Identifying Overvalued Equity

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Abstract

We present a model to identify firms with substantially overvalued equity. The distinguishing feature of our study is that we analyze the valuation implications of an *ex ante* assessment of the likelihood of financial statement fraud. If, as Jensen (2005) suggests, the most costly cases of overvaluation culminate in financial statement fraud, an analysis that combines the likelihood of fraud with other characteristics capturing value-destruction is more likely to identify substantial overvaluation. Consistent with this view, our model predicts year-ahead abnormal stock price declines of over 25 percent, and identifies firms that are nearly five times more likely to subsequently restate earnings.

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1. Introduction

In this paper, we develop an *ex ante* model for identifying firms with overvalued equity. Our model combines an *ex ante* assessment of financial statement fraud with characteristics of the firms' operating, investing, and financing activities implied by Jensen (2005)'s theory of overvalued equity. Our model predicts abnormal stock price declines of over 25 percent, and identifies firms that are almost five times as likely to subsequently correct earnings overstatements. Our results should be of interest to investors who want to avoid large wealth losses, directors who want to identify unrealistic market expectations, and auditors and regulators who want to identify firms with a high risk of accounting impropriety. In addition, the results suggest a proxy for overvaluation that can be used by researchers to investigate why firms become overvalued, whether sophisticated investors anticipate overvaluation, and what forces prevent overvaluation from being corrected sooner.

Our study differs from the large body of research on the relation between firm characteristics and future stock returns in two ways.[1] First, we document the ability of a previously unexamined characteristic to predict returns. In particular, we show that an *ex ante* measure of the probability of financial statement fraud (PROBM) has a significant negative association with future returns, even after controlling for accruals, size, momentum, and glamour characteristics. Although PROBM's ability to detect financial statement fraud is well

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[1] Prior research has shown that firms with the following characteristics experience stock price declines: glamour-like fundamental characteristics such as low P/E, low P/B, low CFO/P (e.g., Lakonishok, Shleifer, and Vishny, 1994; Haugen and Baker 1996; Desai, Rajgopal, and Venkatachalam 2004), extreme high accruals or abnormal accruals (e.g., Sloan 1996; Xie 2001; Collins and Hribar 2002; Chan, Chan, Jegadeesh, and Lakonishok, 2006), high market capitalization (e.g., Fama and French 1992), acquiring firms--particularly when the acquisition is paid in stock (e.g., Loughran and Vijh 1997; Rau and Vermaelen 1998), after firms issue equity or debt (Ritter 1991;Loughran and Ritter 1995; Spiess and Affleck-Graves 1995), and after substantial increases in capital investment (e.g, Fairfield, Whisenant, and Yohn 2003; and Titman, Wei, and Xie 2004). Researchers have also examined several factors in combination: Fama and French (2006) find that book-to-market effects dominate in a joint examination of book-to-market, profitability, and investment effects; Desai, Rajgopal, and Venkatachalam (2004) examine the relation between glamour and accruals and show that the latter is the glamour phenomenon in disguise; Piotroski (2000) and Mohanram (2005) use several financial characteristics to identify the eventual winners in the set of value and glamour firms.

documented (see Section 2), its usefulness in predicting stock price declines has not been examined. Second, we provide evidence that a previously unexamined combination of firm characteristics predicts returns. Specifically, we show that combining PROBM with proxies for value-destroying activities suggested by Jensen (2005)'s agency theory of overvalued identifies substantial overvaluation. Although many studies predict one-year-ahead abnormal stock price declines of 5 to 10 percent, we show that firms meeting our profile of overvalued equity lose a quarter of their value after controlling for risk. Moreover, this result is consistent across time periods and firms of different size.

Jensen argues that the most severe and costly cases of overvaluation culminate in accounting fraud. We therefore begin our analysis by examining the ability of PROBM to predict returns using a sample of 27,427 observations over the period 1993-2004. Our sample begins in 1993 to ensure our tests are out of sample; Beneish (1999) estimated his PROBM model with data from 1982 to early 1993. Individually, PROBM predicts abnormal stock price declines of -9.5 percent, and remains a powerful predictor of returns after controlling for other well-known proxies for overvaluation (e.g., accruals, momentum, size, glamour characteristics). Jensen also suggests that overvaluation leads firms to engage in value-destroying activities. Thus, we next condition PROBM on proxies for manipulation of operating activities, excessive investment, and abnormal issuances of stock. Consistent with Jensen's arguments, such firms have more adverse year-ahead price declines ranging from -11.6 to -14.4 percent.

To conclude our return prediction tests, we develop a simple scoring system that combines firm characteristics into an overvaluation score (O-Score) ranging from zero to five. Firms receive one point for having a high likelihood of earnings overstatement, high sales growth, low operating cash flows to total assets, an acquisition in the last five years, and unusual amounts of equity issuance in the past two years. Thus, firms with unrealistic market expectations (proxied by high sales growth), poor current operating cash flow performance but a high likelihood of earnings overstatement, a history of merger activity, and recent but excessive issuances of stock fit our profile of overvalued equity. And, we show the overvaluation is substantial; firms with O-Scores equal to five experience one-year-ahead abnormal price declines averaging -26.9 percent. This effect is greater than the sum of the main effects for the individual five variables, suggesting that the combination captures a unique profile of firms with substantially overvalued equity. These findings are stable by year and for different levels of market capitalization.

Finally, we evaluate the ability of O-Score to predict earnings restatements, and find that firms with O-Scores equal to five are nearly five times as likely to restate the current period's earnings at some future date. This analysis serves two purposes. First, it confirms Jensen's prediction that overvaluation is associated with a greater risk of earnings overstatement. Second, it helps address concerns of a data-snooping bias. Data-snooping bias is a concern because we build on results from prior research that has evaluated promising characteristics for predicting future returns using similar data sources. We show that O-Score also predicts a consequence of overvaluation other than returns and does so in a relatively recent period. Although we cannot completely rule out the effect of data snooping, these results increase our confidence that the predictive power of the O-Score is not merely a consequence of data-snooping.

We present the remainder of the paper in five parts. We describe the theory and empirical framework Section 2, and in Section 3, we assess whether PROBM predict price declines. In Section 4, we use the manipulation of real activity in combination with PROBM in predicting overvalued equity. In Section 5, we estimate a new model that integrates various predictive attributes and conclude in Section 6.

2. Empirical Framework

According to Jensen (2005), the most severe and most costly cases of overvalued equity culminate in fraudulent accounting practices. Yet, even though the effect of overvaluation should be strongest in cases of accounting fraud, the probability of financial statement fraud has not been examined as a predictor of price declines either on its own or in combination with other firm attributes. Jensen (2005) argues that overvaluation changes the behavior of managers who attempt to report the performance demanded by the market quarter in and quarter out.   He suggests that, before turning to accounting fraud, managers engage in earnings management through real activities manipulation (Graham, Harvey, and Rajgopal 2005) and (within GAAP) exercise of discretion over accounting estimates, invest and issue stock excessively and acquire other firms to sustain their firm's overvaluation.

In section 2.1, we discuss our choice of PROBM as a proxy for the probability of financial statement fraud. In sections 2.2 we discuss tests relating PROBM to future returns, compare PROBM's performance to that of alternative return predictors identified in prior research, and discuss sources of bias. In section 2.3, we argue that changes in managerial behavior result in observable firm characteristics that are useful in identifying earnings overstatement.

2.1 The probability of financial statement fraud

The Beneish (1999) model is appropriate for studying the relation between fraudulent earnings overstatement and equity overvaluation for two reasons. First, Beneish estimates the model using firms that are caught by the SEC or that publicly admit to fraudulently overstating earnings. Second, the firms with actual overstatements fit the substantial overvaluation test in Jensen (2005) because they lose over half their value in the three months surrounding the discovery of the fraud. Indeed, the model predicted the fraud at Enron, Global Crossing, Qwest and several other high profile instances of fraud listed in Table 1 that Jensen uses to motivate his theory of overvalued equity. The mean (median) overvaluation for the twenty instances of fraud reported in Table 1 is 1270 (237) percent—the model correctly identified twelve of these firms as frauds, and did so on average one year and a half *before* the public revelation of the fraud. [2]

The model we use consists of eight predictive ratios that either capture financial statement distortions that can result from fraudulent earnings manipulation or indicate a predisposition to engage in earnings manipulation (see Table 1 for definitions and loadings).[3] There is evidence that the model's ability to predict fraudulent earnings manipulation compares favorably to that of models based on accruals and abnormal accruals (Beneish 1997, 1999; Jones, Krishnan, and Melendrez 2008). [4]

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[2] The model has a false positive rate ranging from 7.2 percent to 13.5 percent, depending on the sample (Beneish 1997, 1999). With the probability cutoff used in Table 1, 15.2 percent of the firms in our sample are potential frauds. In the remainder of the paper, we use the terms overstatement, fraud, and manipulation interchangeably.

[3] The predictive ratios focusing on financial statement distortions capture unusual accumulations in receivables, unusual expense capitalization, declines in depreciation, and the extent to which reported accounting profits are supported by cash profits. The four predictive ratios that suggest propitious conditions for manipulation capture deteriorating gross margins and increasing administration costs, high sales growth (because young growth firms have greater incentives to overstate earnings to make it possible to raise capital), and increasing reliance on debt financing (as this increases the firm's financial risk and the likelihood of earnings overstatement related to debt agreement constraints).

[4] There is a large body of research on earnings management—see Watts and Zimmerman, 1986; Healy and Wahlen, 1999; Beneish, 2001 for reviews. However, studies linking earnings overstatement and overvaluation are scarce. Kothari, Loutskina, and Nikolaev 2007) provide evidence overvalued firms are highly concentrated in extreme positive accrual portfolios suggesting that firms manage accruals upwards to sustain overvaluation, and Badertscher (2008) suggests that overvaluation motivates managers to manage earnings. This evidence suggests using extreme income-increasing accruals as a proxy for earnings overstatement (among others, Sloan 1996; Xie 2001). However, accruals can be high for valid economic reasons that have nothing to do with earnings overstatement (e.g., accelerating growth), and abnormal accruals have been shown to contain a great deal of error (Guay, Kothari, and Watts 1996;McNichols 2000). Indeed, the tests in Beneish (1997) were designed to investigate whether a model could distinguish firms that had high accruals because of earnings manipulation from firms that had high accruals for valid economic reasons. Thus, although one interpretation of the results of papers such as Sloan (1996) or Xie (2001) is earnings management, others are that accruals capture a growth/glamour effect or investor's failure to

The evidence that financial statement data are useful in detecting manipulation and assessing the reliability of accounting earnings has attracted the attention of professionals and educators.[5] Despite its usefulness in detecting fraud, the evidence on the ability of PROBM to predict returns is limited. In a sample of 468 firm-year observations from January 1989 to February 1993, Beneish (1997) shows that firms classified as potential frauds experienced poorer one-year-ahead returns than firms with high accruals. Similarly, Teoh, Wong, and Rao (1998) apply PROBM as an alternative proxy for the occurrence of earnings management in the context of initial public offerings, and document that IPO firms with higher probabilities of manipulation subsequently experience poorer stock market performance.

2.2 Predicting future price declines

Our tests to predict subsequent stock price declines focus on the return-predictive ability of the fraud detection model in Beneish because fraud is a component of Jensen's (2005) theory that has not been studied in a return-prediction context. Our tests examine the following questions: (i) Is PROBM correlated with future returns? (ii) Given other well known predictors of returns, does PROBM have incremental predictive ability? (iii) Does combining PROBM with an evaluation of changes in managers' operating, investing and financing decisions suggested by Jensen (2005)'s theory result in improved predictions of stock price declines?

In terms of investing, we predict a higher probability of overvaluation (and thus of earnings overstatement) for firms with a recent history of acquisitions, particularly when mergers are paid for with stock and involve public targets. Our prediction is based on a large body of

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understand the implications of long-term capital investment (Desai, Rajgopal and Venkachatalam 2004; Fairfield, Whisenant, and Yohn. 2003).

[5] The models have been used as tools for identifying earnings manipulation and assessing earnings quality in financial statement analysis texts (e.g., Fridson 2002; Stickney, Brown, and Wahlen 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). The model received additional attention subsequent to the Enron scandal as Brewer (2004) and others discovered that the model had flagged Enron as early as 1998.

research that suggests that acquisitions with such characteristics are more likely to destroy value (see Jensen and Ruback 1983; Travlos 1987; Fuller, Netter, and Stegemoller 2002; Moeller, Schlingemann, and Stulz 2004). We also predict, following Kedia and Philippon (2008), a higher probability of overvaluation for firms that have a recent history of increased hiring and capital investment.[6]

In terms of financing, we predict a higher probability of overvaluation for firms with a recent history of equity issuance. Our prediction is drawn from research that argues that managers prefer to issue (not to issue) shares if they perceive that their stock is overvalued (undervalued). This research often interprets the evidence of negative returns associated with equity issuances as a signal that the stock is overvalued (see among others, Asquith and Mullins, 1986; Mikkelson and Partch, 1986; Ritter 1991; Spiess and Affleck-Graves 1995; Stein 2003).

In terms of operations, we predict a higher probability of overvaluation for firms that have a history of real activity manipulation and for firms with higher operating volatility. This follows Graham, Harvey and Rajgopal (2005) who find that managers believe volatility is a concern of investors, and that managers are willing to manipulate real activities to meet expectations. We draw on Nichols (2006) to measure operating volatility and on Roychowdhury (2006) to measure real activity manipulation.[7]

The prediction of stock returns is affected by several sources of data bias. Our goal is to evaluate the performance of PROBM using tests that seek to minimize survivorship, look-ahead,

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[6] Kedia and Philippon (2008) suggest that firms that are subsequently required to restate financial statements) over-invest and over-hire as a means of providing the appearance of financial soundness. The appearance of financial soundness is grounded in a large literature that shows more investment by abnormally profitable firms that accumulate more cash and have less debt (see discussions in Hubbard 1998; Stein, 2003).

[7] Roychowdhury (2006) provides evidence consistent with managers' manipulating real operating activities to avoid reporting losses. In particular, he suggests that, to increase income, firms reduce discretionary expenditures; increase production to lower costs of goods sold, and offer discounts to increase revenues. We draw on his work to identify firms with unusually low discretionary expenses, low cash flow from operations, and high production costs.

and data snooping bias.[8] Our tests assessing the predictive value of PROBM are out-of-sample tests using 27,427 observations over the period 1993-2004. These predictive ability tests are implementable (portfolio assignments are made based on prior year's cut-offs), and free of survivorship bias (we retain firms in the analysis until they delist, and do not use firms in the analysis until they list), and look-ahead bias (Beneish estimated his model with data from 1982-1992). However, when we combine PROBM with other well-studied predictors that are implied by Jensen (2005)'s theory into an overvaluation score (O-Score), data snooping bias becomes an important concern. We attempt to address this problem by applying the combination of PROBM with other promising characteristics both to predicting returns in a newer time period, and to a new analysis involving a sample of restatements.

2.3 Predicting earnings overstatement

We assess the performance of the O-Score in predicting the probability of earnings overstatement in large sample of restatements over the period 1993-2004. The context is different from return prediction and the period is new relative to the testing of PROBM. In addition to the single variable prediction model based on O-Score, we follow recent work and control for variables predicted to be associated with a higher probability of earnings overstatement. Specifically, we control for whether firms that have a history of meeting its earnings targets, stricter financial constraints from debt agreements, managers with large holdings of in-the-money options, high price momentum, glamour characteristics—e.g., higher market-price to fundamentals, and larger market capitalizations (e.g., see Jensen, 2005; Effendi,

[8] Survivorship bias occurs when a sample or database systematically excludes a large number of numbers of firms that have become inactive, or conversely when young firms that exhibit good performance are backfilled in commercial databases. Look-ahead bias occurs when the distribution of financial statement data used in prediction is assumed to be known at a given point in time even though many realizations of the data are yet unavailable. Data snooping bias occurs when researchers use common sources of data to build and test return-predictive models that in part use factors previously documented to predict returns.

Srivastava, and Swanson 2007; Kothari, Loutskina, and Nikolaev, 2007; Badertscher, 2008). Further, in a comparison to contemporaneous research, we show that the O-Score loads significantly when added to the model proposed by Dechow, Ge, Larson, and Sloan (2008).

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 2004. 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 (1997, 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.

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. In case of delisting, we follow Beaver, McNichols, and Price (2007) to include delisting returns in the buy-and hold return. The final sample consists of 27,427 firm-year observations from 1993 to 2004.

3.2 Distinguishing PROBM from alternative predictors of future returns

Prior research has shown that a number characteristics are correlated with subsequent returns: (1) accruals, following Sloan's (1996) evidence that accruals are negatively correlated with future returns,[9] (2) the book-to-price ratio, following evidence in Lakonishok, Shleifer, and Vishny (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) price-to-earnings, following evidence that firms with low P/E firms outperform firms with high P/E ratios on a risk-adjusted basis (among others, see Haugen and Baker 1996); (5) firm size, following evidence in, among others, Fama and French (1992), and (6) cash flow from operations to price following evidence in Desai, Rajgopal, and Venkachatalam (2004) that firms with low CFO/P subsequently earn lower returns.

In Table 2, Panel A we report the correlation matrix for the decile rank assignments based on each of these characteristics, as well as PROBM. Correlations of PROBM with three variables are noteworthy. First, PROBM and accrual decile ranks are highly correlated (correlation = 0.662, $p < 0.001$). 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.

[9] Studies have provided similar evidence for alternative measurements of accruals, abnormal accruals, and components of accruals (Xie (2001); Collins and Hribar 2002; Hribar 2002; Thomas and Zhang 2002; Richardson Sloan, Soliman and Tuna 2005; Chan, Chan, Jegadeesh and Lakonishok 2006; Gu and Jain (2006)): evidence that the accrual effect appears to be distinct from post-earnings announcement drift (Collins and Hribar 2001), and from the tendency of stock prices to drift in the direction of analysts' forecast revisions (Barth and Hutton 2004); evidence that sophisticated investors such as analysts, auditors, and institutional investors also fail to fully understand the implications of accruals for future earnings (Bradshaw, Richardson, and Sloan 2001; Collins, Gong, and Hribar 2003; Barth and Hutton 2004; Lev and Nissim 2006); and evidence that top executives understand the implications of accruals for future earnings and trade their equity contingent wealth accordingly (Beneish and Vargus 2002).

Second, the negative correlations between PROBM ranks and both B/P and CFO/P ranks suggest that firms with high probability of overstatement have glamour characteristics—low B/P and low CFO/P. On the other hand, the correlation between PROBM and E/P ranks of 0.126 (p-value<0.001) is not consistent with a glamour profile, but it is consistent with high probability of overstatement being associated with inflated earnings.

In Table 2, Panel B, we investigate whether the returns to a strategy based on PROBM are subsumed by other variables associated with 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:

$$BHSAR_{t+1} = a_0 + a_1 PROBM_t + a_2 Accrual_t + a_3 Momentum_t + a_4 \ln(MVE_t) + a_5 B/P_t + a_6 CFO/P_t + a_7 E/P_t + e_{t+1} \quad (1)$$

The results from the estimation of the 12 annual cross-sectional regressions indicate that scaled PROBM ranks are negatively correlated with one-year-ahead abnormal returns (-0.082, t-statistic=-2.30), and that momentum and B/P are positively correlated with one-year-ahead abnormal returns (0.059, t-statistic=1.76, and 0.062, t-statistic=3.34). The remaining variables including accruals, size, CFO/P, and E/P do not attain significance. Because ranks of E/P, ACC, and CFO/P are highly correlated, we also drop E/P results from the estimation of the 12 annual cross-sectional regressions and obtain similar results. The coefficients on accruals, size, and CFO/P are not distinguishable from zero in either specification. This suggests that after controlling for accruals and other variables associated with future returns, a portfolio strategy based on PROBM earns between 8.2 and 8.4 percent.[10]

[10] We also find a significant coefficient of -8.5 percent on scaled decile ranks formed on PROBM even after controlling for portfolios formed on the component characteristics of PROBM, suggesting the model combines these characteristics into a unique profile of firms likely to overstate earnings.

In Table 3, we compare PROBM and other return-predictive characteristics associated with overvalued equity. Panel A reports the average abnormal returns associated with alternative deciles ranks for our sample. Hedge returns based on extreme deciles equal 13.95% for PROBM, 13.44% for accruals, 3.50% for momentum, 3.27% for size, 8.08% for B/P, 12.57% for CFO/P, and 0.53% for E/P. The top three predictors of price declines are extreme positive accruals (-10.45%), the high PROBM decile (- 9.56%) and the low CFO/P decile (-4.77%). The results based on ranks of individual characteristics contrast with the multivariate results from estimating equation (1) annually.

To further evaluate PROBM's ability to predict price declines, we separate the firms in each decile of accruals, momentum, size, B/P, CFO/P and E/P into high and low PROBM, where high PROBM includes the 4,164 observations in our sample flagged as potential manipulators. The results in Table 3, Panel B and Figure 1 are striking. The performance of the flagged sub-sample is systematically worse than its not-flagged counterpart in each of the 60 deciles. Furthermore, in 59 of the 60 flagged sub-samples, the average abnormal future returns are negative. Extreme high accrual firms with a high likelihood of overstatement have future abnormal returns of -13.25%, while extreme high accrual firms with a low likelihood of overstatement have future abnormal returns of -6.10%. Similarly, we show that firms with extremely poor CFO/P and a high likelihood of overstatement have future abnormal returns of -11.47%, while extremely poor CFO/P firms with a low likelihood of overstatement have future abnormal returns of -0.93%.

We interpret this evidence as indicating that PROBM explains future returns incrementally to accruals, momentum, size, B/P, CFO/P, and E/P, and that PROBM explains returns within deciles of such characteristics. Because PROBM is based on public information, it is perhaps surprising that PROBM has predictive power for future returns. To further assess the validity of PROBM as an indicator of overvalued equity, we report in the Appendix a number of analyses that provide insights as to why PROBM predicts returns, whether PROBM classifications and changes in institutional holdings are related, and whether transaction costs limit opportunities to arbitrage overvaluation in our sample. We also report a number of robustness checks relating to the measurement of abnormal returns and the measurement of earnings management. We find that our results are robust to these additional checks. They suggest that firms with a high probability of overstatement are more likely to be overvalued and experience subsequent price declines.

4. Real activity manipulation and the prediction of overvalued equity

In this section, our goal is to assess whether, conditional on a high likelihood of overstatement, characteristics described by Jensen's (2005) theory better predict price declines. We first combine our proxy for accounting fraud with proxies for potentially value-destroying acquisitions. We then examine our proxy for accounting fraud in combination with abnormal financing and investing activities and the manipulation of real operating decisions. Finally, we present evidence on the predictive ability of the O-Score for future returns.

4.1 Combining prior merger activity with PROBM

In Table 4, we combine prior merger activity with PROBM.   We find that the incidence of mergers in the five years prior to the measurement of PROBM is similar for firms with high and low PROBM—for example mergers occur in 62.4 (59.6) percent of firms flagged (not flagged) as potential frauds. While the proportion of tender offers and public targets is also similar, flagged firms are significantly more likely to have paid for the acquisition in stock (52.1 vs. 37.9 percent).   We show that among firms predicted as potential frauds, those that have merger activity in the prior five years experience poorer one-year-ahead abnormal returns performance (-11.55%). The performance worsens when the merger activity involves public targets (-12.67%), and for acquisitions paid in stock (-13.31%). These findings are consistent with prior research that has shown that many mergers destroy shareholder wealth, particularly those involving publicly traded targets and/or those completed as stock-for stock exchanges (see Jensen, 1986; Travlos, 1987; Agrawal, Jaffe, and Mandelker 1992; Loughran and Vijh 1997; Rau and Vermaelen 1998; Moeller, Schlingeman and Stulz 2004). In untabulated analyses, we find that the one-year-ahead performance of firms with acquisitions and stock acquisitions when the acquirer is in the top price-to-book quintile is -5.04% and -7.32% respectively. Our findings for acquirers in top price-to-book quintile are in line with Rau and Vermaelen (1998) who show that post-acquisition underperformance is predominantly caused by "glamour" acquirers. They report one-year-ahead abnormal returns of -1.25% and -7.03% for glamour acquirers involved in cash-financed and stock-financed mergers (Rau and Vermaelen 1998, 244). However, these returns are significantly less adverse than those combining PROBM with merger activity.

4.2 Combining abnormal investing, financing and operating activities with PROBM

In Table 5, we examine whether firm characteristics related to manipulation of financing, investing and operating activities can improve predictions of overvalued equity. In Panel A we present alternative measures of abnormal financing computed as deviations from an industry benchmark or from a time-series benchmark. We find that combining PROBM with an indication of abnormal stock issuance better predicts future price declines. When we measure excessive net stock issuance relative to the industry median over various periods, we find one-year-ahead performance ranging from -12.44% to -14.36%. This is significantly more adverse than the one-year-ahead return we observe for firms that have abnormal equity financing and are in the top price-to-book quintile (-5.11%), suggesting that the combination of PROBM and abnormal equity financing is capturing more than a glamour effect.[11] This is consistent with the notion that equity issuance points to managers' perception that their stock is overvalued. However, when we combine PROBM with an indication of abnormal debt issuance, we find numerically (but not statistically) larger abnormal performance among firms predicted by PROBM as potential frauds. We conjecture that excessive reliance on debt imposes greater discipline through additional debt agreement constraints, and increases oversight by lenders.

In Panel B, we consider four alternative measures of investment: Investment in PPE (capital expenditures), Operating Investment (capital expenditures plus R&D), Total Investment (Operating investment plus acquisitions less PPE sold), and Net Investment (Total Investment less Depreciation). We assess these measures over periods ranging from one to three years prior to the measurement of PROBM. When the industry is used as a benchmark, abnormal investing occurs when a firm's investing measure exceeds the median value for the corresponding measure in the firm's two-digit SIC code. When the benchmark is the firm itself, abnormal investing occurs when a firm's investing measure in the current year exceeds the prior year. The majority of the tests reveal no evidence that our measures of excessive investment are associated with differential return performance.

In Panel C, we combine PROBM with proxies for the manipulation of operating activities based on Roychowdhury (2006).[12] Combining PROBM with an indication that operating cash

[11] Loughran and Ritter (1995,33) show a large sample of initial (seasoned) equity offerings over the period 1970-1990 underperform their matching firms by -6.7% (-6.3%) in the first year after the offering. Similarly, Spiess and Affleck-Graves (1995, 253) show 12-month post-offering returns ranging from -2.29% and -5.00%.

[12] Specifically, we estimate the following regressions for each two-digit SIC and year combination with at least 8 observations available: (1) CFO on sales and change in sales, (2) production costs (cost of goods sold plus change in inventory) on sales, change in sales, and lagged change in sale, and (3) discretionary expenses (SGA plus advertising plus R&D) on lagged sales. All variables are scaled by lagged total assets, and we include unity scaled by total assets as an additional regressor. We use the residuals as our measure abnormal CFO, abnormal production costs, and abnormal discretionary expenses. For the most recent year, we estimate abnormal CFO, abnormal

flows have been unusually low, we find one-year-ahead performance ranging from -13.04% to -14.11%. This could result from the association between the Roychowdhury measure and operating cash flows, which prior research shows is negatively associated with future returns. However, we find no evidence of differential return performance when combining PROBM with indications of unusually high production costs or unusually low discretionary expenses.

4.3 The O-Score

The preceding evidence suggests that exploiting information about manager's real decisions in firms that are likely to have overstated earnings yields improved predictions of future price declines. We construct the O-Score to range from zero to five and contain the five components of real and accounting activities that predict price declines. Specifically, a firm's O-Score equals five in a given year if, in that year, the firm is classified in the top PROBM quintile, the bottom cash flow from operations to total assets quintile, the top sales growth quintile,[13] and if the firm has engaged in an acquisition in the prior five years, and issued equity in excess of the industry median in either of the prior two years.[14]

We present the results of the O-Score's performance in Table 6. We begin by reporting the one-year-ahead returns associated with each component of the O-Score. The abnormal one-year-ahead return associated with the top quintile of PROBM (-6.23%) is significantly smaller than the corresponding return for the sample complement (2.68%). Similarly the abnormal one-year-ahead return associated with low cash flows from operations (-6.85% vs. 2.91%), high sales

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production costs, and abnormal discretionary expenses using the prior year's regression coefficients and assign the observation to quintiles using the prior year's distribution.

[13] Operating cash flows to total assets strongly correlates with Roychowdhury's (2005) measures of real activities manipulation. We use sales growth because prior work that suggests sales growth is associated with unrealistic market expectations (Lakonishok, Shleifer, and Vishny 1994).

[14] To ensure the rule can be implemented, we use the prior year's quintiles cut-offs to classify a firm in the current year.

growth (-4.79% vs. 2.37%), prior acquisitions (0.21% vs. 1.80%), and prior abnormal financing (-0.11% vs. 2.71%).

Table 6, Panel B presents the one-year-a head returns associated with each value of the O-Score. Firms that obtain an O-Score of zero are the least likely to be overvalued because managers are less likely to have overstated earnings or otherwise engaged in value destroying real activities. Such firms on average earn positive, but relatively small one-year-ahead abnormal returns (4.5%) with approximately half (51.8%) of the observations having negative returns. In contrast, firms that obtain an O-Score of five are the most likely to be overvalued because managers are more likely to have overstated earnings and engaged in value-destroying real activities. These firms on average experience negative one-year-ahead abnormal returns of -26.9%, and 76.4% of the observations are negative. Indeed, the average one-year-ahead abnormal return decreases monotonically and the percent of the observations that are negative increases monotonically with the O-Score. This evidence suggests a high O-Score indicates the firm is likely to be overvalued.

We also point out that the returns for firms with O-Score equal to five are significantly lower (more negative in magnitude) than the sum of the returns to the five characteristics individually, as presented in Panel A. In untabulated analyses, we regress future buy-and-hold size adjusted returns on five indicators for each of the five characteristics in Panel A, as well as an indicator equal to 1 if all five characteristics are present. This corresponds to an O-Score of five, and captures the interaction of the five variables. The coefficient on the interaction is -18.0 percent and is statistically significant. The next highest coefficient is -6.1 percent for CFO/TA, which is also significant. Although we build on prior research that identifies sales growth and operating cash flows as significant predictors of future returns (e.g., Desai, Rajgopal, and

Venkatachalam 2004), this work does not imply that the interaction of our five O-Score variables will have significant explanatory power. Thus, this analysis provides additional assurance that our results are not merely the result of a data-snooping bias.

To corroborate the finding that high O-Scores predict price declines, we conduct two additional tests. In Panel C and Figure 2, we partition the sample by market capitalization and find that the high O-Score results hold for different size classes. For example, when O-Score equals five, the average one-year-ahead abnormal return ranges from -21.4% (firms with market capitalization between \$100 and \$250 million) to -31.5% (firms with market greater than \$1 billion). In Fig. 3, we report the high and low O-Scores by year. We find that the one-year-ahead returns associated with an O-Score equal to five are negative in eleven out of twelve years. We conclude that the O-Score is a powerful predictor of overvalued equity, and is not driven by a subset of firms in a particular period.

Next, we examine the relation between O-Score and the scoring systems of Piotroski (2000) and Mohanram (2005). Piotroski's (2000) F-Score and Mohanram's (2005) G-Score use financial characteristics to identify the eventual winners in the set of value firms (F-Score) and glamour firms (G-Score). Conceptually, overvaluation is linked to the glamour phenomenon because overvalued firms should have high valuations relative to fundamental characteristics. In fact, O-Score uses sales growth as one of the scoring variables, and Lakonishok, Shleifer and Vishny (1994) and Desai, Rajgopal and Venkachatalam (2004) show that sales growth relates to other glamour characteristics. However, the O-Score differs from these other scoring systems because O-Score is designed to identify *eventual losers* from the *entire sample*. In contrast, the F- and G-Scores are designed to identify eventual winners from a subset of the population (value and glamour firms, respectively).

Our O-Score has a relatively modest correlation of -34.1% with the F-Score and -36.3% with the G-Score (both untabulated). These correlations suggest O-Score is distinct from these scoring systems. We also report in Panel D the time-series average of twelve annual cross-sectional regressions of returns on scaled O-, F- and G-Scores to confirm O-Score provides incremental explanatory power for returns. We follow Piotroski (2000) in measuring the F-Score and Mohanram (2005) in measuring the G-Score. The scaled O-Score variable is consistently negative and significant, with coefficients ranging from -.174 in the univariate regression to -.131 in the regression that includes scaled F-Score and scaled G-Score rankings. Thus, O-Score is useful in predicting returns and is not a noisy proxy for these alternative scoring systems.

Finally, we identify a sample of restatements that occur during our time period to assess whether the performance of the O-Score is driven by losses associated with restatement firms.[15] In untabulated analyses, we find similar performance for the O-Score when restatement firms are removed. For example, when O-Score equals 5, the return performance excluding restatements is -26.51% (vs. -26.93% including restatements). Similarly, when O-Score equals 4, the return performance excluding restatements is -7.98% (vs. -8.01% including restatements). This suggests that the O-Score's ability to predict price declines in not simply driven by a few restatement observations. In the next section, we further exploit the restatement data to estimate a model that examines the ability of the O-Score to predict future restatements.

5. Using Characteristics of Overvalued Equity to Predict Fraud

In this section, we examine whether high O-Score firms are more likely to commit fraud. Jensen (2005) suggests that the most severe and costly cases of overvalued equity culminate in

[15] The revelation that financial statements are fraudulent is associated with negative abnormal returns (Beneish 1999, -20 percent over three days [-1, +1], Karpoff, Lee and Martin 2008, -25 percent on the first trigger event and -51 percent across all events). Similarly, firms announcing restatements due to irregularities lose between 15 and 25 percent of their value in the three months (Badertscher, Collins, and Lys 2007) and six months (Hennes, Leone and Miller 2008) after the restatement becomes public.

fraudulent reporting. Thus, this analysis helps address concerns of a data-snooping bias by examining the association between O-Score and overvaluation in an alternative context to return prediction, and in a period that follows the testing of the fraud component of the O-Score. If the O-Score distinguishes overvalued firms, the O-Score should be associated with an increase the probability of fraudulent accounting restatements.

We present two versions of the model. The first uses the O-Score as the only explanatory variable; the second model adds as controls a number of other characteristics proposed in recent research (see section 2). We model the probability that a firm-year will be restated due to fraud as follows:

$$OVERSTATE_{i,t} = \gamma_0 + \gamma_1 O - Score_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$\begin{aligned} OVERSTATE_{i,t} = {} & \gamma_0 + \gamma_1 O - Score + \gamma_2 NOMISS_{i,t} + \gamma_3 ITM_{i,t} + \gamma_4 PB_{i,t} \\ & + \gamma_5 MOM_{i,t} + \gamma_6 SIZE_{i,t} + \gamma_7 PPEGRO_{i,t} + \gamma_8 EEGRO_{i,t} \\ & + \gamma_9 REM_{i,t} + \gamma_{10} OPVOL_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In equation (3), five variables (NOMISS, ITM, PB, MOM, and SIZE) capture capital market incentives and characteristics associated with overvaluation, and four variables capture characteristics of the firm's investing (PPEGRO, EEGRO),[16] and operating activities (REM, OPVAL).

5.1 Sample

We evaluate the models with a sample of 630 restatement firm-years and 24,632 non-restatement firm-years from 1993 through 2004.[17] We estimate our probit regression model on

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[16] We do not adjust PPEGRO for industry benchmarks for consistency with Kedia and Philippon (2007).

[17] We collected sample of restatements from AAERs and Audit Analytics databases. Audit Analytics provides data on restatements announced beginning in 2000. Audit Analytics includes the beginning and ending dates of the restatement, as well as whether the restatement is associated with fraud or with a regulatory investigation. We supplement the Audit Analytics data with SEC Accounting and Audit Enforcement Releases (AAERs) from 1997 through 2007. For AAERs, we review the releases to identify company name and the beginning and ending dates of the fraud.

our sample from 1993 through 1998 (estimation sample) and use data from the 1999 to 2004 in out-of-sample tests (holdout sample). The estimation sample includes 171 restatement firm-years and 13,979 nonrestatement firm-years, while the holdout sample includes 459 restatement firm-years and 10,653 nonrestatement firm-years. We end the estimation period in 1998 to avoid incorporating in the model observations that reflect the incentives and effects associated with stock market bubble of the late 1990s.[18]

Table 7 reports descriptive statistics for the restatement and nonrestatement firm-years in our estimation sample. Restating firms have higher O-Score (p = 0.00), consistent with a significant relation between overvaluation and restatements. Restatement and nonrestatement firm-years differ for many of the variables suggested by Jensen's (2005) theory of overvalued equity. Consistent with a higher likelihood of overvaluation for firms committing fraud, restatement firms have significantly higher price-to-book ratios (PB, p = 0.00) and significantly higher prior returns (MOM, p = 0.04). Restatement firms are not more likely to meet or beat expectations (NOMISS, p = 0.83), but they have greater amounts of in-the-money options (ITM, p = 0.00) suggesting greater equity incentives for managers to overstate earnings (Efendi et al. 2007). Firms that restate have significantly higher growth in property, plant, and equipment (PPEGRO, p = 0.00) and employees (EEGRO, p=0.00). Restating firms have a marginally greater tendency to manipulate operating activities, (REM, p = 0.07) and also have significantly higher operating volatility (OPVAL, p = 0.01).

We report the correlations between our variables in Table 8. OVERSTATE significantly correlates with all other variables except NOMISS. Many economically small correlations are nevertheless significant because of our large sample size, and we focus our discussion on the

[18] If the bubble period is different from other periods, we run the risk of overfitting. However, as the bubble period is worthy of study, we also estimate a model using data just preceding the bubble (1996-1998) and find similar results.

larger correlations between explanatory variables. O-SCORE is significantly correlated with PB, MOM, PPEGRO, EEGRO, and OPVOL. This suggests that high O-Score firms have high valuations relative to fundamentals, high prior returns, and are experiencing relatively high contemporaneous growth and operating volatility.

5.2 Estimation Results

In Table 9, we present the results of estimating model (2) and two alternative versions of model (3). Model (2) includes O-SCORE only and allows us to quantify the difference in the likelihood of fraud across high and low O-SCORE firms. The coefficient on O-SCORE is significantly positive (estimate = 0.122, $p < .0001$), indicating that overvalued firms are more likely to commit fraud than other firms. The likelihood of earnings overstatement is .62 percent when O-SCORE is zero, but rises to 2.95 percent for firms with O-SCORE of 5. Thus, high O-Score firms are nearly five times as likely to overstate their earnings as low O-Score firms.

The first version of model (3) adds additional market-based incentives and characteristics, investing characteristics, and operating characteristics to the O-SCORE. O-SCORE remains significant (estimate = 0.104, $p < .0001$). In addition, ITM ($p = .006$), SIZE ($p < .0001$), and PPEGRO ($p = .031$) have significant positive relations with the earnings overstatements. The positive coefficient on ITM is consistent with the notion that executives are more likely to engage in income-increasing earnings manipulation when they have significant in-the-money options.[19] Our final specification eliminates extraneous variables. Although the

[19] This result is consistent with Efendi, Srivastava, and Swanson. (2007). Although they measure in-the-money options for the executives using ExecuComp, we require a measure of in-the-money options for a broader set of firms. Therefore, we collect weighted average strike prices and options outstanding from Capital IQ for the entire firm (not just executives). ITM denotes in-the-money options, defined as price at the end of the fiscal year (data199) minus the weighted average strike price of options outstanding, multiplied by the options outstanding at the end of the year divided by total assets (data6).

pseudo R-square declines to 4.7 percent, O-SCORE, ITM, SIZE, and PPEGRO remain significant.

Overall, the evidence in Table 9 suggests that O-SCORE is useful in distinguishing firms with overstated earnings. In addition, firms with incentives from equity compensation, large firms, and firms with abnormally high capital expenditures are more likely to have earnings overstatements. In the next section, we evaluate the model as a tool for identifying probable overstatements *ex ante*.

5.3 The model as a classification tool

In this section, we discuss the usefulness of the model as a classification tool. We discuss the probability cutoffs associated with alternative cost assumptions for classification errors. The model can make two types of errors. First, the model can classify a manipulator as a non-manipulator (Type I). Second, the model can classify non-manipulators as manipulators (Type II). Assumptions about the relative costs of these two errors determine the probability cutoff that minimizes these costs.

We compute the in-sample probability cutoffs that would minimize the expected costs of misclassification for alternative assumptions about the relative costs of Type I and Type II errors. We report the equation for computing the costs and the results in Table 10. In Panel A, for the estimation sample, assuming relative costs of 30:1, the model classifies firms as manipulators if the probability of overstatement exceeds 2.67 percent. At this cutoff, the model correctly classified 29.2 percent of manipulators (Type I error rate = 70.8 percent) but also classified 6.2 percent of non-manipulators as manipulators (Type II errors). At a 60:1 cost ratio, the model flags firms as manipulators if the probability of overstatement exceeds 1.84 percent. At this cutoff, the model correctly classifies 47.4 percent of manipulators (Type I error rate = 52.6

percent) but also classifies 15.5 percent of non-manipulators as manipulators. At an 80:1 cost ratio, the model flags firms as manipulators if the probability of overstatement exceeds 1.64 percent. The model correctly classifies 52.6 percent of manipulators (Type I error rate = 47.4 percent) but also classifies 19.8 percent of non-manipulators as manipulators.

In Figure 4 we graphically depict the discriminatory power of the full model (denoted PROBN) in the estimation sample using a receiver operating characteristic (ROC) curve. The ROC curve plots the true positive rate against the false positive rate for cutoffs corresponding to the predicted values of PROBN for firms in the sample. The area under the ROC curve measures the discriminatory power of the classification model. An area of .5 (the dashed line in Figure 5) corresponds to no discriminatory power: each increase in the true positive rate is accompanied by an equal increase in the false positive rate (e.g., a coin flip). An ROC curve that rises quickly toward the top left corner will have an area under the curve of greater than .5. If the area under the ROC curve equals one the classification model has perfect discriminatory power. The area under the ROC curve for PROBN is .68, which is significantly greater than .50 (z-statistic = 8.08, $p < 0.001$).

We also evaluate the model on three alternative holdout samples: the full holdout sample consists of 459 restatements and 10,653 non restatements from 1999 through 2004; the early holdout sample corresponds to the bubble period 1999-2001 (262 restatements and 6,742 non restatements) and the late holdout sample to the post bubble period 2002-2004 (197 restatements and 4,370 non restatements). With a 60:1 cost ratio assumption, the model flags 41.4 percent of manipulators in the full holdout sample while also classifying 22.2 percent of non-manipulators as firms that overstate earnings. The model classifies substantially more firms as manipulators in the early vs. the late holdout sample. That is, the model correctly classifies 46.6 percent of the manipulators in the early holdout sample (vs. 34.5 percent in the late sample), and correspondingly has a higher false positive rate in the early period (24.5 percent vs. 18.8 percent in the late period). We speculate that differences obtain across periods because the bubble period has more pronounced glamour characteristics, while the post-bubble period is characterized by greater regulatory oversight.

In Figure 5 we depict the discriminatory power of the full model in the holdout sample. The discriminatory power in the holdout sample should be diminished compared to the model's performance in the estimation sample because the model is designed to best fit the estimation sample. Thus, the area under the ROC curve is .64, which is significantly greater than the benchmark of .5 ($p < 0.001$, untabulated), indicating significant predictive power of the model in the holdout sample.

6. Conclusions

In this paper, we provide a method for identifying substantial overvaluation. Firms that meet our profile of overvalued equity have a high likelihood of financial statement fraud, high sales growth, low operating cash flows, and a recent history of acquisitions and stock issuance. Firms that meet this profile have large abnormal stock price declines averaging -26.9 percent, and are almost five times as likely to restate current earnings at some future date. We add to existing research by examining the ability of an ex ante measure of the probability of fraud (PROBM) to predict returns both individually and in combination with other characteristics implied by Jensen's theory of overvalued equity. Indeed, our finding that the O-Score's effect is greater than the sum of the main effects of its five components suggesting that, in combination, the score captures something a unique profile of substantially overvalued equity.

Our results are subject to several cautions. Although we document robust results using historical data, and are careful to avoid look-ahead or survivorship biases, the possibility always exists that our results will not hold in alternative samples or sample periods. In addition, we build on prior research that uses similar data sources to document a relation between firm characteristics and future returns. Although we validate our approach by predicting earnings overstatements, which is an alternative context to return prediction, we cannot fully rule out a data-snooping bias.

With these cautions in mind, our profile of overvalued equity should be of interest to investors, managers, and boards interested in identifying the risk of large stock price declines, as well as auditors and regulators who want to identify firms with a high risk of accounting impropriety. In addition, our results should be useful to researchers interested in the causes and consequences of overvaluation by providing an *ex ante* proxy for overvalued equity.

Appendix

Additional Analyses

This Appendix contains analyses addressing the following questions: (1) why PROBM predicts returns, (2) whether PROBM classifications and changes in institutional holdings are related, (3) whether transaction costs limit opportunities to arbitrage overvaluation in our sample, (4) whether the results are robust to alternative measurement of abnormal returns and earnings management.

A1 Why Does PROBM Predict Returns?

Following Shleifer (2000), a complete explanation for the apparent mispricing associated with PROBM should explain (1) why some investors make mistakes, and (2) what prevents smart money investors from correcting the mistakes of others.

We posit that investors are misled when managers manipulate earnings by introducing transitory distortions in the accrual component of current earnings. If PROBM is a useful tool for assessing earnings overstatement, current income-increasing accruals for firms with high (low) PROBM should be less (more) persistent, while negative accruals for firms with high (low) PROBM should be more (less) persistent. We examine the relation between current and future earnings, current and future accruals, and current and future cash flows with the following model:

$$DV_{t+1} = \alpha_0 + \beta_1 CFO_t + \beta_2 CAccPos_t + \beta_3 CAccNeg_t + \beta_4 CAccPos_t * IPR_t + \beta_5 CAccNeg_t * IPR_t + \beta_6 Dep_t + \beta_7 IPR_t + \varepsilon_{t+1}$$

Where DV denotes earnings, cash flows from operations, or accruals, as appropriate, and IPR equals 1 if the firm is flagged at a 20:1 cost ratio (-1.78 < PROBM).[20] We report t-statistics based on standard errors corrected for clustering by firm and year (Petersen 2007).

We report the results for scaled PROBM ranks in Table A1. For earnings in column (1), we find strong persistence for CFO (coefficient = 0.858, t-statistic = 40.43), but weaker persistence for accruals (CAccPos = 0.714, t-statistic = 9.67; CAccNeg = 0.358, t-statistic = 12.19). The coefficients on CAccPos and CAccNeg reflect the persistence of positive and negative accruals, respectively, for firms not flagged as possible manipulators. The coefficients on CAccPos*IPR and CAccNeg*IPR capture the effects of the probability of manipulation on accrual persistence. CAccPos*IPR is negative and significant (coefficient = -0.092, t-statistic = -1.64), while CAccNeg*SPR is positive and significant (coefficient = 0.227, t-statistic = 1.80). Thus, both income-increasing and income-decreasing accruals that have a high probability of overstatement lead to lower future earnings, consistent with PROBM measuring the likelihood that earnings contain income-increasing distortions. Moreover, IPR is significantly negative (coefficient = -0.020, t-statistic = -4.85), suggesting that flagged firms have lower future profitability (return on assets) by 200 basis points.

Future realized earnings reflect both future cash flows and future accruals. It is possible that these results reflect the relation between PROBM and future operating cash flows. In this case, PROBM would not measure the likelihood that earnings contain income-increasing distortions, but instead would capture differences in economic performance. To rule out this possibility, we separately estimate the relation between future CFO and future accruals on current earnings components and IPR and report the results in columns (2) and (3), respectively.

A noteworthy feature of the coefficients reported in columns (2) and (3) is that their sum approximates the estimated coefficient in column (1). Thus, a comparison of results in column (2) to column (3) indicates the source of the relation between the regressors and future earnings reported in column (1). For both CAccPos*IPR and CAccNeg*IPR, the results indicate a stronger relation with future accruals than with future cash flows. In particular, the coefficient on CAccPos*IPR is not significant in the cash flow regression (0.022), but it is significant in the accruals regression (-0.110). Similarly, the coefficient on CAccNeg*IPR is not significant in the cash flow regression (0.028), but it is significant in the accruals regression (0.167). Thus, current accruals that have a high probability of overstatement lead to lower future earnings not because they predict lower future cash flows, but

[20] The independent variables are components of current earnings. Because earnings manipulation typically occurs through working capital accruals, we disaggregate current period earnings into operating cash flows (CFO), current (working capital) accruals, and depreciation (Dep). We estimate separate coefficients for positive (CAccPos) and negative (CAccNeg) current accruals because we expect positive (negative) accruals that are overstated to have lower (higher) persistence. Finally, to capture the effect of PROBM on the implications of accruals for future earnings, we interact PROBM with CaccPos and CaccNeg.

rather because of lower future accruals. These lower future accruals are consistent with the reversal of transitory distortions in current earnings due to earnings overstatement.

A2 Do sophisticated investors exploit PROBM?

Sophisticated investors are *a priori* less likely to be misled by managers' exercise of accounting discretion and potentially better able to effect (at lower cost) a short selling transaction. As a result, we examine how institutional holdings change over time depending on (1) whether they are in the extreme PROBM deciles, and (2) whether firms become flagged/unflagged during the year. Table A2 reports analyses relating to institutional holdings in quarters -3 to +3 relative to the quarter in which a position is initiated in a stock. For each quarter in the analysis, we calculate institutional holdings as the ratio of the number of shares held by all institutions reporting their holdings on Form 13-F to the firm's shares outstanding at the end of the quarter.[21] In Panel A we show that a pattern of quarterly abnormal returns suggesting that, relative to low PROBM firms, high PROBM firms exhibit higher return momentum before quarter 0 and lower return momentum from quarter 0 onwards. Panel A also shows that the percentage of shares held by institutions display a similar pattern of increases in the quarters 0 and +1 whether the firms are on the long or short side of the hedge. For example, the increases in the percentage of shares held by institutions in quarters 0 and +1 for firms in the low probability of manipulation decile (0.20 percent and 0.82 percent) are similar to the corresponding increases in the high probability of manipulation decile (0.37 percent and 0.97 percent). This investment behavior suggests that institutional investors behave as if they ignore information relevant to assessing the probability of manipulation. One possible explanation is that institutions place too much emphasis on past returns, as firms with high (low) PROBM have higher (lower) return momentum. By quarter +3 the patterns changes as institutional investors increase their stake in firms in the low PROBM decile by .62 percent, but decrease their stake in firms in the high PROBM decile by -.14 percent, The difference in patterns is likely due to new information (e.g., quarterly earnings) that reveals poorer prospects.

In Table A2, Panel B, we repeat the analysis for institutions classified as transient, dedicated, or quasi-indexers using the classification developed by Bushee and Noe (2000). Our goal is to evaluate whether certain types of institutional investors are more likely to exploit information relevant to assessing the probability of manipulation. The average holding for "transient" institutions follows a pattern that is quite similar to that of all institutions: Holdings in high PROBM deciles only decline in quarter +3. Furthermore, these transient institutional investors have systematically higher holdings in high PROBM firms rather than low PROBM firms. Although transient investors focus is the short term focus (high turnover), the evidence suggests that they do not appear to exploit public information relevant to the probability of manipulation. The pattern of holdings for "dedicated" institutional investors differs from the two prior patterns. For the high PROBM decile, average holdings decline as early as quarter 0: whereas average holdings equal 8.45% in quarter -1, they drop to 7.65% by quarter +1, and 7.60% by quarter +3. This is consistent with "dedicated" investors having better access to firm's private information, as a result of their investment style (relationship-investing with typically larger equity stakes and low turnover). The pattern of holdings for "quasi-indexers" also differs from the prior patterns. For the high PROBM decile, average holdings never decline, and in fact, they increase faster than the corresponding holdings for the low PROBM decile. In sum, this suggests that institutional investors largely ignore information relevant to assessing the probability of manipulation.

In Table A2, Panel C we restrict the sample to firms with institutional holdings that have PROBM data in two consecutive years. We analyze changes in institutional holdings in consecutive years as a function of whether the PROBM model flagged the firm as a potential manipulation. For each of two different PROBM cut-offs, we present a 2 X 2 matrix. We focus our discussion on PROBM>-1.78 (assuming 20:1 costs of classification errors) as the results are similar. The largest cell corresponds to firms that are not flagged in either year t-1 or year t: for these firms the change in average institutional holdings from year t-1 to t is 1.77 percent. We use this percentage as a benchmark against which to evaluate changes in the other cells: (1) The cell corresponding to firms that are flagged in both year t-1 or year t shows a change of 3.50 percent that is significantly greater from the 1.77 percent benchmark; (2) The cell corresponding to firms that are not flagged in year t-1 but flagged in year t shows a change of 4.03 percent that is significantly greater than the 1.77 percent benchmark; (3) The cell corresponding to firms that are flagged in year t-1 but not flagged in year t shows a change of 0.92 percent that is significantly smaller than the 1.77 percent benchmark. The results for transient and quasi-indexers also suggest that these types of institutional investors behave as if they are misled by managers' accounting manipulations. That is, we find no evidence that sophisticated investors sell on a timely basis when they ought to suspect the firm has a high probability of

[21] Institutional holdings and share data are adjusted for stock splits and obtained from the Spectrum database and CRSP.

manipulation. Further, with the exception of "dedicated" investors, we find that institutional investors actually increase their holdings in firms that become flagged as possible manipulators in the current period.

A.3 Does O-Score predict earnings overstatement after controlling for the variables in Dechow, Ge, Larson, and Sloan (2008)?

We examine whether O-Score is associated with earnings overstatement after controlling for the variables in Dechow, Ge, Larson, and Sloan (2008). We report results based on our full sample of 20,892 firm-year observations with sufficient data to compute their measures and the O-Score. Dechow, Ge, Larson, and Sloan use a variety of accounting, operating, investing, financing, and market characteristics to predict material accounting manipulations. We ensure the O-Score is robust to controlling for the following variables: RSST_ACC equals change in working capital plus change in non-current operating assets plus change in net financial assets, divided by average total assets following Richardson, Solimon, Sloan, and Tuna (2006), CH_REC equals change in receivables divided by average total assets, CH_INV equals change in inventory divided by average total assets, CH_CS equals percentage change in cash sales divided by average total assets, CH_EARN equals change in earnings divided by average total assets, ISSUE equals one if the firm issued securities during the year and zero otherwise, EEGRO denotes growth in number of employees, LEASEDUM equals 1 if future operating lease obligations are greater than zero and zero otherwise, MOM denotes return momentum, defined as size-adjusted returns over the 24 months ending the fourth month after the fiscal year-end, and PB denotes market value of equity (data199*data6) divided by book value of equity (data60).

We report the results in Table A.3. We find that O-Score remains a powerful predictor of earnings overstatements even after controlling for the variables in their model. In particular, the coefficient on O-Score is .078, and is statistically significant ($p < .0001$). Thus, O-Score captures firms that are likely to overstate earnings even after controlling for other known predictors of earnings overstatement.

A.4 Do transaction costs limit opportunities to arbitrage overvaluation in our sample?

We examine hedge returns to PROBM segregated by market capitalization. This analysis is motivated by two considerations. First, research finds that many institutions do not behave as arbitrageurs, suggesting that changes in aggregate institutional holdings may be a flawed proxy for the behavior of sophisticated investors. Second, we measure abnormal returns before transaction costs, yet results in previous sections indicate that the abnormal returns to the either the accrual of the PROBM strategy arise predominantly from the short position. While collateral transaction costs seem unlikely to explain the large returns to the short positions, we are not able to estimate them, and we thus do not know whether these returns are sufficient to compensate investors for the costs and risks associated with short sales.

To assess the reasonableness of these seemingly large abnormal returns, we partition the in four classes of market capitalization: less than \$200 million, between \$200 million and \$500 million, between \$500 million and \$1 billion, and more than \$1 billion. Although arbitrary, we choose cut-offs of \$500 million and a billion because short sellers typically focus on such firms to reduce the risk that a lender demands the return of a stock (Staley 1997), and because many institutions restrict their investing universe to larger firms. We show that the PROBM hedge return is larger for smaller firms. That is, for firms with less than \$200 million in market capitalization, the hedge return is 14.1 percent is greater than the corresponding return for firms with more than \$1 billion in market capitalization (11.8 percent). However, both hedge returns are economically significant, and the short positions generate similar return performance (9.73% for market capitalization less than \$200 million, and 9.59% for market capitalization greater than \$1 billion). This does not appear to be the case for the Accrual hedge return which is only 5.2 percent for firms with more than \$1 billion in market capitalization. Transactions costs decrease and liquidity increases with market capitalization, so we expect arbitrage to be most effective in eliminating mispricing for large firms. However, this finding casts doubt that even arbitrageurs and other sophisticated investors accurately assess the probability of manipulation.

A.5 Are the results robust to alternative measurements of abnormal returns and earnings management?

Our results are robust to a number of alternative tests that use (alternative return expectation models, (2) alternative accrual measures, (3) alternative fraud detection models, (4) value-weighting rather than equally-weighting of securities in the extreme portfolios, and (5) calendar-year firms.

1. *Alternative return expectation models:* Our results based on size-adjusted returns suggest that the short side of the hedge contributes most of the returns to the overall strategy. Because the source of the abnormal return matters for implementing the strategy, we next examine the robustness of the asymmetry in abnormal returns. In particular, we assess the contribution of the long and short positions to the accrual strategy using intercepts from asset pricing regressions of monthly excess returns for PROBM and accrual decile portfolios. Using Fama-French three factor model, the lowest PROBM decile produces a statistically insignificant abnormal return of .4 percent per month (t-statistic = 1.26), while the highest PROBM decile produces significant returns of -1.0 percent per month (t-statistic = -3.29). The resulting spread of 1.4 percent per month is statistically significant (t = 6.91), and arises predominantly from the prediction of overvaluation. Similar obtain from a Fama-French model augmented either with an idiosyncratic volatility factor, a cash flow volatility factor, or a momentum factor. Although there is disagreement as to whether these factor sare priced and even what they represent, the models have been investigated in prior work (Carhart 1997, Francis, Lafond, Olssen, and Schipper 2005, Lewellen, Nagel, and Shanken 2006, Nichols 2006, Liu and Wysocki 2006, Core, Guay, and Verdi 2007). The results for the idiosyncratic and cash flow volatility factors also suggest that the short side of the hedge contributes the majority of the hedge return for both PROBM and accruals. However, for the model augmented with the momentum factor, the short side only accounts for 32.4 percent of the PROBM hedge return and 29.6 percent of the accrual hedge return. Although similar to Mashruwala, Rajgopal, and Shevlin (2006), this result is not surprising because the loading on the momentum factor is systematically negative across all PROBM and accrual deciles. More important, our finding of negative loadings when we regress portfolio returns on the momentum factor alone cast doubts on the validity of including momentum as a risk factor.

2. *Alternative accruals measures.* In addition to total accruals, we compare PROBM to various measures of total and current abnormal accruals in predicting future returns, including the Jones (1991) model, the Dechow, Sloan, and Sweeney (1995) modification to the Jones model, and the Beneish (1998) modification to the Jones model. The hedge returns for these alternative measures are similar to the results we obtain for total accruals and range from 9.3 to 13.4 percent. We also examine current and total abnormal accruals from all three models on a performance-matched basis. In all cases, we find that PROBM produces a larger spread in abnormal returns across extreme deciles than any strategy based on abnormal accruals.

3. *Alternative fraud detection models.* We evaluate two alternative fraud detection models. First we examine a five variable version of the Beneish (1999) model. This model excludes SGAI, DEPI, and LEVI, which were not significant in the original Beneish (1999) model. A strategy based on this five variable model produces abnormal returns of 14.8 percent, similar to the 13.9 percent for the eight variable model we use in our main analysis. Second, we compare PROBM to the fraud detection model presented by Dechow, Ge, Larson, and Sloan (2008) in three ways.[22] One, we find that extreme ranks based on the Dechow, Ge, Larson, and Sloan (2008) produces significant abnormal returns of 13.1 percent; this is similar to PROBM extreme ranks which yield an abnormal returns of 14.0 percent. Two, when trading positions are based on whether firms are flagged as manipulators or not, the abnormal return for the Dechow, Ge, Larson, and Sloan (2008) model (8.2 percent) is significantly lower than the corresponding return for PROBM (11.8 percent). This is not surprising because the Dechow, Ge, Larson, and Sloan (2008) model has a higher false positive rate, and flags 26.5 percent of the observations as manipulators whereas the corresponding rate for PROBM is 15.1 percent. Three, we find that in regressions such as those described by equation (1), PROBM ranks have greater predictive ability than ranks based on the Dechow, Ge, Larson, and Sloan (2008) score. For example, in the pooled estimation, the coefficient on PROBMRank equals 0.069 and is significantly different from zero (t-statistic of 2.38); the coefficient on ranks based on the Dechow, Ge, Larson, and Sloan (2008) score (0.040) is not distinguishable from zero. This suggests that after controlling for Dechow, Ge, Larson, and Sloan (2008) score and other variables associated with future returns, a portfolio return to the PROBM strategy earns 6.9 percent. Overall, these comparisons suggest that PROBM performs better in predicting future abnormal returns.

4. *Value-weighted returns.* We also use monthly value-weighted portfolio returns in our asset pricing tests. Equal-

[22] The Dechow, Ge, Larson, and Sloan (2008) score is computed as -6.684 + *RSST accruals**0.891+*Change in receivables**3.127+ *Change in inventory** 2.821+*Change in cash sales**0.097-*Change in earnings**0.995+*Actual issuance* 0.744. The analysis is based 26,985 firm-year observations rather than the 27,427 observations in our full sample for which data are available.

weighted portfolios place greater weight on small firms, which often have less liquidity and higher transactions costs. We find that value-weighted and equal-weighted returns produce similar results. Specifically, the average monthly value-weighted hedge return for PROBM (accruals) is 1.6 percent (1.4 percent). In our asset pricing tests, the spread in alphas across extreme deciles is also similar to our equal-weighted results (PROBM: 1.6 percent, accruals: 1.4 percent). However, contrary to the Mashruwala, Rajgopal, Shevlin (2006) result for accruals and our equal-weighted results for PROBM, we find that the short side dominates for value-weighted portfolio returns when we include the momentum factor in the asset pricing regression. The alpha for the lowest PROBM decile is .2 percent (t-statistic = 0.47) while the alpha for the highest decile is -1.4 percent (t-statistic = -4.43).

5. Calendar-year firms. Due to the dynamic nature of the trading strategy, the use of value-weighted returns requires monthly rebalancing as some firms enter or leave the portfolios over time. Frequent rebalancing can create microstructure-related biases in the average portfolio returns, as well as reduce the profitability of the strategy due to increased transactions costs. We therefore also examine the effect of restricting our sample to calendar-year firms, which results in only annual rebalancing because firms do not enter or leave the portfolio during the annual holding period beginning in May. For PROBM, the restricted sample produces average monthly value-weighted hedge returns of 1.6 percent and average monthly equal-weighted hedge returns of 1.3 percent. For accruals, the value-weighted returns are 0.9 percent and the equal-weighted returns are 0.8 percent.

Table A1. Regressions of Future Earnings and Earnings Components on Current Period Earnings Components

The sample includes 23,114 firm-year observations from 1993 to 2003. BHSAR denotes the 12 month -month buy and hold size-adjusted return from the beginning of the fourth month following the end of the fiscal year; CFO denotes cash flows from operations (#308); CAcc denotes E – CFO + DEP; E denotes earnings before extraordinary items (#123), DEP denotes depreciation and amortization (#125); CAccPos denotes CAcc if CAcc > 0; 0 otherwise; CAccNeg denotes CAcc if CAcc < 0; 0 otherwise; IPR equals 1 if the firm is flagged at a 20:1 cost ratio (-1.78 < PROBM). PROBMs are computed using the model in Beneish (1999); E, CFO, CAcc and Dep are scaled by average total assets. We report t-statistics based on standard errors corrected for clustering by firm and year (Petersen 2007). *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

$$DV_{t+1} = \alpha_0 + \beta_1 CFO_t + \beta_2 CAccPos_t + \beta_3 CAccNeg_t + \beta_4 CAccPos_t * IPR_t + \beta_5 CAccNeg_t * IPR_t + \beta_6 Dep_t + \beta_7 IPR_t + \varepsilon_{t+1}$$

Panel A. Accruals interacted with scaled PROBM ranks (Scaled Ranks = SPR)

	(1)		**(2)**		**(3)**	
	DV = E_{t+1}		**DV = CFO_{t+1}**		**DV = ACC_{t+1}**	
Variable	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Constant	-0.020	(-4.56)***	0.005	(2.74)**	-0.024	(-5.63)***
CFO	0.858	(40.43)***	0.739	(56.16)***	0.108	(6.75)***
CAccPos	0.714	(9.67)***	0.346	(6.88)***	0.346	(6.89)***
CAccNeg	0.358	(12.19)***	0.222	(8.95)***	0.139	(8.55)***
CAccPos*IPR	-0.092	(-1.64)*	0.022	(0.52)	-0.110	(-2.73)***
CAccNeg*IPR	0.227	(1.80)*	0.028	(0.58)	0.167	(1.79)*
Dep	-0.770	(-11.49)***	0.220	(7.59)***	-0.991	(-14.94)***
SPR	-0.020	(-4.85)***	-0.014	(-5.14)***	-0.005	(-1.36)
Adj. R-square	47.13%		54.43%		13.41%	

TABLE A2. Institutional holdings and PROBM ranks

Panel A presents aize-adjusted returns and average institutional holdings in the quarters surrounding the quarter of portfolio formation. Panels Band C presents consecutive year average institutional holdings and changes therein as a function of flag status. Average institutional holdings is the ratio of the number of shares held by all institutions reporting their holdings on Form 13-F to the firm's shares outstanding at the end of the quarter. Institutional holdings and share data are adjusted for stock splits and obtained from the Spectrum database and CRSP files. The quarter of portfolio formation is the quarter containing the fifth month after the firm's fiscal year-end. Following Beneish (1999), firms are flagged as potential manipulators when PROBM>-1.78 (assuming 20:1 costs of classification errors) or PROBM>-1.89 (assuming 40:1 costs of classification errors).

Panel A: Average Returns and Institutional Holdings

			Market Adj. Quarterly Returns--Quarter Relative to Portfolio Formation						
		N	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**
Low PROBM		2886	-0.47%	1.69%	-0.57%	**9.98%** [a]	**3.22%**	**3.09%**	**0.57%**
High PROBM		2718	**9.83%**	**13.83%**	**8.04%**	4.51%	0.80%	-0.48%	-2.90%
			Average Institutional Holdings--Quarter Relative to Portfolio Formation						
	TYPE	**N**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**
Low PROBM	All institutions	2886	**37.99%** [b]	38.23%	37.88%	38.08%	38.80%	39.21%	39.83%
High PROBM	All institutions	2718	35.79%	37.61%	38.75%	**39.12%**	**40.09%**	**40.56%**	40.42%
			-3	**-2**	**-1**	**0**	**1**	**2**	**3**
Low PROBM	Transient	2886	12.52%	12.88%	12.75%	12.88%	13.13%	13.57%	13.95%
High PROBM	Transient	2718	**13.21%**	**14.00%**	**14.33%**	**14.37%**	**14.78%**	**14.87%**	**14.72%**
Low PROBM	Dedicated	2886	**8.76%**	**8.87%**	8.77%	8.83%	**8.40%**	**8.27%**	**8.13%**
High PROBM	Dedicated	2718	7.97%	8.28%	8.45%	8.44%	7.65%	7.75%	7.60%
Low PROBM	Quasi indexers	2886	**16.71%**	**16.49%**	16.36%	16.37%	17.27%	17.37%	17.75%
High PROBM	Quasi indexers	2718	14.62%	15.34%	15.97%	16.32%	17.67%	17.94%	18.11%

Panel C: Consecutive year changes in average institutional holdings as a function of flag status

Firms Flagged assuming 20:1 costs (PROBM>-1.78))

	Flag in Year t					**No Flag in Year t**				
	N	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**	**N**	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**
Flag in Year t-1	821	**3.50%***	0.90%	0.02%	**2.58%***	2294	***0.92%****	0.80%	-0.47%	0.59%
No Flag in Year t-1	1820	**4.03%***	**2.07%***	-0.15%	**2.11%***	15505	1.77%	0.93%	-0.28%	1.12%

Firms Flagged assuming 40:1 costs (PROBM>-1.89)

	Flag in Year t					**No Flag in Year t**				
	N	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**	**N**	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**
Flag in Year t-1	1060	**3.37%***	0.82%	0.05%	**2.51%***	2573	1.02%	0.93%	-0.44%	0.54%
No Flag in Year t-1	2064	**3.79%***	**2.00%***	-0.11%	**1.90%***	14743	1.75%	0.91%	-0.30%	1.13%

[a] Bold numbers in Panel A indicate that the average abnormal returns in distinguishable from zero at the 5% level of lower.
[b] Bold numbers in Panel B indicate that the mean percent held by institutions in high PROBM differs at the 5% level of lower from the corresponding measure in the low PROBM.
* indicates that the increase is significantly different at the 1% level from the benchmark increase in the noflag/noflag cell

Table A.3. Incremental explanatory power of O-Score compared to variables from Dechow, Ge, Larson, and Sloan (2008).

We construct the O-Score to range from zero to five. A firm's O-Score equals five in a given year if, in that year, the firm's is classified in the top PROBM quintile, the bottom cash flow from operations to total assets (COMPUSTAT #308/#12) quintile, the top sales growth quintile, and if the firm has engaged in an acquisition in the prior five years, and issued equity in excess of the industry median in either of the prior two years; if none of these conditions are met, a firm's O-Score equals zero. To ensure the rule can be implemented, we use the prior year's quintiles cut-offs to classify a firm in the current year. RSST_ACC equals change in working capital plus change in non-current operating assets plus change in net financial assets, divided by average total assets following Richardson, Solimon, Sloan, and Tuna (2006), CH_REC equals change in receivables divided by average total assets, CH_INV equals change in inventory divided by average total assets, CH_CS equals percentage change in cash sales divided by average total assets, CH_EARN equals change in earnings divided by average total assets, ISSUE equals one if the firm issued securities during the year and zero otherwise, EEGRO denotes growth in number of employees, LEASEDUM equals 1 if future operating lease obligations are greater than zero and zero otherwise, MOM denotes return momentum, defined as size-adjusted returns over the 24 months ending the fourth month after the fiscal year-end, and PB denotes market value of equity (data199*data6) divided by book value of equity (data60).

	Estimate	p-value
Intercept	-2.535	0.000
O-SCORE	0.078	0.000
RSST_ACC	-0.063	0.553
CH_REC	0.015	0.962
CH_INV	0.555	0.162
CH_CS	-0.013	0.646
CH_EARN	-0.311	0.021
ISSUE	0.015	0.884
EEGRO	0.038	0.013
LEASEDUM	0.319	0.000
PB	0.004	0.400
MOM	0.036	0.068
Pseudo R-Square	2.49%	
N	20892	

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Figure 1. Accrual, Momentum, Size, B/P, CFO/P, and E/P Decile Portfolio Returns for Firms Flagged and Not Flagged as Probable Manipulators

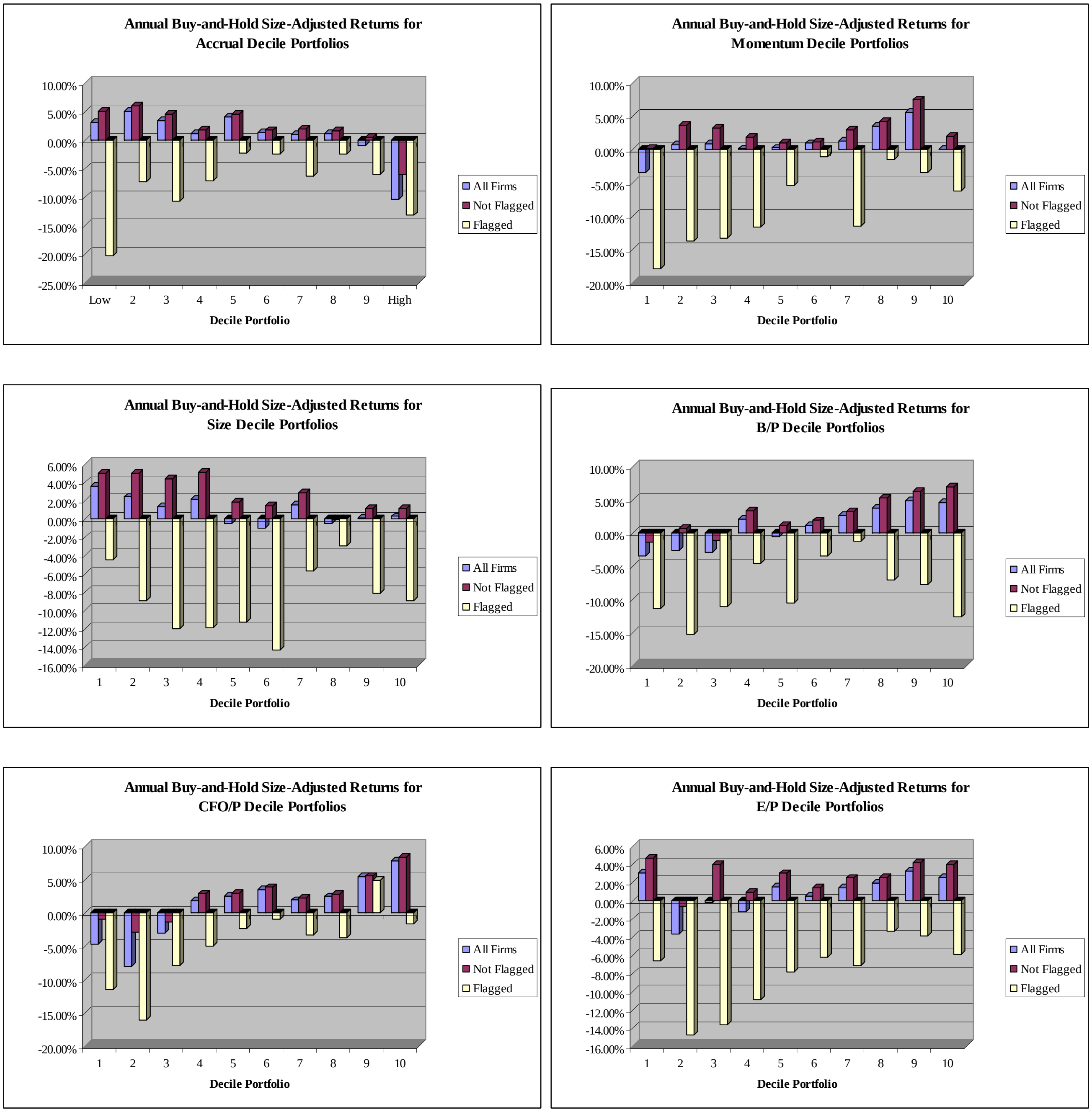

Figure 2. One year ahead buy and hold size-adjusted returns for O-Score by MVE

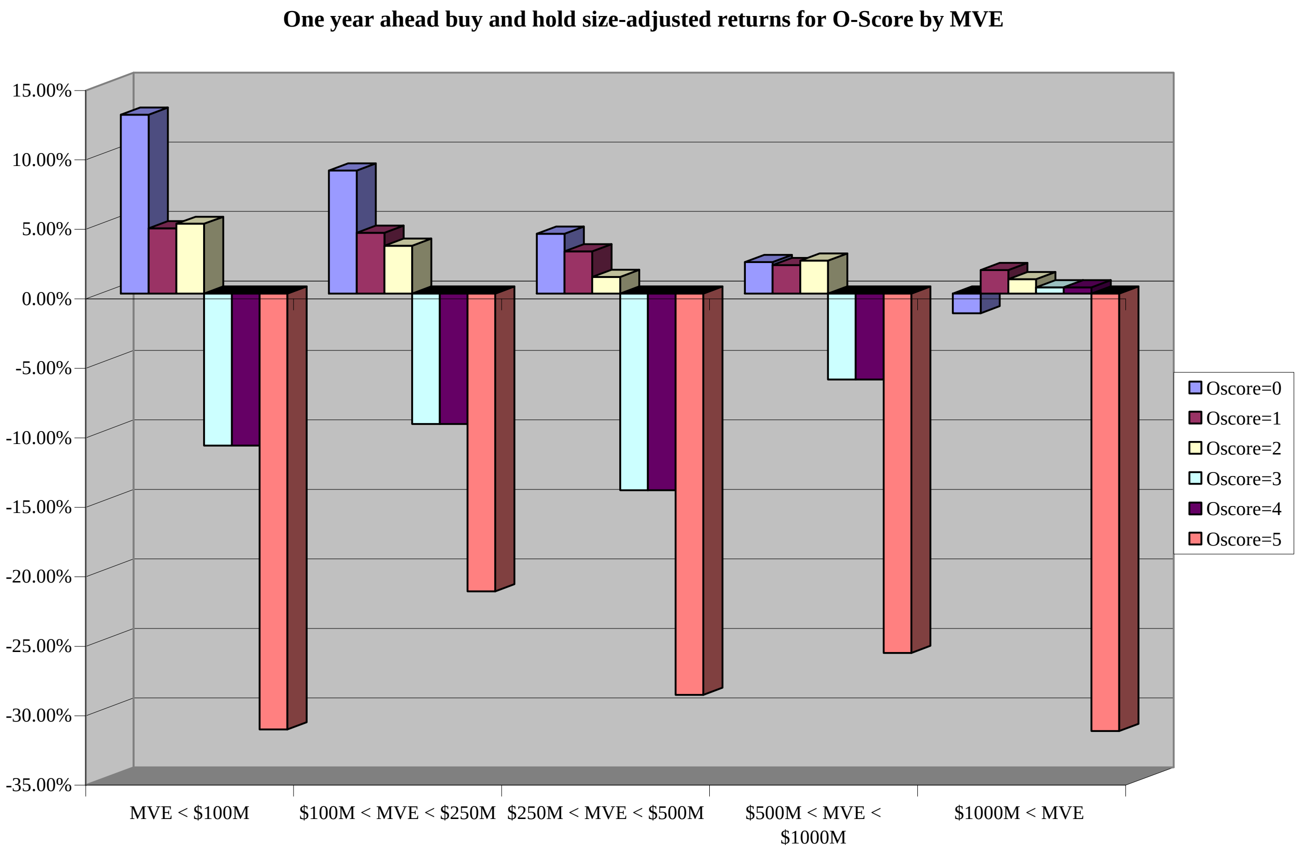

Figure 3. One-year-ahead buy-and-hold size-adjusted returns for high and low O-Score firms by year

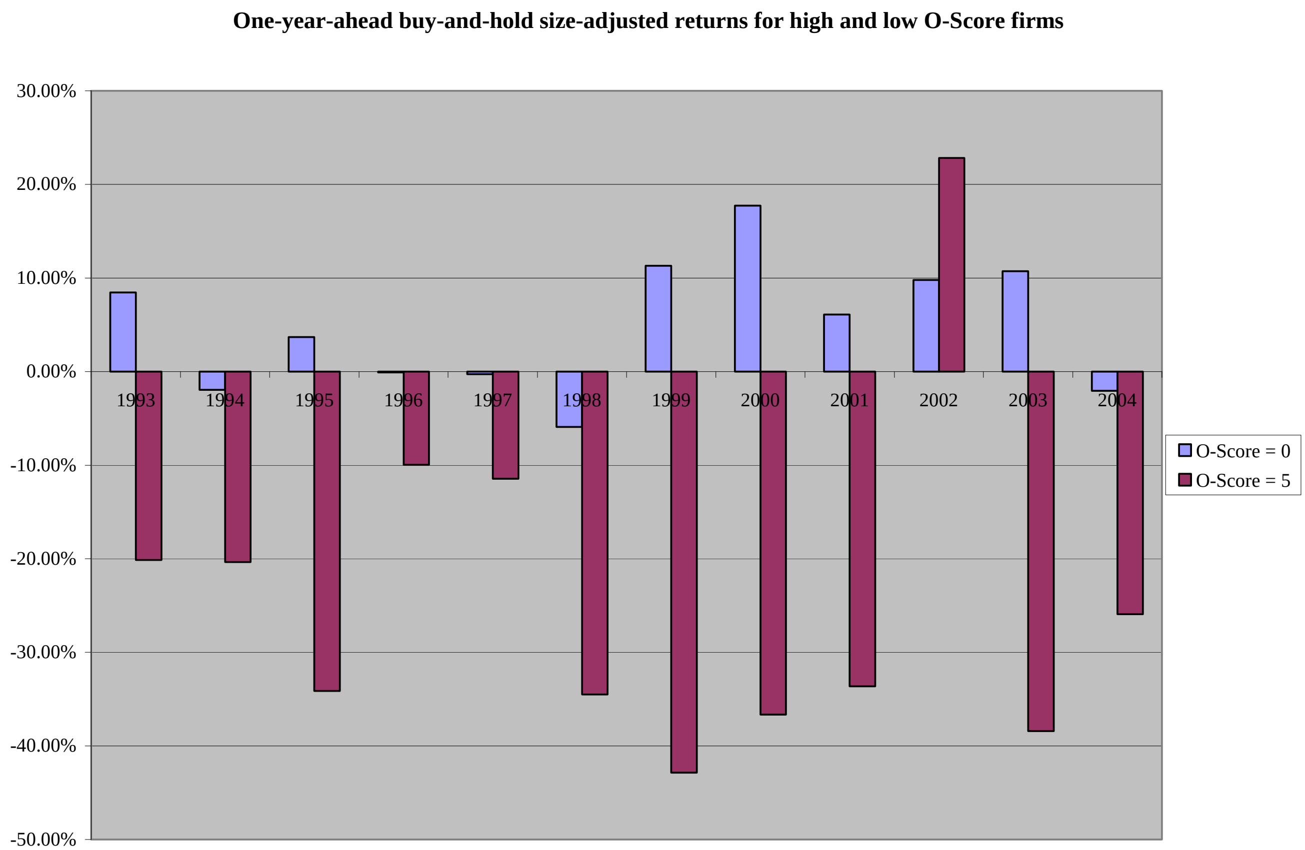

Figure 4. True Positive and False Positive Rates for PROBN in the Estimation Sample

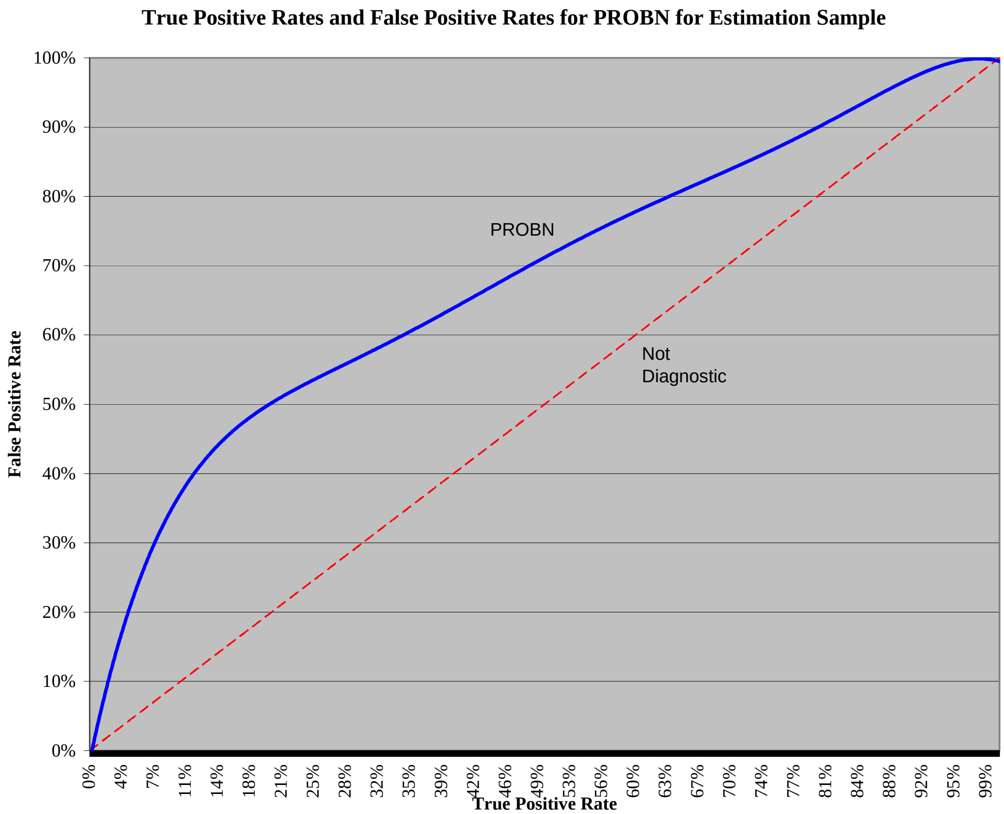

Figure 5. True Positive and False Positive Rates for PROBN for Full Holdout Sample

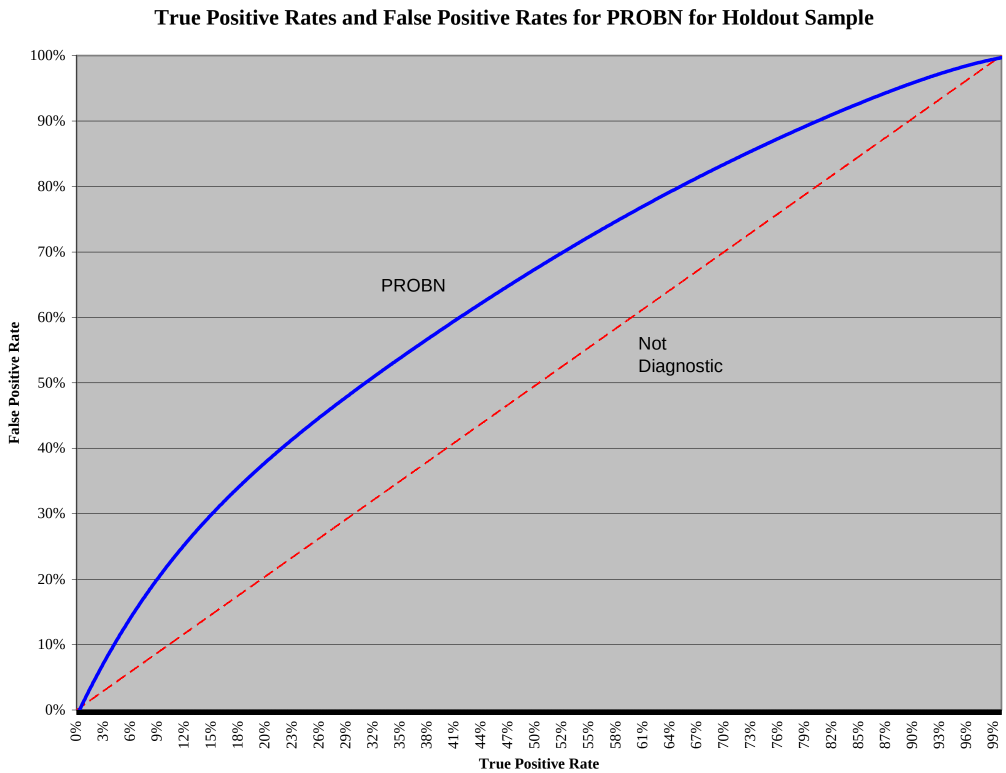

Table 1. Recent High-Profile Fraud Cases Detected by PROBM

This table reports the 20 highest profile fraud cases as reported by auditintegrity.com.***** Firms are flagged as manipulators if PROBM exceeds -1.78 at any time during the period in which either the SEC alleges the firm committed financial reporting violations or the firm publicly admits to such violations. 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 (data2) to sales (data12) in year t divided by the same ratio in year t-1. GMI denotes the ratio of gross margin (data12 – data41) to sales in period t-1 to the same ratio in period t. SGA denotes the ratio of selling, general, and administrative expense (data189) 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 (data14 – data65) to depreciable base (data8+data14-data65) 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 (data18) minus operating cash flows (data308) divided by average total assets (data6). LEVI equals the ratio of long-term debt (data9)+current liabilities (data5) 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 during 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 (%)	Percent Overvalued
Adelphia Communications	**Yes**	1999	2002	4.82	96.8%	3125.00%
American International Group, Inc.	N/A - Financial					
AOL Time Warner, Inc.	**Yes**	2001	2002	25.77	32.2%	147.49%
Cendant Corporation	**Yes**	1996	1998	11.32	38.1%	161.55%
Citigroup	N/A - Financial					
Computer Associates International, Inc.	**Yes**	2000	2002	7.23	36.4%	157.23%
Enron Broadband Services, Inc.	**Yes**	1998	2001	26.04	99.3%	14285.71%
Global Crossing, Ltd	**Yes**	1999	2002	(Delisted due to bankruptcy)		
HealthSouth Corporation	No		2002	2.31	57.3%	234.19%
JDS Uniphase Corporation	**Yes**	1999	2001	32.49	61.0%	256.41%
Lucent Technologies, Inc	**Yes**	1999	2001	11.15	24.7%	132.80%
Motorola	N/A – Abetted Adelphia					
Qwest Communications International	**Yes**	2000	2002	9.84	41.8%	171.82%
Rite Aid Corporation	**Yes**	1997	1999	2.83	59.1%	244.50%
Sunbeam Corporation	**Yes**	1997	1998	1.28	58.8%	242.72%
Tyco International	No		2002	37.55	58.2%	239.23%
Vivendi Universal	No		2002	1.28	27.9%	138.70%
Waste Management Inc	**Yes**	1998	1999	20.82	63.6%	274.73%
WorldCom Inc. - MCI Group	No		2002	1.03	69.8%	331.13%
Xerox Corporation	No		2000	7.73	43.8%	177.94%
					Mean	1270.07%
					Median	236.71%

***** We have no affiliation with auditintegrity.com.

Table 2

Comparison of decile portfolio assignments. This table reports correlations for decile portfolio assignments for various firm characteristics. The sample includes 27,427 firm-year observations from 1993 through 2004. PROBM denotes the probability of manipulation from Beneish (1999); accruals denotes Earnings – CFO; B/P denotes book value of equity (#60) divided by market value (in millions) of common equity at the end of the fiscal year; LMVE denotes the natural logarithm of the market value (in millions) of common equity at the end of the fourth month after fiscal year-end; CFO/P denotes cash flows from operations (#308) divided by the market value (in millions) of common equity at the end of the fiscal year; E/P denotes the market value (in millions) of common equity at the end of the fiscal year divided by income before extraordinary items (#18); Momentum denotes the 12 month size-adjusted return ending at the end of the fourth month after fiscal year-end. All variables are ranked into deciles based on prior year decile cutoffs. Decile ranks are scaled to range from 0 to 1 in the regression reported in Panel B. The Z-statistic is a test that the time-series mean of the t-values from the cross-sectional estimations is significantly different from zero.

Panel A. Correlation matrix for decile portfolio assignments

	PROBM	ACC	Momentum	ln(MVE)	B/P	CFO/P	E/P
PROBM		**0.662**	**0.034**	0.010	**-0.074**	**-0.383**	**0.126**
ACC	**0.662**		0.012	**-0.018**	**0.032**	**-0.384**	**0.289**
Momentum	**0.034**	0.012		**0.119**	**-0.217**	**0.018**	**0.066**
ln(MVE)	0.010	**-0.018**	**0.119**		**-0.284**	**0.100**	**0.096**
B/P	**-0.074**	**0.032**	**-0.217**	**-0.284**		**0.396**	**0.267**
CFO/P	**-0.383**	**-0.384**	**0.018**	**0.100**	**0.396**		**0.493**
E/P	**0.126**	**0.289**	**0.066**	**0.096**	**0.267**	**0.493**	

Panel B. Average coefficients from 12 annual cross-sectional regressions of annual buy-and-hold size-adjusted returns on scaled decile ranks

	Estimate	**t-statistic**	**Z-statistic**	**Estimate**	**t-statistic**	**Z-statistic**
Intercept	-0.017	-0.20	-0.99	-0.015	-0.16	-0.99
PROBM	-0.082	-2.30	-2.22	-0.084	-2.44	-2.29
ACC	-0.025	-0.58	0.10	-0.030	-0.49	0.35
Momentum	0.059	1.16	1.76	0.057	1.11	1.71
ln(MVE)	-0.020	-0.86	-0.87	-0.020	-0.84	-0.83
B/P	0.062	3.34	4.21	0.064	3.24	4.16
CFO/P	0.076	0.98	1.37	0.069	0.75	1.40
E/P	-0.005	-0.14	0.72			
Adj. R^2	0.038			0.036		

Table 3

Comparison of PROBM to other return-predictive characteristics associated with overvalued equity. This table reports annual buy-and-hold size-adjusted returns to various firm characteristics by decile. The sample includes 27,427 firm-year observations from 1993 through 2004. BHSAR denotes the 12 month -month buy and hold size-adjusted return from the beginning of the fourth month following the end of the fiscal year; PROBM denotes the probability of manipulation from Beneish (1999); accruals denotes Earnings – CFO; B/P denotes book value of equity (#60) divided by market value (in millions) of common equity at the end of the fiscal year; LMVE denotes the natural logarithm of the market value (in millions) of common equity at the end of the fourth month after fiscal year-end; CFO/P denotes cash flows from operations (#308) divided by the market value (in millions) of common equity at the end of the fiscal year; E/P denotes the market value (in millions) of common equity at the end of the fiscal year divided by income before extraordinary items (#18); Momentum denotes the 12 month size-adjusted return ending at the end of the fourth month after fiscal year-end. All variables are ranked into deciles based on prior year decile cutoffs. *,**,*** denote that the difference in means across extreme deciles is significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Annual buy-and-hold size-adjusted returns to decile portfolios

	PROBM		Accruals		Momentum		LMVE		B/P		CFO/P		E/P	
Rank	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**
1	2886	4.38%	2816	2.99%	2974	-3.48%	2594	3.52%	2923	-3.46%	2904	-4.77%	2910	3.04%
2	2737	5.21%	2670	4.89%	2787	0.64%	2641	2.37%	2859	-2.70%	2839	-8.00%	2893	-3.69%
3	2647	5.29%	2778	3.32%	2761	0.84%	2627	1.28%	2819	-2.91%	2792	-3.00%	2882	-0.24%
4	2664	3.11%	2771	1.04%	2640	0.07%	2736	2.08%	2636	2.08%	2844	1.84%	2772	-1.23%
5	2694	0.96%	2724	3.95%	2718	0.20%	2771	-0.56%	2774	-0.55%	2627	2.52%	2779	1.50%
6	2804	3.71%	2757	1.30%	2608	0.89%	2768	-1.07%	2624	1.15%	2805	3.46%	2539	0.51%
7	2749	-0.38%	2771	0.98%	2616	1.28%	2792	1.55%	2726	2.65%	2568	1.86%	2605	1.41%
8	2800	-1.06%	2863	1.01%	2755	3.41%	2819	-0.54%	2567	3.75%	2635	2.42%	2602	1.88%
9	2727	-3.12%	2683	-1.05%	2521	5.56%	2803	0.07%	2634	4.79%	2669	5.43%	2534	3.25%
10	2719	-9.56%	2594	-10.45%	3047	0.02%	2876	0.24%	2865	4.62%	2744	7.80%	2911	2.51%
Total	27427	13.95%	27427	13.44%	27427	3.50%	27427	3.27%	27427	8.08%	27427	12.57%	27427	0.53%

Panel B. Returns to decile portfolios for firms with high and low likelihood of earnings overstatement

	Accruals				Momentum				LMVE			
	Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 20:1 costs PROBM>-1.78		Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 20:1 costs PROBM>-1.78		Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 20:1 costs PROBM>-1.78	
Rank	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**
1	2603	4.90%	213	-20.32%	2384	0.09%	590	-17.91%	2206	4.93%	388	-4.53%
2	2458	5.95%	212	-7.33%	2312	3.61%	475	-13.78%	2148	4.96%	493	-8.95%
3	2575	4.42%	203	-10.70%	2363	3.23%	398	-13.34%	2135	4.35%	492	-12.05%
4	2559	1.73%	212	-7.24%	2310	1.75%	330	-11.67%	2257	5.06%	479	-11.92%
5	2503	4.50%	221	-2.32%	2409	0.92%	309	-5.41%	2266	1.84%	505	-11.33%
6	2524	1.64%	233	-2.42%	2334	1.13%	274	-1.14%	2332	1.41%	436	-14.33%
7	2468	1.88%	303	-6.30%	2322	2.90%	294	-11.51%	2361	2.87%	431	-5.70%
8	2486	1.55%	377	-2.52%	2408	4.13%	347	-1.55%	2443	-0.16%	376	-2.97%
9	2068	0.45%	615	-6.09%	2095	7.41%	426	-3.53%	2480	1.14%	323	-8.16%
10	1018	-6.11%	1576	-13.25%	2325	1.94%	722	-6.19%	2634	1.09%	242	-8.94%
Total	23262		4165		23262		4165		23262		4165	

	B/P				CFO/P				E/P			
	Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 20:1 costs PROBM>-1.78		Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 20:1 costs PROBM>-1.78		Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 20:1 costs PROBM>-1.78	
Rank	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**	**N**	**Mean BHSAR**
1	2326	-1.42%	597	-11.39%	1847	-0.93%	1057	-11.48%	2492	4.66%	418	-6.63%
2	2256	0.68%	603	-15.31%	1750	-2.94%	1089	-16.13%	2272	-0.67%	621	-14.76%
3	2310	-1.12%	509	-11.05%	2133	-1.47%	659	-7.97%	2196	3.94%	686	-13.62%
4	2207	3.36%	429	-4.53%	2481	2.84%	363	-5.01%	2269	0.92%	503	-10.90%
5	2371	1.15%	403	-10.54%	2406	2.96%	221	-2.36%	2396	2.99%	383	-7.81%
6	2267	1.87%	357	-3.44%	2605	3.80%	200	-0.99%	2234	1.42%	305	-6.19%
7	2386	3.21%	340	-1.26%	2412	2.20%	156	-3.37%	2317	2.48%	288	-7.17%
8	2250	5.28%	317	-7.11%	2483	2.80%	152	-3.79%	2330	2.50%	272	-3.39%
9	2356	6.28%	278	-7.82%	2530	5.47%	139	4.80%	2259	4.12%	275	-3.87%
10	2533	6.89%	332	-12.69%	2615	8.27%	129	-1.73%	2497	3.92%	414	-5.95%
Total	23262		4165		23262		4165		23262		4165	

Table 4

Combining prior merger activity with PROBM to predict price declines. We obtain merger and acquisition data from SDC. We match our sample firms against all completed acquisitions with transaction values greater than $1 million. We examine whether our sample firms engage in acquisitions in the five years priors to the time at which we measure PROBM. In Panel A, we examine how the occurrence of mergers affects the prediction of future returns for two groups of firms classified as potential frauds, and for the sample complement. The two groups of firms with high probabilities of earnings overstatement are as follows: the 15.2 percent of the firms with the highest PROBM based on a classification rule implied by the Beneish (1999) model, and the top decile of the PROBM distribution in each year. In Panel B, we restrict the sample to firms with high probabilities of earnings overstatement and prior acquisitive activity. We examine the effect of characteristics of the target (public v. private), of the transaction (merger v. tender offer), and whether the form of payment is stock.

Panel A: Combining PROBM and Prior Merger Activity to Identify Overvaluation

Firms Flagged assuming 20:1 costs (PROBM>-1.78)

	N	All	N	M&A =Yes	N	M&A =No	Mean test (p-value)
Firms Flagged	4164	-9.16%	2599	-11.55%	1565	-5.20%	0.009
Firms not Flagged	23254	2.66%	13864	2.87%	9390	2.35%	0.550
High PROBM decile	2718	-9.58%	1650	-13.09%	1068	-4.15%	0.005
All other PROBM deciles	24700	2.01%	14813	2.12%	9887	1.85%	0.755

Panel B: Combining PROBM and Characteristics of Merger Activity to Identify Overvaluation

	N	M&A =Yes	N	Public Targets	N	PrivateTargets	Mean test (p-value)
Firms Flagged	2599	-11.55%	883	-12.67%	1716	-10.98%	0.869
High PROBM decile	1650	-13.09%	551	-14.34%	1099	-12.47%	0.719

	N	M&A =Yes	N	Mergers	N	Tender offers	Mean test (p-value)
Firms Flagged	2599	-11.55%	2554	-11.65%	45	-6.06%	0.146
High PROBM decile	1650	-13.09%	1618	-13.27%	32	-4.02%	0.172

	N	M&A =Yes	N	Paid in Stock	N	Not Paid in Stock	Mean test (p-value)
Firms Flagged	2599	-11.55%	1353	-13.31%	1246	-9.65%	0.001
High PROBM decile	1650	-13.09%	845	-14.29%	805	-11.83%	0.003

Table 5

Prediction of future price declines by combining PROBM with prior abnormal financing (Panel A), prior abnormal investing (Panel B), and prior manipulation of real activities (Panel C). Panel A: We consider alternative definitions of issuance over periods ranging from one to three years prior to the measurement of PROBM. Stock issuance (#108 in COMPUSTAT), Net Stock Issuance equal stock issuance less stock repurchases (#115), Net debt issuance is debt issued (#111) less debt redeemed (#114), all measures are deflated by total assets (#6). When the industry is used as a benchmark, abnormal financing occurs when a firm's issuance measure exceeds the median value for the corresponding measure in the firm's two-digit SIC code. When the benchmark is the firm itself, abnormal financing occurs when a firm's issuance measure in the current year exceeds the prior year. **Panel B:** We consider alternative definitions of investment over periods ranging from one to three years prior to the measurement of PROBM. Investment in PPE is capital expenditures (#128 in COMPUSTAT), Operating Investment in capital expenditures plus R&D (#128+#46) ,Total Investment is Operating investment plus acquisitions (#129) less PPE sold (#107) and Net Investment is Total Investment less Depreciation (#125), and all measures are deflated by total assets (#6). When the industry is used as a benchmark, abnormal investing occurs when a firm's investing measure exceeds the median value for the corresponding measure in the firm's two-digit SIC code. When the benchmark is the firm itself, abnormal investing occurs when a firm's investing measure in the current year exceeds the prior year. **Panel C**: We draw on models Roychowdhury (2006, pp. 344-5) to estimate unexpected discretionary expenditures, unexpected cash flow from operations, and unexpected production costs. Each year, we classify firms in the bottom quintile of unexpected discretionary expenses as firms having unusually low discretionary expenses, firms in the bottom quintile of unexpected cash flow from operations as firms having unusually low cash flow from operations, and firms in the top quintile of unexpected production costs as firms having unusually high production costs.

Panel A: Combining PROBM and Prior Financing Activity to Identify Overvaluation							
Firms Flagged assuming 20:1 costs (PROBM>-1.78)				**Abnormal**		**Normal**	**Mean test**
Industry Benchmark	**N**	**All**	**N**	**Financing**	**N**	**Financing**	**(p-value)**
Stock Issuance in year t	4164	-9.16%	2502	-10.93%	1662	-6.49%	0.007
Stock Issuance in year t or t-1	4164	-9.16%	2574	-10.96%	1590	-6.25%	0.008
Stock Issuance in year t, t-1, or t-2	4164	-9.16%	2778	-10.65%	1386	-6.18%	0.016
Net Stock Issuance in year t	4164	-9.16%	1809	-14.36%	2355	-5.17%	0.001
Net Stock Issuance in year t or t-1	4164	-9.16%	2115	-13.65%	2049	-4.52%	0.001
Net Stock Issuance in year t, t-1, or t-2	4164	-9.16%	2345	-12.44%	1819	-4.94%	0.004
Net Debt Issuance in year t	4164	-9.16%	1168	-13.83%	2996	-7.34%	0.199
Net Debt Issuance in year t or t-1	4164	-9.16%	1697	-13.11%	2467	-6.44%	0.159
Net Debt Issuance in year t, t-1, or t-2	4164	-9.16%	1991	-12.85%	2173	-5.78%	0.240
Time-series Benchmark							
Stock Issuance in year t	4164	-9.16%	1718	-12.65%	2446	-6.71%	0.001
Net Stock Issuance in year t	4164	-9.16%	1196	-10.64%	2968	-8.56%	0.274
Net Debt Issuance in year t	4164	-9.16%	1455	-10.78%	2709	-8.29%	0.342

Table 5 (Continued)

Panel B: Combining PROBM and Prior Investing Activity to Identify Overvaluation

	Firms Flagged assuming 20:1 costs (PROBM>-1.78)						
				Abnormal		**Normal**	**Mean test**
Industry Benchmark	**N**	**All**	**N**	**Investing**	**N**	**Investing**	**(p-value)**
Investment in PPE year t	4164	-9.16%	1383	-8.10%	2781	-9.69%	0.734
Investment in PPE year t or year t-1	4164	-9.16%	1990	-7.98%	2174	-10.24%	0.640
Investment in PPE year t, t-1, or t-2	4164	-9.16%	2309	-7.58%	1855	-11.12%	0.280
Operating Investment in year t	4164	-9.16%	1375	-5.74%	2789	-10.84%	0.120
Operating Investment in year t or year t-1	4164	-9.16%	1910	-7.59%	2254	-10.49%	0.524
Operating Investment in year t, t-1, or t-2	4164	-9.16%	2206	-7.80%	1958	-10.69%	0.408
Total Investment in year t	4164	-9.16%	1735	-9.00%	2429	-9.28%	0.854
Total Investment in year t or year t-1	4164	-9.16%	2288	-9.13%	1876	-9.19%	0.862
Total Investment in year t, t-1, or t-2	4164	-9.16%	2583	-8.98%	1581	-9.45%	0.841
Net Investment in year t	4164	-9.16%	1861	-9.05%	2303	-9.24%	0.987
Net Investment in year t or year t-1	4164	-9.16%	2411	-9.15%	1753	-9.17%	0.755
Net Investment in year t, t-1, or t-2	4164	-9.16%	2673	-8.75%	1491	-9.90%	0.604
Time-series Benchmark							
Investment in PPE year t	4164	-9.16%	1321	-11.66%	2843	-8.00%	0.025
Operating Investment in year t	4164	-9.16%	1270	-11.19%	2894	-8.27%	0.019
Total Investment in year t	4164	-9.16%	1559	-10.96%	2605	-8.08%	0.259
Net Investment in year t	4164	-9.16%	1597	-11.05%	2567	-7.99%	0.157

Table 5 (continued)

Panel C: Combining PROBM and Prior Earnings Management Through Manipulation of Real Activity

	Firms Flagged assuming 20:1 costs (PROBM>-1.78)						
				Abnormal		Normal	Mean test
Industry Benchmark	N	All	N	Activity	N	Activity	(p-value)
Firms with unusually low CFO in year t	4164	-9.16%	971	-14.11%	3193	-7.66%	0.001
Firms with unusually low CFO in year t-2 to t	4164	-9.16%	1269	-13.64%	2895	-7.20%	0.001
Firms with unusually low CFO in year t-4 to t	4164	-9.16%	1420	-13.04%	2744	-7.15%	0.001
Firms with unusually low discretionary exp. in year t	4164	-9.16%	332	-12.56%	3832	-8.87%	0.741
Firms with unusually low discretionary exp. in year t-2 to t	4164	-9.16%	258	-11.74%	3906	-8.99%	0.968
Firms with unusually low discretionary exp. in year t-4 to t	4164	-9.16%	302	-8.69%	3862	-9.20%	0.837
Firms with unusually high production costs in year t	4164	-9.16%	279	-0.67%	3885	-9.77%	0.550
Firms with unusually high production costs. in year t-2 to t	4164	-9.16%	315	-3.68%	3849	-9.61%	0.802
Firms with unusually high production costs. in year t-4 to t	4164	-9.16%	451	-4.82%	3713	-9.69%	0.554

Table 6

The performance of the O-Score. We construct the O-Score to range from zero to five. A firm's O-Score equals five in a given year if, in that year, the firm's is classified in the top PROBM quintile, the bottom Cash flow from operations to total assets (COMPUSTAT #308/#12) quintile, the top sales growth quintile, and if the firm has engaged in an acquisition in the prior five years, and issued equity in excess of the industry median in either of the prior two years; if none of these conditions are met, a firm's O-Score equals zero. To ensure the rule can be implemented, we use the prior year's quintiles cut-offs to classify a firm in the current year. We document the incremental explanatory power of O-Score over Piotroski's (2000) F-Score and Mohanram's (2005) G-Score in Panel D. To compute a firm's F-Score, a firm receives one point for each of the following nine characteristics: positive ROA (data123 divided by average assets (data6)), positive CFO (data308 divided by average assets), positive change in ROA, negative accruals (data123-data308), negative change in leverage (long-term debt (data9) to average assets), positive change in current ratio (data4 divided by data5), no equity issuance (data108 equals 0), positive change in gross margin percent (sales (data12) minus cost of sales (data41) divided by sales), and positive change in total asset turnover (sales divided by average assets). To compute the G-Score, a firm receives one point for each of the following eight characteristics: ROA is greater than the industry median; CFO to average assets is greater than the industry median; negative accruals; the variance of ROA over the past 16 quarters is lower than the industry median; the variance of sales growth (sales in Q0 minus sales in Q-4) over the past 16 quarters is lower than the industry median; the ratio of R&D expense (data46) to average assets is greater than the median; the ratio of capital expenditures (data30 or data128) to average assets is greater than the industry median; and advertising expense (data45) to average assets is greater than the industry median. Industry benchmarks are computed based on two-digit SIC in the previous year. A firm must have a minimum of six quarterly observations to compute the variance of sales growth and the variance of ROA. O-, F-, and G-Scores are scaled to range from 0 to 1 in Panel D.

Panel A: One-year-ahead abnormal returns to individual components of O-Score

Component	Type	N	BHSAR	Type	N	BHSAR	Mean test p-value
PROBM	High quintile	5393	-6.23%	Sample complement	21725	2.68%	0.001
CFO/TA	Low quintile	5552	-6.85%	Sample complement	21566	2.91%	0.001
Sales Growth	High quintile	5536	-4.79%	Sample complement	21582	2.37%	0.001
Acquisitions	Yes	15159	0.21%	No	11959	1.80%	0.057
Ab. Financing	Yes	17317	-0.11%	No	9801	2.71%	0.002

Panel B: One-year-ahead abnormal returns by O-Score

O-Score	N	BHSAR	%Neg
0	3513	4.56%	51.8%
1	8673	2.91%	53.7%
2	7970	2.48%	56.5%
3	4160	-0.37%	61.6%
4	2146	-8.01%	66.0%
5	656	-26.93%	76.4%

Panel C: One-year-ahead abnormal returns by O-Score and size

	MVE < $100M			$100M < MVE < $250M			$250M < MVE < $500M			$500M < MVE < $1000M			$1000M < MVE		
O-Score	**N**	**BHSAR**	**%Neg**	**N**	**BHSAR**	**%Neg**	**N**	**BHSAR**	**%Neg**	**N**	**BHSAR**	**%Neg**	**N**	**BHSAR**	**%Neg**
0	560	12.9%	46%	748	8.9%	50%	581	4.3%	50%	544	2.27%	53%	1080	-1.4%	57%
1	1291	4.7%	56%	1703	4.4%	57%	1297	3.0%	52%	1251	2.05%	53%	3131	1.7%	52%
2	1345	5.0%	59%	1844	3.4%	58%	1252	1.2%	56%	1142	2.37%	56%	2387	1.0%	55%
3	874	5.4%	65%	1055	-2.3%	62%	675	-0.1%	61%	585	-1.25%	60%	971	-3.1%	59%
4	402	-10.9%	70%	577	-9.4%	65%	403	-14.2%	69%	301	-6.19%	63%	463	0.4%	63%
5	122	-31.4%	77%	206	-21.4%	77%	127	-28.9%	79%	103	-25.86%	71%	98	-31.5%	78%

Panel D: Average coefficient estimates and time-series t-statistics from annual cross-sectional regressions of buy-and-hold sized-adjusted returns on scaled O-Score, F-Score, and G-Score ranks

	Intercept	**Scaled O-Score**	**Scaled F-Score**	**Scaled G-Score**	**Adj. R-square**
Estimate	0.074	-0.174			1.52%
t-stat	(3.08)	(-2.50)			
Estimate	-0.065		0.135		0.88%
t-stat	(-1.26)		(1.86)		
Estimate	-0.081			0.169	0.89%
t-stat	(-1.86)			(2.53)	
Estimate	0.028	-0.156	0.070		1.90%
t-stat	(0.69)	(-2.53)	(1.26)		
Estimate	0.005	-0.141		0.105	1.78%
t-stat	(0.18)	(-2.37)		(2.24)	
Estimate	-0.020	-0.131	0.043	0.099	2.07%
t-stat	(-0.47)	(-2.37)	(0.79)	(2.22)	

Table 7

Model estimation variables for overstate and non-overstate firm-years. The sample includes 14150 firm-years from 1993 to 1998 with sufficient data to estimate our probit regression model. We identify 171 firm-years with restatements associated with fraud or regulatory investigation using data from Audit Analytics and SEC AAERs. O-SCORE is an overvaluation score ranging from 0 to 5 where firms receive one point for each of the following characteristics: highest quintile of sales growth; lowest quintile of CFO to total assets; highest quintile of PROBM; net stock issuance (data108-data115) in the current year or prior year is greater than the industry median; and the company acquired another company within the last five years. NOMISS is the proportion of quarterly earnings announcements for the fiscal year where the company avoided a negative raw and negative abnormal three day cumulative abnormal return. ITM denotes in-the-money options, defined as price at the end of the fiscal year (data199) minus the weighted average strike price of options outstanding, multiplied by the options outstanding at the end of the year divided by total assets (data6). MOM denotes return momentum, defined as size-adjusted returns over the 24 months ending the fourth month after the fiscal year-end. PB denotes market value of equity (data199*data6) divided by book value of equity (data60). SIZE denotes the log of total assets (data6). PPEGRO denotes capital expenditures (data128) divided by ending property, plant, and equipment (ata8). EEGRO denotes growth in number of employees (data29). REM denotes propensity to engage in real earnings management over the prior five years, measured as the number of years the firm had abnormal operating cash flow in the bottom quintile plus the number of years the firm had abnormal production costs in the top quintile plus the number of years the firm had abnormal discretionary expenses in the bottom quintile. OPVOL denotes operating volatility measured as the standard deviation of abnormal operating cash flow over the past five years.

	Overstate = 1 (n=171)		Overstate = 0 (n=13,979)		p-value for tests of differences in	
	Mean	**Median**	**Mean**	**Median**	**Means**	**Medians**
O-SCORE	2.327	2.000	1.774	2.000	0.00	0.00
NOMISS	0.588	0.500	0.584	0.500	0.83	0.76
ITM	0.097	0.000	0.031	0.000	0.00	0.00
PB	4.350	2.659	3.128	2.261	0.00	0.00
MOM	0.256	0.033	0.094	-0.101	0.04	0.06
SIZE	6.670	6.058	6.069	5.819	0.00	0.00
PPEGRO	0.334	0.294	0.271	0.221	0.00	0.00
EEGRO	0.749	0.276	0.402	0.108	0.00	0.00
REM	1.503	0.000	1.184	0.000	0.07	0.00
OPVOL	0.054	0.037	0.040	0.022	0.01	0.00

Table 8

Pearson correlations (above diagonal) and Spearman correlations (below diagonal) for overstate and non-overstate firm-years in the model estimation sample. The sample includes 14150 firm-years from 1993 to 1998 with sufficient data to estimate our probit regression model. We identify 171 firm-years with restatements associated with fraud or regulatory investigation using data from Audit Analytics and SEC AAERs. O-SCORE is an overvaluation score ranging from 0 to 5 where firms receive one point for each of the following characteristics: highest quintile of sales growth; lowest quintile of CFO to total assets; highest quintile of PROBM; net stock issuance (data108-data115) in the current year or prior year is greater than the industry median; and the company acquired another company within the last five years. NOMISS is the proportion of quarterly earnings announcements for the fiscal year where the company avoided a negative raw and negative abnormal three day cumulative abnormal return. ITM denotes in-the-money options, defined as price at the end of the fiscal year (data199) minus the weighted average strike price of options outstanding, multiplied by the options outstanding at the end of the year divided by total assets (data6). MOM denotes return momentum, defined as size-adjusted returns over the 24 months ending the fourth month after the fiscal year-end. PB denotes market value of equity (data199*data6) divided by book value of equity (data60). SIZE denotes the log of total assets (data6). PPEGRO denotes capital expenditures (data128) divided by ending property, plant, and equipment (ata8). EEGRO denotes growth in number of employees (data29). REM denotes propensity to engage in real earnings management over the prior five years, measured as the number of years the firm had abnormal operating cash flow in the bottom quintile plus the number of years the firm had abnormal production costs in the top quintile plus the number of years the firm had abnormal discretionary expenses in the bottom quintile. OPVOL denotes operating volatility measured as the standard deviation of abnormal operating cash flow over the past five years. Table entries in bold denote significance at 5%.

	OVER-STATE	O-SCORE	NOMISS	ITM	PB	MOM	SIZE	PPEGRO	EEGRO	REM	OPVOL
OVERSTATE		**0.05**	0.00	**0.05**	**0.04**	**0.02**	**0.04**	**0.04**	**0.03**	**0.02**	**0.03**
O-Score	**0.04**		**-0.02**	**0.06**	**0.16**	**0.17**	**-0.16**	**0.33**	**0.32**	**0.07**	**0.20**
NOMISS	0.00	**-0.02**		0.01	0.01	**0.13**	**0.11**	-0.01	**0.02**	**-0.05**	**-0.06**
ITM	**0.04**	**0.03**	**0.03**		**0.21**	**0.16**	**0.08**	**0.14**	**0.06**	-0.01	**0.05**
PB	**0.03**	**0.18**	**0.04**	**0.15**		**0.27**	**0.16**	**0.22**	**0.07**	**-0.03**	**0.08**
MOM	**0.02**	**0.07**	**0.16**	**0.07**	**0.33**		**0.05**	**0.15**	**0.11**	**-0.03**	**0.03**
SIZE	**0.03**	**-0.15**	**0.11**	**0.09**	**0.26**	**0.15**		**-0.15**	**-0.02**	**-0.11**	**-0.16**
PPEGRO	**0.04**	**0.29**	-0.01	**0.09**	**0.29**	**0.06**	**-0.13**		**0.19**	**0.02**	**0.19**
EEGRO	**0.05**	**0.36**	**0.02**	**0.09**	**0.21**	**0.11**	-0.01	**0.33**		-0.01	**0.06**
REM	**0.03**	**0.11**	**-0.06**	**0.02**	**-0.05**	**-0.07**	**-0.16**	**0.06**	0.01		**0.40**
OPVOL	**0.03**	**0.10**	**-0.05**	**0.08**	**0.03**	**-0.04**	**-0.11**	**0.18**	**0.10**	**0.55**	

Table 9

Probit regression of overstated firm-years on firm characteristics. The sample includes 14150 firm-years from 1993 to 1998 with sufficient data to estimate our probit regression model. We identify 171 firm-years with restatements associated with fraud or regulatory investigation using data from Audit Analytics and SEC AAERs. O-SCORE is an overvaluation score ranging from 0 to 5 where firms receive one point for each of the following characteristics: highest quintile of sales growth; lowest quintile of CFO to total assets; highest quintile of PROBM; net stock issuance (data108-data115) in the current year or prior year is greater than the industry median; and the company acquired another company within the last five years. NOMISS is the proportion of quarterly earnings announcements for the fiscal year where the company avoided a negative raw and negative abnormal three day cumulative abnormal return. ITM denotes in-the-money options, defined as price at the end of the fiscal year (data199) minus the weighted average strike price of options outstanding, multiplied by the options outstanding at the end of the year divided by total assets (data6). MOM denotes return momentum, defined as size-adjusted returns over the 24 months ending the fourth month after the fiscal year-end. PB denotes market value of equity (data199*data6) divided by book value of equity (data60). SIZE denotes the log of total assets (data6). PPEGRO denotes capital expenditures (data128) divided by ending property, plant, and equipment (ata8). EEGRO denotes growth in number of employees (data29). CHREC denotes the change in receivables (data302) divided by average total assets. REM denotes propensity to engage in real earnings management over the prior five years, measured as the number of years the firm had abnormal operating cash flow in the bottom quintile plus the number of years the firm had abnormal production costs in the top quintile plus the number of years the firm had abnormal discretionary expenses in the bottom quintile. OPVOL denotes operating volatility measured as the standard deviation of abnormal operating cash flow over the past five years. ***, **, * denote significance at the 10%, 5%, and 1% levels, respectively.

	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-2.501	<.0001	-3.374	<.0001	-3.322	<.0001
O-SCORE	0.122	<.0001	0.104	<.0001	0.123	<.0001
NOMISS			-0.014	0.907		
ITM			0.346	0.006	0.365	0.003
PB			0.008	0.313		
MOM			-0.019	0.590		
SIZE			0.109	<.0001	0.107	<.0001
PPEGRO			0.370	0.031	0.430	0.009
EEGRO			0.027	0.226		
REM			0.019	0.158		
OPVOL			0.741	0.126		
Pseudo R-square	0.018		0.052		0.047	
N	14150		14150		14150	
Likelihood of overstatement if O-Score = 0	0.62%					
Likelihood of overstatement if O-Score = 5	2.95%					

Table 10

Classification errors in the estimation and holdout samples for alternate relative error cost assumptions. This table reports probability cutoffs and classification error rates for the estimation and hold out samples for alternate assumptions of the relative costs of Type I and Type II errors. Type I errors are defined as incorrectly classifying a manipulating firm as a non-manipulator. Type II errors are defined as incorrectly classifying non-manipulating firms as manipulators. The expected costs of misclassification (ECM) are computed as ECM = $P(M)P_I C_I+[1-P(M)]P_{II}C_{II}$, where P(M) is the prior probability of encountering earnings manipulators (171/14,150 = 1.21%), P_I and P_{II} are the conditional probabilities of Type I and Type II errors, respectively, and C_I and C_{II} are the assumed costs of Type I and Type II errors.

Panel A. Full model, 1993 - 1998 Estimation Period

Relative cost of Type I and Type II errors	Cutoff Probability	Estimation Sample		Full Holdout Sample		Early Holdout (99-01)		Late Holdout (02-04)	
		Type I	Type II	Type I	Type II	Type I	Type II	Type I	Type II
1:1	28.01%	100.00%	0.00%	99.78%	0.07%	99.62%	0.11%	100.00%	0.00%
10:1	7.35%	97.66%	0.23%	96.08%	1.47%	94.66%	2.35%	97.97%	0.12%
20:1	2.74%	71.93%	5.81%	75.82%	10.65%	68.70%	12.79%	85.28%	7.33%
30:1	2.67%	70.76%	6.20%	74.07%	11.10%	66.41%	13.23%	84.26%	7.79%
40:1	2.19%	60.82%	10.27%	66.45%	16.39%	59.16%	18.86%	76.14%	12.56%
50:1	2.19%	60.82%	10.27%	66.45%	16.39%	59.16%	18.86%	76.14%	12.56%
60:1	1.84%	52.63%	15.54%	58.61%	22.24%	53.44%	24.46%	65.48%	18.79%
70:1	1.64%	47.37%	19.80%	53.59%	27.09%	48.47%	28.95%	60.41%	24.20%
80:1	1.64%	47.37%	19.80%	53.59%	27.09%	48.47%	28.95%	60.41%	24.20%

Panel B. Reduced model, 1993 - 1998 Estimation Period

Relative cost of Type I and Type II errors	Cutoff Probability	Estimation Sample		Full Holdout Sample		Early Holdout (99-01)		Late Holdout (02-06)	
		Type I	Type II	Type I	Type II	Type I	Type II	Type I	Type II
1:1	22.44%	100.00%	0.00%	99.78%	0.14%	99.62%	0.23%	100.00%	0.00%
10:1	7.12%	97.08%	0.27%	97.39%	1.38%	96.18%	2.18%	98.98%	0.14%
20:1	3.00%	78.36%	4.19%	81.70%	8.09%	74.81%	9.92%	90.86%	5.25%
30:1	3.00%	78.36%	4.19%	81.70%	8.09%	74.81%	9.92%	90.86%	5.25%
40:1	1.97%	57.31%	13.01%	65.58%	19.46%	59.92%	21.76%	73.10%	15.89%
50:1	1.97%	57.31%	13.01%	65.58%	19.46%	59.92%	21.76%	73.10%	15.89%
60:1	1.82%	53.22%	15.87%	60.78%	22.59%	56.11%	24.29%	67.01%	19.96%
70:1	1.82%	53.22%	15.87%	60.78%	22.59%	56.11%	24.29%	67.01%	19.96%
80:1	1.82%	53.22%	15.87%	60.78%	22.59%	56.11%	24.29%	67.01%	19.96%