Identifying Overvalued Equity

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Abstract

We develop a profile of overvalued equity, and show that firms meeting this profile experience abnormal stock returns *net of transaction costs* of -22 to -25 percent over the twelve months following portfolio formation. We show our model is distinct from predictors proposed in prior work, and our results robust to alternative measurements of expected returns. We also show that overvaluation is not confined to small firms and that institutions do not trade as if they identify overvalued equity. The profitable predictability we document suggests a pricing anomaly relating to the 2.5% of the firms in the population that our model identifies as substantially overvalued. Although we believe markets are generally efficient within the bounds of transaction costs, our evidence suggests that violations of minimally rational use of publicly available information do occur. To the extent that anomalies disappear or attenuate once documented in the literature (Doukas et al. 2002, Schwert 2003), our results are of interest to financial economists and investors.

Keywords: Overvalued Equity; Agency Costs; Earnings Manipulation; Earnings Overstatement; Financial Fraud, O-Score.
JEL Classification: M4, G11

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We develop a profile of overvalued equity, and show that firms meeting this profile experience abnormal stock returns *net of transaction costs* of -22 to -25 percent over the twelve months following portfolio formation. We show our model is distinct from predictors proposed in prior work, and our results robust to alternative measurements of expected returns. We also show that overvaluation is not confined to small firms and that institutions do not trade as if they identify overvalued equity. The profitable predictability we document suggests a pricing anomaly relating to the 2.5% of the firms in the population that our model identifies as substantially overvalued. Although we believe markets are generally efficient within the bounds of transaction costs, our evidence suggests that violations of minimally rational use of publicly available information do occur. To the extent that anomalies disappear or attenuate once documented in the literature (Doukas et al. 2002, Schwert 2003), our results are of interest to financial economists and investors.

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1. Introduction

Sudden price collapses provide *ex-post* evidence of overvalued equity, but are not conclusive about capital market efficiency. In particular, the overvaluation could only be known privately by firms' insiders, or transaction costs and short selling restrictions could prevent outside investors from profiting on their predictions of overvalued equity. Despite the large costs associated with overvalued equity (section 2), there is little in the literature suggesting that such firms are identifiable *ex-ante*, or that trading on a model predicting overvalued equity is profitable. This paper attempts to fill that gap.

We draw on Jensen (2005) to develop a model for *ex ante* identifying firms with overvalued equity. The model combines an assessment of financial statement fraud with characteristics of the firms' operating, investing, and financing activities that suggest value-destroying managerial behavior.[1] Our model predicts abnormal stock price declines of nearly 27% and raw price declines of about 15% over the twelve months after portfolio formation. This contrasts with prior research that predicts one-year-ahead abnormal stock price declines of 5 to 10% with typically little or no drop in price.[2]

We evaluate whether transactions costs and short-selling constraints preclude a profitable trading strategy. This is important because recent evidence suggests that many previously documented stock market anomalies are consistent with minimally rational

[1] Jensen (2005) argues that overvaluation is fertile ground for agency conflicts as managers engage in value-destroying activities to sustain overvaluation: they make operating decisions for cosmetic purposes, engage in risky negative net present value projects, excessively acquire other firms, use the overvalued equity of the firm as currency for these activities, and eventually engage in financial statement fraud after exhausting all other means of meeting the market's expectations.

[2] As we discuss in section 2, several studies provide evidence of return predictability. The magnitude of the abnormal returns documented on the short side implies that the prices of shorted securities either remain flat or slightly increase over the next twelve months. In contrast, the negative raw returns we observe lower arbitrage risk and make short positions more likely to be profitable.

markets (e.g., Lesmond, Schill and Zhou 2004, Basu 2004; Hanna and Ready 2005; Ng, Rusticus, and Verdi 2008). As Rubinstein (2001) points out, markets are minimally rational if abnormal returns are bounded by transactions costs; arbitrageurs may identify the mispricing, but cannot profitably trade on their information to eliminate it. We estimate round trip transactions costs using the LOT Mixed and LOT Y-Split, measures developed by Lesmond, Ogden, and Trzcinka (1999) and Goyenko, Holden, and Trzcinka (2009). These measures offer upper and lower bound estimates of transaction costs, and we find that net of transaction costs our model predicts abnormal price declines ranging between -22% and -25%.

Second, we evaluate whether our results are driven by small firms. Small firms have greater short-selling constraints as smaller capitalizations create a natural barrier to institutional investment—the primary source of security lending (e.g., D'Avolio (2002)). This suggests that we should observe more mispricing for smaller firms. We show, however, that firms that fit our profile of overvalued equity and have market capitalization greater than $1 billion experience abnormal stock price declines net of transaction costs in excess of -29%, and raw price declines in excess of -23%.

Third, we examine the behavior of institutions with respect to firms we predict to be overvalued. Many argue that the trading of sophisticated investors such as institutions keep prices close to fundamental value, at least within the range of transactions costs. If institutions efficiently use the publicly available information necessary to identify overvalued equity, we should observe declines in institutional ownership around, and perhaps before, the quarter of portfolio formation. However, we observe increases in institutional ownership leading up to the quarter of portfolio formation. Moreover, quasi-indexers and transient institutions continue to increase their holdings for two quarters after portfolio formation.

Our model is a 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 (based on the Beneish (1999)'s PROBM measure), 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 glamour characteristics, poor current operating cash flow performance, 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 lose about a quarter of their value. We find that the O-Score 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, for different levels of market capitalization, and for alternative return expectation models.

Our results are based on tests that seek to reduce biases that are frequent in return prediction studies. Our out-of-sample tests over the period 1993-2004 are implementable (portfolio assignments are made based on prior year's cut-offs), 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 1982-1993).

However, when we combine PROBM with other well-studied predictors that are implied by Jensen (2005)'s theory into the O-Score--data snooping bias becomes an important concern.

We address this concern in various ways. First, we apply the combination of PROBM with other promising characteristics to predicting returns in a newer time period. Second, because our analysis identifies 2.5% of the sample as overvalued, we evaluate the return performance of the largest 2.5% of the sample in terms of sales growth or PROBM, and the lowest 2.5% in terms of cash flow from operations. We find the one-year-ahead performance to individual components is considerably less adverse, ranging between -4% and -9%. Third, we apply the O-Score to a number of new analyses such as the prediction of recent earnings restatements,[3] and the prediction future merger activity, excessive issuance and excessive investment. We find that high O-Score firms have more acquisitions, abnormal equity issuances, and restatements of current period earnings in future years than other firms. This suggests that our O-Score results do not merely reflect a spurious association with returns and confirms that O-Score is associated with other consequences of overvalued equity.

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. In addition, it is possible that there are limitations to short selling or unusual borrowing costs that we have not considered. Subject to these

[3] In results that appear in the Appendix, we show 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. We also show that the O-Score has significant incremental explanatory power in predicting recent restatements.

cautions, we interpret the economic significance of the returns we document as consistent with a small but robust pocket of inefficient price setting in equity markets. Moreover, as earlier authors note (Doukas et al. 2002, Schwert 2003), anomalies often disappear or attenuate once documented in the literature, suggesting that anomaly studies such as this one have the potential to inform capital market participants.

We present the remainder of the paper in five parts. We describe empirical framework in 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 and Section 5, presents our conclusion.

2. Empirical Framework

2.1 Background

In this paper, we examine whether substantial overvaluation can be identified before the dramatic stock price decline that inevitably occurs. This is important for several reasons. First, Jensen (2005) argues that overvalued equity creates a form of agency cost that leads managers to engage in value-destroying activities. Second, in addition to losses in investor wealth, overvaluation can create large welfare losses by eroding investor confidence in the integrity of the capital market and inviting remedial action by regulators, who impose (often costly) regulation (Arrow 1973, 1975; Becker 1976; Hirshleiffer 1977; Noreen 1988, Jensen 2007; Karpoff et al., 2008). Third, overvalued equity can result in inefficient outcomes for contracts based on share prices. Consequently, identifying overvalued equity is important not only to individual and institutional investors, but also to boards of directors, regulators and others interested in effective governance of the firm.

The ability to identify substantial overvaluation is also particularly important to academics, regulators, and others interested in understanding the informational and operational efficiency of capital markets. Views on investors' use of information and the presence of frictions in capital markets such as transactions costs blend to form a variety of versions of the efficient markets hypothesis. These versions have been expressed by a number of authors in the literature (e.g., Rubinstein 2001, Schwert 2003), but we organize them according to Rubinstein (2001). Rubinstein (2001) refers to *maximal rationality* as the version of market efficiency where all traders efficiently use all available information. Here, transactions costs do not matter because traders do not make any systematic errors in the way they use available information, resulting in prices that are always right. A slightly weaker version of the efficient markets hypothesis is *rationality*. The rationality version assumes that at least some traders do not make mistakes in using information, and are not constrained by transactions costs in alleviating the mistakes of others.

Rubinstein (2001) acknowledges that the mountain of evidence on return predictability has lead researchers to abandon maximal rationality and rationality in favor of *minimal rationality*. In minimal rationality, at least some investors are aware of mispricing, but mispricing persists because transactions costs and arbitrage risk limit the ability of the smart traders to drive prices back to fundamental value. Thus, minimal rationality permits return predictability, but only within the bounds of transactions costs.

Rubinstein (2001), Schwert (2003), Basu (2004) and others argue that although considerable evidence documents predictable returns,[4] little evidence exists to refute the minimally rational version of the efficient markets hypothesis. For many strategies appearing in the literature, transactions costs seem a likely explanation for the results. For example, Jegadeesh and Titman (2001) demonstrate sizeable returns to portfolios based on prior momentum. Even though these returns amount to 15 percent on an annual basis, Lesmond, Schill and Zhou (2004) suggest that the strategy is not profitable once trading costs are considered.[5] Haugen and Baker (1996) develop a strategy that generates excess returns of approximately 3 percent per month. Nevertheless, Hanna and Ready (2005) document that although excess returns remain after replicating the strategy with momentum and book-to-market portfolios, those excess returns can be explained by transactions costs. Furthermore, Lev and Nissim (2006) suggest that high information and transaction costs prevent profitable implementation of an accruals-based strategy, despite average abnormal returns of approximately 10 percent per year.

[4] 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.
[5] Korajczyk and Sadka (2004) reach different conclusions, however.

Another common result in the literature is variation in abnormal returns based on sophisticated investors. Many large professional investors limit their universe of tradable stocks based on predefined market capitalization cutoffs, such as $1 billion. Thus, larger firms receive a disproportionate amount of attention from sophisticated investors. Because the marginal investor is much more likely to be sophisticated, the prices of large cap firms should be more efficient. Research routinely confirms this conjecture (e.g., Piotroski 2000). In addition, research suggests that return predictability is less severe among stocks held heavily by institutional investors (e.g., Bartov et al. 2000). In summary, although return predictability is undeniable (Doukas et al. 2002), the implications of the evidence for market efficiency are far from settled (Fama 1998, Rubinstein 2001, Schwert 2002, Doukas et al. 2002, Basu 2004).

Jensen (2005) develops a theory of the conflict between managers and owners when the firm becomes substantially overvalued. Although Jensen (2005) does not describe how firms become overvalued, Jensen's (2005) theory does seem to assume a violation of minimal rationality. In particular, he suggests that managers of firms with substantially overvalued equity engage in a series of observable activities that should signal the firm's true value to market participants, yet the overvaluation persists. In the next section, we describe how we measure the firm characteristics that should be associated with overvalued equity if Jensen's (2005) theory is descriptive, and how we aggregate these measures into an overvaluation score (O-Score). If O-Score captures substantial overvaluation predicted by Jensen (2005), O-Score should be associated with large abnormal returns in the future.

However, if these returns are truly anomalous relative to minimal rationality, we expect to observe other patterns in the data as well. First, the returns should not be bounded by transactions costs. We rely on measures of transaction costs developed by Lesmond, Ogden, and Trzcinka (1999) and Goyenko, Holden, and Trzcinka (2009). These authors' methods enable extracting estimates of transaction costs using daily return data, and their estimates are widely used. Consequently, we employ the procedures used in these papers to explicitly estimate abnormal returns net of round trip transactions costs. Second, the existence of the mispricing should not be known to even sophisticated investors who could trade the mispricing away. Thus, we test whether the abnormal returns exist for small and large firms alike, and whether institutions trade as if they are aware of the mispricing. Finding that abnormal returns exceed transactions costs, exist for large firms, and are not anticipated by institutions will constitute strong evidence against minimally rational capital markets, at least for a small but economically important segment of the market.

2.2 Characteristics of overvalued equity

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 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 before eventually turning to accounting fraud to sustain their firm's overvaluation. Thus, Jensen (2005) provides a profile of an overvalued firm: weak fundamental performance but a high likelihood of earnings overstatement, a history of acquisitions, excessive investment and excessive equity issuance, and unrealistic market expectations. Each of these characteristics can be measured (albeit with error).

2.2.1 Fundamental performance

We measure fundamental performance using cash flows from operations. Cash flows from operations measure firm performance without distortions caused by cosmetic earnings management through accounting accruals, and are closely associated with free cash flows to equity. In addition, research by Roychowdhury (2006) suggests that operating cash flows are associated with certain forms of real activities manipulation, and Graham, Harvey and Rajgopal (2005) find that managers are willing to manipulate real activities to meet expectations. [6]

2.2.2 Probability of manipulation

Although overvalued firms have weak fundamental performance, Jensen (2005) suggests that these firms overstate their performance through earnings manipulation. We rely on Beneish (1999) to measure the probability of earnings overstatement. 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

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[6] 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.

months surrounding the discovery of the fraud. In fact, 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.[7] As further described in Appendix A, sdespite its usefulness in detecting fraud, the evidence on the ability of PROBM to predict returns is limited.

2.2.3 Unrealistic market expectations

We identify firms with unrealistic market expectations based on sales growth. Lakonishok, Shleifer, and Vishny (1994) demonstrate that sales growth is a glamour characterstic associated with future returns, and La Porta, Lakonishok, Shleifer, and Vishny (1997) show that those returns are disproportionately concentrated around earnings announcements. This concentration of returns at earnings announcements suggests that the expectations impounded into price contain systematic errors resulting in predictable surprises when future earnings are announced.

2.2.4 A history of acquisitions

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

[7] The model has a false positive rate ranging from 7.2 percent to 13.5 percent, depending on the model and on the sample used (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 to designate this subset of firms.

body of 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).

2.2.5 A history of excessive equity issuance and excessive investing

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 investing, w predict, following Kedia and Philippon (2008), a higher probability of overvaluation for firms that have a recent history of increased hiring and capital investment.[8]

2.3 Constructing the O-Score

We develop an overvaluation score (O-Score) by aggregating the five characteristics associated with overvaluation: operating cash flows to total assets, probability of manipulation, sales growth, prior acquisitions, and prior equity issuances. In particular, we weight each characteristic equally, giving one point if the firm is in the lowest quintile of operating cash flows to total assets, highest quintile of probability of manipulation, highest quintile of annual sales growth, has an acquisition over the past

[8] 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).

five years, and has excessive equity issuances over the past two years. We define equity issuance as excessive if the firm issued more equity than the median firm in the same industry. Thus, O-Score can range from zero to five, with O-Score equal to five (zero) being the most (least) overvalued.

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 (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

[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).

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. 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.[10] 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.[11]

4. Identifying overvalued equity

In this section, we 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, abnormal financing and investing activities and the manipulation of real operating decisions. Then, we combine these characteristics into an Overvaluation Score (O-Score) and present evidence on the predictive ability of the O-Score for future returns.

4.1 Combining PROBM with mergers, financing, investing, and real activity manipulation

In Table 3, Panel A we combine prior merger activity with PROBM. We show that among firms flagged as potential frauds, those that have merger activity in the prior

[10] We obtain similar results when we use (1) the definition of total accruals from Richardson, Sloan, Soliman, and Tuna (2006), and (2) various measures of total and current abnormal, 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, and (3) 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.

[11] 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.

five years experience poorer one-year-ahead abnormal returns performance (-11.55% vs. -5.20%). The performance worsens when the merger activity involves acquisitions paid in stock (-13.31%). Although the incidence of mergers prior to the measurement of PROBM is similar in flagged and non-flagged firms (62.4% vs. 59.6%), flagged firms are significantly more likely to have paid for the acquisition in stock (52.1% vs. 37.9% percent). These findings are consistent with prior research that has shown that many mergers destroy shareholder wealth, particularly 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. This is 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.

In Table 3, Panel B, C and D we examine whether firm characteristics related to manipulation of financing, investing and operating activities can improve predictions of overvalued equity. In Panel B, we show that flagged firms that engage in abnormal equity financing have poorer one-year-ahead performance (-13.65%) than flagged firms that do not (-4.52%), or than firms that have abnormal equity financing and are in the top quintile of price-to-book (-5.11%). This suggests that the combination of PROBM and abnormal equity financing is capturing more than a glamour effect.[12] 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.[13]

In Panel C, we combine PROBM and four alternative measures of abnormal 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). The tests reveal no evidence that our measures of excessive investment are associated with differential return performance for firms flagged by PROBM.

In Panel D, we combine PROBM with proxies for the manipulation of operating activities based on Roychowdhury (2006).[14] Combining PROBM with an indication that

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[12] 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%.

[13] These results are robust to alternative measurements of abnormal financing computed as deviations from an industry benchmark over different time periods or using a time-series benchmark.

[14] 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 production costs, and abnormal discretionary expenses using the

operating cash flows have been unusually low, we find one-year-ahead performance is poorer (-14.11% vs. -7.66%). 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.

4.2 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,[15] 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. 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 present the results of the O-Score's performance in Table 4. 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%)

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prior year's regression coefficients and assign the observation to quintiles using the prior year's distribution.

[15] 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 high sales growth is associated with unrealistic market expectations (Lakonishok, Shleifer, and Vishny 1994).

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

Table 4, 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 abnormal 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. 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.

Panel B also reports data the average round-trip transactions costs for the firms in each O-Score portfolio, based on Lesmond, Ogden, and Trzincka (1999) and Goyenko, Holden, and Trzcinka (2009).[16] Transactions costs generally rise with O-Score; the

[16] Specifically, we estimate round trip transactions costs using two measures developed by Lesmond, Ogden, and Trzcinka (1999) and Goyenko, Holden, and Trzcinka (2009). Lesmond, Ogden,and Trzcinka (1999) develop and test a limited dependent variable (LDV) model that estimate the effective spread

lowest round-trip transactions costs occur for firms with O-Score equal to 1, amounting to 3.1%. The highest round-trip transactions costs occur for firms with the highest O-Score. For these firms, transactions costs amount to 5.22%. However, returns after transactions costs remain economically significant for the high O-Score firms. Raw returns amount to -9.82 percent after considering transactions costs, while size-adjusted returns equal -21.71 percent. This suggests that high O-Score firms have economically significant stock price declines even after transactions costs, in contravention of minimally rational use of available information.

In Table 5, we conduct a battery of tests to assess the robustness of the O-Score results. Because high O-Score firms equal only 2.5 percent of the sample, we assess whether our O-Score results are driven by extreme values of the underlying O-Score characteristics. In Panel A. we report returns to the most extreme 2.5 percent of firms for PROBM, CFO/TA, and sales growth. The most extreme observations for each of these characteristics have substantially weaker returns than our high O-Score firms. Extreme sales growth has the strongest returns at -8.9 percent, and the returns to extreme CFO/TA

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indirectly from daily stock returns. The model assumes that there is informed trading on non-zero-return days, and that there is no informed trading on zero-return days, and that a market model hold on non-zero-return days, but a flat horizontal segment applies on zero-return days. The intuition is that, transaction costs prevent trading on new information unless the expected returns are sufficient to cover the trading cost. As a result, daily returns of 0% occur if the expected return is not large enough to induce a sale or buy transaction. Thus, non-zero returns are observed only if they exceed the required trading cost. We estimate the trading cost as the sum of half of the estimated round trip cost on the month of portfolio formation plus half of the estimated round trip cost twelve months later. We use the daily returns in each month t to estimate round-trip transaction costs, using code generously given to us by Craig Holden and Charles Trzincka. The specific measures we use are the LOT Mixed and LOT Y-Split which are described in Goyenko, Holden, and Trzcinka (2009, 159). The table reports results with transaction costs measured via LOT Mixed yields transaction costs estimates that are 2 to 3 times larger than LOT Y-Split.

and PROBM are -5 percent or higher. This confirms that our O-Score results are not driven by including firms with extreme characteristics in the high O-Score portfolio.

In Panel B, we regress future buy-and-hold size adjusted returns on five indicators for each of the five characteristics of the O-Score, 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 has significant explanatory power. Thus, this analysis provides additional assurance that our results are not merely the result of a data-snooping bias.

In Panels C and D, 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 raw return ranges from -8.9% (firms with market capitalization between $100 and $250 million) to -24.8% (firms with market greater than $1 billion). Regardless of size, more than 65 percent of firms with high O-Scores have negative raw returns over the next year; for the largest firms, 73 percent of raw returns are negative. 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.

In Panel E 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.[17] 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 Appendix B, we further exploit the restatement data to estimate a model that examines the ability of the O-Score to predict future restatements.

4.3 Asset Pricing Regressions for Trading Strategies

In this section we report time-series asset pricing regressions of O-Score portfolio returns to assess the sensitivity of our results to our choice of risk controls. We assign firms to portfolios at the beginning of each month based on the firm's most recent O-Score assignment, using the ranking procedures described above. Monthly portfolio excess returns are then computed as the equal-weighted average return, less the return to

[17] 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.

the 30-day T-bill.[18] For each of our six portfolios, we regress the monthly portfolio excess returns on the following model:

$$\left(R_{i,t} - R_t^f\right) = \alpha_i + \beta_i\left(R_{M,t} - R_t^f\right) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$$

where $R_{i,t}$ denotes the return to decile i for month t, R_t^f denotes the return on the 30-day T-bill for month t, $R_{M,t}$ denotes the return on the value-weighted CRSP index for month t, SMB denotes the Fama-French size factor mimicking portfolio, and HML denotes the Fama-French book-to-market factor mimicking portfolio,

The intercepts from these time-series regressions measure the abnormal return, after controlling for risk, generated by each portfolio. We test whether the extreme portfolios generate abnormal returns by testing the intercept of a hedge portfolio that takes a long (short) position in the lowest (highest) O-Score portfolio. As a summary test of the mispricing, we also test that the intercepts are jointly zero for all deciles by computing the Gibbons, Ross, Shanken (1989) statistic (GRS). The GRS statistic is distributed F with (6, 139-6-3) degrees of freedom.

We report the results in Table 6. The lowest O-Score portfolio produces a marginally significant positive abnormal return of .30 percent per month (t-statistic = 1.67), while the highest O-Score portfolio produces significant returns of -1.85 percent per month (t-statistic = -3.73). The resulting spread of 2.14 percent per month is statistically significant (t = 4.57). The hypothesis that the abnormal returns are jointly zero is rejected (GRS F = 5.61, p = 1.8%). Thus, our evidence based on size-adjusted returns is not sensitive to our choice of risk controls.

[18] We also replicate our analysis with value-weighted portfolios, with similar results.

The analysis in Table 6 assumes a certain functional form for the model of expected returns. MacKinlay (1995) suggests that an upper bound exists to the squared Sharpe ratios that can be explained by rational asset pricing factors, regardless of the functional form. In particular, he suggests that portfolios that generate a squared Sharpe ratio in excess of 0.031 on a monthly basis cannot be explained by traditional sources of fundamental risk. The squared Sharpe ratio for the high O-Score firms equals 0.101, and is significantly greater than the 0.031 benchmark in MacKinlay (1995) ($p < 0.001$, not tabulated). This confirms that omitted risk factors are an unlikely explanation of the returns to the O-Score strategy.

4.4 Portfolio Holdings of Institutional Investors

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 whether they are in the extreme O-Score groups during the year.

Table 7 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.[19] Panel A shows that returns to high O-Score firms are significantly positive during the quarters leading up to portfolio formation but turn significantly negative following portfolio formation. Panel B compares aggregate

[19] Institutional holdings and share data are adjusted for stock splits and obtained from the Spectrum database and CRSP. The data available to us from Spectrum ends in December 2003.

institutional holdings for high O-Score firms to holdings for low O-Score firms. Low O-Score firms experience consistent increases in institutional ownership in the quarters surrounding portfolio formation. In contrast, high O-Score firms experience increases in aggregate institutional ownership only through quarter 0. Institutional ownership declines in quarter +1 and again in quarter +3. This evidence suggests that institutions react to stock price underperformance instead of anticipating such underperformance.

To shed additional light on this issue, we classify all institutions into transient, dedicated, and quasi-indexers consistent with Bushee and Noe (2000). If transient investors are relatively sophisticated users of financial statements, we expect the holdings by these institutions to decline in the periods leading up to and including portfolio formation. However, this conjecture is rejected by the data; transient institutions increase their ownership of high O-Score firms through quarter +2. Transient institutions only reduce their holdings in quarter +3, the quarter in which high O-Score firms experience the worst return performance of the quarters we examine.

In Table 7, Panel C we restrict the sample to firms with institutional holdings that have O-Score data in two consecutive years. We analyze changes in institutional holdings in consecutive years as a function of whether the firm meets the profile of overvalued equity (i.e., high O-Score). For each of two different O-Socre cut-offs, we present a 2 X 2 matrix. We focus our discussion on a cutoff of O-Score = 5 in year t as the results are similar. The largest cell corresponds to firms that do not meet the profile of overvalued equity in either year t-1 or year t: for these firms the change in average institutional holdings from year t-1 to t is 1.9 percent. We use this percentage as a benchmark against which to evaluate changes in the other cells: (1) The cell corresponding to firms that likely overvalued in both year t-1 or year t shows a change of 3.91 percent, driven mainly by quasi-indexers (change of 4.12%); (2) The cell corresponding to firms that are not likely overvalued in year t-1 but are likely overvalued in year t shows a change of 7.81 percent, driven mainly by transient institutions (3.67%); (3) The cell corresponding to firms that have a high O-Score in year t-1 but not in year t shows a change of -0.22 percent, driven by dedicated institutions (-.89 percent). Our finding that transient investors increase their holdings of firms that during the year develop characteristics of overvalued equity is curious because such firms are often considered sophisticated users of financial statement information. However, these investors tend to chase momentum, so one explanation is that transient institutions overweight momentum and underweight other value-relevant information in financial statements and past value-destroying activities. Overall, we find no evidence that sophisticated investors sell on a timely basis when they ought to suspect the firm has a high likelihood of overvaluation.

4.5 O-Score and the prediction of value-destroying real activities

In this section, we provide additional evidence that O-Score does not merely reflect a data snooping bias. We use O-Score in a new context other than return prediction to show that O-Score is associated with other activities consistent with Jensen's (2005) theory of overvalued equity, but not implied by prior return prediction studies. In particular, we examine whether O-Score predicts future acquisitions, abnormal financing, and accounting restatements. Table 8 reports the results. Over 44 percent of firms with high O-Score have acquisitions in the two years following portfolio formation, and high O-Score firms are the most likely to acquire another firm in the future ($p = 0.001$). High O-Score firms are also the most likely to engage in all stock ($p < 0.001$) and mostly stock acquisitions ($p < 0.001$). This is consistent with Jensen's (2005) prediction that overvalued firms engage in acquisitions to maintain the appearance of growth and forestall the day of reckoning.

Compared to low O-Score firms, firms with O-Score equal to five are twice as likely to issue abnormal amounts of equity. This pattern is consistent with Jensen's (2005) conjecture that overvalued companies are likely to use their equity as a form of currency. Compared to all other firms, high O-Score firms are most likely to issue abnormal amounts of equity ($p < 0.001$) and abnormal amounts of debt ($p = 0.001$).

Finally, Jensen (2005) argues that managers of firms with overvalued equity eventually turn to cooking the books in order to report the results demanded by the market. Compared to all other companies, high O-Score firms are most likely to restate current period performance at some point in the future ($p = 0.007$). In particular, 3.8 percent of high O-Score firms overstate current period earnings, compared to 1 percent of low O-Score firms. Overall, these results confirm that O-Score has economic content beyond return prediction that is consistent with the predictions of Jensen's (2005) theory of overvalued equity.

5. Conclusion

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 net of transaction costs that range from -22 to -25 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 a unique profile of substantially overvalued equity.

Our results are based on implementable strategies applied out-of-sample to over 27,000 firms in 1993-2004. We show our model is distinct from predictors proposed in prior work, and our results are robust to alternative measurements of expected returns. We show that overvaluation is not confined to small firms; firms with $1 billion or more in market capitalization experience abnormal stock returns after transaction costs of -29 percent. Finally, we show that institutions do not trade as if they identify 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, future merger, investing and financing activities which are alternative contexts to return prediction, we cannot fully rule out a data-snooping bias.

With these cautions in mind, the profitable predictability we document suggests a pricing anomaly for the 2.5% of the firms in the population that our model identifies as substantially overvalued. Although we believe markets are generally efficient within the bounds of transaction costs, our evidence suggests that violations of minimally rational use of publicly available information do occur. To the extent that anomalies disappear or attenuate once documented in the literature (Doukas et al. 2002, Schwert 2003), our results are of interest to financial economists and investors.

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Appendix A

The probability of financial statement fraud

The Beneish (1999) model 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).[20] 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).[21]

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. 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.

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.

[20] 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).

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

Appendix B

Using Characteristics of Overvalued Equity to Predict Fraud

In this Appendix, 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 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. We model the probability that a firm-year will be restated due to fraud as follows:

$$OVERSTATE_{i,t} = \gamma_0 + \gamma_1 O-Score_{i,t} + \varepsilon_{i,t} \quad \text{(A.1)}$$

$$\begin{aligned} OVERSTATE_{i,t} = {} & \gamma_0 + \gamma_1 O-Score + \gamma_2 NOMISS_{i,t} + \gamma_3 ITM_{i,t} + \gamma_4 PB_{i,t} \\ & + \gamma_5 MOM_{i,t} + \gamma_6 SIZE_{i,t} + \gamma_7 PPEGRO_{i,t} + \gamma_8 EEGRO_{i,t} \\ & + \gamma_9 REM_{i,t} + \gamma_{10} OPVOL_{i,t} + \varepsilon_{i,t} \end{aligned} \quad \text{(A.2)}$$

In equation (A.2), five variables (NOMISS, ITM, PB, MOM, and SIZE) capture capital market incentives and characteristics associated with overvaluation, and variables capture traits of the firm's investing (PPEGRO, EEGRO),[22] and operating activities (REM, OPVAL).

Sample

We evaluate the models with a sample of 630 restatement firm-years and 24,632 non-restatement firm-years from 1993 through 2004.[23] We estimate our probit regression model on 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.[24]

Descriptive statistics for the restatement and nonrestatement firm-years in our estimation sample (untabulated, available on request) are as follows. 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

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

[23] 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. We review AAERS to identify company name and the beginning and ending dates of the fraud.

[24] 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.

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).

The correlations between our variables (untabulated, available on request) are as follows. 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 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.

Estimation Results

In Table A.1, 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.[25] Our final specification eliminates extraneous variables. Although the pseudo R-square declines to 4.7 percent, O-SCORE, ITM, SIZE, and PPEGRO remain significant.

Overall, the evidence in Table A.1 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*.

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

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[25] 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).

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 A.1. 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.

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.

Table A.1

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 A.2

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%

Figure 1. Accrual Decile Portfolio Returns for Firms Flagged and Not Flagged as Probable Manipulators

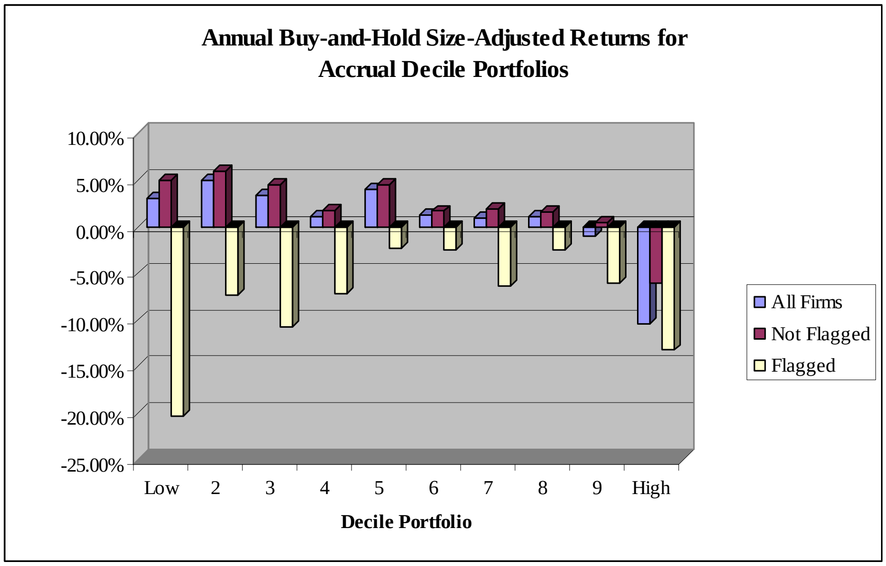

Figure 2. One year ahead buy and hold size-adjusted returns for O-Score by MVE

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

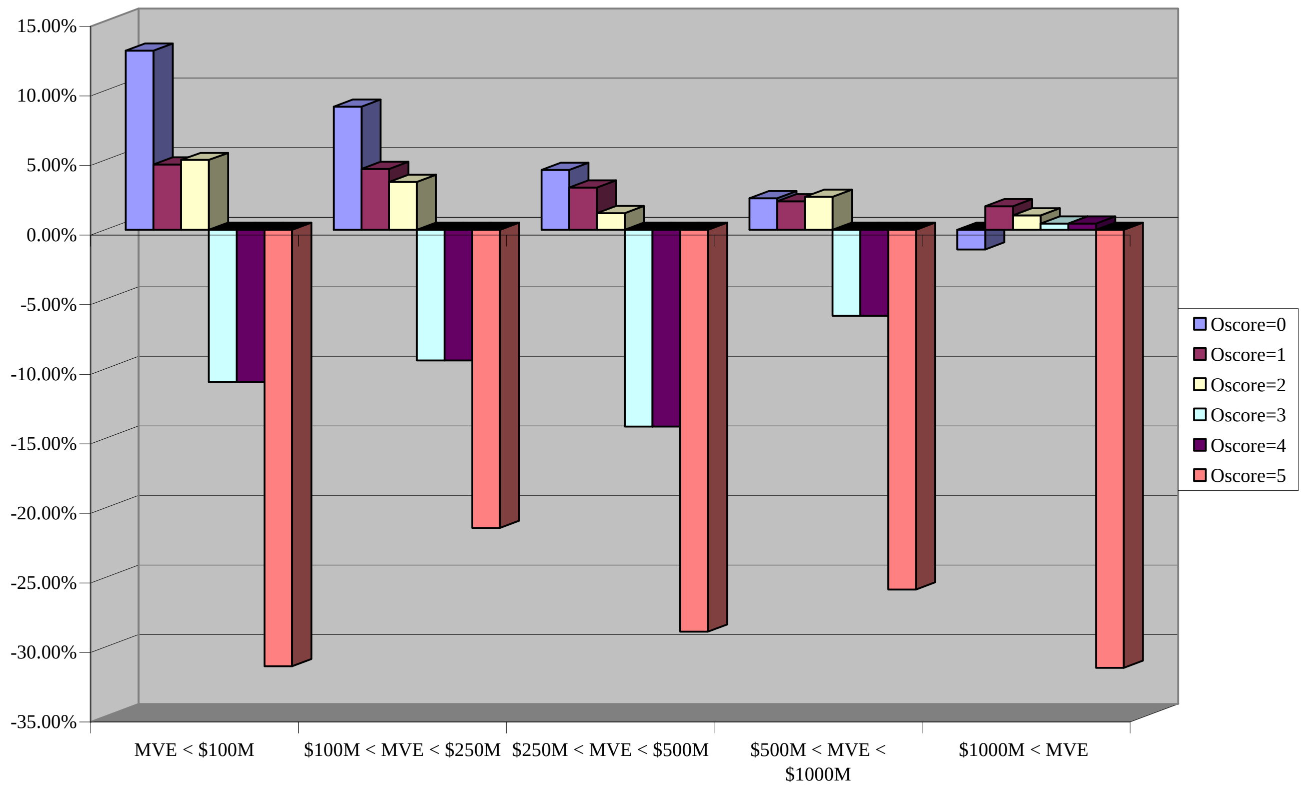

Figure 3. One-year-ahead buy-and-hold size-adjusted returns for high and low O-Score firms by year

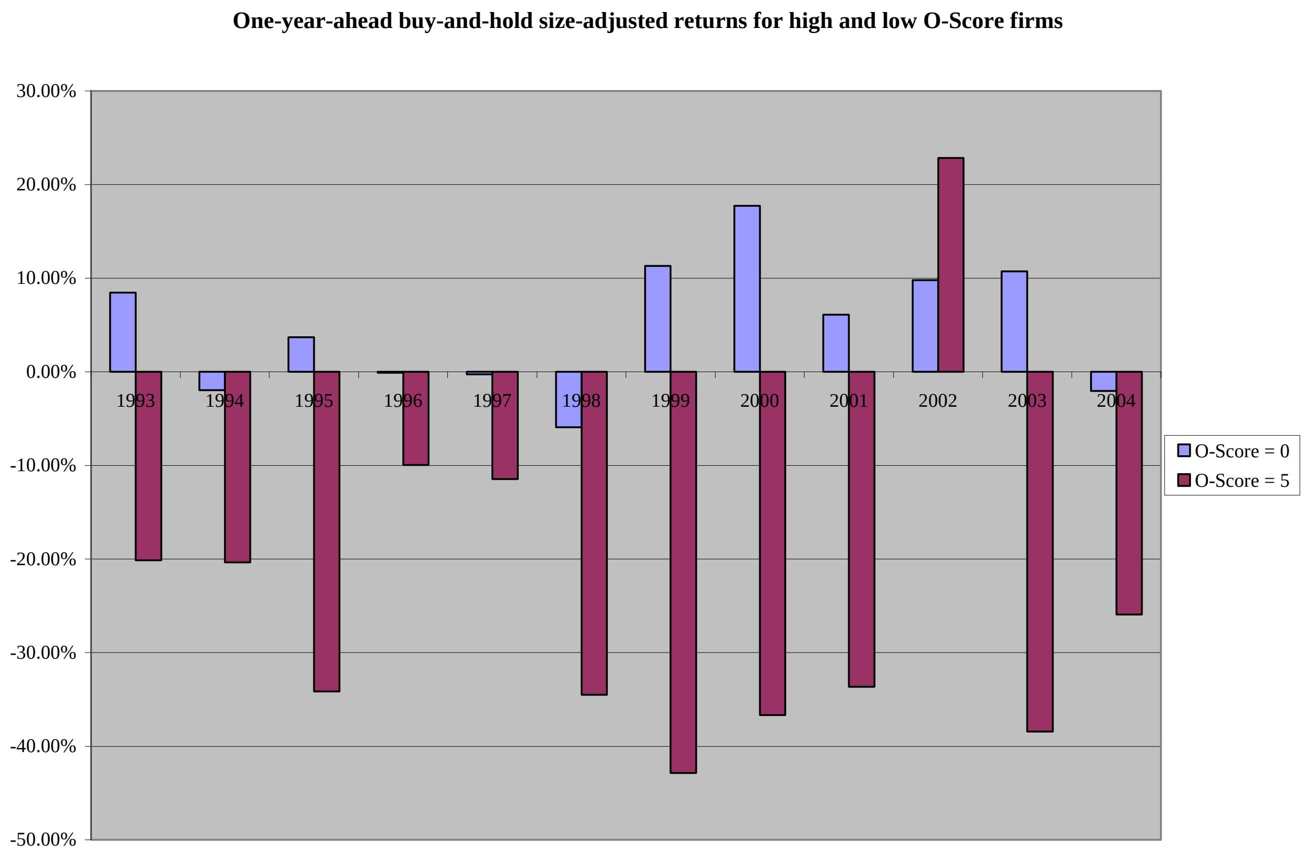

Table 1

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

Prediction of future price declines by combining PROBM with prior merger activity (Panel A), prior abnormal financing (Panel B), prior abnormal investing (Panel C), and prior manipulation of real activities (Panel D). **Panel A:** 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 prior 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 firms classified as potential frauds, and for the sample complement. Firms with high probabilities of earnings overstatement are the 15.2 percent of the firms with the highest PROBM based on a classification rule implied by the Beneish (1999) model. We also consider, for firms with prior acquisitive activity, the role of the form of payment. **Panel B:** We consider alternative definitions of issuance over periods ranging from one to three years prior to the measurement of PROBM, and either industry or time-series benchmarks. Net Stock Issuance equals stock issuance (#108 in COMPUSTAT) less stock repurchases (#115), Net debt issuance is debt issued (#111) less debt redeemed (#114), all measures are deflated by total assets (#6). The table reports measurements relative to a two-digit industry median. That is, 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. **Panel C:** 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). The table reports measurements relative to a two-digit industry median. That is, 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 D**: 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 Firms Flagged by PROBM assuming 20:1 costs (PROBM>-1.78) and Prior Merger Activity to Identify Overvalued Equity

	N	All	N	M&A =Yes	N	M&A =No	Mean test (p-value)
M&A in t-4 to t?	4164	-9.16%	2599	-11.55%	1565	-5.20%	0.009
M&A paid in stock			1353	-13.31%			0.001
M&A paid in cash			1246	-9.65%			

Panel B: Combining Firms Flagged by PROBM assuming 20:1 costs (PROBM>-1.78) and Prior Financing Activity to Identify Overvalued Equity

	N	All	N	Abnormal Financing	N	Normal Financing	Mean test (p-value)
Net Stock Issuance in year t or t-1	4164	-9.16%	2115	-13.65%	2049	-4.52%	0.001
Net Debt Issuance in year t or t-1	4164	-9.16%	1697	-13.11%	2467	-6.44%	0.159

Panel C: Combining Firms Flagged by PROBM assuming 20:1 costs (PROBM>-1.78) and Prior Investing Activity to Identify Overvalued Equity

				Abnormal		Normal	p-value
Investment in PPE year t or year t-1	4164	-9.16%	1990	-7.98%	2174	-10.24%	0.640
Operating Investment in year t or year t-1	4164	-9.16%	1910	-7.59%	2254	-10.49%	0.524
Total Investment in year t or year t-1	4164	-9.16%	2288	-9.13%	1876	-9.19%	0.862
Net Investment in year t or year t-1	4164	-9.16%	2411	-9.15%	1753	-9.17%	0.755

Panel D: Combining Firms Flagged by PROBM assuming 20:1 costs (PROBM>-1.78) and Prior Earnings Management Through Manipulation of Real Activity

	N	All	N	Abnormal Activity	N	Normal Activity	Mean test (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 discretionary exp. in year t	4164	-9.16%	332	-12.56%	3832	-8.87%	0.741
Firms with unusually high production costs in year t	4164	-9.16%	279	-0.67%	3885	-9.77%	0.550

Table 4

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. Transactions costs are an upper bound estimate based on Lesmond, Ogden, and Trzcinka (1999).

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	BHRR	BHSAR	%Neg	Trans Costs	BHRR – Trans	BHSAR - Trans
0	3513	18.76%	4.56%	51.8%	3.23%	15.53%	1.33%
1	8673	15.96%	2.91%	53.7%	3.10%	12.86%	-0.19%
2	7970	16.11%	2.48%	56.5%	3.68%	12.43%	-1.20%
3	4160	13.22%	-0.37%	61.6%	4.58%	8.64%	-4.95%
4	2146	5.18%	-8.01%	66.0%	4.82%	0.36%	-12.83%
5	656	-15.04%	-26.93%	76.4%	5.22%	-9.82%	-21.71%

Table 5

Robustness of O-Score returns. 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 B. 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 B.

Panel A: Average returns to the most extreme 2.5% of observations (N=701) for PROBM, CFO/TA, and Sales Growth components of O-Score

Component	Type	BHSAR
PROBM	Highest 2.5%	-4.6%
CFO/TA	Lowest 2.5%	-5.0%
Sales Growth	Highest 2.5%	-8.9%

Panel B: Regressions of future returns on O-Score and its components

	Pooled OLS, year-clustered s.e.		Yearly cross-sectional regressions	
	Estimate	t-statistic	Estimate	t-statistic
Intercept	0.044	1.71	0.049	2.33
O-Score=5	-0.180	-2.32	-0.145	-2.28
Abnormal Financing	-0.002	-0.08	-0.002	-0.09
Acquisition	-0.007	-0.64	-0.011	-1.14
CFO/TA	-0.061	-1.23	-0.062	-1.31
PROBM	-0.039	-3.50	-0.043	-3.80
Sales Growth	-0.025	-0.76	-0.023	-0.78
Adj. R-Square	0.65%		2.43%	

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

	MVE < $100M			$100M < MVE < $250M			$250M < MVE < $500M			$500M < MVE < $1000M			$1000M < MVE		
O-Score	N	BHRR	%Neg	N	BHRR	%Neg	N	BHRR	%Neg	N	BHRR	%Neg	N	BHRR	%Neg
0	560	28.2%	34%	748	24.0%	38%	581	16.9%	38%	544	14.5%	35%	1080	13.4%	33%
1	1292	21.2%	44%	1703	18.3%	45%	1297	16.2%	39%	1252	13.4%	40%	3137	13.4%	35%
2	1345	21.6%	50%	1844	18.7%	46%	1252	14.7%	45%	1142	14.8%	42%	2389	12.4%	40%
3	874	23.8%	54%	1055	12.3%	53%	675	13.4%	50%	585	9.8%	51%	971	6.7%	48%
4	402	6.2%	61%	577	5.9%	56%	403	-1.8%	60%	301	4.6%	55%	463	9.9%	54%
5	122	-15.4%	66%	206	-8.9%	69%	127	-18.2%	75%	103	-13.7%	66%	98	-24.8%	73%

Panel D: 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 E: 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 6

Asset pricing regressions. This table reports Fama-French asset pricing regressions of monthly O-Score portfolio excess returns on the MKT, SMB, and HML portfolios. MKT denotes the return on the CRSP value-weighted index for month t; SMB denotes the return to the small-minus-big factor mimicking portfolio for size for month t; HML denotes the return to the high-minus-low factor mimicking portfolio for book-to-market equity for month t. '0 minus 5' refers to a regression of the difference between the low and high portfolios on the factors in the asset pricing model.

O-Score		Intercept	MKT	SMB	HML	Adj. R-Sq.
0	Estimate	0.295	0.912	0.564	0.461	77.3%
	t-statistic	(1.67)	(19.63)	(9.17)	(9.52)	
1	Estimate	0.137	1.016	0.508	0.531	88.3%
	t-statistic	(0.98)	(27.90)	(10.53)	(14.01)	
2	Estimate	0.010	1.166	0.318	0.694	88.7%
	t-statistic	(0.06)	(25.18)	(5.18)	(14.40)	
3	Estimate	-0.151	1.333	-0.107	0.982	81.5%
	t-statistic	(-0.45)	(15.07)	(-0.91)	(10.67)	
4	Estimate	-0.885	1.448	-0.103	0.973	81.8%
	t-statistic	(-2.53)	(15.74)	(-0.84)	(10.16)	
5	Estimate	-1.849	1.536	-0.355	0.993	74.1%
	t-statistic	(-3.73)	(11.80)	(-2.06)	(7.33)	
0 minus 5	Estimate	2.144	-0.624	0.919	-0.532	61.2%
	t-statistic	(4.57)	(-5.06)	(5.64)	(-4.15)	

Joint test: all intercepts = 0	
GRS F-Statistic	5.61
p-value	1.8%

Table 7

Institutional holdings and O-Score portfolio assignments. Panel A presents size-adjusted returns in the quarters surrounding portfolio formation. Panel B presents average aggregate institutional holdings and average institutional holdings by investor type (Transient, Dedicated, Quasi-Indexer) in the quarters surrounding the quarter of portfolio formation. Panel C presents consecutive year average institutional holdings and changes therein as a function of O-Score portfolio assignment. 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.

Panel A: Average Returns for High and Low O-Score Firms in Quarters Surrounding Portfolio Formation

		Market Adj. Quarterly Returns--Quarter Relative to Portfolio Formation						
	N	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**
O-Score=0	3513	1.41%	2.12%	1.76%	1.43%	2.09%	2.76%	1.65%
O-Score=5	656	**15.81%**	**14.26%**	**10.27%**	1.20%	***-3.62%***	***-2.29%***	***-9.55%***

Panel B: Average Institutional Holdings for Transient, Dedicated and Quasi-indexers

			Average Institutional Holdings--Quarter Relative to Portfolio Formation						
	TYPE	N	-3	-2	-1	0	1	2	3
O-Score=0	All institutions	3513	44.57%	45.09%	45.29%	45.33%	45.96%	46.66%	47.05%
O-Score=5	All institutions	656	***34.99%***	***37.42%***	***38.98%***	***39.60%***	***39.16%***	***39.84%***	***38.98%***

			Average Institutional Holdings--Quarter Relative to Portfolio Formation						
	TYPE		**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**
O-Score=0	Transient	3513	10.50%	10.82%	11.04%	11.22%	11.80%	12.28%	12.53%
O-Score=5	Transient	656	**13.00%**	**14.10%**	**14.97%**	**14.97%**	**15.30%**	**15.49%**	**14.67%**
O-Score=0	Dedicated	3513	11.14%	11.31%	11.22%	11.18%	10.63%	10.70%	10.47%
O-Score=5	Dedicated	656	***8.35%***	***8.72%***	***8.89%***	***8.85%***	***8.07%***	***8.18%***	***8.18%***
O-Score=0	Quasi indexers	3513	22.92%	22.96%	23.03%	22.94%	23.54%	23.68%	24.07%
O-Score=5	Quasi indexers	656	***13.63%***	***14.60%***	***15.14%***	***15.78%***	***15.78%***	***16.18%***	***16.13%***

Panel C: Consecutive year average institutional holdings and changes as a function of O-Score values

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

	O-Score=5 in Year t					**O-Score<5 in Year t**				
	N	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**	**N**	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**
O-Score=5 in Year t-1	105	**3.91%**	0.42%	-0.63%	**4.12%**	367	***-0.22%***	0.32%	-0.89%	***0.34%***
O-Score<5 in Year t-1	269	**7.81%**	**3.67%**	**1.71%**	**2.42%**	19699	1.90%	1.00%	-0.29%	1.19%

	O-Score>3 in Year t					**O-Score<4 in Year t**				
	N	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**	**N**	**All institutions**	**Transient**	**Dedicated**	**Quasi indexers**
O-Score>3 in Year t-1	673	**2.57%**	0.31%	-0.55%	**2.81%**	1313	***0.39%***	0.21%	-0.35%	***0.53%***
O-Score<4 in Year t-1	2064	**5.64%**	**2.26%**	**0.33%**	**3.05%**	17439	1.82%	1.03%	-0.30%	1.09%

Note: Bold indicates signficantly greater values; bold and italics indicates signicantly lower values. Significance based on two-tailed t-tests.

Table 8

O-Score and future mergers, financing activity, and restatements. 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. We measure the subsequent acquisitive and financing activities over years +1 and +2 in a similar fashion. We identify 630 overstatements from 1993-2004 from Audit Analytics database and the SEC's AAERs. 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. We review AAERS to identify company name and the beginning and ending dates of the fraud.

	N	OSCORE=0	N	OSCORE=1	N	OSCORE=2	N	OSCORE=3	N	OSCORE=4	N	OSCORE=5	OSCORE=5 vs. All Other
Acquisitions													
Firms with Acquisitions in years +1 or +2	3513	30.03%	8674	38.37%	7970	41.09%	4160	38.94%	2146	41.85%	656	44.21%	0.001
Number of Acquisitions	1701	100.00%	6356	100.00%	6239	100.00%	3482	100.00%	2185	100.00%	847	100.00%	
All stock	136	8.00%	592	9.31%	761	12.20%	601	17.26%	434	19.86%	180	21.25%	<0.001
Mostly Stock	176	10.35%	785	12.35%	967	15.50%	739	21.22%	514	23.52%	211	24.91%	<0.001
Financing													
Abnormal Equity Issue in years +1 or +2	3513	22.06%	8673	31.12%	7970	37.64%	4160	40.63%	2146	42.50%	656	44.21%	<0.001
Abnormal Debt Issue in years +1 or +2	3513	37.52%	8673	38.23%	7970	38.24%	4160	39.95%	2146	40.45%	656	43.60%	0.005
Overstatements													
Firms that restate current results in future years	3513	1.05%	8673	1.77%	7970	2.82%	4160	3.29%	2146	3.02%	656	3.81%	0.007