock returns beyond the usual suspects commonly used by quantitative equity managers. Our evidence indicates the efficacy of the model derives from its ability to separate firms whose accruals are more likely to persist from those whose accruals are more likely to reverse. Since Beneish developed his model using forensic accounting principles, and the parameters for the model were estimated using prior period data, our findings serves as out-of-sample validation for the general approach advanced by forensic accountants.

The remainder of the paper proceeds as follows. In the next section, we discuss the Beneish model and its conceptual underpinnings. In Section 3 we explore its ability to predict cross-sectional returns. Finally, in Section 4, we summarize and discuss the implications our findings.

2. The Detection Model

Beneish (1999) profiles firms that manipulate earnings (firms either charged with manipulation by the SEC, or admitted to manipulation in the public press) and develops a model to distinguish manipulators from non-manipulators using financial statement variables. The model presented in Beneish (1999) exclusively uses financial statement data and is thus useful in assessing fraud potential in firms without appeal to security prices (for example, in pricing an initial public offering). In the original paper, this model was estimated using data from the period 1982-1988 and its holdout sample performance assessed in the period 1989-1992.

In the Appendix we briefly describe the computation and intuition behind the model's variables, loadings on those variables, and provide tabulations of the sample distribution over time and across industries. These reveal an increasing frequency of SEC Accounting and Auditing Enforcement Actions over the sample period, and, unsurprisingly, a high concentration of manipulators in software, hardware and retail concerns (13.5%, 9.5% and 6.8% of the sample manipulators.

Beneish validates his models in three ways. First, examining a variant of the model we use in this paper, Beneish (1997) shows that the model's ability to predict earnings manipulation compares favorably to that of accrual expectation models based on Jones (1991). In particular, the model correctly classifies 64% of firms charged with financial reporting violations whereas accrual expectation models identify between 23 and 30% of such firms. Second, Beneish (1997) shows the model distinguishes manipulators from firms with large accruals/abnormal accruals. This is important given the evidence of anomalous returns to extreme accrual deciles (e.g., Sloan 1996). Among firms in the highest accrual decile, Beneish (1997) shows that firms identified as manipulators by the model have significantly more negative one-year-ahead returns. Third, Beneish (1999) shows the model is able to distinguish earnings manipulators from all non-manipulators in the same industry.

Although the study that developed the model we use here was published in 1999, out-of-sample prediction of fraud ended in early 1993. In Table 1, we demonstrate the continued relevance of the model to detect fraud by examining its performance for well-known fraud cases from 1998-2002 (as reported by auditintegrity.com). This period was marked by an unusual number of high profile fraud cases that helped spur forensic accounting to prominence. As Table 1 shows, the model predicted the fraud in 12 of the 17 firms, including Cendant, Enron, Global Crossing, Qwest and several other famous cases. On average, the model detected the fraud a year and a half *before* the public revelation. Of particular note, the model received attention subsequent to the Enron scandal as the investing public discovered that the model had flagged Enron prior to the debacle.[4]

Despite the usefulness of the model in detecting fraud, only limited evidence exists on the ability of PROBM to predict returns. Beneish (1997) shows that firms classified as manipulators experienced poorer one-year-ahead returns than firms with extreme positive accruals. Teoh et al. (1998) applied PROBM as an alternative proxy for the occurrence of earnings management in the context of initial public offerings, and documented that firms with higher probabilities of

[4] On January 25th, 2002, the Wall Street Journal reported that in seizing e-mails at Arthur Andersen, Congress found evidence that the Chicago office of Arthur Andersen had issued two "alerts" to the Houston office in the spring of 2001 with respect to earnings manipulation at Enron. The alerts came from a tailored version of the model that Beneish had estimated under a consulting relationship with Andersen. ("Andersen Knew of `Fraud' Risk at Enron --- October E-Mail Shows Firm Anticipated Problems Before Company's Fall", 01/25/2002, A3).

manipulation subsequently experienced poorer stock market performance. We extend this research by examining the ability of PROBM to predict returns in a broad cross-section of firms, and by conditioning high PROBM on known predictors of one-year-ahead returns.

3. Does PROBM predict future returns?

3.1 Sample

We select the initial sample from the Compustat Industrial, Research, and Full Coverage files for the period 1993 to 2007. We eliminate (1) financial services firms (SIC codes 6000 – 6899), (2) firms with less than $100,000 in sales (Compustat #12) or in total assets (Compustat #6), (3) firms with market capitalization of less than $50 million at the end of the fiscal period preceding portfolio formation, and (4) firms without sufficient data to compute the probability of manipulation. Following Beneish (1999), we winsorize the predictive variables in the probability of manipulation model at the 1 percent and 99 percent levels each year in our sample period to deal with problems caused by small denominators and to control for the effect of potential outliers.

We compute size-adjusted returns following a slightly modified version of the procedures outlined in Lyon, Barber, and Tsai (1999).[5] To form reference portfolios, we first identify decile portfolio breakpoints based on all NYSE firms. We then assign all NYSE, AMEX, and Nasdaq firms to portfolios based on those breakpoints. The smallest portfolio has a disproportionately large number of stocks, so we further sort those stocks into five portfolios based on market cap. The end result is 14 size-based portfolios. We then accumulate returns for 12 months starting with the first day of the next month following portfolio assignment. If a firm delists, we include returns to the delist date as well as any delisting return reported by CRSP. If a delist return is missing, we estimate it using the procedures outlined in Beaver, McNichols, and Price (2007). As in Lyon, Barber, and Tsai (1999), from the month following delisting to the end of the holding period, we assume the proceeds from delisting, if any, were invested in the CRSP size-based portfolio to which the firm belongs.

[5] Although Lyon, Barber, and Tsai (1999) form reference portfolios once per year, we perform our sorts and form reference portfolios monthly. This is because the return windows for our stocks are not aligned by calendar date (i.e. they begin in the fifth month after the end of the fiscal year for each stock).

To compute size-adjusted returns, we accumulate returns for twelve months starting with the fifth month after year end using the same delisting procedures described above, if necessary. We use the stock's market cap at the end of the fourth month following the fiscal year end to identify its reference portfolio. We then subtract the return for the reference portfolio from the return for the firm.

To ensure that the trading strategies that we examine are implementable, we require all firms used in our rankings to have stock return data available in the CRSP tapes at the time rankings are made, and use prior year decile cut-offs to assign firms to deciles of the ranking variable (e.g., the probability of manipulation, accruals, momentum, etc.) in the current year. Our trading strategy return computations are based on taking positions four months after the end of the fiscal year. The final sample consists of 33,848 firm-year observations from 1993 to 2007.

3.2 PROBM and future returns

Although Table 1 and prior research (e.g., Beneish 1999) demonstrate the ability of the Beneish model to identify firms that commit fraud, very few instances of fraud are ever actually revealed. Beneish (1999) examines 74 cases of fraud from 1982 to 1993. Dechow, Ge, Larson, and Sloan (2011), who investigate Accounting and Audit Enforcement Actions (AAERs), report less than 0.5% of the firm-years in their sample are associated with fraud. The Beneish model, however, flags nearly 15% of firm-year observations as potential frauds. In this section, we examine the consequences of flagging such a large proportion of firms as frauds when the rate of discovered fraud is so low.

Table 2 compares returns for firms that are flagged as probable manipulators to the returns of firms that are not flagged. Overall for the full sample, flagged firms generate one-year-ahead size-adjusted returns of -6.6%, while firms that are not flagged experience positive returns of 3.1%. Both of these average returns are statistically significant. Firms that are not flagged outperformed flagged firms by 9.7% on average, and this is also statistically significant.

Table 2 also compares flagged and not-flagged firms by year. The spread in returns across not-flagged and flagged firms is negative in only two years (2002 and 2004), and is significantly negative in only one year (2004). Firms that are not flagged significantly outperform flagged firms in nine years. Overall, Table 2 suggests flagged firms either have troubling accounting issues or face difficult economic circumstances that come to light at a later date. This confirms that merely "looking like a thief" is associated with poor future performance. These results also mitigate concerns over flagging a large number of firms as potential frauds when the rate of discovered fraud is so low.

3.3 Distinguishing PROBM from alternative predictors of future returns

Prior research shows that a number of characteristics are correlated with subsequent returns: (1) accruals, following Sloan's (1996) evidence that accruals are negatively correlated with future returns, (2) the book-to-price ratio, following evidence in Chan et al., (1996) Davis (1994) and Haugen and Baker (1996), who document that firms with high market-to-book ratios subsequently earn lower returns; (3) price momentum, following evidence in Jegadeesh (1990), and Jegadeesh and Titman (1993) that short-run returns tend to continue in the subsequent year; (4) firm size, following evidence in, among others, Fama and French (1992), and (5) the short interest ratio following evidence in Drake et al. (2011) that firms with high short interest ratios subsequently earn lower returns.

In Table 3, we report the correlation matrix for these characteristics. We report Pearson correlations above the diagonal and Spearman correlations below the diagonal. Correlations of PROBM with three variables are noteworthy. First, PROBM and accruals are highly correlated (correlation = 0.669, $p < 0.001$). Many observers speculate that earnings management is an important reason why the implications of accruals differ from those of cash flows, suggesting that earnings management misleads investors. Thus, it is possible that both PROBM and accruals measure earnings manipulation with equal precision and that little incremental value exists in studying PROBM. Second, the negative correlations between PROBM and both Momentum and BTM suggest that firms with high probability of overstatement have momentum and glamour characteristics (low BTM). Third, the correlation between PROBM and Short Interest Ratio is positive and significant (0.042, p-value<0.001) consistent with firms that have a high probability of manipulation attraction the attention of short sellers.

These correlations lead us to investigate whether the returns to a strategy based on PROBM are subsumed by other potential predictors of future returns. We estimate the regression of one-year-ahead buy and hold size-adjusted returns ($BHSAR_{t+1}$) on scaled decile ranks of several predictors:

$$BHSAR_{t+1} = a_0 + a_1 PROBM_t + a_2 Accruals_t + a_3 Momentum_t + a_4 MVE_t + a_5 BTM_t + a_6 SIRatio_t + e_{t+1} \qquad (1)$$

In Table 4, we report the average coefficients from 15 annual cross-sectional regressions like (1). The results indicate that scaled PROBM ranks are negatively correlated with one-year-ahead abnormal returns (-0.084, t-statistic=-2.75), and that Momentum is positively correlated with one-year-ahead abnormal returns (0.085, t-statistic=2.71). The remaining variables including Accruals, MVE, BTM, and SIRatio do not attain significance. This suggests that after controlling for Accruals and other variables associated with future returns, a portfolio strategy based on PROBM earns an 8.4% abnormal return one-year-ahead.

To further evaluate PROBM's ability to predict returns, we separate the firms in each decile of MVE, BTM, Momentum, SIRatio and Accruals into high and low PROBM, where high PROBM includes the 4957 observations in our sample that are flagged as potential manipulators. The results reported in Table 5 and Figure 1 are striking. The performance of the flagged sub-sample is worse than that of its not-flagged counterpart in 49 of the 50 decile breakdowns. Furthermore, the average size-adjusted return of flagged firms is negative in 47 of the 50 deciles.

In Panel A, a size based trading strategy that buys small firms (decile 1) and shorts large firms (decile 10) yields 5% per year. By combining PROBM with size, e.g., buying small not-flagged firms and selling short large flagged firms, the strategy can be improved to yield 14.8% per year. Thus, by superimposing PROBM, the resulting strategy yields returns that are nearly three times larger than those based on size alone. In Panel B, we show that the improvement to a BTM strategy is also quite substantial. Buying value (decile 10) and shorting glamour (decile 1) yields 8.7%. Combining with PROBM, e.g., buying value not-flagged and selling glamour flagged firms the strategy's yield improves to 15.4% per year.

In Panel C, a momentum based trading strategy that buys high (decile 10) and shorts low (decile 1) yields 9.2%. Combining with PROBM, e.g., buying high momentum firms that are not-flagged and selling short low momentum firms that are flagged, the strategy's yield improves to 23.5%. Similarly in Panel D, trading on extreme short interest ratio deciles yields an abnormal return of 6.1% per year, which improves to 15.3% per year by superimposing PROBM. Finally in Panel E, we combine PROBM with Accruals. Accruals alone returns 8.3% and this yield can be improved to 13.3% per year by selling short high accrual flagged firms and buying low accrual firms that are not flagged.

Because PROBM is highly correlated with Accruals (Pearson Correlation of 0.532, per Table 3), we conduct more detailed tests to assess the joint ability of Accruals and PROBM to predict future returns. In Table 6 Panel A, we report average size-adjusted returns when firms are shorted independently into quintiles by both Accruals and PROBM. In Panels B and C of the same table, we report the results of nested (i.e. sequential) sorts. The strong correlation observed in Table 3 is apparent in Table 6 Panel A, as approximately 25% of the sample observations reside in two of the twenty-five portfolios (upper-left and bottom-right).

PROBM is particularly effective in predicting returns among low accrual firms. The positive returns for firms with low accruals are concentrated among the low PROBM firms. Firms with low accruals and low PROBM generate returns of 5.5%. In contrast, firms with low accruals but high PROBM have strong negative returns (-10.2%). For firms in the lowest accrual quintile, firms with low PROBM outperform high PROBM firms by 15.7%. In quintile 2, low PROBM firms outperform by 9.2%. On the other hand, accruals do not distinguish firms in any of the PROBM quintiles. The only exception is the high PROBM quintile, where the high accrual firms actually outperform low accrual firms.

In Panel B, we further isolate the effect of Accruals and PROBM by sorting firms on PROBM within each Accruals quintile. This allows us to "spread-out" the variation in PROBM across firms that have relatively similar Accrual rankings. For low (income-decreasing) accrual firms, low PROBM firms outperform high PROBM firms by 5.4%. For high accrual firms, the spread is larger, such that low PROBM firms outperform high PROBM firms by 7.8%. Returns are also significant for the second lowest accrual quintile, while returns for the fourth quintile barely miss significance (t-statistic = 1.51, not tabulated). Interestingly, firms with large differences in accruals do not have differences in returns when PROBM is extremely high or low.

In panel C, we first sort on PROBM and then sort on Accruals. Results are consistent across all PROBM portfolios: extreme differences in accruals do not result in differences in returns once firms are sorted on PROBM. In contrast, low PROBM firms outperform high PROBM firms across all accrual sorts, and the spread in returns is strikingly consistent. Overall, Table 6 confirms the findings in Table 5, Panel E (as well as the evidence on accruals and future returns in Table 4), and demonstrates that PROBM dominates accruals as a predictor of future returns.

3.4 PROBM and the persistence of earnings components

Many researchers and practitioners speculate that accruals predict returns because they provide information about earnings quality that market participants fail to fully utilize. In this section, we pursue this line of reasoning, and explore the nature of the information conveyed by PROBM.

In particular, we focus on the incremental ability of PROBM to predict the persistence of firms' earnings. Prior studies have demonstrated that the cash flow component of earnings is more persistent than the accruals component (see, for example, Sloan (1996) and Richardson et al. (2005)). We extend this analysis by exploring the differential persistence of one-year-ahead accruals for high and low PROBM firms.

If the forensic accounting principles that underpin this model are useful in separating firms with relatively high/low quality earnings, this fact should be evidenced in a difference in the persistence of future accounting accruals. Specifically, we predict that *income-increasing* accruals for firms with high (low) PROBM should be less (more) persistent, while *income-decreasing* accruals for firms with high (low) PROBM should be more (less) persistent. In other words, for firms whose accrual component *increases* current year income, we expect higher PROBM to be associated with decreased accrual persistence (leading to lower income next year).

Conversely, for firms whose accrual component *decreases* current year income, we expect higher PROBM to increase accrual persistence (leading to higher income next year).

To examine whether PROBM contains such incremental information, we estimate the following relation between future earnings and current earnings components

$$EARN_{t+1} = a_0 + a_1 CFO_t + a_2 AccPos_t + a_3 AccNeg_t + a_4 AccPos_t{*}SPM_t + a_5 AccNeg_t{*}SPM_t + a_6 SPM_t + e_{t+1} \qquad (2)$$

Where EARN denotes operating earnings before depreciation, CFO is cash flows from operations, AccPos (AccNeg) is working capital accruals when these are positive (negative) and zero otherwise, SPM denotes PROBM ranked into deciles and scaled to range from 0 to +1, and all earnings and earnings components are deflated by average assets.

We begin Table 7 by providing a frame of reference. In the first two columns, we report that the current year's earnings have a persistence coefficient of regression of 0.730 and that cash flows are more persistent than accruals (0.853 and 0.457). The results for cash flows are similar to those documented by Sloan (1996) [0.860] but the persistence of accruals is smaller than his [0.765], largely due to the fact that we use working capital accruals and thus exclude depreciation. In the third column, we partition accruals into positive and negative samples. Our results show that, consistent with Beneish and Vargus (2002), the persistence of both positive and negative accruals are significantly lower than that of cash flows.

In the last column, we report the results of tests examining the persistence of accruals conditional on PROBM. We again find strong persistence for CFO (coefficient = 0.866). The coefficients on AccPos and AccNeg reflect the persistence of positive and negative accruals of firms with low PROBM (PROBM=0). Positive accruals with low PROBM have high persistence (coefficient = 0.810, almost as large as CFO) while negative accruals with low PROBM have low persistence (coefficient = .350, indicating these accruals have a much lower likelihood of repeating).

The coefficients on AccPos*SPM and AccNeg*SPM capture the effects of high PROBM on accrual persistence (PROBM=1). AccPos*SPM is negative and significant (coefficient = -0.367) suggesting that for firms in the highest PROBM decile, *income-increasing* accruals are much less persistent (estimate coefficient= 0.810-0.367= 0.443). For comparison, recall for firms in the lowest PROBM decile accruals are nearly as persistent as cash flows (0.810).

Similarly, AccNeg*SPM is positive and significant (coefficient = 0.278), indicating that for firms in the highest PROBM decile*, income-decreasing* accruals are much more likely to persist (estimate coefficient = 0.350+0.278= 0.628). In other words, for high PROBM firms, any income-decreasing accruals this year have a higher probability of repeating next year, leading to lower future earnings.

In sum, we find that PROBM is incrementally informative about the persistence of the accrual component of earnings. First, the one-year-ahead persistence of *income-increasing* accruals is significantly lower for high PROBM firms. Second, any *income-decreasing* accrual reported in the current year is much more likely to persist for high PROBM firms than for low PROBM firms. Both results show that PROBM is useful in predicting future earnings because of its ability to anticipate the reversal of transitory distortion in current years' reported accruals.

4. Summary

Fraudulent financial reporting imposes large costs on financial markets. For example, shareholders of the firms listed in Table 1 collectively lost over $180 billion dollars when these accounting 'irregularities' were announced.[6] Perhaps even more important than the investor wealth losses are the large welfare costs imposed by fraudulent financial reporting when resources are misdirected from their most productive use. These accounting misrepresentations increase transactions costs by eroding investor confidence in the integrity of the capital market. In recent years, we have seen how accounting misrepresentations triggered action by regulators, who impose (often costly) regulation on firms and markets. In short, when it comes to reporting frauds, many must pay for the transgressions of a relative few.

[6]Beneish (1999a) and Karpoff et al. (2008) provide evidence of large market value losses to public revelations of accounting manipulation.

Efforts to combat accounting fraud involve both public and private initiatives. On the one hand, accounting and security market regulators can help curb the practice through legislation and enforcement actions. On the other, private parties, such as more sophisticated investors, play a role by identifying firms that are likely to have manipulated earnings, and holding these firms accountable through market-based disciplining mechanisms.

In this study, we have explored the implications of an earnings manipulation detection model for equity investors. Using the Beneish (1999) model, which was estimated using data from the period 1982-1988 and its holdout sample performance assessed in the period 1989-1992, we show forensic accounting has significant out-of-sample ability to both detect fraud and predict stock returns. Moreover, we provide evidence that the efficacy of the model derives substantially from its ability to predict in advance, the likely persistence (or reversal) of the accrual component of current year earnings.

Our analysis builds on a long line of research that consistently finds stock prices behave as if investors ignore the implications of readily available public information (for example, Bernard and Thomas (1989); Ou and Penman (1989); Jegadeesh and Titman (1993); Lakonishok, Shleifer, and Vishny (1994); Chan, Jegadeesh, and Lakonishok (1996); Sloan (1996), Beneish (1997); Abarbanell and Bushee (1997)). In recent years, much of this research has emanated from accounting researchers. Our hope and expectation is that our evidence will spur further development and interest in the area of forensic accounting.

REFERENCES

Abarbanell, J., and B. Bushee. 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35 (Spring): 1-24.

Beaver, W., M. McNichols, and R. Price. 2007. Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting and Economics* 43(2-3): 341-368.

Beneish, M.D. 1997. Detecting GAAP violation: Implications for assessing earnings management among firms with extreme financial performance. *Journal of Accounting and Public Policy* 16(3): 271-309.

Beneish, M.D. 1999. The detection of earnings manipulation. *Financial Analysts Journal* (September/October): 24-36.

Beneish, M.D. 1999a. Incentives and penalties related to earnings overstatements that violate GAAP. *The Accounting Review* (74): 425-457.

Beneish M.D., and M. E. Vargus. Insider trading, earnings quality, and accrual mispricing. *The Accounting Review* 77(4): 755-791.

Bernard, V.L., and J.K. Thomas. 1989. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27 (Supplement): 1-36.

Chan, L.K., N. Jegadeesh, and J. Lakonishok. 1996. Momentum strategies. *Journal of Finance* 51 (December): 1681-1713.

Ciesielski, J., 1998. What's Happening to the "Quality of Assets"? *The Analyst's Accounting Observer* 7(3), February 19.

Davis, J. L. 1994. The cross-section of realized stock returns: The pre-COMPUSTAT evidence. *Journal of Finance* 49 (December): 1579-1593.

Dechow, P. M., Ge, W., C.R. Larson and R. G. Sloan. 2011. Predicting material accounting misstatments. *Contemporary Accounting Research* 28(1): 1-16.

Drake, M.S., Rees, L. and E.P. Swanson. 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. *The Accounting Review* 86 (1): 101-130.

Dresdner, Kleinwort, Wasserstein (DKW). 2003. Earnings Junkies. Global Equity Research, October 29, London, U.K.

Fama, E. F., and K. R. French. 1992. The cross-section of expected stock returns. Journal of Finance 47 (June): 427-465.

Fridson, M.S. 2002. *Financial Statement Analysis: A Practitioner's Guide*. New York: John Wiley & Sons.

Gladwell, M. 2009. *What the Dog Saw: And Other Adventures.* New York: Little, Brown and Company.

Harrington, C. 2005. Analysis of Ratios for Detecting Financial Statement Fraud. *Fraud Magazine*. (March/April): 24-27.

Haugen, R. A., and N. L. Baker. 1996. Commonality in the determinants of expected stock returns. *Journal of Financial Economics* 41 (July): 401-439.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45 (July): 881-898.

Jegadeesh, N., and S. Titman. 1993 Returns to buying winners and selling losers. *Journal of Finance* 48 (March): 65-91.

Kellogg, I. and L.B. Kellogg. 1991. *Fraud, Window Dressing, and Negligence in Financial Statements.* New York: McGraw-Hill.

Lyon, J., B. Barber, C. Tsai. 1999. Improved methods for tests of long-run abnormal stock returns. *Journal of Finance*: Vol. 54, No. 1, 165-201.

Merrill Lynch, 2000. Financial Reporting Shocks. March 31, New York.

Mishkin, F. 1983. *A Rational Expectations Approach to Macroeconomics*, Chicago: University of Chicago Press.

Morris, G. D. L. 2009. Enron 101: How a group of business students sold Enron a year before the collapse. *Financial History* Spring/Summer: 12-15. (www.moaf.org)

O'Glove, T. L. 1987. *Quality of Earnings.* New York: The Free Press.

Ou, J. A. and S. H. Penman. 1989. Financial statement analysis and the prediction of stock returns. *Journal of Accounting & Economics* 11 (4): 29-46.

Richardson, S. A., R. G. Sloan, M. T. Soliman, and I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. *Jouranl of Accounting & Economics* 39 (3): 437-485.

Siegel, J. G. 1991. *How to Analyze Businesses, Financial Statements, and the Quality of Earnings.* 2nd Edition, New Jersey: Prentice Hall.

Sloan, R.G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (July): 289-315.

Stickney, C., P. Brown, and J. Wahlen. 2003. *Financial Reporting, Financial Statement Analysis, and Valuation*, 5th Edition. Thomson-Southwestern.

Teoh, S.H., T.J. Wong, and G.R. Rao. 1998. Are accruals during initial public offerings opportunistic? *Review of Accounting Studies* 3 (1-2): 209-221.

Wells, J. T. 2001. Irrational ratios. *Journal of Accountancy.* New York: Aug : 80-83.

Appendix --The Probability of Manipulation

1. Estimating PROBM

The sample in Beneish (1999) consisted of 74 firms that manipulated earnings and 2,332 non-manipulators matched by industry over the period 1982-1992. On average, manipulators were smaller, less profitable, more levered and experienced faster growth than industry controls. We estimate the probability of manipulation to overstate earnings (which we denote PROBM for ease of exposition) using the following PROBIT model, as published in Beneish (1999):

PROBM= -4.84 + .920*DSR + .528*GMI + .404*AQI + .892*SGI + .115*DEPI-.172*SGAI +4.679*ACCRUALS - .327*LEVI[7]

Where:

Variable Name	**Description**	**Rationale**
DSR	$Receivables_t[2]/Sales_t[12]/(Receivables_{t-1}/Sales_{t-1})$	Captures distortions in receivables that can result from revenue inflation
GMI	Gross $Margin_{t-1}$/ Gross $Margin_t$, where Gross Margin is 1 minus Costs of Goods Sold [#8]/ Sales	Deteriorating margins predispose firms to manipulate earnings
AQI	$[1-(PPE_t-CA_t)/TA_t] /[1-(PPE_{t-1}-CA_{t-1})/TA_{t-1}]$, where PPE is net [#8], CA are Current Assets [#4]and TA are Total Assets [#6]	Captures distortions in other assets that can result from excessive expenditure capitalization
SGI	$Sales_t[12]/Sales_{t-1}$	Managing the perception of continuing growth and capital needs predisposes growth firms to manipulate sales and earnings.
DEPI	Depreciation $Rate_{t-1}$/ Depreciation $Rate_t$, where depreciation rate equals Depreciation [#14-#65]/(Depreciation+PPE [#8])	Captures declining depreciation rates as a form of earnings manipulation.
SGAI	$SGA_t[189]/Sales_t[12]/(SGA_{t-1}/Sales_{t-1})$	Decreasing administrative and marketing efficiency (larger fixed SGA expenses margins) predispose firms to manipulate earnings
LEVI	$Leverage_t$ /$Leverage_{t-1}$ where Leverage is calculated as debt to assets [(#5+#9)/#6]	Increasing leverage tightens debt constraints and predispose firms to manipulate earnings
Accruals to Total Assets	(Income Before Extraordinary Items [18]- Cash from Operations[308])/ Total $Assets_t[6]$	Capture cases where accounting profits are not supported by cash profits.

[7] Five of the eight variables in the multivariate estimation are statistically significant (DSR, GMI, AQI, SGI, and ACCRUALS); the remaining three (DEPI, SGAI, LEVI) are not (see Beneish 1999, Table 3). To gain additional insight on the relative importance of the individual inputs, Beneish (1999) re-estimated this model 100 times using 100 random estimation samples. At the 5% level, DSR and SGI were significant in all 100 estimations, Accruals in 95 of the 100 estimations, GMI and AQI in 84 of the 100 estimations. In contrast, DEPI, SGAI and LEVI were only significant in 18, 12, and two estimations respectively (see Beneish 1999, Table 4).

2. Intuition behind the Eight Variables

The model thus consists of eight ratios that capture either financial statement distortions that can result from earnings manipulation (DSR, AQI, DEPI and Accruals) or indicate a predisposition to engage in earnings manipulation (GMI, SGI, SGAI, LEVI). Descriptive statistics for these ratios appear in Table A.1 below.

The four predictive ratios that focus on financial statement distortions suggest that manipulators have unusual buildups in receivables (DSR, indicative of revenue inflation), unusual expense capitalization (AQI), and that their reported accounting profits are less supported by cash profits that those of manipulators (Accruals). However, we find no difference in the rate at which firms depreciate their assets (DEPI).

The four predictive ratios that suggest propitious conditions for manipulation are: manipulators have deteriorating gross margins and increasing administration costs (GMI and SGAI, both signals of declining prospects), high sales growth (SGI) because young growth firms have greater incentives to manipulate earnings to make it possible to raise capital, and increasing reliance on debt financing (LEVI) as this increases the firm's financial risk and the likelihood of earnings manipulation related to debt agreement constraints.

Table A.1

Potential Predictive Variables: Descriptive Statistics for the Sample of
74 Manipulators and 2332 Industry-Matched Non-Manipulators in the Period 1982-1992

	Manipulators		Controls		Wilcoxon-Z	Median
Characteristic	Mean	Median	Mean	Median	P-Value[a]	P-Value[a]
Days in Receivables	1.412	1.219	1.030	0.995	0.001	0.001
Gross Margin Index	1.159	1.028	1.017	1.001	0.019	0.078
Asset Quality Index	1.228	1.000	1.031	1.000	0.035	0.824
Sales Growth Index	1.581	1.341	1.133	1.095	0.001	0.001
Depreciation Index	1.072	0.977	1.007	0.972	0.346	0.638
SGA Index	1.107	1.028	1.085	0.990	0.714	0.098
Leverage Index	1.124	1.035	1.033	1.000	0.107	0.039
Accruals to total assets	0.049	0.026	0.015	0.012	0.001	0.018

a. The Wilcoxon Rank-Sum test and the Median test compare the distribution of sample firms' characteristics to the corresponding distribution for non-manipulators. The reported p-values are two tailed and indicate the smallest probability of incorrectly rejecting the null hypothesis of no difference.

3. Incidence of Manipulation

The distribution of sample manipulators over the sample period suggests an increasing frequency of SEC Accounting and Auditing Enforcement Actions time is as follows:

Years	1981-1985	1986-1989	1990-1993	Total
Number of Firms	8	35	31	74

The distribution of manipulators by two-digit SIC suggest the highest concentration is in Business Services (10 firms, 13.5%), followed by Industrial Products (7 firms, 9.5%), and both Electronic Manufacturing and Wholesales-trade tied at (5 firms, 6.8%).

Table A.2
Manipulators by Two-Digit Industry

SIC	Industry Description	N	%
1	Agricultural Production	1	1.4%
10	Metal Mining	1	1.4%
13	Oil and Gas Extraction	1	1.4%
15	General Building Contractors	1	1.4%
20	Food and Kindred Products	1	1.4%
22	Textile Mill Products	3	4.1%
23	Apparel and Other Textile Products	1	1.4%
24	Lumber and Wood Products	1	1.4%
27	Printing and Publishing	2	2.7%
28	Chemicals and Allied Products	4	5.4%
30	Rubber and Misc. Plastics Products	1	1.4%
34	Fabricated Metal Products	1	1.4%
35	Industrial and Related Products	7	9.5%
36	Electronic & Other Electric Equipment	5	6.8%
37	Transportation Equipment	2	2.7%
38	Instruments and Related Products	2	2.7%
45	Transportation by Air	1	1.4%
47	Transportation Services	1	1.4%
48	Communications	1	1.4%
49	Electric, Gas, and Sanitary Services	3	4.1%
50	Wholesale Trade-Durable Goods	5	6.8%
51	Wholesale Trade-Nondurable Goods	1	1.4%
52	Building Materials & Garden Supplies	1	1.4%
54	Food Stores	1	1.4%
56	Apparel and Accessory Stores	1	1.4%
57	Furniture and Home furnishings Stores	3	4.1%

58	Eating and Drinking Places	1	1.4%
59	Miscellaneous Retail	2	2.7%
70	Hotels and Other Lodging Places	1	1.4%
73	Business Services	10	13.5%
75	Auto Repair, Services, and Parking	2	2.7%
78	Motion Pictures	3	4.1%
80	Health Services	1	1.4%
82	Educational Services	2	2.7%
		74	100.0%

Table 1. Performance of Model for High-Profile Fraud Cases during 1998-2002

This table reports the 20 companies identified by auditintegrity.com as the "highest profile" fraud cases uncovered during the 1998 to 2002 time period.* We examine the probability-of-manipulation score (PROBM) for each firm based on financial statement information reported by the firm during the period of alleged manipulation but prior to public discovery. Firms are flagged as manipulators if PROBM exceeds -1.78 at any time during the period of alleged (or admitted) violation. We compute PROBM = -4.84 + .920*DSR + .528*GMI + .404*AQI + .892*SGI + .115*DEPI - .172*SGAI + 4.679*ACCRUALS - .327*LEVI. DSR denotes the ratio of receivables to sales in year t divided by the same ratio in year t-1. GMI denotes the ratio of gross margin to sales in period t-1 to the same ratio in period t. SGA denotes the ratio of selling, general, and administrative expense to sales in period t divided by the same ratio in period t-1. SGI equals sales in t divided by sales in t-1. DEPI denotes the ratio of depreciation to depreciable base in t-1 divided by the same ratio in t. AQI equals all non-current assets other than PPE as a percent of total assets in t divided by the same ratio in t-1. ACC equals income before extraordinary items minus operating cash flows divided by average total assets. LEVI equals the ratio of long-term debt +current liabilities to total assets in t divided by the same ratio in t-1. Year flagged refers to the first year the firm is flagged by the PROBM model as a manipulator. Year discovered refers to the year in which the fraud was first publicly revealed in the business press. Market cap lost denotes the change in market capitalization during the three months surrounding the month the fraud was announced (i.e., months -1, 0, +1). Market cap lost (%) denotes the market capitalization lost in the three months surrounding the fraud announcement month, as a percentage of market capitalization at the beginning of month -1.

Company Name	Flagged as manipulator?	Year Flagged	Year Discovered	Market Cap Lost ($B)	Market Cap Lost (%)
Adelphia Communications	**Yes**	1999	2002	4.82	96.8%
American International Group, Inc.	N/A - Financial				
AOL Time Warner, Inc.	**Yes**	2001	2002	25.77	32.2%
Cendant Corporation	**Yes**	1996	1998	11.32	38.1%
Citigroup	N/A - Financial				
Computer Associates International, Inc.	**Yes**	2000	2002	7.23	36.4%
Enron Broadband Services, Inc.	**Yes**	1998	2001	26.04	99.3%
Global Crossing, Ltd	**Yes**	1999	2002	(Delisted due to bankruptcy)	
HealthSouth Corporation	No		2002	2.31	57.3%
JDS Uniphase Corporation	**Yes**	1999	2001	32.49	61.0%
Lucent Technologies, Inc	**Yes**	1999	2001	11.15	24.7%
Motorola	N/A – Only abetted Adelphia				
Qwest Communications International	**Yes**	2000	2002	9.84	41.8%
Rite Aid Corporation	**Yes**	1997	1999	2.83	59.1%
Sunbeam Corporation	**Yes**	1997	1998	1.28	58.8%
Tyco International	No		2002	37.55	58.2%
Vivendi Universal	No		2002	1.28	27.9%
Waste Management Inc	**Yes**	1998	1999	20.82	63.6%
WorldCom Inc. - MCI Group	No		2002	1.03	69.8%
Xerox Corporation	No		2000	7.73	43.8%
			Mean	10.89	51.94%
			Median	8.79	57.75%

***** This five-year period was marked by a large number of corporate accounting scandals. It also represents an out-of-sample test for the Beneish (1999) model, which was estimated using data from 1982-1988 and tested on a holdout sample from 1989-1992. We have no affiliation with AuditIntegrity.com.

Table 2. Year-by-year Size-Adjusted Returns to Flagged Firms

The table reports the year-by-year size-adjusted returns for firms flagged by the Beneish (1999) model and those that were not. BHSAR denotes annual buy-and-hold returns to an equal-weighted portfolio formed at the start of the first day of the fifth month following the end of the fiscal year, less the returns to a portfolio of firms from the same NYSE/AMEX/NASDAQ size decile (size decile membership determined at the beginning of return window). For firms that delist, any proceeds upon delisting are reinvested in the size portfolio to which the company belongs. Flagged denotes firms that fit the profile of an earnings manipulator based on the PROBM model in Beneish (1999) and a cutoff of -1.78. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

		Not Flagged		Flagged		
Year	N	Percent	BHSAR	Percent	BHSAR	Spread
1993	1798	86.2%	3.5%***	13.8%	-2.5%	6.0%**
1994	2034	83.4%	1.3%	16.6%	-0.6%	1.9%
1995	2305	84.3%	0.9%	15.7%	-16.6%***	17.4%***
1996	2494	82.3%	-2.4%**	17.7%	-13.9%***	11.5%***
1997	2569	81.6%	0.0%	18.4%	-9.4%***	9.4%***
1998	2461	81.2%	8.5%***	18.8%	4.1%	4.4%
1999	2415	82.7%	7.4%***	17.4%	-10.3%**	17.8%***
2000	2203	79.1%	5.1%***	20.9%	-20.7%***	25.8%***
2001	2201	88.2%	-1.1%	11.8%	-18.9%***	17.9%***
2002	2145	90.5%	5.2%***	9.5%	5.4%	-0.2%
2003	2338	89.2%	0.8%	10.8%	-7.4%**	8.1%***
2004	2326	86.5%	3.5%***	13.5%	9.6%**	-6.0%*
2005	2243	88.9%	1.8%**	11.1%	-3.3%	5.1%**
2006	2210	88.4%	5.4%***	11.6%	3.3%	2.1%
2007	2106	89.6%	0.1%	10.4%	-2.9%	2.9%
Full Sample	33848		3.10%***		-6.60%***	9.70%***

Table 3. Correlation matrix

This table reports Pearson (above diagonal) and Spearman (below diagonal) correlations for sample variables. PROBM denotes the probability of earnings manipulation based on the Beneish (1999) model. See the notes to Table 1 for a description of the PROBM model. Accrual denotes earnings before extraordinary items less cash flows from operations scaled by average assets. Momentum denotes raw returns for the six months prior to the BHSAR return window. Market value of equity is measured as of end of the fiscal year. Book-to-market denotes market value of equity divided by common equity. BHSAR denotes annual returns starting the first day of the fifth month following the end of the fiscal year, less the returns to a portfolio of firms with comparable size. For firms that delist, any proceeds upon delisting are reinvested in the size portfolio to which the company belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	PROBM	Accrual	Momentum	Ln(MVE)	BTM	SIRatio	BHSAR
PROBM		0.532***	-0.030***	-0.017***	-0.072***	0.058***	-0.044***
Accrual	0.669***		-0.029***	-0.005	-0.004	-0.002	-0.031***
Momentum	-0.059***	-0.042***		-0.010*	-0.033***	-0.037***	0.030***
Ln(MVE)	-0.010*	-0.037***	0.059***		-0.264***	0.116***	-0.016***
BTM	-0.102***	0.011**	-0.036***	-0.304***		-0.087***	0.029***
SIRatio	0.042***	-0.031***	-0.032***	0.392***	-0.217***		-0.028***
BHSAR	-0.068***	-0.026***	0.071***	0.057***	0.065***	-0.034***	

N = 33,847

Table 4 Multivariate Cross-Sectional Regressions

This table reports the time-series mean from 15 annual cross-sectional (Fama-MacBeth) regressions. The dependent variable is the firm-specific one-year-ahead buy-and-hold size-adjusted return. The independent variables are PROBM (see the notes to Table 1 for a description), Accrual (earnings before extraordinary items less cash flows from operations, all scaled by average assets), Momentum (raw returns for the six months prior to the BHSAR window), MVE (market value of equity), SIRatio (short interest ratio, the number of shares sold short as a percentage of the number of shares outstanding and BTM (book-to-market). Observations are assigned to ten portfolios based on prior year cutoff values. Portfolio assignments are then scaled to range from 0 to 1. T-statistics are based on the time-series distribution of the parameter estimates.

	Average Estimate	t-statistic
Intercept	0.016	0.54
PROBM	-0.084	-2.75
Accruals	0.000	0.02
MVE	-0.016	-0.47
BTM	0.053	1.40
Momentum	0.085	2.71
SIRatio	-0.032	-1.02
Adjusted R-square	2.63%	
N = 15 years		

Table 5. Size-adjusted returns to decile portfolios conditional on PROBM

To construct this table, firms are first sorted into decile portfolios by Market-value-of-equity, Book-to-Market, Momentum, and Accrual each year based on prior year cutoff values, then grouped by PROBM. Flagged (Not Flagged) denotes firms that fit (do not fit) the profile of an earnings manipulator based on the PROBM model from Beneish (1999) and a cutoff of -1.78. Momentum denotes raw returns for the six months prior to the BHSAR return window. Short interest ratio denotes the number of shares sold short as a percentage of the number of shares outstanding, and is measured in the month before portfolio formation. Accrual denotes earnings before extraordinary items less cash flows from operations scaled by average assets. BHSAR denotes annual size-adjusted returns starting the first day of the fifth month following the end of the fiscal year. For firms that delist, any proceeds upon delisting are reinvested in the size portfolio to which the company belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. MVE (Market Value of Equity) Portfolios

	Full Sample		Not Flagged		Flagged		Not Flagged
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	Less Flagged
1	3250	5.0%***	2782	6.2%***	468	-2.4%	8.6%**
2	3275	2.4%	2686	4.2%**	589	-5.8%*	10.0%**
3	3344	2.0%*	2724	4.8%***	620	-10.1%***	14.9%***
4	3394	2.6%**	2807	5.0%***	587	-8.8%***	13.8%***
5	3367	2.2%**	2791	4.0%***	576	-6.1%**	10.0%***
6	3353	0.6%	2859	2.4%**	494	-10.1%***	12.5%***
7	3510	1.0%	2980	2.0%**	530	-4.7%*	6.7%***
8	3353	0.8%	2923	1.3%	430	-2.4%	3.7%
9	3429	0.5%	3045	1.3%	384	-5.8%	7.1%**
10	3573	0.0%	3294	0.7%	279	-8.6%***	9.4%***
Spread		5.0%***		5.5%***		6.2%	

Panel B. Book-to-Market Portfolios

	Full Sample		Not Flagged		Flagged		Not Flagged
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	Less Flagged
1	2439	-4.1%***	1848	-2.4%	591	-9.4%**	7.0%*
2	3598	-1.8%*	2872	0.3%	726	-10.0%***	10.2%***
3	3521	-1.9%*	2925	-0.4%	596	-9.2%***	8.9%***
4	3419	2.9%***	2874	4.3%***	545	-4.4%*	8.7%***
5	3549	1.3%	3050	2.4%**	499	-5.7%**	8.1%***
6	3476	1.8%**	3023	2.7%***	453	-4.5%*	7.1%***
7	3550	3.3%***	3132	3.6%***	418	1.3%	2.3%
8	3354	4.9%***	2962	5.9%***	392	-3.1%	9.0%***
9	3409	4.5%***	3059	6.1%***	350	-9.4%	15.4%***
10	3533	4.6%***	3146	6.2%***	387	-8.1%***	14.2%***
Spread		-8.7%***		-8.6%***		-1.4%	

Panel C. Momentum Portfolios

	Full Sample		Not Flagged		Flagged		Not Flagged
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	Less Flagged
1	4114	-2.3%*	3098	2.2%	1016	-16.1%***	18.4%***
2	3639	-2.0%**	3028	0.0%	611	-12.3%***	12.3%***
3	3395	-1.3%	2898	-0.2%	497	-7.4%***	7.2%***
4	3223	0.9%	2879	1.7%*	344	-5.9%**	7.6%***
5	3145	0.6%	2814	1.4%	331	-6.1%**	7.5%**
6	3114	3.2%***	2782	3.6%***	332	-0.3%	3.9%
7	2958	3.0%***	2629	3.9%***	329	-4.2%	8.2%***
8	3291	3.6%***	2904	5.0%***	387	-6.7%**	11.7%***
9	3236	5.4%***	2825	6.3%***	411	-0.5%	6.8%**
10	3733	6.9%***	3034	7.4%***	699	4.8%	2.6%
Spread		9.2%***		5.2%**		20.9%***	

Panel D. Short Interest Ratio Portfolios

	Full Sample		Not Flagged		Flagged		Not Flagged
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	Less Flagged
1	3189	3.6%***	2824	5.1%***	365	-7.6%***	12.6%***
2	3124	5.2%***	2734	4.8%***	390	7.9%	-3.1%
3	3114	1.4%	2752	2.9%***	362	-10.2%***	13.1%***
4	3063	4.5%***	2694	5.8%***	369	-5.0%	10.8%***
5	3064	2.7%**	2735	3.7%***	329	-6.1%*	9.8%**
6	3285	2.5%**	2879	4.2%***	406	-9.0%***	13.2%***
7	3489	2.5%**	3088	3.4%***	401	-4.5%	8.0%**
8	3847	-0.5%	3283	0.9%	564	-8.6%***	9.5%***
9	3839	-0.7%	3128	0.7%	711	-6.7%**	7.4%***
10	3834	-2.4%**	2914	0.0%	920	-10.2%***	10.3%***
Spread		6.1%***		5.0%***		2.7%	

Panel E. Accrual Portfolios

Portfolio	Full Sample N	Full Sample BHSAR	Not Flagged N	Not Flagged BHSAR	Flagged N	Flagged BHSAR	Not Flagged Less Flagged
1	3326	3.3%**	3079	5.1%***	247	-18.5%***	23.5%***
2	3327	2.8%**	3094	3.7%***	233	-9.8%**	13.5%***
3	3364	3.9%***	3134	4.4%***	230	-3.1%	7.4%*
4	3354	2.1%**	3120	2.8%***	234	-7.5%*	10.3%***
5	3230	4.1%***	2974	4.7%***	256	-2.9%	7.6%**
6	3274	1.4%	3006	1.7%*	268	-1.6%	3.3%
7	3319	1.7%*	2990	2.3%**	329	-4.1%	6.4%**
8	3510	2.6%**	3069	3.2%***	441	-2.0%	5.2%
9	3544	0.7%	2834	1.9%*	710	-3.9%	5.8%**
10	3600	-5.0%***	1591	-0.5%	2009	-8.5%***	8.0%***
Spread		8.3%***		5.6%**		-9.9%**	

Table 6. Size-adjusted returns to accrual and PROBM quintile portfolios

To construct Panel A, firms are independently sorted on accruals and PROBM based on prior year cutoff values. Panels B and C report nested sorts. In Panel B (C) firms are sorted on accruals (PROBM) first and, within each accrual (PROBM) portfolio, further sorted into PROBM (accrual) portfolios. For the first-pass sorts in Panels B and C, firms are sorted into portfolios based on prior year cutoff values. The second pass sorts in Panels B and C are based on current year cutoff values. See the notes to Table 1 for a description of the PROBM model. Accrual denotes earnings before extraordinary items less cash flows from operations scaled by average assets. BHSAR denotes annual size-adjusted returns starting the first day of the fifth month following the end of the fiscal year. For firms that delist, any proceeds upon delisting are reinvested in the size portfolio to which the company belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Independent sorts

	Low Probm		2		3		4		High Probm		
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	N	BHSAR	N	BHSAR	Spread
Low Acc	4307	5.5%***	989	2.7%	442	1.0%	330	-2.1%	585	-10.2%***	15.7%***
2	1677	5.6%***	2614	4.4%***	1137	1.0%	674	0.5%	616	-3.7%	9.2%***
3	493	-1.0%	1993	4.4%***	2188	1.9%**	1117	4.8%***	713	0.3%	-1.2%
4	185	0.2%	755	4.3%*	2401	4.1%***	2319	1.0%	1169	-0.7%	0.9%
High Acc	58	-6.5%	164	9.3%*	576	3.9%*	2465	0.2%	3881	-5.0%***	-1.5%
Spread		12.0%		-6.6%		-2.8%		-2.3%		-5.2%*	

Panel B. PROBM sorted within Accrual portfolios

	Low Probm		2		3		4		High Probm		
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	N	BHSAR	N	BHSAR	Spread
Low Acc	1325	2.1%	1334	8.2%***	1333	6.2%***	1334	2.0%	1327	-3.3%*	5.4%*
2	1337	5.3%***	1348	5.4%***	1345	2.9%*	1348	2.4%*	1340	-1.1%	6.4%**
3	1296	3.4%**	1304	3.4%***	1302	0.8%	1304	3.0%**	1298	3.2%	0.2%
4	1360	4.0%**	1368	2.6%**	1369	4.7%***	1368	-0.2%	1364	-0.4%	4.4%
High Acc	1421	3.2%**	1434	0.2%	1430	-3.9%***	1434	-5.5%***	1425	-4.6%**	7.8%***
Spread		-1.1%		8.1%***		10.1%***		7.5%***		1.3%	

Panel C. Accruals sorted within PROBM portfolios

	Low Acc		2		3		4		High Acc		
Portfolio	N	BHSAR	N	BHSAR	N	BHSAR	N	BHSAR	N	BHSAR	Spread
Low PROBM	1338	2.9%	1346	8.3%***	1347	5.3%***	1346	5.7%***	1342	1.7%	1.2%
2	1297	3.9%**	1307	4.5%***	1302	4.2%***	1307	4.8%***	1300	3.7%**	0.1%
3	1345	0.9%	1351	2.6%**	1350	2.7%*	1351	3.7%***	1345	3.2%**	-2.2%
4	1375	0.6%	1381	2.9%*	1387	1.6%	1381	-0.1%	1379	0.9%	-0.3%
High PROBM	1388	-5.3%***	1396	0.2%	1394	-2.4%	1396	-4.9%***	1388	-7.8%***	-2.5%
Spread		8.2%***		8.1%***		7.7%***		10.6%***		9.5%***	

Table 7. Regression of future earnings on current period earnings components

This table reports results from pooled, cross-sectional time-series regressions of future earnings on current earnings components, scaled PROBM, and interactions. EARN denotes income before extraordinary items excluding depreciation divided by average assets; CFO denotes cash from operations divided by average assets; ACC denotes income before extraordinary items excluding depreciation less CFO; ACCPOS denotes ACC if positive, 0 otherwise; ACCNEG denotes ACC if negative, 0 otherwise; and SPM denotes PROBM ranked into deciles and scaled to range from 0 (lowest PROBM) to +1 (highest PROBM). ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	0.010***	-0.001	-0.005	-0.014***
EARN	0.730***			
CFO		0.853***	0.862***	0.866***
ACC		0.457***		
ACC*SPM				
ACCPOS			0.528***	0.810***
ACCNEG			0.417***	0.350***
ACCPOS*SPM				-0.367**
ACCNEG*SPM				0.278***
SPM				0.018***
Adj R-sq	46.40%	50.79%	50.84%	51.02%
N	29641			

Figure 1A: Market value of equity portfolios

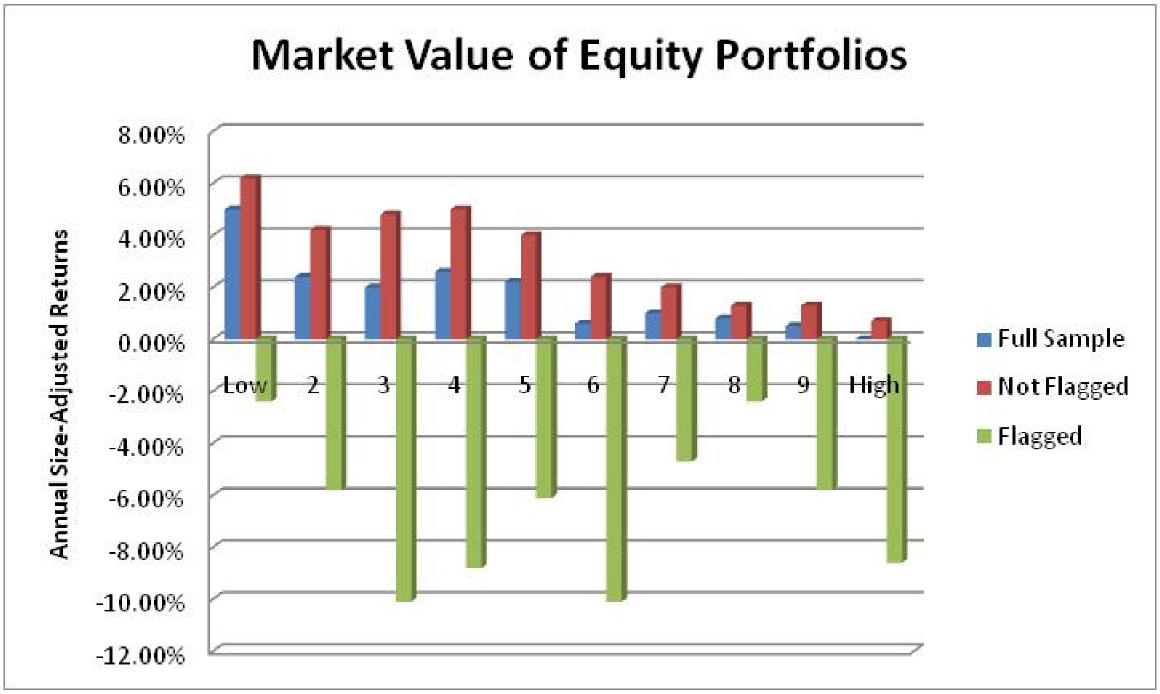

Figure 1B: Book-to-market portfolios

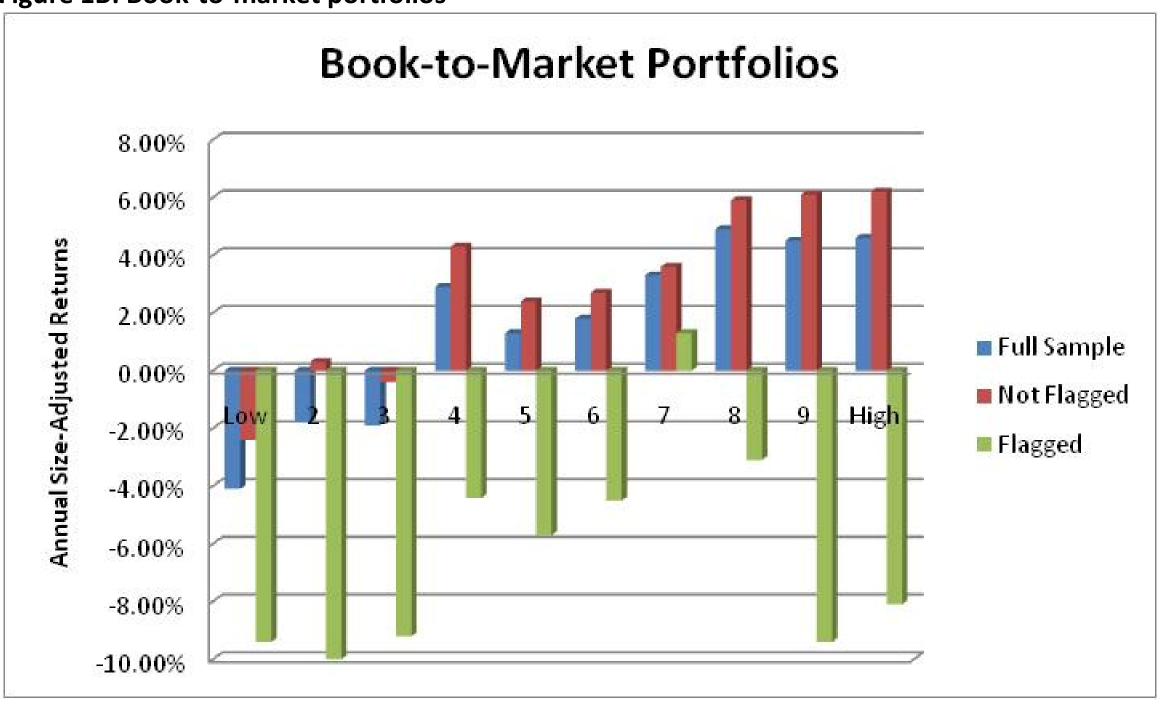

Figure 1C: Momentum portfolios

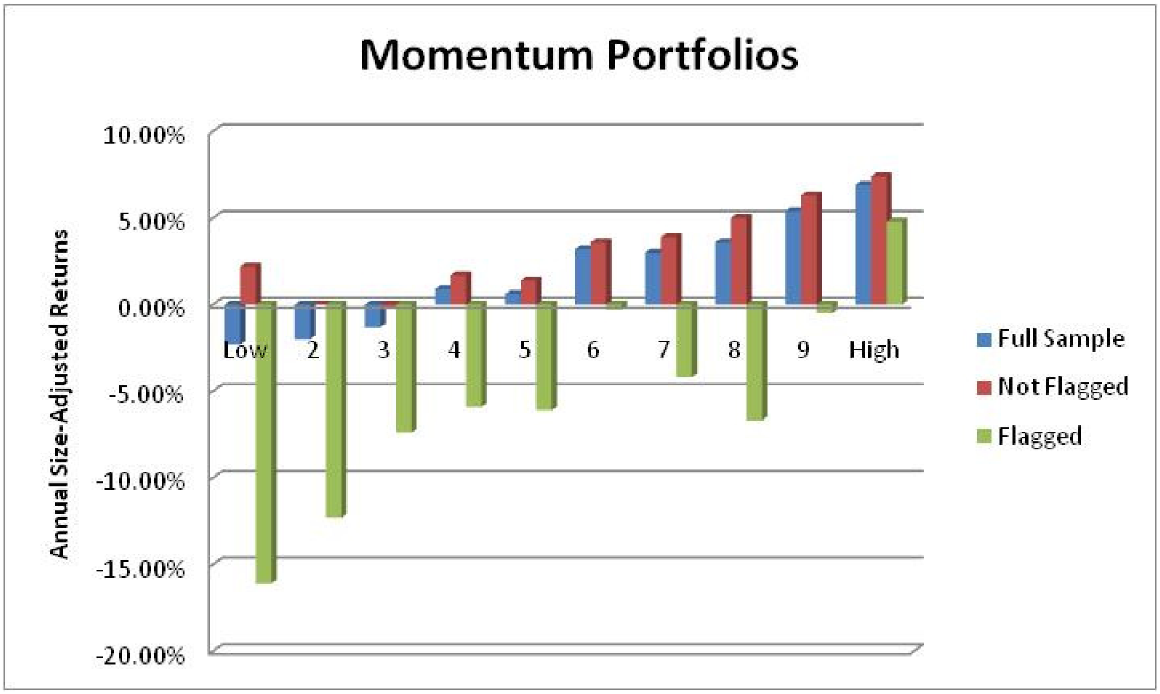

Figure 1D: Short Interest Portfolios

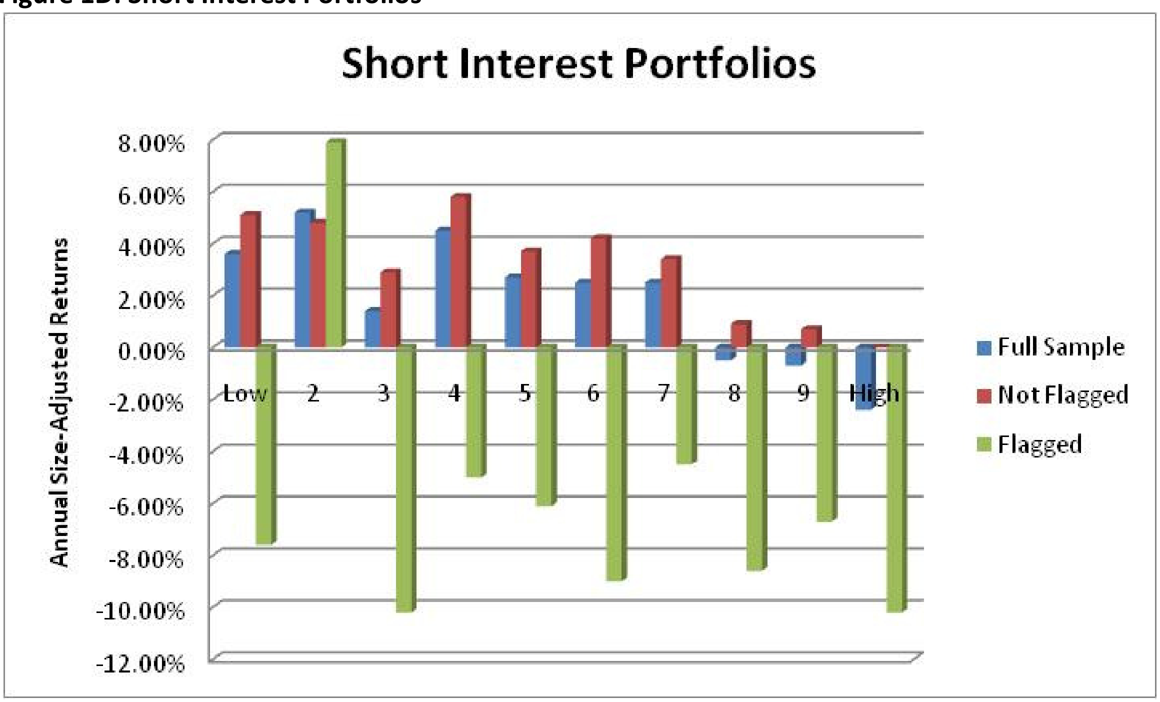

Figure 1E: Accrual portfolios