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Abstract

Average realized returns equal average expected returns plus average unexpected returns. If anomalies are driven by risk, average expected returns should be close to average realized returns. If anomalies are driven by mispricing, unexpected returns should be more important. We estimate accounting-based expected returns to zero-cost trading strategies formed on anomaly variables such as 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, expected return estimates differ dramatically from average return estimates. The evidence suggests 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 behind capital markets anomalies, which 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 an array of economic explanations for capital markets anomalies (see Appendix A for a brief review). 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, new classical finance argues that risk and expected returns vary with firm characteristics in a systematic way, and that anomalies are driven by time-varying expected returns (risk) (e.g., Cochrane (1996), Berk, Green, and Naik (1999), Zhang (2005), and Liu, Whited, and Zhang (2009)).

We aim to 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 account for the bulk of average realized returns. Building on the latest accounting literature on expected return estimation, we use the residual income model to estimate expected returns for zero-cost trading strategies formed on a comprehensive list of anomaly variables. Under the model, the expected return can be calculated as the internal 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)). Using accounting-based models has the added advantage that accounting identities always hold regardless of investor rationality or lack thereof.

Our key message is that expected return estimates differ drastically from average return estimates for most anomalies, suggesting that mispricing, not risk, is the main driving force behind anomalies. In particular, 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 terms of 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 slightly more than two standard errors from zero. 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, whereas the average return estimate is within one standard error of zero.

However, for all the other anomaly variables, the average return estimates and the expected return estimates differ dramatically in terms of economic magnitude. In the data, 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 returns, which range 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 zero-cost 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 estimate of -0.6% ($t = -3.0$), its magnitude does not come close to its average return estimate of -5.6% ($t = -2.8$).

What makes matters worse is that the expected return estimates even have the opposite signs as the average return estimates 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%.

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, Dijk, and Zhang (2009)). We find that our basic inferences are robust to the use of profitability forecasts based on cross-sectional regressions.

Second, in a stream of influential articles, Easton, Taylor, Shroff, and Sougiannis (2002), Easton (2006, 2007), 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 can estimate the expected returns and the expected growth rates for a portfolio simultaneously. To evaluate the impact of the growth rate assumption, we implement these alternative estimation methods on our testing portfolios. We find that these methods often predict growth rate spreads that go in the opposite direction as the growth rate spreads in the data. These counterfactual predictions cast serious doubt on the validity of these alternative methods for estimating expected returns. While we do not improve on the treatment of growth rates in the Gebhardt et al. procedure, our results suggest that their procedure is probably among the best accounting-based expected return models in the contemporary literature.

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

2 Empirical Design

We describe our data in Section 2.1 and delineate the expected return estimation in Section 2.2.

2.1 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 dividend 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 B 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., Rosenberg, Reid, and Lanstein (1985), Fama and French (1993), and Lakonishok, Shleifer, and Vishny (1994)). We follow Fama and French in measuring this anomaly variable. Small firms earn higher average returns than big firms (e.g., Banz (1981)). We calculate ME as the market equity (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 in the future three to five years (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. From Daniel and Titman (2006), CI measures the part of firm growth in market equity that is not due to stock returns. From Fama and French (2008),

NSI measures the annual change in the logarithm of the number of real shares outstanding, which adjusts 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 benchmark investment, which is defined as 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 measured as 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. Following Sloan, we measure AC as 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)). The definition of 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. We measure return-on-assets, ROA, as income before extraordinary items (Compustat quarterly item IBQ) divided by last quarterly's assets (item ATQ).

Failure probability (FP). The financial distress anomaly says that more distressed firms earn abnormally lower average returns than less distressed firms (e.g., Dichev (1998) and 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 equity, and log price per share.

Momentum (MOM). Jegadeesh and Titman (1993) show that stocks that perform well in the recent six to twelve months continue to earn higher average returns in the future six to twelve months than stocks that perform poorly in the recent six to twelve months. Following Jegadeesh and Titman, 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 $t+1$. 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 sort all NYSE stocks on their most recent SUEs, and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into five groups. 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 in the definition of failure probability.

To construct the ROA quintiles, we sort NYSE stocks based on the ranked values of quarterly ROA, and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles. We use quarterly earnings in portfolio sorts only in the months immediately after the most recent earnings announcement (Compustat quarterly item RDQ). For example, if the earnings for the fourth fiscal quarter in year t are announced on March 5 (or March 25) of year $t+1$, we use the announced earnings to calculate ROA to form portfolios at the beginning of April and to calculate the resulting portfolio returns over April of year $t+1$. In particular, 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 sort all NYSE stocks on CRSP on the prior six-month returns and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles. We hold the portfolios for six months, and calculate the value-weighted returns with and without dividends.

2.2 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.[1]

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

[1]A large literature in accounting uses valuation models to estimate expected returns. Many studies calculate expected returns from analysts earnings forecasts under the residual income model (e.g., Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), Guay, Kothari, and Shu (2005), Hou, Dijk, and Zhang (2009), and Lee, So, and Wang (2010)). Easton, Taylor, Shroff, and Sougiannis (2002), Easton (2006), and Easton and Sommers (2007) implement the residual income model by estimating the expected returns and the implied growth rates simultaneously at the portfolio level (see Section 4 for more discussion on these methods). Francis, LaFond, Olsson, and Schipper (2004) and Brav, Lehavy, and Michaely (2005) use Value Line analysts expectations to estimate expected returns. Pastor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Chava and Purnanandam (2010) apply these estimation methods to address important questions in finance.

expectations. We compute a finite horizon estimate of equity value for each firm:

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

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 ($k =$ 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:

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

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 rebalanced momentum portfolios, for each month we sort all NYSE stocks on CRSP on the prior six-month realized returns and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles. We hold the portfolios for six months and value-weight the expected returns across firms in a given portfolio for each month. 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. The procedure for the SUE portfolios is similar. For each month we sort all NYSE stocks on their most recent past SUE, and use the NYSE breakpoints to split NYSE, Amex, and Nasdaq stocks into quintiles. We hold the resulting portfolios for six months and calculate the value-weighted $E_0[R]$ estimated for each month. For the monthly rebalanced ROA portfolios, we use NYSE breakpoints to sort all stocks into quintiles based on the most recent ROA at the beginning of each month. For the FP quintiles, we sort all NYSE, Amex, and Nasdaq stocks on the most recent FP into quintiles in each month. We calculate the value-weighted $E_0[R]$ for each portfolio in each month.

Two Modified Estimation Procedures

The baseline estimation of the implied costs of equity uses analysts earnings forecasts from IBES as expected earnings. 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 zero-cost 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 issues, 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 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 data requirements such that 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 simplified 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 the current 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, 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.

Descriptive Statistics

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.

3 Expected Return Estimates as Implied Costs of Equity

After we discuss intermediate results on forecasting profitability in Section 3.1, we turn to our central results on expected return estimation in Section 3.2.

3.1 Forecasting Profitability

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 (although 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).

3.2 Expected Return Estimates

Table 3 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). To preview the result, Table 3 shows that for most anomalies, the average return and the expected return estimates differ dramatically across the testing portfolios. This evidence suggests that most anomalies are driven by predictable unexpected returns (mispricing), as opposed to time-varying expected returns (risk).

Panel A shows that the expected value premiums from different estimation methods are similar in magnitude, and are all significantly positive. 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. However, 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 (relatively) close to the average return estimate. Both of the expected return estimates are more than eight standard errors from zero. From Panel B, the expected return estimates of the small-minus-big quintile range from 1.8% to 3.1% per annum, which are close to the average return estimate of 3%. However, while the average return estimate is insignificant, the expected return estimates 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 zero-cost 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. Wu, 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.

The remaining four panels in Table 3 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 positive, 3.8%, and is highly significant. This evidence is consistent with Chava and Purnanandam (2010), who also show that more distressed firms have higher implied costs of equity than less distressed firms in the baseline GLS estimation. We add to their work by showing that their inferences are robust to their use of analysts earnings forecasts because the two modified procedures deliver largely similar results.

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 highly significant. The estimates from the two modified procedures are largely similar: −2.1% and −2.7%, which are again highly significant. Finally, Panel L shows that the winner-minus-loser quintile 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.

In summary, the central message from Table 3 is clear. The average return estimates and the expected return estimates are drastically different across the testing portfolios, except for the value premium. This evidence means that mispricing, not risk, is the main driving force behind most anomalies. We also show that the expected return estimates from the modified estimation procedures are largely similar to those from the baseline procedure. This evidence means that bias in analysts forecasts is not quantitatively important for estimating expected returns at the portfolio level.

4 Estimating Expected Returns and Expected Growth Rates Simultaneously

The basic inferences are based on the GLS procedure of estimating expected returns. Easton, Taylor, Shroff, and Sougiannis (2002, ETSS hereafter), Easton (2006, 2007), and Easton and Sommers

(2007) argue that the assumed growth rates beyond the short forecast horizon in the GLS procedure can be different from the growth rates in the data, and that this difference can introduce bias in the expected return estimates. These authors propose methods to estimate the expected returns and expected growth rates of a given portfolio simultaneously. To evaluate the impact of the growth rate assumption on our basic inferences, we implement these alternative methods on our testing portfolios. We find that these methods often yield counterfactual implications for the cross-section of expected growth. In our view these results invalidate the use of these alternative methods. While these results do not improve on the treatment of growth rate in the GLS estimation, they do suggest that the GLS procedure is probably among the best that the latest accounting literature has to offer.

4.1 Methodology

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

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

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:

$$P_{it} = B_{it} + \frac{Y_{it+1}^{IBES} - r_i \times B_{it}}{r_i - g_i} \tag{4}$$

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:

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

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

$$\frac{Y_{it+1}^{IBES}}{B_{it}} = \gamma_0 + \gamma_1 \frac{P_{it}}{B_{it}} + \mu_{it} \tag{6}$$

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:

$$P_{it} = B_{it} + \frac{(Y_{it} - r_i \times B_{it-1})(1 + g_i')}{r_i - g_i'} \tag{7}$$

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:

$$\frac{Y_{it}}{B_{it-1}} = r_i + \frac{r_i - g_i'}{1 + g_i'} \frac{P_{it} - B_{it}}{B_{it-1}} \tag{8}$$

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:

$$\frac{Y_{it}}{B_{it-1}} = \delta_0 + \delta_1 \frac{P_{it} - B_{it}}{B_{it-1}} + \mu_{it} \tag{9}$$

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 Estimation Results

Preliminaries

Panel A of Table 4 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). Although this estimation is not subject to analysts forecasting bias, 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 be available to forecast ROE, the sample size is larger. In particular, 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.

Expected Growth Rate Estimates

Table 5 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. To facilitate comparison, we also report the average dividend growth rates in the data, $A[G]$. We follow Hansen, Heaton, and Li (2005) and Chen, Petkova, and Zhang (2008) in measuring dividend growth rates at the portfolio level (see Appendix C for details). We find that implied growth rate spreads across the testing portfolios often go in the opposite direction as those in the data. This counterfactual pattern casts doubt on the validity of the alternative methods of estimating expected returns.

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 expected 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 expected 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%.

Why do these alternative methods deliver counterfactual implications of expected growth? In our view 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 perpetuity 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).

Expected Return Estimates

Table 6 reports expected return estimates using the alternative methods that determine expected returns and growth rates simultaneously for the testing portfolios. Because of the counterfactual results on expected growth rates reported in Table 5, 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 Sougiannis (2002) show that their baseline procedure works well at the aggregate level in that it delivers reasonable equity premium estimates. Table 6 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.

Similar drastic 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 observe from the remaining four panels of Table 6 that the average return estimates also diverge from the expected return estimates for the rest of the anomaly variables.

5 Conclusion

We use valuation models to estimate expected returns to anomalies-based trading strategies 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 central message is that except for the value premium, expected return estimates differ dramatically from average realized returns. The evidence suggests that mispricing, not risk, is the main driving force behind most capital markets anomalies.

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A A Brief Review of Explanations of Capital Markets Anomalies

Explanations of capital markets anomalies can be broadly categorized into two groups. Behavioral finance argues that investors make systematic mistakes in pricing assets, and that these mistakes give rise to predictable pricing errors manifested as anomalies. New classical finance argues that risk and expected returns vary systematically with firm characteristics, and that time-varying expected returns give rise to anomalous empirical relations between average returns and firm characteristics.

A decomposition of average realized returns into expected returns and unexpected returns can disentangle the two competing schools of thought. In behavioral models, average realized returns should equal average unexpected returns, whereas in new classical models, average realized returns should equal average expected returns.

A.1 Behavioral Finance

To focus on predictable pricing errors, behavioral models typically shut down the channel of time-varying expected returns by assuming constant discount rates. Barberis, Shleifer, and Vishny (1998) propose a model of investor sentiment. In the model 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. Barberis et al. argue that conservatism can explain the underreaction evidence that security prices underreact to news over short horizons between one to 12 months as in earnings momentum and price momentum. 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 and send stock prices to unsustainable levels. Barberi et al. argue that 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) develop a model of 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. Self-attribution means that individuals too strongly attribute events confirming the validity of their prior actions to high ability and disconfirming events to extent noise or sabotage. When investors exhibit self-attributive overconfidence, new public signals are viewed on average as confirming the validity of their private signals, and cause continuous overreaction. The continuous overreaction explains the underreaction evidence, whereas eventual correction in the stock price explains the overreaction evidence.

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 extract 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.

A.2 New Classical Finance

New classical models focus on time-varying expected returns as the driving force of anomalies. By retaining the assumption of rational expectations, these models shut down the channel of predictable unexpected returns. Building on Cochrane (1991, 1996) and Berk, Green, and Naik (1999), a stream of recent papers by Zhang (2005), Lyandres, Sun, and Zhang (2008), Li, Livdan, and Zhang (2009), Liu, Whited, and Zhang (2009), Chen, Novy-Marx, and Zhang (2010), Liu and Zhang (2010), Wu, Zhang, and Zhang (2010) elaborate a unified conceptual framework for understanding capital markets anomalies. In particular, Zhang argues that because of costly reversibility (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. But 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.

Based on the first principles of firms' optimal investment decision, Liu, Whited, and Zhang (2010) argue that expected stock returns are related to the ratio of expected next-period marginal benefits of investment over 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, all else equal, investment and the discount rate (the expected return) are negatively correlated. Firms with low discount rates have more projects with positive net present value and consequently invest more than firms with high discount rates. Lyandres, Sun, and Zhang (2008) and Li, Livdan, and Zhang (2009) use this logic to explain the new issues puzzle of Ritter (1991) and Loughran and Ritter (1995). Treating accruals as working capital investment, Wu, Zhang, and Zhang (2010) apply this logic to explain Sloan's (1996) accrual anomaly. This discount rate channel makes sense of evidence interpreted as overreaction 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 stock returns than stocks with low earnings surprises, low short-term prior returns, high financial distress, and low return on assets, respectively. In particular, Chen, Novy-Marx, and Zhang (2010) show that controlling for profitability (a measure of expected marginal product of capital) largely explains Campbell, Hilscher, and Szilagyi's (2008) distress anomaly. Liu, Whited, and Zhang (2009) and Liu and Zhang (2010) show that expected growth of investment-to-capital and expected marginal product of capital are quantitatively important for explaining earnings momentum and price momentum, respectively. This cash flow channel makes sense of evidence interpreted as underreaction in behavioral finance.

B 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 if 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 variable 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:

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

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:

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

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.

$$TA \equiv (\triangle CA - \triangle CASH) - (\triangle CL - \triangle STD - \triangle TP) - DEP, \tag{A3}$$

in which $\triangle CA$ is the change in current assets (item ACT), $\triangle CASH$ is the change in cash or cash equivalents (item CHE), $\triangle CL$ is the change in current liabilities (item LCT), $\triangle STD$ is the change in debt included in current liabilities (item DLC), $\triangle TP$ 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:

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

where

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

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 firms 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.

C Measuring Portfolio Dividend Growth Rates

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. To describe our procedure precisely, we introduce additional notations: 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; $G^P_{t,t+1}$ = 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. P_t can be a shorthand for $P_{t,t}$ as the market value of equity of a portfolio when formed in year 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:

$$\frac{D_{t,t+1}}{P_t} = R_{t,t+1} - G^P_{t,t+1}. \tag{A5}$$

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:

$$G_{t+1} = \left(\frac{D_{t,t+1}/P_t}{D_{t-1,t}/P_{t-1}}\right)\left(G^P_{t-1,t}+1\right) - 1. \tag{A6}$$

Because the right-hand side of equation (A6) 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 (A6), $P_{t-1,t}/P_{t-1}$, 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 momentum, SUE, and ROA portfolios, 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 (A5) and (A6) 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 with and without dividends 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 (A5) and (A6) directly on the monthly observations of returns to construct dividend growth rates for these portfolios.

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 $1/[1+\exp(-\text{Distress})]$. 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 2.1 and Appendix B for detailed variable definitions.

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

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 : 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 2.1 and Appendix B 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.

	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$	$A[R]$	$E_0[R]$	$E_1[R]$	$E_2[R]$
	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	6.8	11.3	10.0	10.7
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	11.2	10.2	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	13.2	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	6.4	−1.7	−2.2	−2.3
[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	3.3	−17.1	−23.7	−23.5

Table 4 : 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 2.1 and Appendix B for detailed variable definitions.

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

Table 5 : 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 2.1 and Appendix B 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.

	$A[G]$	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	6.2	10.7	12.2	12.0
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	9.2	11.9	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	12.6	14.0	12.7	13.3
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	6.5	3.3	0.4	1.4
[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	7.3	8.3	1.7	4.6

Table 6 : 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 2.1 and Appendix B 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.

	$A[R]$	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	7.2	13.7	14.2	13.8
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	11.5	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	13.8	15.9	14.0	14.7
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	6.6	2.2	−0.2	0.9
[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	3.4	6.6	−0.7	3.3