The Predictable Cost of Earnings Manipulation

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Abstract

Although financial reporting fraud generates considerable losses, we find that investors do not fully exploit publicly available information relevant for detecting fraud. We show that firms with a high probability of overstated earnings have lower future earnings, less persistent income-increasing accruals, and lower future returns. The trading strategy based on the probability of manipulation ranks subsumes the relation between accruals and future performance and yields a hedge return of 13.9%, mostly arising from the short position. Although this suggests a limits-to-arbitrage explanation, we show that institutional investors actually increase their holdings in firms with a high probability of manipulation, and that hedge returns remain large for firms with market capitalization in excess of $1 billion. Thus, the returns concentrated on the short side of the strategy appear to arise not from asymmetric arbitrage costs, but from asymmetric errors in the expectations of (even sophisticated) market participants.

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1. Introduction

Fraudulent financial reporting imposes a huge cost on financial markets. For example, Cendant shareholders lost $13 billion dollars when the firm announced potential accounting 'irregularities' on April 15, 1998. In addition to losses in investor wealth, fraudulent financial reporting creates large welfare losses: Such unethical behavior misdirects resources from their most productive use; increases transactions costs by eroding investor confidence in the integrity of the capital market; and invites action by regulators, who impose (often costly) regulation on firms and markets (Arrow 1973, 1975; Becker 1976; Hirshleiffer 1977; Noreen 1988, Jensen 2007). Indeed, Jensen (2005) predicts that managers engage in questionable accounting practices among other value-destroying activities to sustain overvalued shares, and Beneish (1999a) and Karpoff et al. (2007) provide evidence of large market value losses to public revelations of accounting manipulation.

These costs provide investors with substantial incentives to identify firms that have likely manipulated earnings. With respect to an investor's portfolio decisions, the cost of incorrectly identifying a non-manipulator is the sacrifice of the expected return on the stock. However, this cost is small because many investments offer comparable expected return. On the other hand, the benefit of correctly identifying a manipulator is the avoidance of large losses such as those incurred by the shareholders of Cendant. These incentives suggest that market participants should efficiently act on information relevant for assessing the likelihood of financial reporting fraud. On the other hand, research consistently finds that prices behave as if investors ignore the implications of readily available public information (Bernard and Thomas 1989, 1990; Ou and Penman 1989; Jegadeesh and Titman 1993; Lakonishok, Shleifer, and Vishny 1994; Chan, Jegadeesh, and Lakonishok 1996; Sloan 1996, Beneish 1997; Lee and Swaminathan 2000).

In this paper, we examine a fraud assessment model that predicted the fraud in Cendant, as well as Enron, Global Crossing, Qwest and several other high profile instances of fraud listed in Table 1. Of the 20 top instances of fraud in Table 1 (as reported by auditintegrity.com), the model correctly identified twelve of the firms as manipulators, and did so on average a year and a half prior to the public revelation of the fraud. Although, the model mistakenly flags some non-fraud firms, its usefulness in identifying fraud firms is well-documented (see Section 2). The model combines operating and financial characteristics of firms to assess the probability of manipulation (PROBM). If market participants efficiently use information about these characteristics to identify fraud firms, the probability of manipulation as measured by this model should have no relation with future returns, after controlling for risk. However, if market participants fail to use available information to assess the probability of manipulation, PROBM should negatively relate to future returns.

Our results confirm that firms with a high probability of manipulation have low future returns relative to firms with a low probability of manipulation. The hedge returns to a strategy based on PROBM average 13.9 percent per year. However, in examining the market's use of information relevant to assessing fraud, it is important to control for the well-known market anomaly related to accruals. This is because earnings manipulation typically occurs through exercise of discretion over accruals, and because accruals is one of the eight inputs into the PROBM model. Our tests contrasting PROBM and accruals reveal that (1) PROBM is a powerful predictor of returns *within* accrual decile ranks, (2) PROBM *subsumes* the relation between accruals and future returns, and (3) although accruals deliver comparable hedge returns (13.4 percent), PROBM provides this abnormal return with significantly *less volatility* (PROBM Sharpe ratio of 0.63 compared to 0.43 for accruals). A conservative interpretation of our results

is that PROBM is not simply a manifestation of accruals; an aggressive interpretation is that the accrual anomaly is merely a manifestation of the return consequences of undetected earnings manipulation.[1]

In light of the incentives for capital markets participants to use this information efficiently, our findings raise the question of why PROBM predicts returns. We show that PROBM has implications for future earnings that market participants seemingly ignore or misunderstand. Specifically, firms in the highest decile of PROBM have lower future return on assets by 90 basis points, but prices behave as if market participants expect these firms to have *higher* profitability by 600 basis points. We also find that PROBM subsumes accrual mispricing: given PROBM, only positive accruals with a high probability of overstatement are mispriced.

Our size-adjusted hedge returns suggest that the short position contributes most of the returns to the strategy. Because how the hedge return arises is important for both implementing the strategy and understanding the source of the mispricing, we first refine our measure of expected returns with a variety of factor pricing model regressions to verify the contribution of the side of the hedge. We find that the short side also dominates when we examine alphas for PROBM deciles from the Fama-French three factor model and from four factor models based on either an idiosyncratic volatility factor, or a cash flow volatility factor.

Because the short side carries high transactions costs and arbitrage risk, the existence of the hedge returns on the short side may prevent arbitrageurs from trading to correct the mispricing. However, sophisticated investors who already hold the stock can always sell if they suspect the firm has a high probability of manipulation. Consequently, we examine the trading

[1] Although they investigate a different research question, Kothari et al. (2007) reach a similar conclusion. Kothari et al. (2007) suggest that Jensen's (2005) agency theory of overvalued equity explains the accrual anomaly. Because PROBM identifies firms with a high probability of overstatement, our finding that PROBM subsumes the relation between accruals and future returns is consistent with mispricing resulting from managers misleading investors by cooking the books to sustain their firm's stock price.

behavior of institutional investors to assess whether sophisticated investors accurately assess the probability of manipulation. Surprisingly, even sophisticated investors appear to be fooled. Institutional investors actually increase their holdings in firms that become flagged as possible manipulators in the current period.

Research finds that many institutions do not behave as arbitrageurs, suggesting that changes in aggregate institutional holdings may be a flawed proxy for the behavior of sophisticated investors (e.g., Bushee and Noe 2000). We therefore also examine hedge returns to PROBM segregated by market capitalization. Transactions costs decrease and liquidity increases with market capitalization, so we expect arbitrage to be most effective in eliminating mispricing for large firms. However, we find hedge returns of nearly 12 percent for firms with market capitalization of over $1 billion. This casts doubt that even arbitrageurs and other sophisticated investors accurately assess the probability of manipulation.

Overall, our results have several important implications. First, we show that PROBM is not simply a manifestation of the accrual anomaly, but the accrual anomaly may merely be a manifestation of the return consequences of undetected earnings manipulation. Second, we show that information about the likelihood of earnings manipulation is a strong predictor of returns. In his discussion of the agency costs of overvalued equity, Jensen (2005) suggests that boards of directors should take a more skeptical view of the company's prospects; the strong relation between PROBM and future returns suggests the need for greater skepticism among investors and other users of financial statements, too.

Finally, our results question a key assumption about the role of arbitrageurs in capital markets. Both theories of market efficiency and theories of limited arbitrage assume that unconstrained actions of rational arbitrageurs will eliminate the mispricing created by others.

However, our results that (1) institutions increase their holdings in firms that become flagged as possible manipulators and (2) hedge returns remain large for large firms suggest that even smart investors do not fully exploit information useful for assessing the likelihood of manipulation. Thus, the returns concentrated on the short side of the strategy appear to arise not from asymmetric arbitrage costs, but from asymmetric errors (across extreme PROBM deciles) in the expectations of (even sophisticated) market participants.

We present the remainder of the paper in six parts. We describe the model for assessing the probability of manipulation in section 2. Section 3 presents the data and method. We distinguish PROBM from accruals in section 4. We examine why PROBM predicts returns in section 5, and why smart money investors do not eliminate the mispricing in section 6. We summarize the paper and conclude in Section 7.

2. The Probability of Manipulation

We rely on models in Beneish (1997, 1999) to estimate the probability of manipulation. Beneish profiles firms that manipulate earnings (firms charged with or admitting to manipulation) and develops a model to distinguish manipulators from non-manipulators using financial statement variables. Specifically, the model we use to estimate the probability of manipulation to overstate earnings (which we denote PROBM for ease of exposition) is:[2]

$$\text{PROBM} = -4.84 + .920*\text{DSR} + .528*\text{GMI} + .404*\text{AQI} + .892*\text{SGI} + .115*\text{DEPI} - .172*\text{SGAI}) + 4.679*\text{ACCRUALS} - .327*\text{LEVI} \quad (1)$$

Where:

$\text{DSR} = (\text{Receivables}_t[2]/\text{Sales}_t[12]/(\text{Receivables}_{t-1}/\text{Sales}_{t-1})$

[2] In this paper, we use the more parsimonious model in Beneish (1999). As well, the model does not rely on market data, and this makes it useful for assessing fraud potential in firms with initial public offerings. The 1999 model is estimated and tested using a sample consisting of 74 firms that manipulated earnings and 2332 COMPUSTAT non-manipulators matched by industry over the period 1982-1992.

$$GMI= \left(\frac{Sales_{t-1}[12] - Costs\ of\ Goods\ Sold_{t-1}[41]}{Sales_{t-1}[12]}\right) / \left(\frac{Sales_{t}[12] - Costs\ of\ Goods\ Sold_{t}[41]}{Sales_{t}[12]}\right)$$

$$AQI= \left(1 - \frac{Current\ Assets_{t}[4] + PPE_{t}[8]}{Total\ Assets_{t}[6]}\right) / \left(1 - \frac{Current\ Assets_{t-1} + PPE_{t-1}}{Total\ Assets_{t-1}}\right)$$

$$SGI= Sales_{t}[12]/Sales_{t-1}$$

$$DEPI= \left(\frac{Depreciation_{t-1}[14\ less\ 65]}{Depreciation_{t-1} + PPE_{t-1}[8]}\right) / \left(\frac{Depreciation_{t}}{Depreciation_{t} + PPE_{t}}\right)$$

$$SGAI= \left(\frac{SGA\ Expense_{t}[189]}{Sales_{t}[12]}\right) / \left(\frac{SGA\ Expense_{t-1}}{Sales_{t-1}}\right)$$

$$LEVI= \left(\frac{LTD_{t}[9] + Current\ Liabilities_{t}[5]}{Total\ Assets_{t}[6]}\right) / \left(\frac{LTD_{t-1} + Current\ Liabilities_{t-1}}{Total\ Assets_{t-1}}\right)$$

$$ACCRUALS= (IBX\ [18]-CFO[308])/\ TA_{t}[6]$$

This model consists of eight ratios that capture either financial statement distortions that can result from earnings manipulation (DSR, AQI, DEPI and Accruals) or indicate a predisposition to engage in earnings manipulation (GMI, SGI, SGAI, LEVI). The predictive ratios focusing on financial statement distortions capture unusual accumulations in receivables (DSR, indicative of revenue inflation), unusual expense capitalization and declines in depreciation (AQI and DEPI, both indicative of expense deflation), and the extent to which reported accounting profits are supported by cash profits (Accruals). The four predictive ratios that suggest propitious conditions for manipulation capture deteriorating gross margins and increasing administration costs (GMI and SGAI, both signals of declining prospects), high sales growth (SGI) because young growth firms have greater incentives to manipulate earnings to make it possible to raise capital, and increasing reliance on debt financing (LEVI), as this increases the firm's financial risk and the likelihood of earnings manipulation related to debt agreement constraints.

Beneish validates his models in three ways. First, examining a variant of the model we use in this paper, Beneish (1997) shows that the model's ability to predict earnings manipulation

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

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 et al. 2003) and in articles directed at auditors, certified fraud examiners, and investment professionals (e.g., Cieselski 1998, Merrill Lynch 2000, Wells 2001, DKW 2003, Harrington 2005). The model received additional attention subsequent to the Enron scandal as Brewer (2004) and others discovered that the model in Beneish (1999) had flagged Enron as early as 1998.[3]

Given the costs associated with financial statement fraud in capital markets, one would expect market participants to exploit all information useful for assessing fraud, not just PROBM. As a result, no relation should exist between PROBM and future returns. However, prior research provides ample evidence that market participants either ignore or underutilize financial statement

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

information—e.g., Ou and Penman (1989) on the prediction of earnings changes, Bernard and Thomas (1989) on the predictability of earnings surprises, and Beneish, Lee and Tarpley (2001) on the predictability of extreme returns.

Particularly relevant is Sloan (1996) on the predictability of returns to portfolios formed on extreme aggregate accruals. If market participants fail to efficiently use information in aggregate accruals, they are unlikely to efficiently use the information in PROBM, which relies on specific accruals and financial metrics that are less familiar to market participants. Because earnings manipulation creates distortions in reported earnings, we predict that firms with a high (low) likelihood of earnings manipulation experience (1) lower (higher) future earnings, and (2) less (more) persistent accruals. If investors do not fully assess the probability of manipulation, they will not fully identify these consequences of earnings overstatement. Consequently, we predict that firms with a high (low) probability of earnings manipulation experience lower (higher) future returns.

Earnings manipulation typically occurs through accruals. For this reason, PROBM uses accruals as one of the model inputs. Because an extensive literature establishes that accruals predict future returns, we develop tests to distinguish PROBM from accruals in section 4.

3. Method

3.1. Sample

We select the initial sample from the Compustat Industrial, Research, and Full Coverage files for the period 1993 to 2003.[4] 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

[4] Because the Beneish (1999) model was tested on data through 1992, we begin the sample period in 1993.

manipulation. Following Beneish (1997, 1999), we winsorize the predictive variables in the probability of manipulation model at the 1 percent and 99 percent levels each year in our sample period to deal with problems caused by small denominators and to control for the effect of potential outliers.

To ensure that the trading strategies that we examine are implementable, we (1) require all firms used in our rankings to have stock return data available in the CRSP tapes at the time rankings are made, and (2) use *prior year* decile cut-offs to assign firms to deciles of accruals and probability of manipulation 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 follow Beaver et al (2007) to include delisting returns in the buy-and hold return. The final sample consists of 27,427 firm-year observations from 1993 to 2003.

3.2 Sample Characteristics

In Table 2, we describe the characteristics of our sample. Accrual and PROBM decile ranks are highly correlated (correlation = 0.660, $p < 0.001$, untabulated), and we report the descriptive statistics both by PROBM decile (Panel A) and Accrual decile (Panel B) to highlight similarities and differences across the rankings.[5]

Both partitions reveal a pattern of increasing earnings and decreasing cash flows. However, the accrual rankings generate a monotonic pattern in earnings and a larger spread in earnings (0.285) than the corresponding spread generated by PROBM (0.175). By contrast, the pattern of earnings is not monotonic: earnings in the highest PROBM decile are lower than

[5] We define accruals as income before extraordinary items minus cash from operations, scaled by average total assets. In unreported tests, we also examine several measures of abnormal accruals derived from aggregate accrual expectation models based on modifications of the Jones (1991) model. As well, because recent work suggests that such constructs measure earnings management with error (e.g., see McNichols (2000) among others), we follow Kothari et al. (2005) and adjust both accruals and current accruals from such models by computing performance-matched abnormal accruals. Because the analyses in the paper are not sensitive to using accruals or abnormal accruals, we only report results based on total accruals.

earnings in PROBM deciles 4 to 9. In addition, the mean and median accrual in the highest PROBM decile (0.023 and 0.006) is significantly lower than the corresponding values for the highest accrual decile (0.115 and 0.095) and conversely for the lowest deciles. This suggests that, at least in the extreme deciles, PROBM and accrual ranks are capturing different information. On the other hand, if the mapping between accruals and returns is linear, these statistics suggest that we should observe larger returns to a strategy based on accruals.

We also report descriptive statistics for other financial characteristics across PROBM deciles in Panel C. Extreme PROBM deciles do not significantly differ on price-to-book. However, firms in the extreme deciles of PROBM significantly differ on other characteristics such as price-to-earnings, cash flow-to-price, earnings surprises (measured as the change in the quarterly earnings for the quarter of the annual earnings announcement, scaled by market value at the end of the month before the annual earnings announcement), return momentum, return volatility and size. Because prior research shows that these characteristics are related to future returns, we control for these variables in subsequent tests.

4. Distinguishing PROBM Hedge Returns from Accruals

Following Sloan (1996), a number of studies provide evidence consistent with accrual mispricing.[6] A frequent explanation for accrual mispricing is that market participants fail to distinguish the differential implications of accruals and cash flows for future earnings. Moreover, many observers speculate that earnings management is an important reason why the implications

[6] Studies provide evidence of mispricing for alternative measurements of accruals, abnormal accruals, and components of accruals (Xie (2001), Chan et al. (2001), Collins and Hribar (2002), Hribar (2002), Thomas and Zhang (2002), Richardson et al. (2005), Gu and Jain (2006)): evidence that accrual mispricing 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 et al. (2001), Collins et al. (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)).

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.

We propose four tests to distinguish PROBM from accruals. If PROBM is a noisy proxy for accruals, then (1) PROBM hedge returns should be lower because PROBM ranks firms on accruals with error, (2) PROBM ranks should not have predictive power within accrual decile ranks, (3) controlling for accruals, PROBM decile ranks should have no relation with future returns, and (4) PROBM Sharpe ratios should be lower than accrual Sharpe ratios. If these four predictions are refuted, PROBM identifies mispricing not captured by aggregate accruals. We present results from these tests in Table 3 and discuss them below.

4.1 PROBM and Accrual hedge returns

We investigate the returns to an investment strategy based on PROBM and Accruals in Panel A. We present mean size-adjusted returns for deciles formed on PROBM and Accruals. The one-year holding period begins on the first day of the fifth month following a firm's fiscal year end. Because fiscal year ends vary across sample firms, we assign firms into deciles based on the prior years' decile cut-offs.

The return to the hedge portfolio formed by taking a long position in the lowest PROBM decile and a short position in the highest PROBM decile earns a hedge return of 13.9 percent. These results suggest that PROBM predicts the direction of future returns. Although both sides of the hedge exhibit abnormal return performance, the short side of the hedge (9.6 percent) accounts for nearly 70 percent of return. The results from a long (short) position in firms in the lowest (highest) accrual decile are similar: the hedge return is 13.4 percent and 10.4 percent (78

percent of the hedge return) comes from the short side.[7] The similarity of the results across PROBM and accrual partitions raises the question of whether the variables are capturing the same information and lead us to investigate how the strategies perform in relation to each other.

4.2 PROBM explains returns within accrual deciles

For our next step in distinguishing PROBM from accruals, we extend the analysis in Beneish (1997) to all accrual deciles. Our results, reported in Table 3, Panel B, confirm Beneish (1997)'s finding in accrual decile 10: firms flagged as manipulators (firms with PROBM exceeding probability cut-offs associated with various assumptions about the cost of classification errors) have more negative returns than non-manipulators in the highest decile (e.g., -13.25 percent vs. -6.11 percent). Indeed, we find that one-year-ahead returns of firms flagged as manipulators are systematically negative no matter what their accrual decile classification.[8]

We interpret this evidence as indicating that PROBM has incremental predictive ability relative to accruals. Indeed, a strategy of selling short flagged manipulators in accrual decile 10 and buying non-manipulators in decile 1 would yield a hedge return of 18.15 percent, 471 basis points higher than the hedge return corresponding to the extreme accrual deciles (13.44 percent).

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[7] Kraft et al. (2006) point out that none of the accrual anomaly studies perform robustness tests to assess the sensitivity of the results to extreme BHSAR observations. As a robustness check we eliminate the firms in the top and bottom 1% of BHSAR each year. We find that the hedge return is virtually unchanged (18.2 % for extreme accruals and 19.6% for extreme PROBM deciles). However, the components of the hedge change: the long side earns smaller abnormal returns (3.2 % for extreme low accruals and 5.4% for extreme low PROBM), and the short side experiences more adverse abnormal returns (-15.0 % for extreme high accruals and -14.3% for extreme high PROBM),

[8] Moreover, the spread generated within an accrual decile generally exceeds the spread across the two adjacent accrual deciles. For example, with a 20:1 cost ratio, PROBM generates a 6.8 percent spread in the fifth accrual decile. However, the spread across accrual deciles four and six is -.26 percent (1.04 – 1.30). This suggests that scoring firms on PROBM does not merely sort firms on accruals within accrual deciles.

4.3 PROBM rankings subsume the relation between Accruals and future returns

In Panel C, we investigate whether one strategy's hedge returns subsume the other while controlling for omitted variables associated with future returns. We estimate the regression below for each year in our sample as well as by pooling observations across years:

$$BHSAR_{t+1} = a_0 + a_1 PROBMRank_t + a_2 AccrualRank_t + a_3 BETA_t + a_4 B/P_t + a_5 RET_t + a_6 \ln(MVE_t) + a_7 RetVol_t + a_8 CFO/P_t + a_8 UE_t + e_{t+1} \quad (3)$$

where BHSAR is the one-year ahead size-adjusted return from the beginning of the fifth month following the fiscal year-end; PROBMRank is the PROBM decile rank and AccrualRank is defined as the accrual decile rank. Decile ranks are scaled to range from 0 to 1. Under the assumption of linearity in the relation between rankings and returns, the coefficient on PROBMRank (AccrualRank) is the return to the PROBM (accrual) hedge portfolio after controlling for the effect of all the other variables.

The remaining variables are included to investigate whether the hedge returns can be explained by omitted variables associated with future returns.[9] These variables are recast as deviations from the mean, scaled by the in-sample standard deviation of the variable. In several studies that use size-adjusted returns to document accrual mispricing, researchers have controlled for BETA, book-to price (B/P), returns in the prior year (RET_{t-1}), firm size (ln(MVE)) and earnings surprise (UE) [e.g., Beneish and Vargus (2002), Collins et al. (2003), Barth and Hutton (2004)]. We add cash flow from operations to price (CFO/P) following evidence in Desai et al.

[9] Prior research that has shown that the following characteristics are correlated with subsequent returns: (1) the book-to-price ratio, following evidence in Chan et al. (1996), Davis (1994), and Haugen and Baker (1996), who document that firms with high market-to-book ratios subsequently earn lower returns; (2) returns in the prior year , following evidence in Jegadeesh (1990), and Jegadeesh and Titman (1993) that short-run returns tend to continue in the subsequent year; (3) price-to-earnings, following evidence that firms with low P/E ratios outperform firms with high P/E ratios on a risk-adjusted basis (among others, Haugen and Baker 1996); (4) beta and firm size, following evidence in, among others, Fama and French (1992), that the market factor size explains future returns; (5) unexpected earnings, to capture the post-announcement drift documented by (among others) Freeman and Tse (1989) and Bernard and Thomas (1989).

(2004) that strategies based on CFO/P explain the returns to accrual-based strategies, and return volatility (RETVOL) as an additional control for risk.

Panel C reports results for a pooled estimation of equation (3), and we report t-statistics based on the Huber/White sandwich estimator with clustering by year. The coefficient estimate on PROBMRank equals 0.077 and is significantly different from zero (t-statistic of 2.57) but the coefficient on AccrualRank (0.046) is not distinguishable from zero. This suggests that after controlling for accruals and other variables associated with future returns, a portfolio return to PROBM strategy earns 7.7 percent.

In Panel D of Table 3 we estimate these regressions year-by-year with similar results, and the corresponding portfolio return to PROBM strategy is 7.1 percent. This evidence indicates that PROBM predicts one-year-ahead returns, and that PROBM subsumes the explanatory power of accruals in predicting one-year-ahead returns. We interpret this evidence as suggesting that earnings manipulation plays an important role in accrual mispricing.

4.4 PROBM produces a higher Sharpe ratio than Accruals

For our final test to distinguish PROBM from accruals, we report the Sharpe ratios associated with both strategies. Market participants care not only about the mean return delivered by an investment strategy, but also about the volatility associated with that mean return. Although both strategies produce comparable returns on average, the two strategies could differ on the extent to which they expose market participants to volatility. For this analysis, we construct monthly returns for all deciles in each strategy. We assign firms to portfolios at the beginning of each month based on the firm's most recent accrual decile assignment, using the ranking procedures described above. We form the hedge return as the return to the lowest decile less the return of the highest decile in each month. We calculate the Sharpe ratio as the time-

series average of this monthly hedge return, divided by its time-series standard deviation. The results, reported in Panel E of Table 3, show the PROBM Sharpe ratio of 0.63 is nearly 50 percent larger than the Accrual Sharpe ratio of 0.43. As with the annual returns, the average monthly returns do not significantly differ (t-statistic = 0.80, p = 0.213). However, the variance of the accrual hedge is significantly larger than the variance of the PROBM hedge (F-value = 1.42, p = 0.02). Thus, the PROBM strategy produces its expected return with significantly less volatility than does the accrual-based strategy.

Finally, we report the correlation between the returns to the PROBM strategy and the accrual strategy. Though statistically significantly, the correlation is economically moderate (corr = 0.24, p = .002). As with the preceding analyses, this modest correlation confirms that the returns to PROBM are distinct from the returns to accruals.

Overall, we conclude that PROBM significantly differs from accruals in its predictive content for future returns. A conservative interpretation of our results is that PROBM is not simply a manifestation of accruals; an aggressive interpretation is that the accrual anomaly *is* merely a manifestation of the return consequences of undetected earnings manipulation.

5. Why Does PROBM Predict Returns?

Following Shleifer (2000), a complete explanation for the apparent mispricing associated with PROBM should explain (1) why some investors make mistakes, and (2) what prevents smart money investors from correcting the mistakes of others. This section examines the market's pricing of PROBM. Section 6 examines the behavior of sophisticated investors and limits to arbitrage.

5.1. The implications of PROBM for future earnings

In this section, we examine the relation between PROBM and future earnings, cash flows, and accruals. This analysis serves two purposes. First, it provides additional validation of the PROBM model as an assessment of earnings manipulation. Manipulation typically introduces transitory distortions in the accrual component of current earnings. Thus, positive accruals for firms with high (low) PROBM should be less (more) persistent, while negative accruals for firms with high (low) PROBM should be more (less) persistent. Second, the analysis provides a starting point for understanding why PROBM predicts returns. Specifically, if PROBM has implications for future earnings that market participants do not exploit, PROBM will be associated with future returns as future earnings realizations reveal seemingly predictable expectation errors.

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

$$\begin{aligned} DV_{t+1} = {} & \alpha_0 + \beta_1 CFO_t + \beta_2 CAccPos_t + \beta_3 CAccNeg_t + \beta_4 CAccPos_t * ScaledRanks_t \\ & + \beta_5 CAccNeg_t * ScaledRanks_t + \beta_6 Dep_t + \beta_7 ScaledRanks_t + \varepsilon_{t+1} \end{aligned}$$

where DV denotes earnings, cash flows from operations, or accruals, as appropriate, and ScaledRanks denotes scaled PROBM decile ranks (SPR) or scaled accrual decile ranks (SAR), each scaled to range from -1 to +1. We report t-statistics based on the Huber/White sandwich estimator with clustering by year.

We report the results for scaled PROBM ranks in Panel A. For earnings in column (1), we find strong persistence for CFO (coefficient = 0.867, t-statistic = 42.38), but weaker persistence for accruals (CAccPos = 0.762, t-statistic = 8.88; CAccNeg = 0.526, t-statistic = 9.05). The coefficients on CAccPos and CAccNeg reflect the average persistence of positive and negative accruals, respectively. The coefficients on CAccPos*SPR and CAccNeg*SPR capture the effects of the probability of manipulation on accrual persistence. CAccPos*SPR is negative and significant (coefficient = -0.270, t-statistic = -2.87), while CAccNeg*SPR is positive and significant (coefficient = 0.221, t-statistic = 4.49). Thus, both income-increasing and income-decreasing accruals that have a high probability of overstatement lead to lower future earnings, consistent with PROBM measuring the likelihood that earnings contain income-increasing distortions.

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

A noteworthy feature of the coefficients reported in columns (2) and (3) is that their sum approximates the estimated coefficient in column (1).[10] Thus, a comparison of results in column (2) to column (3) indicates the source of the relation between the regressors and future earnings reported in column (1). For both CAccPos*SPR and CAccNeg*SPR, the results indicate a stronger relation with future accruals than with future cash flows. For example, the coefficient on

[10] For example, CFO has a coefficient of .743 in column (2) and .113 in column (3). The sum is .856 (.743+.113), which is close to the estimated coefficient of .867 in column (1).

CAccPos*SPR is not significant in the cash flow regression (-.064), but it is significant in the accruals regression (-.193). Thus, current accruals that have a high probability of overstatement lead to lower future earnings not because of lower future cash flows, but rather because of lower future accruals. These lower future accruals are consistent with the reversal of transitory distortions in current earnings due to earnings manipulation.

In panel B, we replicate these analyses with scaled accrual ranks to further compare PROBM and accruals. The noteworthy feature in column (1) of Panel B is that the persistence of accruals is not a function of the magnitude of accruals. CAccPos*SAR is neither economically nor statistically significant (coefficient = .005, t-statistic = .05), and CAccNeg*SAR is not statistically significant (coefficient = .197, t-statistic = 1.42).[11] In contrast to the results for PROBM, columns (2) and (3) of Panel B reveal that the associations between future earnings and the variables CAccPos*SAR and CAccNeg*SAR are dominated by the relations with future cash flows. Moreover, a non-trivial portion of the relation between SAR and future earnings arises from SAR's relation with future cash flows.

Overall, these results suggest that PROBM differs from accruals by (1) more effectively identifying firms with transitory distortions due to manipulation and (2) reflecting less of the firm's fundamental performance in the form of implications for future cash flows.

5.2. The market's assessment of PROBM's implications for future earnings

Following Sloan (1996), we use the framework proposed by Mishkin (1983) to investigate whether the market rationally prices the implications of the probability of manipulation for one-year-ahead earnings. Initially, we estimate the following system:

[11] The lack of significance could be due to multicollinearity between accruals and scaled accrual ranks (SAR). The regressions in Panel B have a maximum characteristic index of 23.7, much greater than the threshold of 10 that indicates multicollinearity (Belsley, Kuh, and Welsch 1980). Although coefficient estimates are unbiased, t-statistics are unreliable for the results in panel B. In contrast, the characteristic indices for Panel A do not exceed 6.5, suggesting multicollinearity is not a problem in the analysis with scaled PROBM ranks (SPR)...

$$
\begin{aligned}
E_{t+1} &= \alpha_0 + \beta_1 EPos_t + \beta_2 ENeg_t + \beta_3 EPos * SPR_t + \beta_4 ENeg * SPR_t + \beta_5 SPR_t + \varepsilon_{t+1} \\
BHSAR_{t+1} &= \phi_1 \left[E_{t+1} - \alpha_0 - \beta_1' EPos_t - \beta_2' ENeg_t - \beta_3' EPos * SPR_t - \beta_4' ENeg * SPR_t - \beta_5' SPR_t \right] + \upsilon_{t+1}
\end{aligned} \quad (4)
$$

E	= Income before extraordinary items (#123) divided by average total assets;
CFO	= Cash flows from operations (#308) divided by average total assets;
Acc	= E – CFO;
BHSAR	= Twelve-month buy and hold size-adjusted return from the beginning of the month following the annual earnings announcement;
EPos	= E if E > 0; 0 otherwise;
ENeg	= E if E < 0; 0 otherwise;
SPR	= Scaled PROBM rankings. PROBMs are computed using the model in Beneish (1999). PROBMs are ranked annually using the prior year decile rank cutoffs. Ranked PROBMs are scaled to have a zero mean and range from -1 (lowest PROBM) to +1 (highest PROBM);

The first equation in this system estimates the forecasting coefficients (β_i) of earnings and PROBM for predicting one-year-ahead earnings. We disaggregate earnings into positive and negative because our predictions about persistence conditional on the PROBM differ according to the sign of earnings. Thus, we expect that positive earnings associated with a high probability of manipulation will be less persistent ($\beta_3<0$) and negative earnings associated with a high probability of manipulation will be more persistent ($\beta_4>0$). With respect to the influence of the probability of manipulation on the level of one-year-ahead earnings, we test the hypothesis in the forecasting equation that high probability of manipulation leads to lower earnings ($\beta_5<0$).

The second equation in this system estimates the valuation coefficients (β'_i) that the market assigns to earnings components and PROBM. The Mishkin framework provides a statistical comparison between the forecasting coefficients (measures of the predictive ability of current earnings and PROBM for one-year-ahead earnings) and the valuation coefficients (measures of the market's pricing of current earnings and of PROBM).

We implement the tests of rational pricing by estimating this system of equations jointly using a two-stage iterative generalized nonlinear least squares procedure. We first estimate the unconstrained system without imposing any constraints on the coefficients. In the second stage,

we test whether the valuation coefficients differ from the forecasting coefficients obtained in the first stage by imposing rational pricing constraints $\beta'_i = \beta_i$, for all i. Under the null hypothesis that the market rationally prices current earnings and PROBM with respect to their association with one-year-ahead earnings, Mishkin shows that the following likelihood ratio statistic is asymptotically $\chi^2(q)$ distributed:

$$2 \times N \times Ln(SSR^c/SSR^u),$$

where

q = the number of rational pricing constraints imposed;
N = the number of observations in the sample;
SSR^c = the sum of squared residuals from the constrained regressions in the second stage;
SSR^u = the sum of squared residuals from the unconstrained regressions in the first stage.

We report the results of this analysis in Table 6, Panel A.[12] The results for the persistence tests from the forecasting equation are consistent with our predictions. The estimate for EPosM is negative and significant (-0.180, t-statistic=-7.91) suggesting that positive earnings are less persistent when the probability is high that these earnings are manipulated. Second, the estimate for ENegM is positive and significant (0.179, t-statistic=21.25) suggesting that negative earnings are more persistent when the probability is high that current earnings are manipulated. The estimate for SPR is negative and significant (-0.009, t-statistic= -4.36) suggesting that one-year-ahead earnings are lower when the probability is high that current earnings are managed.

Our tests of mispricing reveal, consistent with Sloan (1996), that the persistence of earnings is not mispriced. However, the market perception of the effect of the probability of manipulation of current earnings implicit in the pricing regression (0.060) is significantly different from that implied by the earnings forecasting regression (-0.009) (likelihood

[12] This analysis requires one-year-ahead earnings to be available and is based on 23,114 firm-year observations. This is smaller than the sample used in the returns tests (27,427 firm-year observations) which is not restricted to avoid the look-ahead bias.

ratio=49.28, p-value<0.001). This result suggests that investors not only fail to discount current earnings for the probability that such earnings have been manipulated, but that on average they expect return on assets to be 690 basis points higher than that implied by the forecasting equation.[13]

Next, we disaggregate earnings into cash flows and accrual components to ascertain the implications of the probability of manipulation for future earnings and returns are robust to controlling for accruals. To ensure the persistence and mispricing effects of the probability of manipulation are distinct from the effects of accruals, we estimate two versions of the following system:

$$\begin{aligned} E_{t+1} &= \alpha_0 + \beta_1 CFO_t + \beta_2 CAccPos_t + \beta_3 CAccNeg_t + \beta_4 CAccPos * SPR_t \\ &\quad + \beta_5 CAccNeg * SPR_t + \beta_6 Dep_t + \beta_7 SPR_t + \varepsilon_{t+1} \\ BHSAR_{t+1} &= \phi_1 \big[E_{t+1} - \alpha_0 - \beta_1' CFO_t - \beta_2' CAccPos_t - \beta_3' CAccNeg_t - \beta_4' CAccPos * SPR_t \\ &\quad - \beta_5' CAccNeg * SPR_t - \beta_6' Dep - \beta_7' SPR_t \big] + \upsilon_{t+1} \end{aligned} \quad (5)$$

where:

E	= Income before extraordinary items (#123) divided by average total assets;
BHSAR	= Twelve-month buy and hold size-adjusted return from the beginning of the month following the annual earnings announcement.
CFO	= Cash flows from operations (#308) divided by average total assets;
CAcc	= E – CFO + Dep;
Dep	= Depreciation and amortization (#125) divided by average total assets;
CAccPos	= CAcc if CAcc > 0; 0 otherwise;
CAccNeg	= CAcc if CAcc < 0; 0 otherwise;
SPR	= Scaled PROBM ranks. PROBMs are computed using the model in Beneish (1999). PROBMs are ranked annually using the prior year decile rank cutoffs. Ranked PROBMs are scaled to have a zero mean and range from -1 (lowest PROBM) to +1 (highest PROBM).

We report the first version of (5), which decomposes earnings into cash flow and accrual components but omits SPR, in Panel B of Table 6. We also disaggregate current accruals into positive and negative accruals because our later predictions about persistence conditional on SPR

[13] This effect is economically significant. The median firm in the sample has ROA of 4.3 percent (430 basis points).

differ according to the sign of accruals. In general, our results are consistent with Sloan as they suggest that cash flows and accruals are mispriced.

In Panel C, we report estimation of the full specification in (5). The results for the forecasting equation are identical to those reported in column (1) of Table 4, Panel A. Therefore, our discussion focuses on the market's interpretation of the implications of PROBM for future earnings. The results reveal mispricing only for CFO and SPR. The coefficient on SPR is positive (0.006, t-statistic=3.56) indicating a small positive ROA effect to changes in the likelihood of manipulation. However, as in Panel A, the market perception of the effect of the probability of manipulation of current earnings implicit in the pricing regression (0.039) is significantly greater than that implied by the earnings forecasting regression (likelihood ratio=13.53, p-value<0.001). Thus, investors not only fail to discount current earnings for the probability that such earnings have been manipulated, but on average they expect return on assets to be 450 basis points higher than that implied by the forecasting equation. Interestingly, the Panel C results suggest that the SPR variable largely subsumes the mispricing of accruals documented in Panel B. In particular, the market does not misprice positive or negative current accruals after controlling for the mispricing associated with the probability of manipulation. This result is consistent with earnings manipulation as an important contributor to accrual mispricing and PROBM as a useful indicator of earnings manipulation.

Overall, the results in Table 5 suggest that the probability of manipulation has implications for future earnings, that investors do not fully impound those implications into price, and that these effects are robust to controlling for accruals.[14] The pricing tests reported in

[14] If PROBM derives its relation to future earnings and returns from accruals, the results from replacing SPR with a similar variable based on the deciles of accruals should lead to similar results. In unreported analyses, we find that this is not the case. In particular, we find that the scaled accrual decile variable is *positively* related to future earnings, and that investors do not misprice the implications of this variable for future earnings.

Table 5 are subject to several limitations. The Mishkin test is a joint test of market rationality and the ability of our model to correctly capture the market's expectation of earnings. Thus, if the test rejects market rationality, one interpretation is that the earnings expectation model is misspecified. To the extent that our earnings expectation model is incomplete, the Mishkin (1983) framework assumes that stock prices are efficient with respect to all omitted variables that are correlated with earnings components or with PROBM. Nevertheless, together with the evidence on hedge returns based on PROBM ranks, the market mispricing results indicate that PROBM is useful in predicting future earnings and future returns.

6. What Keeps Smart Money from Eliminating the Mispricing?

In this section, we explore potential reasons for why sophisticated investors do not eliminate the mispricing associated with PROBM. We examine alternative models of expected return, the return volatility in extreme deciles, the investing behavior of institutions in firms with extreme PROBM, and the hedge returns from a size partition of the sample.[15]

6.1 Asset Pricing Regressions for Trading Strategies

We conduct sensitivity analyses on the model generating abnormal returns because the symmetry (or lack thereof) in the relation between accruals and future returns has important implications for the viability of the accrual strategy for the large set of traders that take long positions only, the profitability of the strategy after transactions costs, and, consequently the continued survival of the mispricing into the future. Our results based on size-adjusted returns suggest that the short side of the hedge contributes most of the returns to the overall strategy. Because the source of the abnormal return matters for implementing the strategy as well as

[15] Mashruwala et al. (2006) offer a limits-to-arbitrage and transaction costs explanation for the continued survival of accrual mispricing: they find that firms in the extreme deciles have high idiosyncratic stock return volatility (their proxy for arbitrage risk) and low prices and volume (their proxy for transaction costs). Lev and Nissim (2006) find that institutional investors do not arbitrage away the accrual anomaly because the characteristics of firms in the extreme deciles (small size, low profits and high risk) are not prudent investments.

understanding why PROBM predicts returns, we next examine the robustness of the asymmetry in abnormal returns. In particular, we assess the contribution of the long and short positions to the accrual strategy using intercepts from asset pricing regressions of monthly excess returns for PROBM and accrual decile portfolios.

We assign firms to portfolios at the beginning of each month based on the firm's most recent accrual decile assignment, using the ranking procedures described above. Monthly portfolio excess returns are then computed as the equal-weighted average return, less the return to the 30-day T-bill.[16] For this analysis, we limit the sample to the 1994 to 2003 period because some accrual portfolios have small numbers of observations in 1993. Consequently, the time-series for each decile portfolio consists of 120 months. For each decile portfolio, we regress the monthly portfolio excess returns on a variant of 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 decile portfolio. We test whether the extreme deciles generate abnormal returns by testing the significance of the intercepts. As a summary test of the mispricing generated by the accrual and PROBM strategies, we also test that the intercepts are jointly zero for all deciles by computing the Gibbons, Ross, Shanken (1989) statistic (GRS). The

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

GRS statistic is distributed F with (10, 120-10-K) degrees of freedom, where K is the number of factors in the asset pricing model.

We also present the residual return variance for each portfolio. Under the view that residual return variance indicates the ease with which arbitrageurs can find suitable substitutes, residual return variance measures the arbitrage risk associated with each portfolio. We test for equality of variances across portfolios by computing the ratio of the variances, which is distributed F with (120-K-1, 120-K-1) degrees of freedom, where K is the number of factors.

We report the results in Table 6 Panel A for decile portfolios formed on PROBM and accruals.. For brevity, we only tabulate the intercepts, t-statistics, adjusted R^2, and residual return volatility. The lowest decile produces a statistically insignificant abnormal return of .4 percent per month (t-statistic = 1.26), while the highest decile produces significant returns of -1.0 percent per month (t-statistic = -3.29). The resulting spread of 1.4 percent per month is statistically significant (t = 6.91). The hypothesis that the abnormal returns are jointly zero is rejected (GRS F = 7.66, $p < .0001$). The residual return volatility is higher for the extreme deciles than the intermediate deciles, and residual return variance for the highest decile is significantly greater than that for the lowest decile. This suggests significantly more arbitrage risk for the firms in the highest decile of PROBM.

The results are similar for Accruals. The lowest accrual decile portfolio generates a statistically insignificant .3 percent abnormal return (t-statistic = 0.71), while the highest accrual decile portfolio generates a significant -1.0 percent abnormal return (-2.96). The difference across extreme portfolios is thus approximately 1.4 percent per month (roughly 16.8 percent per year) and is statistically significant (t-statistic = 5.63). The test that the intercepts are jointly zero is rejected (GRS F = 3.68, $p < .0001$). Although not significantly different from each other, both

extreme portfolios possess large residual return variance relative to the intermediate accrual deciles. This suggests arbitrage risk is greatest for these portfolios.

In Table Panel B, we report summary statistics of analyses involving alternative return generating models that add to the Fama-French model either an idiosyncratic volatility factor, a cash flow volatility factor, or a momentum factor. Although there is disagreement as to whether these factor are priced and even what they represent, the models have been investigated in prior work (Carhart 1997, Francis et al. 2005, Lewellen et al. 2006, Nichols 2006, Liu and Wysocki 2006, Core et al. 2007). The results for the idiosyncratic and cash flow volatility factors also suggest that the short side of the hedge contributes the majority of the hedge return for both PROBM and accruals. However, for the model augmented with the momentum factor, the short side only accounts for 32.4 percent of the PROBM hedge return and 29.6 percent of the accrual hedge return. Although similar to Mashruwala et al. (2006), this result is not surprising because the loading on the momentum factor is systematically negative across all PROBM and accrual deciles. More important, our finding of negative loadings when we regress portfolio returns on the momentum factor alone cast doubts on the validity of including momentum as a risk factor.[17]

The results from Table 6 have two implications which we explore next. First, consistent with our size-adjusted returns, we find that the short side of the strategy contributes almost all of the returns to the overall hedge. That mispricing is limited to firms with a high probability of overstatement is consistent with an earnings management explanation. Second, residual return variance is consistently higher in the highest decile of accrual or PROBM relative to the intermediate deciles. This suggests that the abnormal returns to the short side of the accrual strategy are accompanied by higher risks associated with arbitrage, which may help explain the

[17] When we use value-weighed portfolios, we find that the short-side dominates for all of our models, even when we include the momentum factor.

persistence of the accrual anomaly (Mashruwala et al. 2006). We examine this issue in the next section.

6.2 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 (1) whether they are in the extreme PROBM deciles, and (2) whether firms become flagged/unflagged during the year. Table 8 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.[18] In Panel A we show that limiting the trading strategy to firms for which institutional holdings data are available, we obtain a hedge size-adjusted return (13.48 percent) similar to that observed for the sample as a whole. Panel A also shows that the percentage of shares held by institutions display a similar pattern of increases in the quarters 0 and +1 whether the firms are on the long or short side of the hedge. For example, the increases in the percentage of shares held by institutions in quarters 0 and +1 for firms in the low probability of manipulation decile (.64 percent and 1.06 percent) are similar to the corresponding increases in the high probability of manipulation decile (0.38 percent and 1.24 percent). This investment behavior suggests that institutional investors behave as if they ignore information relevant to assessing the probability of manipulation. On the other hand, the patterns in quarters +2 and +3 is markedly different. That is, institutional investors increase their stake in firms in the low PROBM decile by .87 percent and .76 percent in quarters +2 and +3, but decrease their stake in firms in the high PROBM decile by -.15 percent and -.46 percent in quarters +2 and +3. The

[18] 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.

difference in patterns is likely due to new information (e.g., quarterly earnings) that reveals poorer prospects.

In Table 8, Panel B we restrict the sample to firms with institutional holdings that have PROBM data in two consecutive years. We analyze changes in institutional holdings in consecutive years as a function of whether the PROBM model flagged the firm as a potential manipulation. For each of two different PROBM cut-offs, we present a 2 X 2 matrix. We focus our discussion on PROBM>-1.78 (assuming 20:1 costs of classification errors) as the results are similar. The largest cell corresponds to firms that are not flagged in either year t-1 or year t: for these firms the change in average institutional holdings from year t-1 to t is 2.02 percent. We use this percentage as a benchmark against which to evaluate changes in the other cells: (1) The cell corresponding to firms that are flagged in both year t-1 or year t shows a change of 1.74 percent that is not distinguishable from the 2.02 percent benchmark; (2) The cell corresponding to firms that are not flagged in year t-1 but flagged in year t shows a change of 3.67 percent that is greater than the 2.02 percent benchmark; (3) The cell corresponding to firms that are flagged in year t-1 but not flagged in year t shows a change of 0.74 percent that is smaller than the 2.02 percent benchmark. We interpret the evidence as suggesting that institutional investors are misled by managers' accounting manipulations. That is, we find no evidence that sophisticated investors sell on a timely basis when they ought to suspect the firm has a high probability of manipulation. Further, we find that institutional investors actually increase their holdings in firms that become flagged as possible manipulators in the current period.

6.3 Hedge Returns by Market Capitalization

In this section, we examine hedge returns to PROBM segregated by market capitalization. This analysis is motivated by two considerations. First, research finds that many

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

To assess the reasonableness of these seemingly large abnormal returns, we partition the in four classes of market capitalization: less than $200 million, between $200 million and $500 million, between $500 million and $1 billion, and more than $1 billion. Although arbitrary, we choose cut-offs of $500 million and a billion because short sellers typically focus on such firms to reduce the risk that a lender demands the return of a stock (Staley 1997), and because many institutions restrict their investing universe to larger firms. In Table 9, we show that the PROBM hedge return is larger for smaller firms. That is, for firms with less than $200 million in market capitalization, the hedge return is 14.1 percent is greater than the corresponding return for firms with more than $1 billion in market capitalization (11.8 percent). However, both hedge returns remain economically significant. This does not appear to be the case for the Accrual hedge return which is only 5.2 percent for firms with more than $1 billion in market capitalization. Transactions costs decrease and liquidity increases with market capitalization, so we expect arbitrage to be most effective in eliminating mispricing for large firms. However, this finding casts doubt that even arbitrageurs and other sophisticated investors accurately assess the probability of manipulation.

7. Conclusion

We examine the implications for future earnings and returns associated with a fraud detection model that predicted fraud in high profile cases such as Enron, Adelphia, Qwest, Global Crossing, and others. Firms with a high probability of overstated earnings have lower future earnings and more transitory income-increasing accruals than similar firms with a low probability of manipulation. Firms with a high probability of manipulation also have lower future returns, suggesting that market participants do not fully use publicly available information relevant for detecting fraud. This is surprising given the enormous costs associated with fraud. However, this result is consistent with numerous studies finding underutilization of public information generally.

To explore why sophisticated investors do not correct the mispricing, we first verify that our trading strategy results are robust to alternative models of expected return. Using size-adjusted returns and alphas from Fama-French factor model regressions, we find that the short position dominates the returns to the strategy. Because greater transactions costs and arbitrage risk accompany the short position, sophisticated investors could be limited in their ability to trade on the mispricing. However, we find that institutional investors actually increase their holdings in firms that become flagged as possible manipulators during the period. Moreover, the returns to the strategy remain large (approximately 12 percent annually) for firms with market capitalization greater than $1 billion. Because arbitrage is least costly for such firms, these results suggest that even sophisticated investors do not efficiently assess the probability of earnings manipulation.

Because the fraud detection model relies on accruals, and because accruals also predict returns, we carefully distinguish the predictable returns from the two strategies. We show that

PROBM is a powerful predictor of returns within accrual decile ranks; that PROBM subsumes the relation between accruals and future returns; and that PROBM has a higher Sharpe ratio than accruals. At a minimum, these results indicate that the mispricing captured by PROBM is not identified by accruals. Alternatively, our results could indicate that accrual mispricing stems largely from undetected earnings manipulation.

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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 -1.89 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. 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 (%)
Adelphia Communications	**Yes**	1999	2002	4.82	96.8%
American International Group, Inc.	N/A - Financial				
AOL Time Warner, Inc.	**Yes**	2001	2002	25.77	32.2%
Cendant Corporation	**Yes**	1997	1998	11.32	38.1%
Citigroup	N/A - Financial				
Computer Associates International, Inc.	**Yes**	2000	2002	7.23	36.4%
Enron Broadband Services, Inc.	**Yes**	1998	2001	26.04	99.3%
Global Crossing, Ltd	**Yes**	1999	2002	(Delisted due to bankruptcy)	
HealthSouth Corporation	No		2002	2.31	57.3%
JDS Uniphase Corporation	**Yes**	1999	2001	32.49	61.0%
Lucent Technologies, Inc	**Yes**	1999	2001	11.15	24.7%
Motorola	N/A – Abetted Adelphia				
Qwest Communications International	**Yes**	2000	2002	9.84	41.8%
Rite Aid Corporation	**Yes**	1997	1999	2.83	59.1%
Sunbeam Corporation	**Yes**	1997	1998	1.28	58.8%
Tyco International	No		2002	37.55	58.2%
Vivendi Universal	No		2002	1.28	27.9%
Waste Management Inc	**Yes**	1998	1999	20.82	63.6%
WorldCom Inc. - MCI Group	No		2002	1.03	69.8%
Xerox Corporation	No		2000	7.73	43.8%

Table 2. Descriptive Statistics for Sample Firms

This table reports means (medians) for our sample of 27,427 firm-years between 1993 and 2003. PROBM denotes the probability of manipulation from Beneish (1999); Earnings denotes income before extraordinary items (#123) divided by average total assets; CFO denotes operating cash flows (#308) divided by average total assets; accruals denotes Earnings – CFO; Price-to-Book denotes market value (in millions) of common equity at the end of the fiscal year divided by book value of equity (#60); Price-to-Earnings denotes the market value (in millions) of common equity at the end of the fiscal year divided by income before extraordinary items (#18); 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; RET(t-1) denotes the 12 month size-adjusted return ending at the end of the fourth month after fiscal year-end; Ret Vol denotes the standard deviation of returns for the prior 24 months; 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; and UE denotes unexpected earnings, computed as the change in income before extraordinary items divided by the market value (in millions) of common equity at the end of the fiscal year. Panel A (B) reports earnings, accruals, and CFO for PROBM (accrual) deciles. Panel C reports other characteristics by PROBM decile. *,**,*** denote that the difference in means across extreme deciles is significance at the 10%, 5%, and 1% levels, respectively.

Panel A. PROBM Deciles

	Lowest PROBM	2	3	4	5	6	7	8	9	Highest PROBM	Difference (Low-High)
N	2886	2737	2647	2664	2694	2804	2749	2800	2727	2719	
Earnings	-0.176	0.005	0.028	0.044	0.045	0.046	0.045	0.049	0.039	-0.001	-0.175***
	(-0.077)	(0.031)	(0.041)	(0.046)	(0.051)	(0.054)	(0.053)	(0.055)	(0.053)	(0.041)	
Accruals	-0.235	-0.107	-0.081	-0.063	-0.052	-0.039	-0.027	-0.010	0.012	0.023	-0.257***
	(-0.186)	(-0.099)	(-0.074)	(-0.058)	(-0.046)	(-0.036)	(-0.023)	(-0.010)	(0.011)	(0.006)	
CFO	0.059	0.112	0.108	0.107	0.098	0.085	0.072	0.059	0.028	-0.023	0.082***
	(0.099)	(0.124)	(0.112)	(0.105)	(0.098)	(0.088)	(0.076)	(0.065)	(0.042)	(0.014)	

Panel B. Accrual Deciles

	Lowest Accruals	2	3	4	5	6	7	8	9	Highest Accruals	Difference (Low-High)
N	2816	2670	2778	2771	2724	2757	2771	2863	2683	2594	
Earnings	-0.216	-0.009	0.022	0.032	0.038	0.039	0.045	0.049	0.053	0.069	-0.285***
	(-0.132)	(0.026)	(0.040)	(0.042)	(0.042)	(0.043)	(0.048)	(0.054)	(0.057)	(0.078)	
Accruals	-0.279	-0.128	-0.094	-0.073	-0.057	-0.043	-0.027	-0.009	0.022	0.115	-0.393***
	(-0.225)	(-0.122)	(-0.090)	(-0.069)	(-0.053)	(-0.039)	(-0.025)	(-0.007)	(0.023)	(0.095)	
CFO	0.061	0.120	0.117	0.105	0.095	0.082	0.072	0.058	0.031	-0.045	0.106***
	(0.102)	(0.149)	(0.132)	(0.115)	(0.098)	(0.085)	(0.076)	(0.064)	(0.037)	(-0.022)	

Panel C. Other Characteristics by PROBM Decile

	Lowest PROBM	2	3	4	5	6	7	8	9	Highest PROBM	Difference (Low-High)
N	2886	2737	2647	2664	2694	2804	2749	2800	2727	2719	
Price-to-Book	4.264	5.623	3.489	4.713	2.966	2.936	3.031	5.940	3.287	4.405	-0.141
	(2.070)	(1.929)	(1.946)	(1.968)	(2.020)	(2.063)	(2.158)	(2.235)	(2.406)	(2.784)	
Price-to-Earnings	2.681	19.812	20.146	20.303	34.370	31.921	21.890	33.474	19.951	25.923	-23.242***
	(-2.252)	(13.584)	(14.957)	(15.391)	(15.415)	(15.919)	(16.004)	(16.612)	(16.234)	(14.427)	
Cash Flow-to-Price	0.113	0.153	0.143	0.128	0.111	0.090	0.068	0.050	0.021	-0.011	0.124***
	(0.092)	(0.131)	(0.122)	(0.113)	(0.097)	(0.082)	(0.064)	(0.044)	(0.024)	(0.005)	
Ret(t-1)	0.042	0.086	0.094	0.034	0.058	0.063	0.049	0.073	0.135	0.251	-0.209***
	(-0.136)	(-0.038)	(-0.024)	(-0.047)	(-0.037)	(-0.031)	(-0.040)	(-0.050)	(-0.050)	(-0.048)	
Ret Vol	0.265	0.195	0.176	0.158	0.162	0.165	0.172	0.186	0.214	0.254	0.011***
	(0.230)	(0.168)	(0.149)	(0.135)	(0.137)	(0.142)	(0.150)	(0.161)	(0.187)	(0.225)	
ln(MVE)	5.614	6.164	6.334	6.462	6.504	6.452	6.330	6.154	5.963	5.812	-0.198***
	(5.291)	(5.893)	(6.127)	(6.259)	(6.358)	(6.265)	(6.090)	(5.939)	(5.759)	(5.515)	
UE	-0.074	-0.017	-0.010	-0.004	-0.004	0.003	0.001	-0.001	0.002	-0.006	-0.067***
	(-0.013)	(-0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	

TABLE 3. Distinguishing PROBM from Accruals

This table reports comparisons of PROBM- and accruals-based trading strategies. Panels A reports annual buy-and-hold size-adjusted returns by PROBM and accrual decile. Panel B compares returns for firms flagged as probable manipulators to firms not flagged as manipulators per the PROBM model within accrual deciles. Panel C reports results from pooled regression of annual buy-and-hold size-adjusted returns on scaled PROBM and scaled accrual decile ranks, with controls for other characteristics associated with returns. Panel D reports the time-series average from yearly cross-sectional regressions of annual buy-and-hold size-adjusted returns on scaled PROBM and scaled accrual decile ranks, with controls for other characteristics associated with returns. Panel E reports Sharpe ratios from the monthly PROBM and accrual hedge portfolio returns. BHSAR denotes the 12 month -month buy and hold size-adjusted return from the beginning of the fourth month following the end of the fiscal year; PROBM denotes the probability of manipulation from Beneish (1999); accruals denotes Earnings – CFO; Price-to-Book denotes market value (in millions) of common equity at the end of the fiscal year divided by book value of equity (#60); Price-to-Earnings denotes the market value (in millions) of common equity at the end of the fiscal year divided by income before extraordinary items (#18); 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; RET(t-1) denotes the 12 month size-adjusted return ending at the end of the fourth month after fiscal year-end; Ret Vol denotes the standard deviation of returns for the prior 24 months; 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; and UE denotes unexpected earnings, computed as the change in income before extraordinary items divided by the market value (in millions) of common equity at the end of the fiscal year. Control variables other than accruals are recast as deviations from the mean, scaled by the in-sample standard deviation of the variable. We report t-statistics in Panel B based on Huber/White standard errors. 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. *,**,*** denote that the difference in means across extreme deciles is significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Hedge Portfolio Returns (N = 27,427 firm-years)

PROBM:	Lowest PROBM	2	3	4	5	6	7	8	9	Highest PROBM	Hedge
N	2886	2737	2647	2664	2694	2804	2749	2800	2727	2719	
BHSAR	0.044	0.052	0.053	0.031	0.010	0.037	-0.004	-0.011	-0.031	-0.096	0.139***

Accruals:	Lowest Accruals	2	3	4	5	6	7	8	9	Highest Accruals	Hedge
N	2816	2670	2778	2771	2724	2757	2771	2863	2683	2594	
BHSAR	0.030	0.049	0.033	0.010	0.040	0.013	0.010	0.010	-0.010	-0.104	0.134***

Table 3. (continued)

Panel B. Annual Buy-and-Hold Size-Adjusted Returns for Firms Flagged as Manipulators within each Accrual Decile

Accrual	Whole Sample		Firms Flagged assuming 20:1 costs PROBM>-1.78		Firms Not Flagged assuming 20:1 costs PROBM<-1.78		Firms Flagged assuming 40:1 costs PROBM>-1.89		Firms Not Flagged assuming 40:1 costs PROBM<-1.89	
Rank	N	Mean BHSAR	N	Mean BHSAR	N	Mean BHSAR	N	Mean BHSAR	N	Mean BHSAR
1	2816	2.99%	213	-20.32%	2603	4.90%	230	-14.68%	2586	4.57%
2	2670	4.89%	212	-7.33%	2458	5.95%	233	-3.85%	2437	5.73%
3	2778	3.32%	203	-10.70%	2575	4.42%	235	-6.75%	2543	4.25%
4	2771	1.04%	212	-7.24%	2559	1.73%	254	-8.77%	2517	2.03%
5	2724	3.95%	221	-2.32%	2503	4.50%	254	-1.87%	2470	4.55%
6	2757	1.30%	233	-2.42%	2524	1.64%	274	-2.56%	2483	1.72%
7	2771	0.98%	303	-6.30%	2468	1.88%	360	-5.40%	2411	1.94%
8	2863	1.01%	377	-2.52%	2486	1.55%	464	3.18%	2399	0.60%
9	2683	-1.05%	615	-6.09%	2068	0.45%	778	-5.31%	1905	0.69%
10	2594	-10.45%	1576	-13.25%	1018	-6.11%	1792	-12.95%	802	-4.86%

Panel C. Results from Pooled Regressions (N = 27,198 firm-years)

				Controls							
	Constant	PROBM Ranks[a]	Accrual Ranks	Beta	B/P	Return Momentum	ln(MVE)	Ret Vol	CFO/P	UE	Adj. R-sq.
Estimate	-0.053	0.077	0.046	0.007	0.017	0.004	-0.010	-0.027	0.010	0.002	0.6%
t-statistic	(-2.90)	(2.57)	(1.06)	(0.35)	(1.78)	(0.25)	(-1.71)	(-0.87)	(0.58)	(0.29)	

Panel D. Time-Series Averages of Annual Cross-Sectional Regressions (N = 12 years)

				Controls							
	Constant	PROBM Ranks[a]	Accrual Ranks	Beta	B/P	Return Momentum	ln(MVE)	Ret Vol	CFO/P	UE	Average Adj. R-sq.
Estimate	-0.040	0.071	0.041	-0.009	0.014	0.025	-0.011	-0.008	0.019	0.001	5.1%
t-statistic	(-1.69)	(2.05)	(1.40)	(-0.44)	(1.54)	(1.46)	(-1.36)	(-0.21)	(1.02)	(0.08)	
Z-statistic	(-1.72)	(2.18)	(0.71)	(0.02)	(1.78)	(1.89)	(-2.26)	(-1.59)	(1.39)	(0.03)	

Table 3. (continued)

Panel E. Sharpe Ratios

	PROBM	Accruals	Difference	t-statistic	F-value	p-value
Sharpe Ratio	0.631	0.439				
Mean return (monthly)	0.0149	0.0125	0.0024	0.80		0.213
Standard deviation	0.0236	0.0286	-0.0049		1.46	0.020
Corr (PROBM, Accruals)	0.237					0.002

Table 4. Regressions of Future Earnings and Earnings Components on Current Period Earnings Components
The sample includes 23,114 firm-year observations from 1993 – 2003. BHSAR denotes the 12 month -month buy and hold size-adjusted return from the beginning of the fourth month following the end of the fiscal year; CFO denotes cash flows from operations (#308); CAcc denotes E – CFO + DEP; E denotes earnings before extraordinary items (#123), DEP denotes depreciation and amortization (#125); CAccPos denotes CAcc if CAcc > 0; 0 otherwise; CAccNeg denotes CAcc if CAcc < 0; 0 otherwise; SPR denotes scaled PROBM ranks. PROBMs are computed using the model in Beneish (1999); PROBMs are ranked annually using the prior year decile rank cutoffs; ranked PROBMs are scaled to have a zero mean and range from -1 (lowest PROBM) to +1 (highest PROBM); SAR denotes scaled accrual ranks. Accruals are ranked annually using the prior year decile rank cutoffs; ranked accruals are scaled to have a zero mean and range from -1 (lowest accruals) to +1 (highest accruals); E, CFO, CAcc and Dep are scaled by average total assets. We report t-statistics based on Huber/White standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

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

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

	(1) DV = E_{t+1}		(2) DV = CFO_{t+1}		(3) DV = ACC_{t+1}	
Variable	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Constant	-0.021	(-4.70)***	0.004	(1.91)*	-0.023	(-5.76)***
CFO	0.867	(42.38)***	0.743	(61.28)***	0.113	(7.19)***
CAccPos	0.762	(8.88)***	0.366	(5.37)***	0.368	(5.16)***
CAccNeg	0.526	(9.05)***	0.270	(9.66)***	0.236	(7.70)***
CAccPos*SPR	-0.270	(-2.87)***	-0.064	(-1.06)	-0.193	(-2.38)**
CAccNeg*SPR	0.221	(4.49)***	0.065	(3.13)***	0.131	(4.05)***
Dep	-0.782	(-10.21)***	0.216	(8.00)***	-0.995	(-13.85)***
SPR	0.006	(1.91)*	0.001	(0.31)	0.006	(2.30)**
Adj. R-square	47.1%		54.4%		13.5%	

Panel B. Accruals interacted with scaled accrual ranks (Scaled Ranks = SAR)

	(1) DV = E_{t+1}		(2) DV = CFO_{t+1}		(3) DV = ACC_{t+1}	
Variable	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Constant	-0.029	(-5.86)***	0.002	(1.05)	-0.029	(-5.28)***
CFO	0.883	(42.33)***	0.750	(59.90)***	0.121	(7.79)***
CAccPos	0.338	(3.71)***	0.093	(1.02)	0.201	(1.31)
CAccNeg	0.449	(2.80)***	0.396	(2.32)**	0.080	(0.37)
CAccPos*SAR	0.005	(0.05)	0.132	(1.87)*	-0.100	(-0.67)
CAccNeg*SAR	0.197	(1.42)	0.216	(1.38)	0.005	(0.02)
Dep	-0.552	(-7.06)***	0.313	(12.04)***	-0.867	(-10.25)***
SAR	0.038	(6.29)***	0.014	(4.11)***	0.023	(4.56)***
Adj. R-square	47.4%		54.5%		13.7%	

Table 5. Estimation of the Stock Price Reaction to the Differential Information in Earnings and Earnings Components by PROBM for Future Earnings

The sample includes 23,114 firm-year observations from 1993 – 2003. BHSAR denotes the 12 month -month buy and hold size-adjusted return from the beginning of the fifth month following the end of the fiscal year; CFO denotes cash flows from operations (#308); CAcc denotes E – CFO + DEP; E denotes earnings before extraordinary items (#123), DEP denotes depreciation and amortization (#125); EPos denotes E if E > 0; 0 otherwise; ENeg denotes E if E < 0; 0 otherwise; CAccPos denotes CAcc if CAcc > 0; 0 otherwise; CAccNeg denotes CAcc if CAcc < 0; 0 otherwise; SPR denotes scaled PROBM ranks. PROBMs are computed using the model in Beneish (1999); PROBMs are ranked annually using the prior year decile rank cutoffs; ranked PROBMs are scaled to have a zero mean and range from -1 (lowest PROBM) to +1 (highest PROBM); SAR denotes scaled accrual ranks. Accruals are ranked annually using the prior year decile rank cutoffs; ranked accruals are scaled to have a zero mean and range from -1 (lowest accruals) to +1 (highest accruals); E, CFO, CAcc and Dep are scaled by average total assets. We report t-statistics based on Huber/White standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. The Differential stock price reaction to Earnings by PROBM

$$E_{t+1} = \alpha_0 + \beta_1 EPos_t + \beta_2 ENeg_t + \beta_3 EPos*SPR_t + \beta_4 ENeg*SPR_t + \beta_5 SPR_t + \varepsilon_{t+1}$$
$$BHSAR_{t+1} = \phi_1 [E_{t+1} - \alpha_0 - \beta_1' EPos_t - \beta_2' ENeg_t - \beta_3' EPos*SPR_t - \beta_4' ENeg*SPR_t - \beta_5' SPR_t] + \upsilon_{t+1}$$

	Forecasting		Expectation	
	Estimate	Approx. t-statistic	Estimate	Approx. t-statistic
ERC			1.109	31.53***
Constant	-0.013	-3.41***	-0.002	-0.32
EPos	0.837	50.49***	0.608	7.99***
ENeg	0.737	40.1***	0.722	20.26***
EPos*SPR	-0.180	-3.94***	-0.211	-1.93*
ENeg*SPR	0.179	5.71***	0.187	4.61***
SPR	-0.009	-2.42**	0.060	6.10***

Test of selected restrictions:

Variable	*Restriction*	*LR statistic*[b]
EPos	$\beta_1 = \beta_1'$	8.87
ENeg	$\beta_2 = \beta_2'$	0.17
EPos*SPR	$\beta_3 = \beta_3'$	0.08
ENeg*SPR	$\beta_4 = \beta_4'$	0.01
SPR	$\beta_5 = \beta_5'$	49.28***
All	$\beta_i = \beta_i', \ \forall i$	100.47***

TABLE 5 (continued)
Panel B. The stock price reaction to earnings components

$$E_{t+1} = \alpha_0 + \beta_1 CFO_t + \beta_2 CAccPos_t + \beta_3 CAccNeg_t + \beta_4 Dep_t + \varepsilon_{t+1}$$
$$BHSAR_{t+1} = \phi_1 \left[E_{t+1} - \alpha_0 - \beta_1' CFO_t - \beta_2' CAccPos_t - \beta_3' CAccNeg_t - \beta_4' Dep \right] + \upsilon_{t+1}$$

	Forecasting		Expectation	
	Estimate	Approx. t-statistic	Estimate	Approx. t-statistic
ERC			1.116	31.10***
Constant	-0.023	-5.25***	-0.016	-1.93*
CFO	0.866	45.51***	0.696	20.88***
CAccPos	0.590	9.69***	1.033	11.93***
CAccNeg	0.376	12.00***	0.585	10.39***
Dep	-0.747	-11.59***	-0.794	-6.78***

Test of selected restrictions:

Variable	*Restriction*	*LR statistic*[b]
CFO	$\beta_1 = \beta_1'$	25.56***
CAccPos	$\beta_2 = \beta_2'$	25.79***
CAccNeg	$\beta_3 = \beta_3'$	13.46***
Dep	$\beta_4 = \beta_4'$	0.15
All	$\beta_i = \beta_i', \ \forall i$	105.78***

(TABLE 5, continued)
Panel C. The Stock Price Reaction to Positive and Negative Accruals by PROBM

$$E_{t+1} = \alpha_0 + \beta_1 CFO_t + \beta_2 CAccPos_t + \beta_3 CAccNeg_t + \beta_4 CAccPos*SPR_t + \beta_5 CAccNeg*SPR_t + \beta_6 Dep_t + \beta_7 SPR_t + \varepsilon_{t+1}$$

$$BHSAR_{t+1} = \phi_1 [E_{t+1} - \alpha_0 - \beta_1' CFO_t - \beta_2' CAccPos_t - \beta_3' CAccNeg_t - \beta_4' CAccPos*SPR_t - \beta_5' CAccNeg*SPR_t - \beta_6' Dep - \beta_7' SPR_t] + \upsilon_{t+1}$$

	Forecasting		Expectation	
	Estimate	Approx. t-statistic	Estimate	Approx. t-statistic
ERC			1.115	31.00***
Constant	-0.021	-4.70***	-0.019	-2.27***
CFO	0.866	42.38***	0.714	21.32***
CAccPos	0.761	8.88***	0.852	4.43***
CAccNeg	0.526	9.05***	0.579	6.23***
CAccPos*SPR	-0.270	-2.87***	-0.020	-0.09
CAccNeg*SPR	0.221	4.49***	0.107	1.09
Dep	-0.781	-10.21***	-0.687	-5.67***
SPR	0.006	1.91*	0.039	4.44***

Test of selected restrictions:

Variable	*Restriction*	*LR statistic*[b]
CFO	$\beta_1 = \beta_1'$	20.63***
CAccPos	$\beta_2 = \beta_2'$	0.18
CAccNeg	$\beta_3 = \beta_3'$	0.28
CAccPos*SPR	$\beta_4 = \beta_4'$	1.33
CAccNeg*SPR	$\beta_5 = \beta_5'$	1.27
Dep	$\beta_6 = \beta_6'$	0.57
SPR	$\beta_7 = \beta_7'$	13.53***
All	$\beta_i = \beta_i', \ \forall i$	130.78***

TABLE 6. Sensitivity of abnormal returns to alternative models of expected return

Panel A reports alphas from Fama regressions of monthly PROBM and accrual decile portfolio returns on the MKT, SMB, and HML portfolios. Panel B summarizes results from annual buy-and-hold size adjusted returns and alphas from various four factor models using monthly returns. 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. 'Low – High' refers to a regression of the difference between the low and high portfolios on the factors in the asset pricing model.

Panel A. Alphas from Fama-French three factor model regressions for PROBM and accrual decile portfolios

	Alpha	t-stat	Adj. R^2	$\sigma^2(e)x10^4$
Lowest	0.004	(1.26)	80.32%	1.24
2	0.004	(1.85)	85.01%	0.49
3	0.003	(1.80)	87.28%	0.32
4	0.001	(0.41)	87.59%	0.26
5	0.000	(-0.03)	89.23%	0.27
6	0.000	(0.20)	86.52%	0.37
7	-0.003	(-1.85)	87.87%	0.39
8	-0.003	(-1.62)	88.00%	0.46
9	-0.005	(-1.76)	83.09%	0.96
Highest	-0.010	(-3.29)	85.69%	1.09
Low - High	0.014	-6.91	20.67%	
GRS	7.655		**F**	0.876
p-value	<.0001		**p-value**	0.761

	Alpha	t-stat	Adj. R^2	$\sigma^2(e)x10^4$
Lowest	0.003	(0.71)	79.98%	1.73
2	0.002	(1.02)	86.43%	0.61
3	0.001	(0.65)	83.87%	0.53
4	0.000	(-0.28)	88.28%	0.32
5	0.001	(0.40)	89.32%	0.25
6	-0.001	(-0.45)	86.66%	0.28
7	-0.002	(-0.92)	88.61%	0.30
8	-0.001	(-0.62)	87.49%	0.40
9	-0.002	(-1.17)	89.57%	0.43
Highest	-0.010	(-2.96)	81.78%	1.16
Low - High	0.014	-5.63	20.26%	
GRS	3.677		**F**	0.673
p-value	0.0001		**p-value**	0.983

Panel B: Sensitivity analyses on abnormal return estimation and the contribution of short position

		N	PROBM Hedge	Contribution of short position	Accrual Hedge	Contribution of short position
Beneish and Nichols (2007)	BHSAR	27,427	13.90%	69.1%	13.44%	77.8%
Jensen Alphas	FF+Idiosyncratic volatility	27,427	17.77%	85.3%	13.99%	98.8%
Jensen Alphas	FF+Cash flow volatility	27,427	17.32%	98.6%	13.67%	66.5%
Jensen Alphas	FF+momentum	27,427	17.40%	32.4%	17.03%	29.6%

TABLE 7: Institutional holdings and PROBM ranks

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

Panel A: Average Institutional Holdings

			Average Institutional Holdings Quarter Relative to Portfolio Formation						
	N	One-year-ahead Size-Adj. Return	-3	-2	-1	0	1	2	3
Firms with Available Insitutional Holdings Data									
Low PROBM	2191	6.71%	42.21%	41.86%	42.47%	43.11%	44.17%	45.04%	45.80%
High PROBM	2098	-6.77%	41.38%	42.14%	42.71%	43.09%	44.33%	44.18%	43.72%
Low Accruals	2088	6.61%	42.61%	42.47%	42.94%	43.58%	44.59%	45.23%	45.82%
High Accruals	2110	-8.96%	42.52%	42.81%	43.58%	43.75%	44.55%	44.54%	43.80%

Panel B: Consecutive year average institutional holdings and changes as a function of flag status

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

	Flag in Year t				No Flag in Year t			
	N	Mean year t	Mean year t-1	Difference	N	Mean year t	Mean year t-1	Difference
Flag in Year t-1	580	46.09%	44.35%	1.74%	1665	48.17%	47.43%	0.74%*
No Flag in Year t-1	1279	49.78%	46.11%	3.67%*	11361	52.77%	50.75%	2.02%

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

	Flag in Year t				No Flag in Year t			
	N	Mean year t	Mean year t-1	Difference	N	Mean year t	Mean year t-1	Difference
Flag in Year t-1	766	46.95%	45.88%	1.07%	1870	48.21%	47.19%	1.02%*
No Flag in Year t-1	1468	49.60%	45.98%	3.62%*	10781	52.98%	50.95%	2.03%

* indicates that the increase is significantly different at the 1% level from the benchmark increase in the noflag/noflag cell

TABLE 8. PROBM and Accrual Hedge Returns by Market Capitalization

This table reports annual buy-and-hold size-adjusted returns beginning the fifth month after fiscal year end by market capitalization. Market capitalization is measured at the end of the fiscal year. PROBM denotes the probability of manipulation from Beneish (1999). Accruals denotes earnings (#123) minus operating cash flows (#308), divided by average total assets. See Table 1 for construction of PROBM and accrual decile ranks.

	Observations	Long (short) observations		Hedge Returns		
Market Capitalization	in size group	PROBM	Accruals	PROBM	Accrual	Difference
<$200MM	9597	1454 (1162)	1366 (1276)	14.10%	15.60%	-1.50%
$200<MVE< $500	5962	623 (680)	619 (640)	17.10%	15.50%	1.60%
$500<MVE< $1000	3852	328 (346)	321 (320)	10.40%	10.80%	-0.40%
> $1000MM	8016	481 (531)	510 (358)	11.80%	5.20%	6.60%
Full Sample	27427	2886 (2719)	2816 (2594)	13.90%	13.40%	0.50%