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ESTIMATES

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Does Risk Explain Anomalies? Evidence from Expected Return Estimates
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ABSTRACT

We construct accounting-based costs of equity for dollar neutral long-short trading strategies formed on a comprehensive list of anomaly variables. These variables include book-to-market, size, composite issuance, net stock issues, abnormal investment, asset growth, investment-to-assets, accruals, earnings surprises, failure probability, return on assets, and short-term prior returns. Our findings are striking. Except for the value premium, cost of equity estimates differ dramatically from average realized returns. If accounting-based costs of equity are reasonable proxies for expected returns, the evidence implies that returns of most anomalies are unexpected, and that mispricing, not risk, is the main driving force of capital markets anomalies.

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1 Introduction

We ask whether risk or mispricing is the main driving force of capital markets anomalies. Anomalies are empirical relations between average returns and firm characteristics not explained by standard asset pricing models. Over the past three decades, anomalies have become important in asset allocation, capital budgeting, security analysis, hedge fund strategies, and many other applications. Understanding their driving forces is one of the most important questions in capital markets research.

Two competing schools of thoughts have proposed different economic explanations for anomalies. Behavioral finance contends that investors make systematic mistakes in pricing assets, and that anomalies are driven by predictable pricing errors (mispricing) (e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)). In contrast, retaining the assumption of rational expectations, neoclassical finance argues that risk and expected returns covary with firm characteristics systematically, and that anomalies are driven by this covariation (risk) (e.g., Cochrane (1996), Berk, Green, and Naik (1999), and Zhang (2005)).

We further the risk-versus-mispricing debate by estimating accounting-based expected returns to anomalies-based trading strategies. The basic idea is simple. Average realized returns equal average expected returns plus average unexpected returns. If anomalies are driven by risk, average expected returns should account for the bulk of average realized returns. If anomalies are driven by mispricing, average unexpected returns should be close to average realized returns. We use the residual income model to estimate expected returns to dollar neutral long-short strategies formed on a comprehensive list of anomaly variables. Under the model, the expected return can be calculated as the implied rate of return that equates the present value of expected future residual incomes to the current stock price (e.g., Gebhardt, Lee, and Swaminathan (2001)).

Our key message is that expected return estimates differ dramatically from average return estimates for most anomalies. If the implied costs of equity provide reasonable estimates of expected returns, the evidence suggests that mispricing, not risk, is the main driving force of anomalies. The

high-minus-low quintiles formed on Sloan's (1996) accruals, Titman, Wei, and Xie's (2004) abnormal corporate investment, Daniel and Titman's (2006) composite issuance, and Fama and French's (2008) net stock issues all earn negative average realized returns. Ranging from -4.0% to -7.5% per annum, these average returns are at least 2.4 standard errors from zero. In contrast, the expected return estimates of these long-short quintiles are all between -0.1% to zero (and insignificant), meaning that these anomalies are mostly driven by unexpected returns. Although the high-minus-low quintile formed on Cooper, Gulen, and Schill's (2008) asset growth has an expected return of -0.6% ($t = -3.0$), its magnitude does not come close to its average return of -5.6% ($t = -2.8$).

The expected return estimates even have the opposite signs to the average realized returns for the high-minus-low quintiles formed on Jegadeesh and Titman's (1993) prior six-month returns (momentum), Chan, Jegadeesh, and Lakonishok's (1996) earnings surprises, Campbell, Hilscher, and Szilagyi's (2008) failure probability, and Chen, Novy-Marx, and Zhang's (2010) return on assets. The high-minus-low earnings surprises, return on assets, and momentum quintiles have average returns of 4.9% , 6.5% , and 6.4% per annum, respectively, all of which are at least three standard errors from zero. However, their expected return estimates are all significantly negative, ranging from -0.1% to -1.7% . The high-minus-low failure probability quintile has an average return of -8.1% ($t = -5.0$), but its expected return is significantly positive, 3.8% .

The only exception to the large differences between expected returns and average realized returns is the value premium. The expected return estimate of the value-minus-growth quintile is 6.3% per annum, which is close to the average return estimate of 5.2% in economic magnitude. The expected return estimate, which is about 12 standard errors from zero, is also more precise than the average return estimate, which is only slightly more than two standard errors from zero. Related to the value premium, the expected return estimate of the small-minus-big quintile is 3.1% , which is close to the average return estimate of 3% . The expected return estimate is more than 7.5 standard errors from zero, but the average return estimate is within one standard error of zero.

We also address several recent critiques on the Gebhardt, Lee, and Swaminathan (2001) estimation of expected returns. First, because the baseline procedure uses analysts earnings forecasts that are limited to a small sample and that are likely even biased, we modify this procedure to avoid the use of analysts forecasts. Instead, we forecast future profitability using cross-sectional regressions similar to those in Fama and French (2006) (see also Hou, van Dijk, and Zhang (2009)). We find that the results are robust to the use of profitability forecasts from cross-sectional regressions.

Second, in a stream of influential articles, Easton, Taylor, Shroff, and Sougiannis (2002), Easton (2006), and Easton and Sommers (2007) criticize the Gebhardt, Lee, and Swaminathan (2001) procedure on the ground that the assumed growth rates beyond the short forecast horizon can be inconsistent with the actual growth rates in the data. This inconsistency can introduce bias in the expected return estimates. These authors propose methods that estimate the expected returns and the expected growth rates for a given portfolio simultaneously. Implementing these alternative estimation methods on our testing portfolios, we find that these methods often predict growth rate spreads that go in the opposite direction to the growth rate spreads in the data. These counterfactual predictions cast doubt on the validity of these alternative methods for estimating expected returns. Our evidence suggests that the Gebhardt et al. procedure is probably among the best accounting-based expected return models in the contemporary literature.

Our work builds on the large literature that uses valuation models to estimate expected returns. Following Gebhardt, Lee, and Swaminathan (2001), many studies calculate expected returns from analysts earnings forecasts under the residual income model (e.g., Claus and Thomas (2001), Gode and Mohanram (2003), Guay, Kothari, and Shu (2005), Lee, So, and Wang (2010), and Nekrasov and Ogneva (2010)). Implied costs of equity have been used as proxies for firm-level expected returns to study the effect of firms' information environment on cost of equity in the accounting literature (e.g., Botosan (1997), Botosan, Plumlee, and Xie (2004), Francis, LaFond, Olsson, and Schipper (2004), Dhaliwal, Krull, Li, and Moser (2005), Hail and Leuz (2006, 2009), Ashbaugh-Skaife, Collins, Kinney, and LaFond (2008), and Core, Guay, and Verdi (2008)). Pastor, Sinha,

and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Chava and Purnanandam (2010) apply the Gebhardt et al. procedure to study the aggregate risk-return tradeoff, international asset pricing, and default risk in finance, respectively. With the notable exceptions of Gebhardt et al. and Chava and Purnanandam, the anomalies literature bases its inferences exclusively on average realized returns (see Fama (1998) for a review). To the best of our knowledge, we are among the first to estimate the ex ante expected returns to a comprehensive list of anomalies-based trading strategies.

The rest of the paper is organized as follows. Section 2 describes our basic idea, the data, and the estimation methods. Section 3 presents the expected return estimates for all the anomalies. Section 4 deals with recent critiques on the estimation methodology. Finally, Section 5 concludes.

2 Research Design

We describe our basic idea, the data, and the estimation methods in this section.

2.1 The Basic Idea

Explanations of anomalies largely fall into two broad categories. First, behavioral finance argues that investors make systematic mistakes in pricing assets, and that these mistakes produce predictable pricing errors manifested as anomalies. Second, neoclassical finance argues that risk and expected returns covary systematically with firm characteristics, and that this covariation produces anomalous empirical relations between average returns and firm characteristics. Decomposing average realized returns into expected returns and unexpected returns helps disentangle the two competing explanations. In behavioral models, the anomalous returns are unexpected, and average returns should equal average unexpected returns, whereas in neoclassical models, the anomalous returns are expected, average returns should equal average expected returns.

We elaborate on this basic premise of our tests. We first briefly review competing explanations of anomalies, and then illustrate how our tests can shed light on the risk-versus-mispricing debate.

Competing Explanations of Anomalies: A Brief Review

To focus on predictable pricing errors, behavioral models typically shut down the channel of time-varying expected returns by assuming constant discount rates. In the model of Barberis, Shleifer, and Vishny (1998), investors exhibit two types of psychological biases, conservatism and representative heuristics. Conservatism means that investors are slow in updating their beliefs in the face of new evidence. This bias lead to investors' underreaction to news, generating return continuation over short horizons between one to 12 months. Representative heuristics means that after a consistent history of earnings growth over several years, investors might wrongfully believe that the past history is representative of future growth prospects. These investors then overreact to past news over longer horizons, and send stock prices to unsustainable levels. This bias can explain the overreaction evidence that stocks that have had a long record of good news tend to become overpriced and have low average subsequent returns, and that stocks that have had a long record of bad news tend to become underpriced and have high average subsequent returns.

Daniel, Hirshleifer, and Subrahmanyam (1998) model investor overconfidence. Overconfidence means that investors overestimate the precision of their private information signals, but not public information signals. Overconfident investors tend to overweight their private signals relative to their prior, and cause the stock price to overreact. Future public information will slowly pull prices back to their fundamental value so as to generate long-term reversals. Self-attribution means that individuals too strongly attribute events confirming the validity of their prior actions to high ability and disconfirming events to external noise or sabotage. When investors exhibit self-attribution, new public signals are viewed on average as confirming the validity of their private signals, triggering further overreaction to their private signals. The continuous overreaction explains short-term continuation, whereas the eventual correction in the stock price explains long-term reversal.

Hong and Stein (1999) construct a model populated by two sets of boundedly rational investors, news-watchers and momentum traders. News-watchers observe private information, but fail to ex-

tract each other's information from prices. Coupled with slow information diffusion across the population, the stock price underreacts in the short run. Momentum traders exploit this effect by trend chasing, but their activity eventually leads to overreaction in the stock price at long horizons.

At the other extreme, neoclassical models shut down the channel of predictable unexpected returns to focus on the correlation between expected returns and firm characteristics. Zhang (2005) argues that because of higher costs in cutting than in expanding the scale of productive assets, value firms are less flexible than growth firms in scaling down to mitigate the impact of negative shocks. Because value firms have less profitable assets than growth firms, value firms want to disinvest more, especially in recessions. Because disinvesting is more costly, the cash flows of value firms are more adversely affected by bad economic conditions than the cash flows of growth firms. As such, value stocks are riskier and earn higher expected returns than growth stocks.

Liu, Whited, and Zhang (2010) argue that expected returns are linked to expected next-period marginal benefits of investment divided by current-period marginal costs of investment. Stocks with high book-to-market, low investment-to-assets, low equity issues, and low asset growth earn higher expected returns because their low investment levels imply low current-period marginal costs of investment. Intuitively, firms with low discount rates have more projects with positive net present value and consequently invest more than firms with high discount rates. This discount rate channel explains the overreaction evidence in behavioral finance. In addition, stocks with high earnings surprises, high short-term prior returns, low financial distress, and high return on assets have higher expected next-period marginal benefits of investment and consequently higher expected returns. This cash flow channel explains the underreaction evidence in behavioral finance.

Expected Returns versus Average Realized Returns

As explained above, behavioral models explain anomalies as predictable pricing errors, whereas neoclassical models interpret anomalies as the covariation between expected returns and firm characteristics. In particular, the assumption of rational expectations in neoclassical models means that

forecasting errors (such as pricing errors) are not forecastable (e.g., Muth (1961)). As such, if we can model expected returns perfectly, a sort on a given firm characteristic such as book-to-market should only produce a corresponding spread in expected returns and a zero spread in pricing errors in neoclassical models such as Zhang (2005). In contrast, in behavioral models such as Barberis, Shleifer, and Vishny (1998), the anomalous returns to the value-minus-growth quintile are unexpected, and the discount rate is flat across all firms. As such, a book-to-market sort should produce a zero spread in expected returns and a corresponding spread in pricing errors.

The basic premise of our test design assumes that we have a good measure of expected returns. Because no expected return measures are perfect, our tests are subject to Fama's (1998) joint hypothesis problem. Indeed, we can only test whether anomalies are consistent with investors' expectations within a given expected return model. However, by introducing the relatively overlooked accounting-based expected return measures into the anomalies literature, we view our empirical analysis as informative and valuable.

2.2 Data

The monthly data on stock returns, stock prices, and number of shares outstanding are obtained from the Center for Research in Security Prices (CRSP). We obtain stock returns with and without dividends for all NYSE, Amex, and Nasdaq stocks from CRSP. We use nonfinancial firms (excluding firms with four-digit SIC codes between 6000 and 6999) listed on the CRSP monthly stock return files and the Compustat annual industrial files from 1965 through 2008. The sample size varies across anomaly variables due to data availability. Only firms with ordinary common equity are included, meaning that we exclude ADRs, REITs, and units of beneficial interest.

Anomaly Variables

We examine an extensive list of anomaly variables. To facilitate comparison, we closely follow the prior literature in defining these variables (see Appendix A for detailed variable definitions).

Book-to-market (B/M) and *size (ME)*. High *B/M* stocks earn higher average returns than low *B/M* stocks (e.g., Fama and French (1993) and Lakonishok, Shleifer, and Vishny (1994)). We follow Fama and French in measuring *B/M*. Small firms earn higher average returns than big firms (e.g., Banz (1981)). *ME* is price per share times shares outstanding from CRSP.

Composite issuance (CI) and *net stock issues (NSI)*. Firms that issue new equity underperform, and firms that buy back shares outperform matching firms with similar characteristics (e.g., Ritter (1991), Loughran and Ritter (1995), Ikenberry, Lakonishok, and Vermaelen (1995), and Michaely, Thaler, and Womack (1995)). We use two variables to summarize the external financing anomalies. Daniel and Titman's (2006) *CI* measures the part of firm growth in market equity that is not due to stock returns. Fama and French's (2008) *NSI* measures the annual change in the logarithm of the number of real shares outstanding, adjusted for distribution events such as splits and rights offerings.

Abnormal investment (AI), *asset growth (AG)*, *investment-to-assets (I/A)*, and *accruals (AC)*. Titman, Wei, and Xie (2004) show that firms with abnormally high investment earn lower average returns than firms with abnormally low investment. *AI* is the deviation of the current year's investment from the past three-year moving average of investment. Cooper, Gulen, and Schill (2008) show that firms with high asset growth earn lower average returns than firms with low asset growth. *AG* is the annual percentage change in total assets. Lyandres, Sun, and Zhang (2008) and Chen, Novy-Marx, and Zhang (2010) show that high *I/A* firms earn lower average returns than low *I/A* firms. *I/A* is the annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus the annual change in inventory (item INVT) divided by the lagged total assets (item AT). Sloan (1996) shows that high *AC* firms earn lower average returns than low *AC* firms. *AC* is changes in non-cash working capital minus depreciation expense scaled by average total assets.

Standardized Unexpected Earnings (SUE) and *return on assets (ROA)*. High *SUE* stocks earn higher average returns than low *SUE* stocks (e.g., Ball and Brown (1968), Bernard and Thomas (1989), and Chan, Jegadeesh, and Lakonishok (1996)). *SUE* for stock *i* in month *t* is

$(e_{iq} - e_{iq-4})/\sigma_{it}$, where e_{iq} is the most recently announced quarterly earnings per share (Compustat quarterly item EPSPIQ) as of month t for stock i , e_{iq-4} is earnings per share announced four quarters ago, and σ_{it} is the volatility of $e_{iq} - e_{iq-4}$ over the prior eight quarters. Chen, Novy-Marx, and Zhang (2010) show that high *ROA* firms earn higher average returns than low *ROA* firms. *ROA* is income before extraordinary items (item IBQ) divided by last quarter's assets (item ATQ).

Failure probability (FP). More distressed firms earn abnormally lower average returns than less distressed firms (e.g., Campbell, Hilscher, and Szilagyi (2008)). Following Campbell et al., we measure distress as a linear function of the ratio of earnings over the market value of the firm, monthly excess return relative to the S&P 500 index, market leverage, stock return volatility, relative size, the ratio of cash over the market value of the firm, market-to-book, and log price per share.

Momentum (MOM). Jegadeesh and Titman (1993) show that stocks that perform well in the recent past continue to earn higher average returns in the future six to twelve months than stocks that perform poorly in the recent past. We measure momentum as prior six-month returns.

Portfolio Construction

We construct one-way quintile portfolios based on the anomaly variables. In June of each year t from 1965 to 2008, we sort all NYSE stocks on CRSP on book-to-market, size, composite issuance, net stock issues, abnormal investment, asset growth, investment-to-assets, and accruals. We use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into one-way quintiles, and calculate annual value-weighted returns from July of year t to June of year $t + 1$. We use the NYSE breakpoints to alleviate the impact of micro-cap firms (e.g., Fama and French (2008)). Firms with negative book equity for the fiscal year ending in calendar year $t - 1$ are excluded.

For each month from January 1977 to December 2008, we use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into five groups based on their most recent *SUEs*. We hold the resulting portfolios for six months, and calculate value-weighted returns. The sample starts from January 1977 due to the availability of quarterly earnings data. Following Campbell, Hilscher, and

Szilagyi (2008), for each month from January 1975 to December 2008, we sort all NYSE, Amex, and Nasdaq stocks on CRSP on failure probability into five groups. We use Compustat accounting data for a fiscal quarter in portfolio sorts in the months immediately after the quarter’s public earnings announcement dates (Compustat quarterly item RDQ). We calculate the one-year buy-and-hold value-weighted returns of stocks with and without dividends for each portfolio. The starting period of the sample is restricted by the availability of quarterly data on total liabilities.

To construct the *ROA* quintiles, we use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles based on their quarterly *ROA*. We use quarterly earnings in portfolio sorts only in the months immediately after the most recent earnings announcement (Compustat quarterly item RDQ). Monthly value-weighted returns on the quintiles are calculated for the current month, and the portfolios are rebalanced monthly. Finally, following Jegadeesh and Titman (1993), for each month from July 1965 to June 2008, we use the NYSE breakpoints of the prior six-month returns to split NYSE, Amex, and Nasdaq stocks into quintiles. Skipping one month, we hold the resulting portfolios for the subsequent six months, and calculate the value-weighted returns.

2.3 Expected Return Estimation

The estimation method is from Gebhardt, Lee, and Swaminathan (2001, GLS hereafter). GLS compute the expected return as the internal rate of return (implied cost of equity) that equates the present value of expected future cash flows in the residual income model to the current stock price.

The Baseline Procedure

We closely follow GLS’s procedure in our baseline estimation. We use the analyst earnings forecasts from Institutional Brokers’ Estimate System (IBES) as the proxy for the market’s earnings expectations. We compute a finite horizon estimate of equity value for each firm:

$$P_t = B_t + \frac{FROE_{t+1} - E_0[R]}{1 + E_0[R]} B_t + \frac{FROE_{t+2} - E_0[R]}{(1 + E_0[R])^2} B_{t+1} + TV, \quad (1)$$

in which $E_0[R]$ denotes the expected return estimate from the baseline estimation. B_t is the book value from the most recent financial statement divided by the number of shares outstanding in the current month. $FROE_{t+\tau}$ is forecasted return on equity (*ROE*) for period $t + \tau$. For the first three years, we compute it as $FEPS_{t+\tau}/B_{t+\tau-1}$, in which $FEPS_{t+\tau}$ is the mean forecasted earnings per share (*EPS*) for year $t + \tau$ from IBES, and $B_{t+\tau-1}$ is the book value per share for year $t + \tau - 1$.

We use the mean analysts' one-year and two-year ahead earnings forecasts ($FEPS_{t+1}$ and $FEPS_{t+2}$, respectively) and the long-term growth rate estimate (Ltg) from IBES to compute the three-year-ahead earnings forecast as $FEPS_{t+3} = FEPS_{t+2}(1 + Ltg)$. Beyond the third year, we forecast $FROE$ using a linear interpolation to the industry median *ROE*. To calculate the industry median *ROE*, we sort all stocks into the 48 industries classified by Fama and French (1997). The industry median *ROE* is the ten-year (at least five-year) moving median of past *ROEs* of all firms in the industry. Loss firms are excluded from the calculation of the industry median.

Book equity per share is $B_{t+\tau} = B_{t+\tau-1} + FEPS_{t+\tau} - FDPS_{t+\tau}$, in which $FDPS_{t+\tau}$ is the forecasted dividend per share for year $t + \tau$, estimated using the current dividend payment ratio ($k = \text{dividends for the most recent fiscal year divided by earnings over the same time period, } 0 \leq k \leq 1$), i.e., $FDPS_{t+\tau} = k \times FEPS_{t+\tau}$. For firms with negative earnings we divide the dividends by 0.06 times total assets to derive an estimated payout ratio. Payout ratios of less than zero are assigned a value of zero, and payout ratios greater than one are assigned a value of one. We forecast earnings up to 12 future years and estimate a terminal value TV for cash flows beyond year 12:

$$TV = \sum_{i=3}^{T-1} \frac{FROE_{t+i} - E_0[R]}{(1 + E_0[R])^i} B_{t+i-1} + \frac{FROE_{t+T} - E_0[R]}{E_0[R](1 + E_0[R])^{T-1}} B_{t+T-1}. \quad (2)$$

We estimate the implied cost of equity, $E_0[R]$, for each firm in each month by substituting the forecasted future earnings, book values, and terminal values into equation (1) and solving for $E_0[R]$ from the resulting nonlinear equation. For portfolios that are annually rebalanced at the end of June of year t , we value-weight $E_0[R]$ measured at the end of December of year $t-1$ across firms in

each testing portfolio to obtain portfolio-level expected returns. This timing convention means that we match the expected returns at the end of year $t-1$ with ex post returns from July of year t to June of year $t+1$. The six-month lag between January and June of year t is imposed per Fama and French (1993) to allow accounting information to be released to the market. For the monthly re-balanced momentum, *SUE*, *ROA*, and *FP* portfolios, although $E_0[R]$ is available monthly because P_t and $FEPS_t$ are updated monthly, $E_0[R]$ is the expected future one-year return.

Two Modified Estimation Procedures

The baseline estimation of the implied costs of equity uses analysts earnings forecasts from IBES as the market's earnings expectations. Two potential issues arise with this procedure in our application. First, analysts earnings forecasts tend to be overly optimistic (e.g., O'Brien (1988)), and as a result, expected return estimates implied by these forecasts tend to be upward biased (e.g., Easton and Sommers (2007)). If this bias varies systematically with anomaly variables (for example, analysts might be more optimistic toward growth firms, high accrual firms, and firms that issue equity), the estimates of expected returns to long-short strategies will also be biased. Second, because analysts tend to follow larger, more visible stocks, expected return estimates are limited to a small sample of stocks that have analysts coverage. This limitation can affect the results for anomalies-based trading strategies that often involve stocks that are not followed by analysts.

To address these concerns, we use two modified procedures for estimating implied costs of equity. The baseline approach uses analysts earnings forecasts in forming forecasted return on equity, $FROE_{t+\tau}$. We instead forecast future one-, two-, and three-year ahead *ROEs* using cross-sectional regressions similar to those in Fama and French (2006). Specifically, we estimate Fama-MacBeth (1973) cross-sectional regressions of future realized $ROE_{t+\tau} = Y_{t+\tau}/B_{t+\tau-1}$, in which $\tau = 1, 2, 3$, and $Y_{t+\tau}$ is τ -year ahead realized earnings per share. Fama and French forecast $Y_{t+\tau}/B_t$, but we forecast $Y_{t+\tau}/B_{t+\tau-1}$ to provide direct inputs into the implied costs of equity estimation.

In the first modified procedure, we use Fama and French's (2006) full specification, including the

logarithm of book-to-market, the logarithm of market equity, a dummy variable that is one for firms with negative earnings for fiscal year t (zero otherwise), Y_t/B_t , $-AC_t/B_t$ with $-AC_t$ being accruals per share for firms with negative accruals (zero otherwise), $+AC_t/B_t$ with $+AC_t$ being accruals per share for firms with positive accruals (zero otherwise), asset growth for fiscal year t , a dummy variable that is one for firms that pay no dividends for fiscal year t , and the ratio of dividends to book equity. The full list of predictors imposes strict data requirements, and the resulting sample size is similar to that in the baseline procedure. To enlarge the sample size, in the second modified procedure we use a shortened list of predictors to forecast ROE , including only the log book-to-market, the log market equity, the negative earnings dummy, Y_t/B_t , and asset growth. To avoid look-ahead bias, we use ten-year rolling windows (at least five years) up to year t to forecast future ROE .

Because we forecast ROE directly, as opposed to earnings per share, the baseline estimation of the implied costs of equity needs to be adjusted accordingly. To compute future book equity per share, we still use the clean surplus relation: $B_{t+\tau} = B_{t+\tau-1} + (1 - k) \times FEPS_{t+\tau}$, in which k is the dividend payout ratio. However, the forecasted earnings per share $FEPS_{t+\tau}$ is calculated as $FROE_{t+\tau} \times B_{t+\tau-1}$, in which $FROE_{t+\tau}$ with $\tau = 1, 2, 3$ is the forecasted ROE from the cross-sectional regressions. All other aspects of the estimation procedure remain the same as in the baseline procedure. Our modified procedures are in the same spirit as Hou, van Dijk, and Zhang (2009), who use cross-sectional regressions to forecast the earnings of individual firms. However, because earnings might appear nonstationary, we opt to forecast ROE directly. Comparing the estimates across the baseline and modified procedures can shed light on whether biases in analysts earnings forecasts cause any bias in the expected returns to anomalies-based trading strategies.

3 Expected Return Estimates as Implied Costs of Equity

Section 3.1 presents preliminary analysis, and Section 3.2 discusses our key results.

3.1 Preliminary Analysis

Panel A of Table 1 reports the descriptive statistics for the sample used in the baseline implied costs of equity estimation. Because doing so requires analysts earnings forecasts from IBES, the average numbers of firms in the cross-section for the B/M , CI , and AI quintiles are only 2,201, 1,393, and 1,513, respectively. Panel B reports the descriptive statistics for the sample used in the implied costs of equity estimation in which we use the full ROE forecasting regressions from Fama and French (2006). Although this procedure is immune to analysts forecasting bias, the sample size is comparable with that based on IBES. In particular, the average numbers of firms in the cross-section for the B/M , CI , and AI quintiles are 2,091, 1,134, and 1,540, respectively. The reason is that the full Fama-French specification requires firms to have nonmissing observations for many forecasting variables simultaneously. To increase the sample size, we also implement the simplified Fama-French ROE forecasting regressions with a shorter list of variables. Panel C shows that doing so substantially increases the sample size relative to that in Panel B. The average numbers of firms in the cross-section for the B/M , CI , and AI quintiles increase to 2,893, 1,534, and 2,025, respectively.

Table 2 reports the average slopes and their t -statistics for annual cross-sectional profitability forecasting regressions using the Fama-MacBeth (1973) methodology. We report the regression results from the full sample. (As noted, we use ten-year rolling windows to estimate the cross-sectional regressions when estimating implied costs of equity to guard against look-ahead bias.) Lagged ROE is the strongest predictor of future ROE . In the full specification, the average slope on lagged ROE for one-year ahead ROE is 0.63, which is more than 18 standard errors from zero. The evidence shows considerable persistence in the ROE . The slope decays to 0.39 in forecasting three-year ahead ROE , which is still more than 13 standard errors from zero. The evidence from the short specification is similar. The average slope on lagged ROE for one-year ahead ROE is 0.61, which is more than 18 standard errors from zero. Size forecasts future ROE with significantly positive slopes, meaning that big firms are more profitable than small firms. For the most part,

B/M forecasts ROE with significantly negative slopes. As such, growth firms are more profitable than value firms. Firms that do not pay dividends are less profitable than firms that do pay dividends. Firms with high dividends to book equity ratios are more profitable than firms with low dividends to book equity ratios. The evidence is largely consistent with Fama and French (2006).

Table 3 presents descriptive statistics for the implied costs of equity estimated from the baseline procedure as well as the two modified procedures. Because we do not require a common sample for all the anomaly variables, the descriptive statistics vary across samples that correspond to different anomaly variables. The most important pattern from Table 3 is an upward bias in expected return estimates derived from analysts earnings forecasts in the benchmark estimation. In particular, the mean expected return averaged across different samples in the benchmark procedure is 11.8% per annum, whereas the mean expected returns are 10.1% and 10.5% in the two modified procedures. As such, the upward bias in the mean expected return ranges from 1.3% to 1.7%. Using medians yields similar results. The median expected return averaged across different samples in the benchmark estimation is 11.5%, whereas those from the modified procedures are 9.9% and 10.3%. As such, the upward bias in the median expected return ranges from 1.2% to 1.6%. Finally, the volatilities of expected return estimates from different estimation procedures are largely similar.

3.2 Expected Return Estimates for Dollar Neutral Long-Short Strategies

Table 4 reports the key message of the paper. The table shows the expected returns for all the testing portfolios from the implied costs of equity estimation. To facilitate comparison, we also report the average realized returns for the testing portfolios in the sample used for the baseline estimation. Despite the fact that the IBES sample tilts toward big firms, the magnitude of the anomalies measured with average realized returns in the IBES sample are largely similar to those in a broad sample without restricting firms to be covered by IBES (not reported). We find that for most anomalies, the average return and the expected return estimates differ dramatically across the testing portfolios.

Panel A shows that the expected value premiums from different estimation methods of implied

costs of equity are (relatively) close. A similar observation also holds for all the other anomaly variables. As such, the upward bias documented in Table 3 does not seem to vary systematically with firm characteristics. In the baseline procedure, the value quintile earns a higher expected return than the growth quintile: 14.9% versus 8.6% per annum. The spread of 6.3% is 12 standard errors from zero. This expected return spread is close to the average return spread of 5.2% across the book-to-market quintiles. The precision of the expected return estimate is substantially higher than that of the average return spread, which is only 2.2 standard errors from zero. In the two modified implied costs of equity procedures, the estimates of the expected value premium are both 8.5%, which are also close to the average return. Both of the expected return estimates are more than eight standard errors from zero. From Panel B, the expected returns of the small-minus-big quintile range from 1.8% to 3.1% per annum, which are close to the average return of 3%. While the average return is insignificant, the expected returns are all more than five standard errors from zero.

The similarity between average return and expected return estimates ceases to exist for the rest of the anomaly variables. From Panel C, the high-minus-low *CI* quintile earns an average return of -4.2% , which is more than 2.5 standard errors from zero. In contrast, the expected return estimates are substantially lower in magnitude, ranging from -0.1% to -1.1% . Although the estimates from the modified procedures are significant, the estimate from the baseline procedure is not. The results for the *NSI* and *AI* portfolios are largely similar to those for the *CI* portfolios. The three anomaly variables produce significantly negative average returns for the high-minus-low portfolios, but their expected return estimates are economically small and often statistically insignificant. In particular, Panel D shows that the high-minus-low *NSI* quintile earns an average return of -7.5% per annum, which is three standard errors from zero. In contrast, the expected return estimates of this zero-cost quintile range from -0.1% to -0.5% , which are all within 1.9 standard errors from zero. From Panel E, the high-minus-low *AI* quintile earns an average return of -4.0% , which is more than 2.4 standard errors from zero. However, the expected return estimates of this long-short quintile range from -0.1% to -1.0% , and two of three estimates are insignificant.

For the *AG* and *I/A* portfolios, although the expected return estimates of the high-minus-low quintiles are significantly negative, their magnitude is substantially lower than that of the average return estimates. From Panel F, the average return of the high-minus-low *AG* quintile is -5.6% per annum, which is 2.8 standard errors from zero. However, the expected return estimates range from -0.6% to -1.5% , albeit significant. Panel G shows that the average return of the high-minus-low *I/A* quintile is -3.4% ($t = -1.8$). In contrast, the expected return estimates only fall in the range between -0.5% and -1.0% , and do not come close to matching the magnitude of the average return. From Panel H, the high-minus-low *AC* quintile earns an average return of -4.8% ($t = -3.6$). The baseline procedure yields a slightly negative expected return estimate. The two modified procedures yield expected return estimates of -0.5% and -0.3% . Although at least marginally significant, these estimates are substantially lower in magnitude than the average return estimate.¹

The remaining four panels report that the expected return estimates for the high-minus-low quintiles formed on earnings surprises, failure probability, return on assets, and momentum deviate even more from their average return estimates. In particular, the expected returns and the average returns have the opposite signs. The high-minus-low earnings surprises quintile earns an average return of 4.9% per annum, which is 5.5 standard errors from zero. In contrast, the expected return estimates range from -0.1% to -1.0% , and are all significant. The average return of the high-minus-low failure probability quintile is -8.1% , which is five standard errors from zero. However, the baseline estimation shows that its expected return is significantly positive, 3.8% . From Panel K, the high-minus-low *ROA* quintile earns an average return of 6.5% per annum, which is 3.3 standard errors from zero. In contrast, the expected return estimate from the baseline procedure is -1.7% , which is significant. The estimates from the two modified procedures are largely similar: -2.1% and -2.7% , which are again significant. Finally, Panel L shows that the winner-minus-loser quintile

¹Wu, Zhang, and Zhang (2010) also document that the expected return spread across the extreme accrual quintiles is too small in magnitude relative to the average return spread. Their estimates are based only on the baseline implied costs of equity estimation. We show that the expected return estimates from the modified procedures are largely similar to those from the baseline procedure, meaning that bias in analysts forecasts is not important for estimating expected returns of the accrual portfolios.

earns an average return of 6.4% ($t = 3.3$). In contrast, the expected return estimates for the winner-minus-loser quintile range from -1.7% to -2.3% , which are all at least 17 standard errors from zero.

To summarize, the key message from Table 4 is clear. The average return estimates and the expected return estimates are dramatically different across the testing portfolios, except for the value premium. Further, the expected return estimates for the long-short strategies from the modified estimation procedures are largely similar to those from the baseline procedure. As such, bias in analysts forecasts does not vary systematically with firm characteristics, at least at the portfolio level.

Our evidence is consistent with Gebhardt, Lee, and Swaminathan (2001), who show that value stocks have higher implied costs of equity than growth stocks, and that winners have slightly lower implied costs of equity than losers. We also add to Chava and Purnanandam (2010), who show that more distressed firms have higher implied costs of equity than less distressed firms. We expand these studies in two aspects. First, both papers only use the baseline estimation procedure for implied costs of equity. We show that the basic inferences are robust to the use of analysts earnings forecasts. Second, more important, our coverage of anomalies is substantially broader, including most of the major anomalies studied in empirical finance in the past two decades.

3.3 Expected Return Estimates Conditional on Long-Term Growth Forecasts

As noted by Gebhardt, Lee, and Swaminathan (2001), the estimation procedure of the implied costs of equity involves many simplifying assumptions that can give rise to measurement errors in expected return estimates. While we have tried to address the bias in the market's earnings expectations by using cross-sectional *ROE* forecasts, a remaining issue is the possible correlation between earnings forecasts and expected returns. For example, the fixed 12-year forecasting horizon might be too short for some growth firms. In particular, many bio-technology firms are loss firms that are not likely to turn profitable in the near future. For these firms, their earnings forecasts and expected return estimates are likely to be biased downward.

To deal with this bias, we follow Gebhardt, Lee, and Swaminathan (2001) and redo our tests

using portfolios sorted on long-term growth forecasts. In June of each year, we form three terciles based on analysts long-term growth forecasts with roughly equal number of firms. We then split each growth tercile into quintiles based on a given anomaly variable of interest. (We use long-term growth terciles instead of quintiles to ensure a sufficient number of stocks in each double-sorted portfolio.) The goal of the two-way sorts is to reduce the dispersion in long-term growth within each portfolio. In fact, the correlations between long-term growth and the anomaly variables are low even before the two-way sorts. The correlation between the prior six-month return (MOM) and long-term growth is 2.8%, and the correlation between composite issuance (CI) and long-term growth is 2.4%. All the other correlations have even smaller magnitudes, most of which are below 1%.

Table 5 reports expected return estimates for dollar neutral long-short strategies conditional on long-term growth forecasts. We observe that our basic inference that expected returns are strikingly inconsistent with average realized returns is robust to the control of long-term growth forecasts. The high-minus-low CI quintile has significantly negative average returns in the median and high long-term growth terciles. However, most of the implied costs of equity are insignificantly negative. For the NSI , AI , AG , I/A , and AC quintiles, their high-minus-low quintiles have large and negative average returns in most cases. However, their expected return estimates often have inconsistent signs, and even when their signs are negative, their magnitude does not come close to the magnitude of average realized returns. The long-short SUE , FP , ROA , and MOM quintiles earn significantly positive average returns across the long-term growth terciles. However, their expected return estimates are mostly negative and significant. The value premium is again the only exception with consistent signs and magnitude between average realized returns and expected returns. For the small-minus-big quintile, expected returns have consistent signs with, but large magnitude than average returns.

4 Estimating Expected Returns and Expected Growth Rates Simultaneously

As an alternative way to evaluate the impact of the growth rate assumption on our basic inference, we implement methods that estimate expected returns and expected growth for a given portfolio simultaneously proposed by Easton, Taylor, Shroff, and Sougiannis (2002, ETSS hereafter), Easton (2006), and Easton and Sommers (2007). We find that these methods yield counterfactual implications for expected growth. The results cast doubt on these alternative methods, and suggest that the GLS procedure is probably among the best accounting-based expected return models.

4.1 Methodology

To describe these alternative methods, we start with the residual income model:

$$V_{it} = B_{it} + \sum_{\tau=1}^{\infty} \frac{Y_{it+\tau} - r_i \times B_{it+\tau-1}}{(1 + r_i)^\tau}, \quad (3)$$

in which V_{it} is the intrinsic value per share of firm i at time t , B_{it} is book value per share, Y_{it} is earnings per share, and r_i is the cost of equity.

The Baseline ETSS Estimation

ETSS operationalize the residual income model by assuming that (starting from the period from t to $t+1$) the residual earnings as a perpetuity grows at a constant annual rate of g_i . This assumption means that we can reformulate equation (3) as:

$$P_{it} = B_{it} + \frac{Y_{it+1}^{IBES} - r_i \times B_{it}}{r_i - g_i}, \quad (4)$$

in which P_{it} is price per share of firm i at time t , Y_{it+1}^{IBES} is the IBES analysts forecasts (known at time t) of earnings for time $t + 1$, and g_i is the expected growth rate in residual income beyond time $t + 1$ required to equate $P_{it} - B_{it}$ and the present value of the infinite residual income stream.

Some algebra shows that equation (4) is equivalent to:

$$\frac{Y_{it+1}^{IBES}}{B_{it}} = g_i + \frac{P_{it}}{B_{it}}(r_i - g_i). \quad (5)$$

We follow ETSS and implement this equation using Fama-MacBeth (1973) cross-sectional regressions across all the firms within a given portfolio:

$$\frac{Y_{it+1}^{IBES}}{B_{it}} = \gamma_0 + \gamma_1 \frac{P_{it}}{B_{it}} + \mu_{it}, \quad (6)$$

where $\gamma_0 = g$ with g being the implied (average) growth rate for the portfolio, and $\gamma_1 = r - g$ with r being the expected return for the portfolio. We call this procedure the baseline ETSS estimation.

The Modified ETSS Estimation

Following the same idea as in the modified procedures for estimating implied costs of equity, we also replace the left-hand side of equation (6) with the forecasted one-year ahead *ROE* from the Fama-French (2006) *ROE* forecasting regressions. Doing so includes the sample observations not covered by analysts and avoids potential bias in analysts forecasts. We call this procedure the modified ETSS estimation. We use the forecasted *ROE* from the full Fama-French profitability regressions. Using the simplified specification yields largely similar results (not reported).

The O’Hanlon-Steele Estimation

O’Hanlon and Steele (2000) and Easton (2006) reformulate equation (3) in a different way:

$$P_{it} = B_{it} + \frac{(Y_{it} - r_i \times B_{it-1})(1 + g'_i)}{r_i - g'_i}, \quad (7)$$

in which g'_i is the perpetual growth rate starting from the current period’s residual income for the period from $t-1$ to t . (In contrast, g_i in equation (4) is the implied perpetual growth rate starting from the next period’s residual income from t to $t+1$.) The implied growth rate, g'_i , produces a residual income stream such that the present value of this stream equals the difference between P_{it} and B_{it} .

Some algebra shows that equation (7) is equivalent to:

$$\frac{Y_{it}}{B_{it-1}} = r_i + \frac{r_i - g'_i}{1 + g'_i} \frac{P_{it} - B_{it}}{B_{it-1}}. \quad (8)$$

We follow O’Hanlon and Steele (2000) and Easton (2006) and implement this equation with the following cross-sectional regression for a portfolio of stocks:

$$\frac{Y_{it}}{B_{it-1}} = \delta_0 + \delta_1 \frac{P_{it} - B_{it}}{B_{it-1}} + \mu_{it}, \quad (9)$$

where $\delta_0 = r$ with r being the portfolio-level expected return and $\delta_1 = (r - g')/(1 + g')$ with g' being the expected growth rate for the portfolio. We call this estimation the O’Hanlon-Steele procedure.

We estimate annual value-weighted Fama-MacBeth (1973) cross-sectional regressions in each period using the Weighted Least Squares with the weights given by market capitalization. We use value-weights to facilitate comparison with the results from the implied costs of equity estimation. We implement the estimation procedures for all testing quintile portfolios. To test whether a given high-minus-low quintile has an average return of zero, we estimate the cross-sectional regressions for the two extreme quintiles in question jointly, and test the null hypothesis using the Fama-MacBeth standard errors for the implied expected returns of the high-minus-low quintile. The test on whether a given high-minus-low quintile has an implied growth rate of zero is defined analogously.

4.2 Expected Growth Estimates

To cross-validate the expected growth estimates from these methods, we measure average dividend growth rates for all the testing portfolios, and compare them with the estimated growth rates.

Measuring Portfolio Dividend Growth Rates in the Data

We measure portfolio dividend growth using returns with and without dividends, following Hansen, Heaton, and Li (2005) and Chen, Petkova, and Zhang (2008). Consider portfolios that are annually rebalanced. Define P_t = market equity value at the end of June for year t of the stocks allocated

to the portfolio when formed at the end of June for year t ; $P_{t,t+1}$ = market equity value at the end of June for year $t + 1$ of the stocks allocated to the portfolio at the end of June for year t ; $D_{t,t+1}$ = dividends paid between portfolio formation of year t and $t + 1$ on the stocks allocated to the portfolio at year t ; $R_{t,t+1}$ = return with dividends at the end of June of year $t + 1$ on a portfolio formed in year t ; $G_{t,t+1}^P$ = return without dividends (rate of capital gain) observed at the end of June for year $t + 1$ on a portfolio formed in year t . When there are two time subscripts on a variable, the first subscript indicates the time when the portfolio is formed and the second subscript gives the time when the variable is observed. We use P_t as a shorthand for $P_{t,t}$.

For each portfolio, we construct the dividend yield, $D_{t,t+1}/P_t$, from the value-weighted realized portfolio returns with and without dividends:

$$\frac{D_{t,t+1}}{P_t} = R_{t,t+1} - G_{t,t+1}^P. \quad (10)$$

Because monthly total returns are compounded to get annual returns in CRSP, the dividend yield includes dividends and the reinvestment returns earned from the time a dividend is paid to the end of the annual return period. We measure portfolio dividend growth rates as:

$$G_{t+1} = \left(\frac{D_{t,t+1}/P_t}{D_{t-1,t}/P_{t-1}} \right) (G_{t-1,t}^P + 1) - 1. \quad (11)$$

Because the right-hand side of equation (11) equals $\left(\frac{D_{t,t+1}/P_t}{D_{t-1,t}/P_{t-1}} \right) \left(\frac{P_{t-1,t}}{P_{t-1}} \right) - 1$, the equation says that the dividend growth rate is (dividends at $t + 1$ per dollar invested at t multiplied by dollars invested at t)/(dividends at t per dollar invested at $t - 1$ multiplied by dollars invested at $t - 1$). The reinvested capital gain embedded in equation (11), $P_{t-1,t}/P_{t-1}$, is important: high $P_{t-1,t}/P_{t-1}$ means more dollars to invest at t and higher dividend growth rates.

For monthly rebalanced portfolios such as the momentum, *SUE*, and *ROA* quintiles, we aggregate monthly portfolio returns with and without dividends from July of year t to June of year $t + 1$ to annual returns with and without dividends for year t . We then apply equations (10) and (11)

on the aggregated annual returns with and without dividends to construct annual dividend growth rates for the portfolios. Aggregating over monthly returns with and without dividends to obtain annual returns alleviates the effect of dividend seasonality on the calculation of portfolio dividend growth rates. For the failure probability portfolios, monthly observations of returns are already one-year buy-and-hold returns. As such, we apply equations (10) and (11) directly on the monthly observations of returns to construct dividend growth rates for these portfolios.

Although the growth rates from equation (11) are calculated using dividend yields and rates of capital gain from two adjacent periods, the sample average of these growth rates provides a good estimate of long-term growth rate. Chen, Petkova, and Zhang (2008), for example, show that in the 1945–2005 sample the high-minus-low B/M quintile has an average growth rate of 3.2% per annum, close to its long-term growth rate of 2.7% calculated as the annuity of future dividend growth rates.

Estimation Results

Panel A of Table 6 reports the descriptive statistics for the sample for the baseline ETSS estimation. The average numbers of firms in the cross-section for the B/M , CI , and AI quintiles reduce to 3,026, 1,649, and 1,753, respectively. Panel B reports the results for the sample used in the modified ETSS estimation in which we use the full ROE forecasting regressions from Fama and French (2006). The sample size is comparable with that based on IBES in the baseline ETSS procedure. The average numbers of firms in the cross-section for the B/M , CI , and AI quintiles are 2,851, 1,507, and 1,859, respectively. Panel C describes the sample for the O’Hanlon-Steele estimation. Because this procedure does not use IBES or require a long list of variables to forecast ROE , the sample size is larger. The average numbers of firms in the cross-section for the B/M , CI , and AI quintiles increase to 3,369, 1,749, and 1,983, respectively.

Table 7 reports the estimated growth rates from the baseline ETSS method that uses the IBES earnings forecasts, g_0 , the growth rates from the modified ETSS method that uses the Fama-French (2006) ROE forecasts, g_1 , and the growth rates from the O’Hanlon-Steele method, g_2 . We find

that implied growth rate spreads often go in the opposite direction as those observed in the data.

From Panel A, value firms have higher growth rates on average than growth firms in the data: 9.1% versus 5.0% per annum. The spread of 4.1% is 1.3 standard errors from zero. However, the alternative methods all predict that value firms have significantly lower expected growth rates than growth firms. In particular, the baseline ETSS procedure generates a negative growth rate spread of -4.9% for the high-minus-low B/M quintile, which is more than 2.5 standard errors from zero. The modified ETSS and the O’Hanlon-Steele procedures produce even larger spreads, -15.4% and -13.9% , respectively, which are at least ten standard errors from zero. From Panel B, small firms grow faster than big firms in the data, although the growth rate spread of 5.2% per annum is insignificant. However, the alternative methods all predict that big firms grow faster than small firms. The baseline and modified ETSS procedures predict that big firms grow faster than small firms by 5% , which is at least four standard errors from zero. The O’Hanlon-Steele procedure implies that big firms grow faster than small firms by 10.9% , which is about 4.5 standard errors from zero.

The observed growth spreads are small, positive, and insignificant for the high-minus-low quintiles formed on AI , AG , and I/A in the data. However, the alternative methods often produce significantly positive implied growth rate spreads. In particular, the high-minus-low AI quintile in the data has a growth rate of 1.2% per annum, which is within 0.5 standard errors of zero. However, the modified ETSS method implies a growth rate of 8.6% , which is more than six standard errors from zero. The implied growth rate spread from the O’Hanlon-Steele method is even higher, 15.5% , which is more than nine standard errors from zero. The growth rate spreads are small, negative and insignificant for the high-minus-low quintiles formed on CI and AC . However, the ETSS methods often produce significantly positive growth rate spreads. The high-minus-low CI quintile has a growth rate of -1.1% per annum in the data, which is within 0.5 standard errors of zero. However, the baseline ETSS method implies a growth rate spread of 9.2% ($t = 3.7$). The high-minus-low NSI quintile has an economically large growth rate of -6.6% , albeit insignificant. However, the baseline ETSS estimation yields an expected growth rate of 3.6% ($t = 2.1$).

The predicted growth rate spreads across the extreme *SUE* quintiles are mixed. The baseline ETSS method implies a growth rate spread of 2.2% per annum, which is more than 4.5 standard errors from zero. However, the two related methods imply growth rate spreads of -1.8% and -1.3% that are more than four standard errors from zero. For comparison, the high-minus-low *SUE* quintile has a positive growth rate of 4.1% in the data ($t = 7.6$). The high-minus-low momentum quintile has a growth rate of 6.5% ($t = 7.3$) in the data. The implied growth rates for this portfolio from the ETSS methods are all positive, but the magnitudes range from 0.4% to 3.3%, which are lower than the observed growth rate. The high-minus-low *FP* quintile has a large positive growth rate of 17.8% per annum, which is more than four standard errors from zero. In contrast, the ETSS methods all forecast strongly negative implied growth rates around -20% , which are all more than 15 standard errors from zero. The observed and the implied growth rates also diverge somewhat for the *ROA* portfolios. The high-minus-low *ROA* quintile has a growth rate of 5.4% in the data ($t = 4.6$), while the ETSS methods forecast significantly positive growth rates ranging from 9.5% to 13.2%.

Discussion

Why do these alternative methods deliver counterfactual implications of expected growth? The inherent specification errors within these methods are the likely culprits. For example, the cross-sectional regression in equation (6) is derived under strong assumptions. The regression assumes that there are measurement errors in Y_{it+1}^{IBES} and P_{it}/B_{it} and specification errors in equation (5). Specification errors can arise from two sources. First, the residual earnings might not be a perpetuity that grows at a constant rate. Second, P_{it}/B_{it} and $r_i - g_i$ might be correlated cross-sectionally, meaning that the average of $r_i - g_i$ cannot be treated as a constant slope in the cross-sectional regression. The ETSS procedure assumes that all these errors have a mean of zero, meaning that equation (5) can be estimated using linear cross-sectional regressions.

The cross-sectional regression in equation (9) also involves strong assumptions. In particular, specification errors can arise from three sources. First, the residual earnings might not be a per-

petuity that grows at a constant rate. Second, $(P_{it} - B_{it})/B_{it-1}$ and $(r_i - g'_i)/(1 + g'_i)$ might be correlated cross-sectionally, so that the average of $(r_i - g'_i)/(1 + g'_i)$ cannot be treated as a constant slope in the cross-sectional regression. Third, because $(r_i - g'_i)/(1 + g'_i)$ is nonlinear in r_i and g'_i , Jensen's inequality means that the average of $(r_i - g'_i)/(1 + g'_i)$ cannot be replaced with $(r - g')/(1 + g')$. The O'Hanlon-Steele procedure assumes that all these errors have a mean of zero, so that equation (8) can be transformed into the cross-sectional regression in equation (9).

Finally, our measure of portfolio dividend growth in equation (11) accounts for reinvested capital gains from portfolio rebalancing. For example, the higher dividend growth rates of value portfolios from year t to $t + 1$ come from higher reinvested capital gains from year $t - 1$ to t , meaning more dollars to invest at the beginning of year t . These reinvested capital gains are an important part of the expected value premium (e.g., Chen, Petkova, and Zhang (2008)). The dividend growth rates of value portfolios would be lower without reinvesting these capital gains. It is not clear how the ETSS and O'Hanlon-Steele methods can capture these reinvested capital gains.

4.3 Expected Return Estimates

Table 8 reports expected return estimates using the alternative methods that determine expected returns and growth rates simultaneously. Because of the counterfactual results on expected growth rates reported in Table 7, it is not surprising that the expected return estimates diverge from those obtained from the GLS procedure as well as average returns. Easton, Taylor, Shroff, and Sougianis (2002) show that their baseline procedure works well at the aggregate level in that it delivers reasonable equity premium estimates. Table 8 shows that the ETSS procedure fails to provide reasonable expected return estimates for anomalies-based trading strategies.

Panel A shows that the average return of the high-minus-low B/M quintile is 4.2% per annum ($t = 1.7$) in the sample for the baseline ETSS procedure. Unlike the positive average return, the expected return estimates are all negative: -2.1% ($t = -1.0$) from the baseline ETSS estimation, -12.7% ($t = -12.2$) from the modified ETSS estimation, and -9.4% ($t = -6.0$) from the O'Hanlon-

Steele estimation. Panel B shows that the average return of the small-minus-big quintile is 2.2% per annum, which is within one standard error of zero. In contrast, the expected return estimates from the baseline and modified ETSS procedures are -6.4% and -7.5% , respectively, which are both more than 5.5 standard errors from zero. The estimate from the O’Hanlon-Steele procedure is -11.8% , which is more than 4.5 standard errors from zero. From Panel C, although the average return of the high-minus-low *CI* quintile is significantly negative, the expected return estimate from the baseline ETSS procedure is significantly positive, 5.2% , which is three standard errors from zero.

Similarly large differences between average returns and expected returns are also evident for the *NSI*, *AI*, *AG*, *I/A*, and *AC* quintiles. The high-minus-low *AI* and *I/A* quintiles both earn insignificantly negative average returns. However, the modified ETSS procedure and the O’Hanlon-Steele procedure both produce significantly positive expected return estimates, which are more than six standard errors from zero. The high-minus-low *AG* and *AC* portfolios both earn significantly negative average returns. However, the modified ETSS procedure and the O’Hanlon-Steele procedure both show significantly positive expected return estimates, which are more than five standard errors from zero. The baseline ETSS procedure generates insignificant expected return estimates for the high-minus-low quintiles formed on all these anomaly variables. Without going through the details, we can report based on the remaining four panels of Table 8 that the average return estimates also diverge from the expected return estimates for the remaining anomaly variables.

5 Conclusion

We use valuation models to estimate expected returns to a comprehensive list of anomalies-based trading strategies, including those formed on book-to-market, size, composite issuance, net stock issues, abnormal investment, asset growth, investment-to-assets, accruals, standardized unexpected earnings, failure probability, return on assets, and short-term prior returns. The key message is that except for the value premium, expected return estimates differ dramatically from average realized returns. If the accounting-based costs of equity are good proxies for expected returns, the evidence

suggests that mispricing, not risk, is the main driving force of capital markets anomalies.

Our interpretation of the evidence as a serious challenge to risk-based explanations of anomalies is not without caveats. The interpretation depends on the quality of implied costs of equity as proxies for expected returns. We have tried to address some of these caveats including the bias in expected return estimates derived from imperfect growth forecasts. Another caveat arises when expected returns are stochastic. Hughes, Liu, and Liu (2009) show that with stochastic expected returns, implied costs of equity differ from expected returns by a function of expected return and cash flow volatilities, their correlation, and cash flow growth and leverage (see also the discussion in Lambert (2009)). Unfortunately, given the tightly parameterized structure in Hughes et al., it is not clear how to estimate these differences in the data. Nevertheless, to what extent these differences can account for the striking inconsistencies between expected returns and average realized returns for anomalies-based trading strategies remains an interesting question.

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A Variable Definitions

B/M is the book equity at the fiscal yearend divided by the market equity in December. The book equity is the stockholders' equity (Compustat annual item SEQ), minus preferred stock, plus balance sheet deferred taxes and investment tax credit (item TXDITC) if available, minus post-retirement benefit asset (item PRBA) if available. If stockholder's equity value is missing, we use common equity (item CEQ) plus preferred stock par value (item PSTK). Preferred stock is preferred stock liquidating value (item PSTKL) or preferred stock redemption value (item PSTKRV) or preferred stock par value (item PSTK) in that order of availability. If these variables are missing, we use book assets (item AT) minus liabilities (item LT). The market equity (ME) is price per share times shares outstanding from CRSP.

The five-year composite issuance (CI) measure from Daniel and Titman (2006) is defined as:

$$\iota(t - \tau) = \log \left(\frac{ME_t}{ME_{t-\tau}} \right) - r(t - \tau, t), \quad (\text{A1})$$

where $r(t - \tau, t)$ is the cumulative log return on the stock from the last trading day of calendar year $t-6$ to the last trading day of calendar year $t-1$ and ME_t ($ME_{t-\tau}$) is total market equity on the last trading day of calendar year t ($t-6$) from CRSP. In economic terms, $\iota(t-\tau)$ measures the part of firm growth in market equity that is not due to stock returns. This measure is not affected by corporate decisions such as splits and stock dividends. However, issuance activities such as new equity issues, employee stock options, or any other actions that trade ownership for cash or services increase the composite issuance. In contrast, repurchase activities such as open market share repurchases, dividends, or any other action that pays cash out of a firm decrease the composite issuance.

The net stock issues (NSI) are the annual change in the logarithm of the number of real shares outstanding, which adjusts for distribution events such as splits and rights offerings. Following Fama and French (2008), we construct the net stock issues measure using the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year end in $t-1$ divided by the split-adjusted shares outstanding at the fiscal year end in $t-2$. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item ADJEX_C). If the Compustat shares or adjustment factors for calculating net stock issues are missing, we set the measure to be zero. NSI calculated in this way can be positive or negative.

Following Titman, Wei, and Xie (2004), we measure abnormal investment, AI , that applies for the portfolio formation year t , as:

$$AI_{t-1} \equiv \frac{CE_{t-1}}{(CE_{t-2} + CE_{t-3} + CE_{t-4})/3} - 1 \quad (\text{A2})$$

in which CE_{t-1} is capital expenditure (Compustat annual item CAPX) scaled by its sales (item SALE) in year $t-1$. The last three-year average capital expenditure aims to project the benchmark investment at the portfolio formation year. Using sales as the deflator assumes that the benchmark investment grows proportionately with sales. Asset growth, AG , for the portfolio formation year t is defined as the percentage change in total assets (Compustat annual item AT) from fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar year $t-1$.

Following Sloan (1996), we measure total accruals, AC , for the last fiscal year ending in calendar year $t-1$ as changes in non-cash working capital minus depreciation expense scaled by average total assets, which is the mean of the total assets (Compustat annual item AT) for the fiscal years

ending in $t-1$ and $t-2$. The non-cash working capital is the change in non-cash current assets minus the change in current liabilities less short-term debt and taxes payable.

$$TA \equiv (\Delta CA - \Delta CASH) - (\Delta CL - \Delta STD - \Delta TP) - DEP, \quad (A3)$$

in which ΔCA is the change in current assets (item ACT), $\Delta CASH$ is the change in cash or cash equivalents (item CHE), ΔCL is the change in current liabilities (item LCT), ΔSTD is the change in debt included in current liabilities (item DLC), ΔTP is the change in income taxes payable (item TXP), and DEP is depreciation and amortization expense (item DP).

Campbell, Hilscher, and Szilagyi (2008, the third column in Table 4) measure a firm's failure probability (FP) as $1/[1 + \exp(-\text{Distress}_t)]$, in which the distress measure is constructed as:

$$\begin{aligned} \text{Distress}_t = & -9.164 - 20.264 NIMTAAVG_t + 1.416 TLMTA_t - 7.129 EXRETAVG_t \\ & + 1.411 SIGMA_t - 0.045 RSIZE_t - 2.132 CASHMTA_t + 0.075 MB_t - 0.058 PRICE_t \end{aligned} \quad (A4)$$

where

$$\begin{aligned} NIMTAAVG_{t-1,t-12} & \equiv \frac{1 - \phi^3}{1 - \phi^{12}} (NIMTA_{t-1,t-3} + \dots + \phi^9 NIMTA_{t-10,t-12}) \\ EXRETAVG_{t-1,t-12} & \equiv \frac{1 - \phi}{1 - \phi^{12}} (EXRET_{t-1} + \dots + \phi^{11} EXRET_{t-12}) \end{aligned}$$

The coefficient $\phi = 2^{-1/3}$ means that the weight is halved each quarter. $NIMTA$ is net income (Compustat quarterly item NIQ) divided by the sum of market equity and total liabilities (item LTQ). The moving average $NIMTAAVG$ is designed to capture the idea that a long history of losses is a better predictor of bankruptcy than one large quarterly loss in a single month. $EXRET = \log(1 + R_{it}) - \log(1 + R_{S\&P\ 500,t})$ is the monthly log excess return on each firm's equity relative to the S&P 500 index. The moving average $EXRETAVG$ is designed to capture the idea that a sustained decline in stock market value is a better predictor of bankruptcy than a sudden stock price decline in a single month. $TLMTA$ is the ratio of total liabilities (item LTQ) divided by the sum of market equity and total liabilities. $SIGMA$ is the volatility of each firm's daily stock return over the past three months. $RSIZE$ is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index. $CASHMTA$, used to capture the liquidity position of the firm, is the ratio of cash and short-term investments (item CHEQ) divided by the sum of market equity and total liabilities. MB is the market-to-book equity. $PRICE$ is the log price per share of the firm. We also winsorize the market-to-book ratio and all other variables in the construction of F -prob at the 5th and 95th percentiles of their pooled distributions across all firm-months. Finally, we winsorize $PRICE$ at \$15.

Table 1 : Descriptive Statistics, Samples for Estimating Implied Costs of Equity

We present descriptive statistics including the mean, standard deviation, min, 25% percentile, median, 75% percentile, and max for all the anomaly variables. We also report the sample period and average number of firms in the cross-section for each sample that corresponds to a given anomaly variable. Book-to-market (B/M) is the book equity divided by the market equity at the end of fiscal year, and the book equity is measured as in Fama and French (1993). Size (ME) is market capitalization in millions of dollars. Composite issuance (CI) is the cumulative log five-year growth rate of total market equity minus the cumulative log five-year stock return. Net stock issues (NSI) are the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-1$ divided by the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-2$. Abnormal investment (AI) is the deviation of the current year investment-to-sales ratio from the past three-year moving average investment-to-sales. Asset growth (AG) is the percentage change in total assets from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$. Investment-to-assets (I/A) is the annual change in property, plant, and equipment plus the annual change in inventory divided by lagged total assets. Accruals (AC) are changes in non-cash working capital minus depreciation expense (scaled by average total assets) as in Sloan (1996). Earnings surprise (SUE) is the unexpected earnings defined as the most recent quarterly earnings per share minus earnings per share four quarters ago divided by the standard deviation of the unexpected earnings from the prior eight quarters. The distress measure is constructed as in Compbell, Hilscher, and Szilagyi (2008) and the failure probability (FP , in percent) is calculated as $1/[1 + \exp(-Distress)]$. Return-on-assets (ROA) is the most recent earnings divided by one-quarter-lagged total assets. Past five-year sales growth (SG) is the sales growth from year $t-5$ to t . Prior returns (MOM) are prior six-month returns at each portfolio formation month. See Section 2.2 and Appendix A for detailed variable definitions.

	Sample	# Firms	Mean	Std	Min	25%	50%	75%	Max
Panel A: The baseline implied costs of equity estimation									
<i>B/M</i>	80–08	2201	1.51	5.48	0.07	0.40	0.66	1.01	59.67
<i>ME</i>	80–08	2201	2147.63	6225.35	9.53	132.02	413.53	1368.66	57017.85
<i>CI</i>	80–08	1393	0.00	0.41	−1.67	−0.19	−0.05	0.16	1.70
<i>NSI</i>	80–08	2200	0.04	0.10	−0.22	0.00	0.01	0.03	0.65
<i>AI</i>	80–08	1513	0.29	0.51	−0.81	0.06	0.21	0.41	3.77
<i>AG</i>	80–08	1812	0.18	0.36	−0.40	0.01	0.09	0.22	2.66
<i>I/A</i>	80–08	1912	0.10	0.17	−0.36	0.02	0.07	0.14	1.13
<i>AC</i>	80–08	1631	−0.03	0.08	−0.32	−0.07	−0.04	0.01	0.30
<i>SUE</i>	80–08	2006	−0.10	3.41	−77.89	−0.63	0.05	0.67	37.06
<i>FP</i>	80–08	2038	0.06	0.13	0.01	0.03	0.04	0.06	2.88
<i>ROA</i>	80–08	2161	0.04	0.12	−0.64	0.00	0.04	0.08	0.40
<i>MOM</i>	80–08	2317	0.08	0.33	−0.80	−0.10	0.05	0.22	3.79
Panel B: The modified implied costs of equity estimation (the full Fama-French <i>ROE</i> forecasting regression)									
<i>B/M</i>	75–08	2091	1.41	3.38	0.11	0.50	0.82	1.28	34.44
<i>ME</i>	75–08	2091	1073.27	2792.25	3.10	45.07	174.47	723.69	22248.26
<i>CI</i>	75–08	1134	−0.05	0.43	−1.84	−0.22	−0.07	0.12	1.61
<i>NSI</i>	75–08	2091	0.03	0.10	−0.24	0.00	0.00	0.02	0.69
<i>AI</i>	75–08	1540	0.26	0.48	−0.77	0.04	0.18	0.37	3.58
<i>AG</i>	75–08	2091	0.14	0.29	−0.35	0.00	0.08	0.19	1.94
<i>I/A</i>	75–08	2076	0.09	0.16	−0.37	0.02	0.07	0.14	0.96
<i>AC</i>	75–08	1951	−0.03	0.08	−0.31	−0.07	−0.03	0.01	0.29
<i>SUE</i>	77–08	2119	0.48	29.41	−63.94	−0.59	0.07	0.68	1369.95
<i>FP</i>	75–08	2121	0.07	0.14	0.01	0.03	0.04	0.07	2.77
<i>ROA</i>	77–08	2268	0.04	0.12	−0.68	0.00	0.04	0.08	0.40
<i>MOM</i>	75–08	3108	0.09	0.34	−0.77	−0.10	0.05	0.22	4.80
Panel C: The modified implied costs of equity estimation (the simplified Fama-French <i>ROE</i> forecasting regression)									
<i>B/M</i>	75–08	2893	1.38	3.03	0.11	0.53	0.86	1.30	30.93
<i>ME</i>	75–08	2893	1070.64	2811.91	3.08	44.16	167.96	705.14	22495.58
<i>CI</i>	75–08	1534	−0.05	0.44	−1.86	−0.23	−0.07	0.13	1.65
<i>NSI</i>	75–08	2891	0.03	0.10	−0.24	0.00	0.00	0.02	0.70
<i>AI</i>	75–08	2025	0.26	0.46	−0.73	0.04	0.19	0.37	3.40
<i>AG</i>	75–08	2396	0.14	0.29	−0.36	0.00	0.08	0.19	1.95
<i>I/A</i>	75–08	2556	0.09	0.16	−0.38	0.01	0.06	0.13	0.98
<i>AC</i>	75–08	2181	−0.03	0.09	−0.31	−0.07	−0.03	0.01	0.30
<i>SUE</i>	77–08	2844	0.29	26.57	−184	−0.58	0.08	0.69	1355.05
<i>FP</i>	75–08	2920	0.08	0.15	0.01	0.03	0.04	0.07	3.05
<i>ROA</i>	77–08	3128	0.04	0.12	−0.68	0.00	0.04	0.08	0.40
<i>MOM</i>	75–08	3109	0.09	0.34	−0.77	−0.10	0.05	0.22	4.67

Table 2 : Multiple Regressions to Forecast Profitability

The table shows average slopes and their Fama-MacBeth t -statistics from annual cross-sectional regressions to predict profitability, $Y_{t+\tau}/B_{t+\tau-1}$, one, two, and three years ahead ($\tau = 1, 2, 3$). Y_t , D_t , and AC_t are earnings, dividends, and accruals per share for the fiscal year ending in calendar year t . $-AC_t$ is accruals for firms with negative accruals (zero otherwise) and $+AC_t$ is accruals for firms with positive accruals (zero otherwise). B_t is book equity per share at the end of fiscal year t . AG_t is the asset growth from the fiscal year ending in calendar year $t - 1$ to the fiscal year ending in calendar year t . ME_t is market capitalization (price times shares outstanding) at the end of fiscal year t . $Neg Y_t$ is a dummy that is one for firms with negative earnings for fiscal year t (zero otherwise), and $No D_t$ is a dummy that is one for firms that pay no dividends during fiscal year t . The sample is from 1963 to 2008. Int. is the regression intercept, and the R^2 is adjusted- R^2 .

τ	Int.	$\ln B_t/M_t$	$\ln ME_t$	Neg Y_t	Y_t/B_t	$-AC_t/B_t$	$+AC_t/B_t$	AG_t	No D_t	D_t/B_t	R^2
Panel A: The full Fama-French (2006) specification											
Average slopes											
1	0.01	-0.03	0.01	-0.04	0.63	-0.10	-0.03	-0.03	-0.02	0.12	0.43
2	0.00	-0.02	0.01	-0.07	0.39	-0.09	0.01	-0.05	-0.02	0.38	0.21
3	0.01	-0.01	0.01	-0.07	0.27	-0.09	0.02	-0.05	-0.02	0.52	0.13
t -statistics											
1	0.67	-4.09	3.26	-2.69	18.39	-5.80	-2.98	-4.60	-4.71	2.61	
2	0.15	-2.65	3.18	-3.59	13.45	-3.51	0.42	-6.61	-4.70	8.10	
3	0.29	-1.96	3.26	-3.27	9.67	-5.16	1.14	-5.60	-4.32	12.34	
Panel B: The simplified Fama-French specification											
Average slopes											
1	0.00	-0.02	0.01	-0.05	0.61			-0.04			0.43
2	-0.00	-0.02	0.01	-0.07	0.40			-0.06			0.20
3	0.00	-0.01	0.01	-0.06	0.31			-0.06			0.13
t -statistics											
1	0.23	-4.25	4.26	-2.88	18.33			-5.76			
2	-0.09	-2.62	4.86	-3.48	11.25			-8.06			
3	0.05	-1.78	5.15	-3.10	9.85			-8.72			

Table 3 : Descriptive Statistics of Implied Costs of Equity

We present descriptive statistics including the mean, standard deviation, min, 25% percentile, median, 75% percentile, and max for the implied costs of equity estimated on each sample corresponding to a given anomaly variable. The sample period, the average number of firms in the cross-section for each sample, and the variable definitions are reported in Table 1.

	Mean	Std	Min	25%	50%	75%	Max
Panel A: The implied costs of equity from the baseline estimation, $E_0[R]$							
<i>B/M</i>	12.02	4.84	1.63	9.58	11.53	13.54	36.74
<i>ME</i>	12.02	4.84	1.63	9.58	11.53	13.54	36.74
<i>CI</i>	11.59	4.17	2.73	9.45	11.20	13.01	33.29
<i>NSI</i>	12.02	4.84	1.63	9.58	11.53	13.54	36.73
<i>AI</i>	11.37	2.98	2.20	9.54	11.30	13.10	20.00
<i>AG</i>	11.93	4.86	1.66	9.42	11.40	13.50	36.13
<i>I/A</i>	11.93	4.81	1.52	9.44	11.43	13.52	35.98
<i>AC</i>	11.92	4.81	1.59	9.43	11.44	13.53	36.01
<i>SUE</i>	11.68	3.32	0.57	9.78	11.62	13.47	31.96
<i>FP</i>	11.75	3.88	1.50	9.68	11.54	13.42	36.30
<i>ROA</i>	11.89	4.25	1.47	9.67	11.57	13.51	36.67
<i>MOM</i>	11.71	3.41	0.50	9.79	11.68	13.55	32.61
Panel B: The implied costs of equity from the modified estimation, $E_1[R]$ (with the full Fama-French (2006) <i>ROE</i> forecasting regression)							
<i>B/M</i>	10.27	4.56	1.57	7.71	9.93	12.09	30.56
<i>ME</i>	10.27	4.56	1.57	7.71	9.93	12.09	30.56
<i>CI</i>	10.37	4.30	2.41	8.05	9.97	11.90	30.67
<i>NSI</i>	10.27	4.56	1.57	7.71	9.93	12.09	30.56
<i>AI</i>	10.08	3.17	2.05	8.03	10.06	12.03	19.10
<i>AG</i>	10.27	4.56	1.57	7.71	9.93	12.09	30.56
<i>I/A</i>	10.27	4.56	1.57	7.71	9.93	12.09	30.56
<i>AC</i>	10.16	4.51	1.54	7.61	9.82	11.99	30.09
<i>SUE</i>	9.77	3.62	1.37	7.45	9.70	11.91	28.68
<i>FP</i>	9.73	4.46	1.11	7.15	9.41	11.68	33.82
<i>ROA</i>	10.18	4.65	1.45	7.51	9.80	12.11	32.85
<i>MOM</i>	9.96	3.68	1.58	7.60	9.91	12.15	28.22
Panel C: The implied costs of equity from the modified estimation, $E_2[R]$ (with the shortened Fama-French (2006) <i>ROE</i> forecasting regression)							
<i>B/M</i>	10.63	4.52	1.36	8.16	10.41	12.52	30.56
<i>ME</i>	10.63	4.52	1.36	8.16	10.41	12.52	30.56
<i>CI</i>	10.67	4.19	2.23	8.39	10.38	12.31	29.88
<i>NSI</i>	10.63	4.51	1.37	8.16	10.41	12.52	30.46
<i>AI</i>	10.45	3.22	1.80	8.45	10.49	12.43	19.47
<i>AG</i>	10.53	4.55	1.39	7.97	10.25	12.46	30.06
<i>I/A</i>	10.55	4.59	0.63	7.99	10.29	12.52	30.08
<i>AC</i>	10.42	4.52	1.35	7.85	10.14	12.38	29.92
<i>SUE</i>	10.25	3.74	1.11	7.97	10.24	12.41	30.96
<i>FP</i>	10.19	4.50	0.91	7.64	9.95	12.20	34.11
<i>ROA</i>	10.63	4.73	1.20	7.98	10.31	12.60	33.66
<i>MOM</i>	10.40	3.79	1.29	40 8.08	10.41	12.61	30.39

Table 4 : Average Realized Returns and Expected Returns, Implied Costs of Equity, Baseline and Modified

We report the average realized returns, $A[R]$, the implied costs of equity from the baseline residual income model that uses the forecasted earnings from IBES, $E_0[R]$, the implied costs of equity from the modified residual income model that uses the Fama-French (2006) forecasted ROE , $E_1[R]$, and the implied costs of equity from the modified residual income model that uses the simplified Fama-French forecasted ROE , $E_2[R]$. In June of each year t from 1980 to 2008, we sort all NYSE stocks on book-to-market (B/M), size (ME), composite issuance (CI), net stock issues (NSI), abnormal investment (AI), asset growth (AG), investment-to-assets (I/A), and total accruals (AC) for the fiscal year ending in calendar year $t - 1$ and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into five quintiles. Value-weighted portfolio returns are calculated from July of year t to June of year $t + 1$. We also sort all NYSE stocks each month on the prior six-month returns (MOM) and earnings surprises (SUE), and use the NYSE breakpoints to split all stocks into quintiles. We hold the portfolios for six months and calculate value-weighted returns. Each month we use NYSE/Amex/Nasdaq breakpoints to sort all stocks on Campbell, Hilscher, and Szilagzi's (2008) failure probability (FP) into quintiles and calculate one-year value-weighted returns for each portfolio. Each month we also use NYSE breakpoints to sort all stocks on quarterly return-on-assets (ROA) and calculate value-weighted returns for the current month. Earnings and other Compustat quarterly accounting data for a fiscal quarter are used in portfolio sorts in the months immediately after its public earnings announcement month (Compustat quarterly item RDQ). See Section 2.2 and Appendix A for detailed variable definitions. "H-L" is the high-minus-low portfolios and "[t]" is heteroscedasticity-and-autocorrelation-consistent t -statistics testing a given H-L moment is zero. The sample periods are described in Table 1. All entries other than [t] are in annualized percent.

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	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$
	Panel A: B/M				Panel B: ME				Panel C: CI				Panel D: NSI			
Low	12.1	8.6	7.2	7.5	15.8	12.7	10.9	11.3	15.1	10.4	10.1	10.6	16.1	10.3	9.4	10.0
3	14.8	11.0	10.1	10.8	14.2	11.1	10.0	10.4	13.4	9.8	9.1	9.5	13.1	9.8	9.0	9.5
High	17.3	14.9	15.7	16.0	12.8	9.6	8.7	9.4	10.9	10.3	9.0	9.8	8.6	10.2	8.9	9.6
H-L	5.2	6.3	8.5	8.5	-3.0	-3.1	-2.2	-1.8	-4.2	-0.1	-1.1	-0.8	-7.5	-0.1	-0.5	-0.5
[t]	2.2	12.0	8.4	9.2	-0.8	-7.6	-6.0	-5.3	-2.8	-0.2	-4.2	-2.6	-3.0	-0.4	-1.6	-1.9
	Panel E: AI				Panel F: AG				Panel G: I/A				Panel H: AC			
Low	15.0	10.0	9.1	9.4	16.1	10.2	9.6	9.8	14.2	10.5	9.6	9.9	13.9	9.9	8.9	9.1
3	14.2	9.9	9.6	10.2	13.2	9.7	9.6	10.0	13.2	9.7	9.3	9.7	14.4	9.8	9.1	9.4
High	11.1	9.9	8.1	8.9	10.5	9.6	8.1	8.5	10.8	9.9	8.6	9.1	9.1	9.8	8.4	8.8
H-L	-4.0	-0.1	-1.0	-0.5	-5.6	-0.6	-1.5	-1.2	-3.4	-0.5	-1.0	-0.9	-4.8	-0.0	-0.5	-0.3
[t]	-2.4	-0.2	-2.7	-1.1	-2.8	-3.0	-5.6	-4.4	-1.8	-3.0	-5.6	-4.5	-3.6	-0.1	-3.3	-1.8
	Panel I: SUE				Panel J: FP				Panel K: ROA				Panel L: MOM			
Low	8.6	10.1	9.2	9.9	13.8	9.2	7.8	8.2	5.9	11.0	9.8	10.6	5.6	11.2	9.9	10.6
3	10.9	10.1	8.9	9.5	12.4	11.2	9.8	10.4	10.1	10.5	10.0	10.3	11.0	10.1	9.0	9.7
High	13.5	10.0	8.3	8.9	5.7	13.1	10.8	11.5	12.4	9.3	7.7	8.0	13.7	9.7	7.8	8.4
H-L	4.9	-0.1	-0.9	-1.0	-8.1	3.8	3.0	3.3	6.5	-1.7	-2.1	-2.7	8.1	-1.5	-2.1	-2.2
[t]	5.5	-3.1	-19.2	-18.5	-5.0	34.8	21.0	25.8	3.3	-22.0	-19.3	-35.1	4.4	-15.7	-23.3	-23.0

Table 5 : Expected Return Estimates Conditional on Long-Term Growth Forecasts

In June of year t , we sort stocks into terciles based on analysts long-term growth forecasts. In each growth tercile, firms are sorted again into quintiles based on the NYSE breakpoints for the following firm characteristics: book-to-market (B/M), size (ME), composite issuance (CI), net stock issues (NSI), abnormal investment (AI), asset growth (AG), investment-to-assets (I/A), and total accruals (AC). We calculate value-weighted portfolio returns from July of year t to June of year $t + 1$. In each growth tercile, we also use the NYSE breakpoints of the prior six-month returns (MOM), earnings surprises (SUE), and return-on-assets (ROA) and the NYSE/Amex/Nasdaq breakpoints of failure probability (FP) to split the stocks into quintiles each month. We calculate six-month value-weighted returns for the MOM , SUE , and ROA portfolios and one-year value-weighted returns for the FP portfolios. $A[R]$ is average realized returns. $E_0[R]$ is the implied costs of equity from the baseline estimation. $E_1[R]$ is the implied costs of equity from the modified estimation with the Fama-French (2006) ROE forecasts. $E_2[R]$ is the implied costs of equity from the modified estimation with the simplified Fama-French ROE forecasts. H-L is the high-minus-low quintiles and $[t]$ is heteroscedasticity-and-autocorrelation-consistent t -statistics. The sample periods are described in Table 1. Implied costs of equity are in annualized percent.

		Low Ltg		2		High Ltg				Low Ltg		2		High Ltg		
		H-L	$[t]$	H-L	$[t]$	H-L	$[t]$			H-L	$[t]$	H-L	$[t]$	H-L	$[t]$	
B/M	$A[R]$	4.0	1.7	3.5	1.2	7.8	2.8	$E_0[R]$	7.0	8.7	6.0	10.7	6.3	11.0		
	$E_1[R]$	8.4	5.9	5.6	11.0	7.9	8.6	$E_2[R]$	8.7	5.9	6.3	9.6	7.8	10.3		
ME	$A[R]$	-0.9	-0.3	-2.3	-0.7	-1.7	-0.4	$E_0[R]$	-2.7	-4.6	-3.6	-7.2	-3.6	-11.1		
	$E_1[R]$	-2.4	-4.5	-2.5	-6.7	-2.6	-13.6	$E_2[R]$	-1.7	-4.0	-2.3	-5.5	-2.5	-10.1		
CI	$A[R]$	-1.0	-0.6	-5.6	-2.7	-9.1	-4.3	$E_0[R]$	0.2	0.7	0.6	2.1	0.3	0.9		
	$E_1[R]$	0.6	1.1	0.1	0.3	-0.7	-2.1	$E_2[R]$	0.1	0.4	0.2	0.5	0.5	0.8		
NSI	$A[R]$	-3.7	-1.9	-5.6	-2.5	-10.2	-3.6	$E_0[R]$	-0.5	-1.8	0.4	1.8	-0.7	-2.0		
	$E_1[R]$	0.7	1.8	0.0	0.2	-1.1	-5.3	$E_2[R]$	0.1	0.3	0.1	0.6	-0.9	-4.4		
AI	$A[R]$	-1.8	-1.2	-1.5	-0.9	-4.6	-1.3	$E_0[R]$	0.8	3.9	0.4	1.5	-0.3	-1.3		
	$E_1[R]$	0.8	1.9	-0.4	-1.0	-1.2	-3.2	$E_2[R]$	1.2	2.7	0.4	0.9	-0.4	-1.1		
AG	$A[R]$	-0.4	-0.2	-6.4	-3.0	-9.1	-1.8	$E_0[R]$	-0.4	-2.0	-0.2	-0.8	-1.2	-4.8		
	$E_1[R]$	0.1	0.2	-0.8	-3.3	-1.6	-5.2	$E_2[R]$	0.3	0.9	-0.7	-2.8	-1.5	-4.7		
I/A	$A[R]$	-0.5	-0.2	-3.0	-1.7	-7.3	-1.6	$E_0[R]$	0.0	-0.4	-0.2	-1.3	-1.2	-6.8		
	$E_1[R]$	0.2	0.6	-0.4	-2.1	-1.9	-6.7	$E_2[R]$	0.5	1.9	-0.4	-2.3	-1.3	-5.1		
AC	$A[R]$	-1.1	-0.4	-6.1	-2.2	-6.8	-2.7	$E_0[R]$	0.2	0.7	0.0	0.0	0.4	1.5		
	$E_1[R]$	-0.2	-0.9	-0.4	-1.9	-0.2	-1.0	$E_2[R]$	0.2	0.6	-0.1	-0.8	0.0	0.1		
SUE	$A[R]$	3.6	3.1	4.3	3.2	5.3	3.1	$E_0[R]$	-0.3	-3.6	-0.3	-4.1	0.1	1.8		
	$E_1[R]$	-1.2	-18.6	-0.8	-11.9	-0.6	-7.2	$E_2[R]$	-1.3	-15.4	-0.7	-10.8	-0.7	-7.4		
FP	$A[R]$	-2.7	-1.5	-6.1	-3.0	-10.7	-5.0	$E_0[R]$	3.6	21.5	3.7	27.0	3.3	30.2		
	$E_1[R]$	3.2	12.6	3.2	19.4	2.7	16.7	$E_2[R]$	3.7	19.5	3.7	21.5	2.7	18.1		
ROA	$A[R]$	3.3	1.3	3.8	1.5	8.8	3.3	$E_0[R]$	-1.8	-20.4	-1.9	-21.6	-0.9	-5.8		
	$E_1[R]$	-1.3	-8.3	-1.8	-14.2	-2.0	-12.1	$E_2[R]$	-2.4	-20.0	-2.4	-25.2	-2.1	-12.6		
MOM	$A[R]$	4.3	1.8	7.5	3.5	13.0	4.9	$E_0[R]$	-1.3	-9.1	-1.4	-12.7	-1.7	-17.4		
	$E_1[R]$	-2.4	-18.7	-1.9	-23.7	-2.4	-24.3	$E_2[R]$	-2.5	-18.9	-2.0	-22.1	-2.5	-23.8		

Table 6 : Descriptive Statistics, Samples for Estimating Expected Returns and Expected Growth Rates Simultaneously

We present descriptive statistics including the mean, standard deviation, min, 25% percentile, median, 75% percentile, and max for all the anomaly variables. We also report the sample period and average number of firms in the cross-section for each sample that corresponds to a given anomaly variable. Book-to-market (B/M) is the book equity divided by the market equity at the end of fiscal year, and the book equity is measured as in Fama and French (1993). Size (ME) is market capitalization in millions of dollars. Composite issuance (CI) is the cumulative log five-year growth rate of total market equity minus the cumulative log five-year stock return. Net stock issues (NSI) are the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-1$ divided by the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-2$. Abnormal investment (AI) is the deviation of the current year investment-to-sales ratio from the past three-year moving average investment-to-sales. Asset growth (AG) is the percentage change in total assets from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$. Investment-to-assets (I/A) is the annual change in property, plant, and equipment plus the annual change in inventory divided by lagged total assets. Accruals (AC) are changes in non-cash working capital minus depreciation expense (scaled by average total assets) as in Sloan (1996). Earnings surprise (SUE) is the unexpected earnings defined as the most recent quarterly earnings per share minus earnings per share four quarters ago divided by the standard deviation of the unexpected earnings from the prior eight quarters. The distress measure is constructed as in Compbell, Hilscher, and Szilagyi (2008) and the failure probability (FP , in percent) is calculated as $1/[1 + \exp(-\text{Distress})]$. Return-on-assets (ROA) is the most recent earnings divided by one-quarter-lagged total assets. Past five-year sales growth (SG) is the sales growth from year $t-5$ to t . Prior returns (MOM) are prior six-month returns at each portfolio formation month. See Section 2.2 and Appendix A for detailed variable definitions.

	Sample	# Firms	Mean	Std	Min	25%	50%	75%	Max
Panel A: The baseline ETSS estimation									
<i>B/M</i>	80-08	3026	1.58	6.59	0.05	0.37	0.63	0.98	79.12
<i>ME</i>	80-08	3026	1899.10	5580.70	8.92	127.32	368.64	1195.65	50932.74
<i>CI</i>	80-08	1649	0.01	0.43	-1.68	-0.19	-0.04	0.18	1.76
<i>NSI</i>	80-08	2777	0.05	0.12	-0.22	0.00	0.01	0.04	0.80
<i>AI</i>	80-08	1753	0.32	0.58	-1.05	0.06	0.22	0.43	4.37
<i>AG</i>	80-08	2296	0.22	0.46	-0.42	0.01	0.10	0.25	3.58
<i>I/A</i>	80-08	2415	0.11	0.19	-0.36	0.02	0.07	0.15	1.32
<i>AC</i>	80-08	2061	-0.03	0.09	-0.33	-0.07	-0.03	0.01	0.33
<i>SUE</i>	80-08	2442	-0.10	3.42	-84.30	-0.63	0.05	0.66	39.43
<i>FP</i>	80-08	2222	0.07	0.15	0.01	0.03	0.04	0.06	3.41
<i>ROA</i>	80-08	2560	0.04	0.12	-0.80	0.00	0.04	0.08	0.40
<i>MOM</i>	80-08	2710	0.08	0.34	-0.82	-0.11	0.05	0.22	4.13
Panel B: The modified ETSS estimation (the full Fama-French <i>ROE</i> forecasting regression)									
<i>B/M</i>	75-08	2851	1.43	3.73	0.10	0.48	0.79	1.24	40.52
<i>ME</i>	75-08	2851	959.22	2509.42	2.64	46.09	164.44	645.51	20150.88
<i>CI</i>	75-08	1507	-0.05	0.45	-1.87	-0.22	-0.06	0.14	1.72
<i>NSI</i>	75-08	2850	0.04	0.12	-0.24	0.00	0.01	0.04	0.79
<i>AI</i>	75-08	1859	0.27	0.53	-0.88	0.03	0.18	0.38	3.90
<i>AG</i>	75-08	2851	0.17	0.35	-0.38	0.00	0.09	0.22	2.36
<i>I/A</i>	75-08	2824	0.10	0.17	-0.39	0.02	0.07	0.15	1.15
<i>AC</i>	75-08	2654	-0.03	0.09	-0.34	-0.07	-0.03	0.02	0.33
<i>SUE</i>	77-08	2579	0.31	25.18	-76.97	-0.61	0.06	0.68	1334.37
<i>FP</i>	75-08	2337	0.09	0.18	0.01	0.03	0.04	0.07	3.56
<i>ROA</i>	77-08	2564	0.00	0.16	-0.88	0.00	0.04	0.08	0.40
<i>MOM</i>	75-08	2805	0.09	0.37	-0.79	-0.12	0.04	0.23	4.64
Panel C: The O'Hanlon-Steele estimation									
<i>B/M</i>	65-08	3369	1.55	5.14	0.04	0.48	0.79	1.22	64.94
<i>ME</i>	65-08	3369	973.60	3049.27	1.54	39.13	139.05	559.04	27092.75
<i>CI</i>	65-08	1749	-0.05	0.41	-1.64	-0.22	-0.07	0.12	1.60
<i>NSI</i>	65-08	3369	0.04	0.11	-0.23	0.00	0.01	0.03	0.88
<i>AI</i>	65-08	1983	0.25	0.47	-1.04	0.04	0.17	0.35	3.48
<i>AG</i>	65-08	2825	0.17	0.39	-0.49	0.00	0.09	0.21	3.19
<i>I/A</i>	65-08	2973	0.10	0.20	-0.47	0.02	0.07	0.14	1.50
<i>AC</i>	70-08	2431	-0.02	0.09	-0.41	-0.07	-0.03	0.02	0.37
<i>SUE</i>	77-08	3311	0.20	23.56	-195.56	-0.60	0.07	0.69	1341.16
<i>FP</i>	75-08	2975	0.09	0.19	0.01	0.03	0.04	0.08	3.89
<i>ROA</i>	77-08	3310	0.00	0.16	-1.00	0.00	0.04	0.08	0.40
<i>MOM</i>	65-08	3765	0.08	0.38	-0.84	-0.12	0.04	0.22	5.94

Table 7 : Expected Growth Rates, the Baseline and Modified Easton Models, the O’Hanlon-Steele Model

We report the estimated growth rates from the baseline Easton et al. (2002) model that uses the forecasted earnings from IBES, g_0 , the growth rates from the modified Easton et al. model that uses the Fama-French (2006) forecasted ROE , g_1 , and the estimated growth rates from the O’Hanlon-Steele model, g_2 . For comparison, we also report the average dividend growth rates from the dividend discounting model, $A[G]$. In June of each year t from 1980 to 2008, we sort all NYSE stocks on book-to-market (B/M), size (ME), composite issuance (CI), net stock issues (NSI), abnormal investment (AI), asset growth (AG), investment-to-assets (I/A), and total accruals (AC) for the fiscal year ending in calendar year $t - 1$ and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles. Value-weighted portfolio returns are calculated from July of year t to June of year $t + 1$. We also sort all NYSE stocks each month on the prior six-month returns (MOM) and earnings surprises (SUE), and use the NYSE breakpoints to split all stocks into quintiles. We hold the portfolios for six months and calculate value-weighted returns. Each month we use NYSE/Amex/Nasdaq breakpoints to sort all stocks on Campbell, Hilscher, and Szilagzi’s (2008) failure probability (FP) into quintiles and calculate one-year value-weighted returns for each portfolio. Each month we also use NYSE breakpoints to sort all stocks on quarterly return-on-assets (ROA) and calculate value-weighted returns for the current month. Earnings and other Compustat quarterly accounting data for a fiscal quarter are used in portfolio sorts in the months immediately after its public earnings announcement month (Compustat quarterly item RDQ). See Section 2.2 and Appendix A for detailed variable definitions. “H–L” is the high-minus-low portfolios and “[t]” is heteroscedasticity-and-autocorrelation-consistent t -statistics testing a given H–L moment is zero. The sample periods are in Table 1. All entries other than [t] are in annualized percent.

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	$A[G]$	g_0	g_1	g_2	$A[G]$	g_0	g_1	g_2	$A[G]$	g_0	g_1	g_2	$A[G]$	g_0	g_1	g_2
	Panel A: B/M				Panel B: ME				Panel C: CI				Panel D: NSI			
Low	5.0	6.3	17.5	18.6	10.5	2.2	4.8	3.9	6.9	1.6	8.2	11.3	11.0	5.2	8.9	10.3
3	7.7	5.3	10.8	10.1	7.5	13.1	8.9	11.2	5.9	6.6	8.6	9.0	9.4	5.0	9.0	11.7
High	9.1	1.4	2.2	4.7	5.3	7.4	10.0	14.8	5.8	10.9	8.6	11.9	4.4	8.8	9.4	13.4
H–L	4.1	–4.9	–15.4	–13.9	–5.2	5.1	5.2	10.9	–1.1	9.2	0.4	0.6	–6.6	3.6	0.5	3.1
[t]	1.3	–2.6	–27.1	–10.7	–1.1	4.0	5.6	4.5	–0.4	3.7	0.4	0.5	–1.2	2.1	0.8	3.6
	Panel E: AI				Panel F: AG				Panel G: I/A				Panel H: AC			
Low	7.3	8.3	3.4	4.2	8.8	10.3	5.4	4.9	7.4	6.2	5.9	8.9	8.2	8.8	8.1	9.5
3	6.5	6.1	8.5	9.2	5.8	6.8	9.7	10.6	5.7	6.9	10.0	11.6	7.3	9.3	9.9	12.0
High	8.5	8.4	12.1	19.6	9.4	15.1	11.6	18.8	8.5	14.1	11.1	16.1	7.1	8.2	11.5	17.6
H–L	1.2	0.1	8.6	15.5	0.6	4.8	6.2	13.9	1.1	8.0	5.2	7.3	–1.1	–0.6	3.5	8.1
[t]	0.4	0.0	6.1	9.7	0.1	1.3	5.8	11.0	0.4	2.2	7.6	8.4	–0.3	–0.2	4.9	6.5
	Panel I: SUE				Panel J: FP				Panel K: ROA				Panel L: MOM			
Low	8.1	11.2	14.8	14.6	11.7	11.5	15.3	17.6	6.7	6.2	5.9	7.4	10.6	5.2	12.0	11.7
3	8.8	12.9	12.5	11.6	9.0	12.7	11.2	12.6	7.6	10.5	11.9	11.0	11.8	9.0	13.3	12.3
High	12.2	13.3	13.0	13.3	29.4	–8.6	–3.9	–4.4	12.1	15.7	19.1	19.8	14.0	13.6	12.9	13.5
H–L	4.1	2.2	–1.8	–1.3	17.8	–20.0	–19.2	–22.0	5.4	9.5	13.2	12.5	3.4	8.5	0.8	1.8
[t]	7.6	4.7	–10.1	–4.1	4.1	–15.8	–23.2	–15.3	4.6	16.1	34.0	20.9	8.4	9.7	3.1	5.9

Table 8 : Average Returns and Expected Returns, the Baseline and Modified Easton Models, the O’Hanlon-Steele Model

We report the average realized returns, $A[R]$, the expected returns from the baseline Easton et al. (2002) model that uses the forecasted earnings from IBES, r_0 , the expected returns from the modified Easton et al. model that uses the Fama-French (2006) forecasted ROE , r_1 , and the expected returns from the O’Hanlon-Steele model, r_2 . In June of each year t from 1980 to 2008, we sort all NYSE stocks on book-to-market (B/M), size (ME), composite issuance (CI), net stock issues (NSI), abnormal investment (AI), asset growth (AG), investment-to-assets (I/A), and total accruals (AC) for the fiscal year ending in calendar year $t - 1$ and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles. Value-weighted portfolio returns are calculated from July of year t to June of year $t + 1$. We also sort all NYSE stocks each month on the prior six-month returns (MOM) and earnings surprises (SUE), and use the NYSE breakpoints to split all stocks into quintiles. We hold the portfolios for six months and calculate value-weighted returns. Each month we use NYSE/Amex/Nasdaq breakpoints to sort all stocks on Campbell, Hilscher, and Szilagzi’s (2008) failure probability (FP) into quintiles and calculate one-year value-weighted returns for each portfolio. Each month we also use NYSE breakpoints to sort all stocks on quarterly return-on-assets (ROA) and calculate value-weighted returns for the current month. Earnings and other Compustat quarterly accounting data for a fiscal quarter are used in portfolio sorts in the months immediately after its public earnings announcement month (Compustat quarterly item RDQ). See Section 2.2 and Appendix A for detailed variable definitions. “H–L” is the high-minus-low portfolios and “[t]” is heteroscedasticity-and-autocorrelation-consistent t -statistics testing a given H–L moment is zero. The sample periods are in Table 1. All entries other than [t] are in annualized percent.

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	$A[R]$	r_0	r_1	r_2	$A[R]$	r_0	r_1	r_2	$A[R]$	r_0	r_1	r_2	$A[R]$	r_0	r_1	r_2
	Panel A: B/M				Panel B: ME				Panel C: CI				Panel D: NSI			
Low	12.7	10.7	18.6	19.6	15.4	4.9	5.3	5.0	15.3	8.1	12.4	14.6	17.0	10.5	12.4	13.2
3	15.2	9.9	11.7	11.8	14.1	14.0	10.8	12.6	14.1	10.5	12.1	12.5	14.2	9.3	11.7	13.8
High	16.9	8.6	5.9	7.9	13.2	11.3	12.8	16.4	12.1	13.2	10.8	14.0	9.7	11.2	10.8	14.6
H–L	4.2	–2.1	–12.7	–9.4	–2.2	6.4	7.5	11.8	–3.2	5.2	–1.6	–1.9	–7.3	0.8	–1.7	–0.2
[t]	1.7	–1.0	–12.2	–6.0	–0.6	5.6	5.6	4.7	–2.0	3.0	–2.1	–2.0	–2.7	0.7	–2.6	–0.2
	Panel E: AI				Panel F: AG				Panel G: I/A				Panel H: AC			
Low	15.0	11.8	7.2	6.7	15.9	12.1	7.8	6.6	14.4	10.9	9.1	10.7	14.3	11.7	10.3	10.7
3	14.2	10.4	11.9	12.5	13.7	10.8	12.8	13.2	13.7	10.9	12.8	13.9	14.8	12.8	12.6	14.5
High	12.5	11.2	14.2	20.8	11.7	16.7	13.3	19.9	11.9	15.5	12.8	17.4	10.7	11.1	13.4	19.0
H–L	–2.5	–0.6	6.9	12.8	–4.3	4.6	5.4	12.6	–2.5	4.6	3.7	6.2	–3.6	–0.6	3.1	8.4
[t]	–1.4	–0.2	6.4	9.7	–2.2	1.9	5.8	9.3	–1.2	1.8	6.2	7.0	–3.7	–0.3	5.1	6.9
	Panel I: SUE				Panel J: FP				Panel K: ROA				Panel L: MOM			
Low	9.2	13.9	17.0	17.1	14.3	14.8	17.0	19.1	6.6	6.8	6.7	7.0	6.2	13.5	14.0	13.5
3	10.9	15.9	14.5	13.6	12.6	15.3	13.0	14.3	10.4	13.6	13.6	12.5	11.3	15.3	15.6	14.5
High	13.9	16.3	14.6	14.9	7.2	–9.4	–4.5	–4.5	12.8	18.5	20.2	21.5	14.6	16.0	14.2	14.8
H–L	4.6	2.4	–2.5	–2.2	–7.2	–24.2	–21.6	–23.6	6.2	11.7	13.5	14.5	8.4	2.4	0.2	1.3
[t]	5.6	7.5	–16.6	–8.1	–4.4	–16.8	–19.6	–17.0	3.4	21.9	30.8	24.9	4.5	7.1	0.7	4.7