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Do Anomalies Exist *Ex Ante*?*

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Abstract. The anomalies literature in capital markets research in finance and accounting is based (almost) exclusively on average realized returns. In contrast, we construct accounting-based expected returns for dollar-neutral long-short trading strategies formed on a wide array of anomaly variables, including 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 and the size premiums, the cost of equity estimates differ drastically from the average realized returns.

JEL Classification: G12, G14

1. Introduction

We ask whether capital markets anomalies exist *ex ante*. Anomalies are empirical relations between expected returns and firm characteristics not explained by standard asset pricing models. The anomalies literature bases its inferences almost exclusively on average realized returns. However, this approach has limitations. First, expected return estimates from realized returns are imprecise because of large standard errors in estimated factor loadings and factor risk premiums (e.g., Fama and French, 1997). Second, average returns might not converge to expected returns in finite samples (e.g., Elton, 1999). Finally, the time variation in expected returns often works against the convergence of average returns to the expected returns (e.g., Campello, Chen, and Zhang, 2008).

Deviating from the bulk of the literature, we estimate accounting-based expected returns to dollar-neutral long-short strategies formed on a

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comprehensive list of anomaly variables. Following Gebhardt, Lee, and Swaminathan (2001), we calculate the expected return as the implied rate of return that equates the present value of expected future residual incomes to the stock price under the residual income model. Our key message is that expected return estimates differ drastically from average return estimates for a vast majority of anomalies.

For instance, the high-minus-low quintiles formed on Sloan's (1996) accruals (*AC*), Titman, Wei, and Xie's (2004) abnormal investment (*AI*), Daniel and Titman's (2006) composite issuance (*CI*), and Pontiff and Woodgate's (2008) net stock issues (*NSI*) all earn negative average realized returns. Ranging from −4.2% to −7.1% per annum, the average returns are all more than 3.5 standard errors from zero. In contrast, the expected returns of the long-short quintiles are all between −0.2% and 0% (and insignificant), meaning that the anomalies are mostly driven by unexpected returns. Although the high-minus-low quintile formed on Cooper, Gulen, and Schill's (2008) asset growth (*AG*) has an expected return of −0.7% ($t = -3.6$), its magnitude does not come close to its average return of −5.3% ($t = -3.5$).

The expected return estimates even have opposite signs to the average realized returns for the high-minus-low quintiles on Jegadeesh and Titman's (1993) momentum (*MOM*), Chan, Jegadeesh, and Lakonishok's (1996) earnings surprises, Campbell, Hilscher, and Szilagyi's (2008) failure probability, and Hou, Xue, and Zhang's (2012) return on assets (*ROA*). The high-minus-low earnings surprises, *ROA*, and *MOM* quintiles have average returns of 4.5, 6.4, and 6.6% per annum, respectively, which are all significant. However, their expected returns are all significantly negative, ranging from −0.1% to −1.6%. The high-minus-low failure probability quintile has an average return of −7.7% ($t = -4.6$), but its expected return is significantly positive at 3.8%.

The only exceptions to the large differences between expected returns and average returns are the value and the size premiums. The expected return of the value-minus-growth quintile is 6.6% per annum, which is close to the average return estimate of 4.8% in economic magnitude. The expected return estimate, which is more than 15 standard errors from zero, is more precise than the average return estimate, which is only 2.6 standard errors from zero. Similar 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 3.5%. The expected return estimate is significant, but the average return estimate is not.

Our basic finding is robust to several perturbations on the expected return estimates. First, because the baseline Gebhardt, Lee, and Swaminathan

(2001) procedure uses analysts' earnings forecasts that are limited to a small sample and that are likely to be even biased, we modify this procedure to avoid the use of analyst 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, 2012). Our key message is unchanged when we use profitability forecasts from cross-sectional regressions.

Second, several articles criticize the Gebhardt *et al.* 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 (e.g., Easton and Sommers, 2007). These authors propose methods that estimate the expected return and the expected growth rate for a given portfolio simultaneously. Implementing these alternative estimation methods on our testing portfolios, we continue to find that the expected returns deviate drastically from the average returns.

In addition to Gebhardt, Lee, and Swaminathan (2001), many studies calculate expected returns from analysts' earnings forecasts under the residual income model. Claus and Thomas (2001) estimate the *ex ante* equity risk premium. Pastor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Chava and Purnanandam (2010) study the aggregate risk-return tradeoff, international asset pricing, and default risk, respectively. Chen, Kacperczyk, and Ortiz-Molina (2011) examine the relation between labor union and cost of equity. Berger, Chen, and Li (2012) quantify the relation between a firm's information quality and its cost of equity. However, no prior studies provide expected return estimates for a comprehensive array of anomalies strategies.

The rest of the article is organized as follows. Section 2 describes our empirical design. Section 3 presents the expected return estimates for all the anomalies-based portfolios. Section 4 deals with alternative expected return measures. Finally, Section 5 summarizes and interprets the results.

2. Empirical Design

We describe the data and our estimation methods.

2.1 DATA

The monthly data on stock returns, stock prices, and number of shares outstanding are from the Center for Research in Security Prices (CRSP). We obtain returns with and without dividends for all New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National

Association of Securities Dealers Automated Quotations (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 2011. The sample size varies across anomalies due to data availability. Only firms with ordinary common equity are included, meaning that American Depositary Receipts (ADRs), Real Estate Investment Trusts (REITs), and units of beneficial interest are excluded.

2.1.a *Anomaly variables*

To facilitate comparison, we closely follow the prior literature in defining these variables (see Appendix A1 for detailed variable definitions).

*Book to market and size (*market equity*).* High book to market (B/M) stocks earn higher average returns than low B/M stocks (e.g., Fama and French, 1993; 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). Market equity (*ME)* is price per share times shares outstanding from CRSP.

CI and NSI. Firms that issue new equity underperform and firms that buy back shares outperform matching firms with similar characteristics (e.g., Ritter, 1991; Ikenberry, Lakonishok, and Vermaelen, 1995; Loughran and Ritter, 1995; 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 *ME* that is not due to stock returns. Fama and French's (2008) and Pontiff and Woodgate'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.

AI, AG, investment to assets, and 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 3-year moving average of investment. Cooper, Gulen, and Schill (2008) show that firms with high *AG* earn lower average returns than firms with low *AG*. *AG* is the annual percentage change in total assets. Lyandres, Sun, and Zhang (2008) show that high investment to assets (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 noncash working capital minus depreciation expense scaled by average total assets.

Standardized unexpected earnings and ROA. High Standardized unexpected earnings (SUE) stocks earn higher average returns than low SUE stocks (e.g., Bernard and Thomas, 1989; 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 (EPS) (Compustat quarterly item EPSPIQ) as of month t for stock i, e_{iq-4} is EPS announced four quarters ago, and σ_{it} is the volatility of $e_{iq} - e_{iq-4}$ over the prior eight quarters. 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.

MOM. Jegadeesh and Titman (1993) show that stocks that perform well in the recent past continue to earn higher average returns in the future 6 to 12 months than stocks that perform poorly in the recent past. MOM is measured as prior 6-month returns.

2.1.b *Portfolio construction*

We construct one-way quintile portfolios based on the anomaly variables. In June of each year t, we sort all NYSE stocks on CRSP on B/M, size, CI, NSI, AI, AG, I/A, and AC. 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 microcap firms (e.g., Fama and French, 2008). Firms with negative book equity for the fiscal year ending in calendar year $t-1$ are excluded.

We use the NYSE breakpoints to split NYSE, AMEX, and NASDAQ stocks into five groups each month based on their most recent SUE. We hold the resulting portfolios for 6 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 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 1-year buy-and-hold value-weighted returns of stocks with and without dividends for each portfolio. The sample starts from January 1975 due to the availability of quarterly data on total liabilities.

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, for each month, we use the NYSE breakpoints of the prior 6-month returns to split NYSE, AMEX, and NASDAQ stocks into quintiles. Skipping 1 month, we hold the resulting portfolios for the subsequent 6 months and calculate the value-weighted returns.

2.2 EXPECTED RETURN ESTIMATION

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

2.2.a *The baseline GLS procedure*

We closely follow the GLS 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:

$$P_t = B_t + \frac{\mathrm{FROE}_{t+1} - E_0[R]}{1 + E_0[R]} B_t + \frac{\mathrm{FROE}_{t+2} - E_0[R]}{(1 + E_0[R])^2} B_{t+1} + \mathrm{TV}, \qquad (1)$$

in which $E_0[R]$ is the expected return 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. $\mathrm{FROE}_{t+\tau}$ is forecasted return on equity (*ROE*) for period $t+\tau$.

For the first 3 years, we compute $\mathrm{FROE}_{t+\tau}$ as $\mathrm{FEPS}_{t+\tau}/B_{t+\tau-1}$, in which $\mathrm{FEPS}_{t+\tau}$ is the mean forecasted 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' 1-year and 2-year-ahead earnings forecasts (FEPS_{t+1} and FEPS_{t+2}) and the long-term growth rate estimate (Ltg) from IBES to compute the 3-year-ahead earnings forecast as $\mathrm{FEPS}_{t+3}=\mathrm{FEPS}_{t+2}(1+\mathrm{Ltg})$. Beyond the third year, we forecast *ROE* (FROE) using a linear interpolation to the industry median *ROE*. To calculate the industry median *ROE*, we sort all stocks into the forty-eight industries classified by Fama and French (1997). The industry median *ROE* is the 10-year (at least 5-year) moving median of past *ROE*s of all firms in the industry. Loss firms are excluded from the calculation of the industry median.

Book equity per share is $B_{t+\tau}=B_{t+\tau-1}+\mathrm{FEPS}_{t+\tau}-\mathrm{FDPS}_{t+\tau}$, in which $\mathrm{FDPS}_{t+\tau}$ 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, $0\le k\le 1$), that is, $\mathrm{FDPS}_{t+\tau}=k\times\mathrm{FEPS}_{t+\tau}$. 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 twelve future years and estimate a terminal value (TV) for cash flows beyond Year 12:

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

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 TV 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 6-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 *MOM*, *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 1-year return.

2.2.b *Two modified GLS 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). 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 (e.g., 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 would 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 analyst's 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 GLS estimation uses analysts' earnings forecasts in forming forecasted *ROE*, $\text{FROE}_{t+\tau}$. We deviate by forecasting future 1-, 2-, and 3-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 $\text{ROE}_{t+\tau} = Y_{t+\tau}/B_{t+\tau-1}$, in which $\tau = 1, 2, 3$, and $Y_{t+\tau}$ is τ-year ahead realized EPS. 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 modification, we use Fama and French's (2006) full specification, including the logarithm of B/M, the logarithm of ME, 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 AC per share for firms with negative AC (zero otherwise), $+AC_t/B_t$ with $-AC_t$ being AC per share for firms with positive AC (zero otherwise), AG for fiscal year t, a dummy variable that is one for firms that pay no dividends for fiscal year t, and 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 FROE, including only the log B/M, the log ME, the negative earnings dummy, Y_t/B_t, and AG. To avoid look-ahead bias, we use 10-year rolling windows (at least 5 years) up to year t to forecast future ROE.

Since we forecast ROE directly, as opposed to EPS, the baseline GLS procedure needs to be adjusted accordingly. To compute future book equity per share, we still use the clean surplus relation: $B_{t+\tau} = B_{t+\tau-1} + (1-k) \times \text{FEPS}_{t+\tau}$, in which k is the dividend payout ratio. However, $\text{FEPS}_{t+\tau}$ is calculated as $\text{FROE}_{t+\tau} \times B_{t+\tau-1}$, in which $\text{FROE}_{t+\tau}$ 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.[1] Comparing the estimates across the baseline and modified procedures can shed light on whether biases in analysts' earnings forecasts induce any bias in the expected returns to anomalies-based trading strategies.

3. Expected Returns as Implied Costs of Equity

Section 3.1 presents descriptive statistics, and Section 3.2 discusses our key results.

3.1 DESCRIPTIVE ANALYSIS

Panel A of Table I reports the descriptive statistics for the sample used in the baseline implied costs of equity estimation. Since 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 2,191, 1,405, and 1,518, 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 2,063, 1,144, and 1,529, 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.

[1] Our modified procedures are in the same spirit as Hou, van Dijk, and Zhang (2012), who use cross-sectional regressions to forecast earnings. However, because earnings might appear nonstationary, we opt to forecast ROE.

Table I. Descriptive statistics, samples for estimating implied costs of equity

We winsorize each sample at the 0.5 and 99.5 percentiles to control for extreme outliers. "# Firms" is the average number of firms in a given sample. *B/M* is book to market. *ME* is market capitalization in millions of dollars. *CI* is composite issuance. *NSI* is net stock issues. *AI* is abnormal investment. *AG* is asset growth. *I/A* is investment to assets. *AC* is total *AC*. *SUE* is standardized unexpected earnings. *FP* (in percentage) is failure probability calculated as in Campbell, Hilscher, and Szilagy (2008). *ROA* is return on assets. *MOM* is prior 6-month returns. See Appendix A1 for detailed variable definitions.

	Sample	# Firms	Mean (SD)	Min	25%	50%	75%	Max
	Panel A: the baseline implied costs of equity estimation							
B/M	80–11	2,191	1.51 (5.33)	0.06	0.41	0.67	1.03	57.79
ME	80–11	2,191	2,322.68 (6700.75)	9.63	138.53	442.03	1488.16	61,472.74
CI	80–11	1,405	0.00 (0.41)	−1.67	−0.19	−0.04	0.16	1.74
NSI	80–11	2,190	0.03 (0.10)	−0.21	0.00	0.01	0.03	0.65
AI	80–11	1,518	0.28 (0.51)	−0.82	0.05	0.20	0.40	3.71
AG	80–11	1,798	0.17 (0.36)	−0.41	0.00	0.09	0.22	2.62
I/A	80–11	1,899	0.10 (0.17)	−0.35	0.02	0.06	0.14	1.13
AC	80–11	1,619	−0.03 (0.08)	−0.32	−0.07	−0.04	0.01	0.29
SUE	80–11	1,987	−0.07 (2.03)	−12.72	−0.63	0.05	0.66	7.22
FP	80–11	2,041	0.07 (0.14)	0.01	0.03	0.04	0.06	3.03
ROA	80–11	2,154	0.01 (0.03)	−0.16	0.00	0.01	0.02	0.10
MOM	80–11	2,270	0.09 (0.35)	−0.79	−0.10	0.05	0.22	4.41
	Panel B: the modified implied costs of equity estimation (the full Fama-French *ROE* forecasting regression)							
B/M	75–11	2,063	1.40 (3.33)	0.11	0.49	0.81	1.28	34.02
ME	75–11	2,063	1,246.08 (3,195.18)	3.34	52.88	203.98	851.09	25,258.27
CI	75–11	1,144	−0.05 (0.43)	−1.83	−0.22	−0.07	0.12	1.65
NSI	75–11	2,063	0.03 (0.10)	−0.23	0.00	0.00	0.02	0.64
AI	75–11	1,529	0.26 (0.58)	−0.69	0.03	0.18	0.36	4.91
AG	75–11	2,063	0.13 (0.29)	−0.36	−0.01	0.08	0.19	1.94
I/A	75–11	2,048	0.09 (0.16)	−0.37	0.01	0.06	0.13	0.97
AC	75–11	1,927	−0.03 (0.08)	−0.31	−0.07	−0.03	0.01	0.28
SUE	77–11	2,140	−0.03 (1.88)	−11.30	−0.59	0.07	0.67	6.82
FP	75–11	2,141	0.08 (0.15)	0.01	0.03	0.04	0.07	3.00
ROA	77–11	2,315	0.01 (0.03)	−0.18	0.00	0.01	0.02	0.10
MOM	75–11	2,321	0.10 (0.36)	−0.74	−0.11	0.05	0.23	4.63
	Panel C: the modified implied costs of equity estimation (the simplified Fama-French *ROE* forecasting regression)							
B/M	75–11	2,851	1.39 (3.04)	0.11	0.53	0.85	1.30	30.76
ME	75–11	2,851	1,209.49 (3,138.27)	3.25	49.26	191.97	810.47	24,584.66
CI	75–11	1,541	−0.05 (0.44)	−1.84	−0.22	−0.07	0.13	1.69
NSI	75–11	2,850	0.03 (0.10)	−0.23	0.00	0.00	0.02	0.68
AI	75–11	2,007	0.25 (0.46)	−0.73	0.03	0.18	0.36	3.34
AG	75–11	2,348	0.14 (0.29)	−0.37	−0.01	0.08	0.19	1.94
I/A	75–11	2,506	0.08 (0.16)	−0.38	0.01	0.06	0.13	0.97
AC	75–11	2,138	−0.03 (0.08)	−0.31	−0.07	−0.03	0.01	0.29
SUE	77–11	2,140	−0.03 (1.88)	−11.30	−0.59	0.07	0.67	6.82
FP	75–11	2,951	0.08 (0.16)	0.01	0.03	0.04	0.08	3.24
ROA	77–11	3,199	0.01 (0.03)	−0.18	0.00	0.01	0.02	0.10
MOM	75–11	3,118	0.09 (0.35)	−0.77	−0.10	0.05	0.22	5.01

Table II. Multiple regressions to forecast profitability (1963–2011)

The table shows average slopes and their Fama-MacBeth t-statistics from annual cross-sectional regressions to predict profitability, $Y_{t+\tau}/B_{t+\tau-1}$, 1, 2, and 3 years ahead ($\tau = 1, 2, 3$). Y_t, D_t, and AC_t are earnings, dividends, and AC, respectively, per share for the fiscal year ending in calendar year t. $-AC_t$ is AC for firms with negative AC (zero otherwise) and $+AC_t$ is AC for firms with positive AC (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. Int. is the regression intercept, and the R^2 is adjusted R^2.

τ	Int.	$\ln B_t/M_t$	$\ln \mathrm{ME}_t$	Neg Y_t	Y_t/B_t	$-\mathrm{AC}_t/B_t$	$+\mathrm{AC}_t/B_t$	AG_t	No D_t	D_t/B_t	R^2
Panel A: the full Fama-French (2006) specification											
Average slopes											
1	0.00	−0.02	0.01	−0.04	0.61	−0.11	−0.02	−0.04	−0.02	0.14	0.43
2	−0.01	−0.02	0.01	−0.07	0.38	−0.11	0.02	−0.05	−0.02	0.39	0.20
3	−0.01	−0.01	0.01	−0.06	0.26	−0.10	0.03	−0.04	−0.02	0.51	0.13
t-statistics											
1	−0.10	−4.17	3.62	−2.92	18.74	−6.04	−2.19	−5.07	−5.14	3.06	
2	−0.35	−2.65	3.54	−3.86	13.54	−3.83	0.87	−7.20	−4.93	8.48	
3	−0.30	−1.98	3.67	−3.62	9.96	−5.27	1.46	−5.56	−4.65	13.18	
Panel B: the simplified Fama-French specification											
Average slopes											
1	0.00	−0.02	0.01	−0.05	0.60			−0.04			0.42
2	−0.01	−0.02	0.01	−0.07	0.39			−0.06			0.20
3	−0.01	−0.01	0.01	−0.06	0.30			−0.06			0.12
t-statistics											
1	−0.40	−4.52	4.72	−3.22	18.41			−6.34			
2	−0.53	−2.82	5.28	−3.84	11.26			−8.48			
3	−0.43	−1.81	5.73	−3.43	9.82			−8.82			

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 2,851, 1,541, and 2,007, respectively.

Table II reports the average slopes and their t-statistics for annual cross-sectional profitability forecasting regressions using the Fama-MacBeth (1973) methodology in the full sample. Lagged ROE is the strongest predictor of future ROE. In the full specification, the average slope on lagged ROE for 1-year-ahead ROE is 0.61. The slope decays to 0.26 in forecasting 3-year-ahead ROE. The evidence from the short specification is similar.

Size forecasts future *ROE* with significantly positive slopes, meaning that big firms are more profitable than small firms. B/M forecasts *ROE* with (mostly) 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 are more profitable than firms with low dividends-to-book equity. The evidence is largely consistent with Fama and French (2006).

Table III presents descriptive statistics for the implied costs of equity estimated from the baseline GLS procedure and the two modified procedures. Since we do not require a common sample for all the anomaly variables, the descriptive statistics vary across samples that correspond to different anomaly variables. Most important, Table III reports an upward bias in expected return estimates derived from analysts' earnings forecasts in the benchmark estimation. The mean expected return averaged across different samples in the benchmark procedure is 11.84% per annum, whereas the mean expected returns are 10.09 and 10.45% in the two modified procedures. As such, the upward bias in the mean expected return ranges from 1.39% to 1.75%. However, the volatilities of expected return estimates from different estimation procedures are largely similar.

3.2 EXPECTED RETURNS FOR DOLLAR-NEUTRAL LONG-SHORT STRATEGIES

Table IV reports the key message of the article. For most anomalies, the average return and the expected return estimates differ dramatically across the testing portfolios. The table reports for each set of anomaly portfolios, the expected returns from the baseline, and the modified 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 GLS estimation.[2]

Panel A shows that the expected value premiums from different estimation methods of implied costs of equity are not far from each other. A similar observation also holds for all the other anomaly variables. As such, the upward bias documented in Table III does not seem to vary systematically with firm characteristics. In the baseline GLS procedure, the value quintile

[2] Although the IBES sample tilts toward big firms, the magnitudes of the anomalies in average realized returns in the IBES sample are largely similar to those in the samples for the modified GLS estimation (untabulated).

Table III. Descriptive statistics of implied costs of equity

We present 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 for each sample, and the variable definitions are reported in Table I.

	Mean (SD)	Min	25%	50%	75%	Max
	Panel A: the baseline GLS estimation, $E_0[R]$					
B/M	12.07 (4.82)	1.73	9.59	11.58	13.63	36.04
ME	12.07 (4.82)	1.73	9.59	11.58	13.63	36.04
CI	11.66 (4.16)	2.87	9.49	11.26	13.09	32.66
NSI	12.07 (4.81)	1.73	9.59	11.57	13.63	36.04
AI	11.45 (2.99)	3.04	9.58	11.37	13.20	20.37
AG	11.97 (4.81)	1.81	9.43	11.44	13.58	35.42
I/A	11.98 (4.79)	1.70	9.47	11.48	13.61	35.38
AC	11.98 (4.77)	1.78	9.49	11.49	13.62	35.32
SUE	11.62 (3.36)	0.80	9.72	11.56	13.42	32.49
FP	11.70 (4.04)	1.29	9.56	11.45	13.37	36.55
ROA	11.86 (4.38)	1.30	9.59	11.51	13.47	36.85
MOM	11.65 (3.46)	0.51	9.73	11.61	13.49	33.12
	Panel B: The modified GLS estimation, $E_1[R]$ (the full *ROE* forecasting regression)					
B/M	10.23 (4.84)	0.93	7.60	9.84	12.04	32.55
ME	10.23 (4.84)	0.93	7.60	9.84	12.04	32.55
CI	10.37 (4.59)	1.70	7.96	9.89	11.88	32.40
NSI	10.23 (4.84)	0.93	7.60	9.84	12.04	32.55
AI	9.97 (3.28)	1.39	7.91	9.95	11.96	19.38
AG	10.23 (4.84)	0.93	7.60	9.84	12.04	32.55
I/A	10.24 (4.84)	0.94	7.61	9.84	12.04	32.66
AC	10.13 (4.78)	0.94	7.50	9.74	11.95	32.22
SUE	9.67 (3.78)	1.07	7.31	9.58	11.82	31.97
FP	9.77 (4.96)	0.81	7.04	9.32	11.64	37.56
ROA	10.19 (5.08)	1.16	7.38	9.69	12.06	36.12
MOM	9.85 (3.82)	1.28	7.45	9.77	12.05	31.36
	Panel C: The modified GLS estimation, $E_2[R]$ (the simplified *ROE* forecasting regression)					
B/M	10.66 (4.86)	0.26	8.06	10.35	12.53	33.86
ME	10.66 (4.86)	0.26	8.06	10.35	12.53	33.86
CI	10.71 (4.59)	1.24	8.32	10.34	12.32	33.86
NSI	10.66 (4.86)	0.26	8.06	10.35	12.52	33.86
AI	10.43 (3.43)	0.26	8.36	10.44	12.42	30.10
AG	10.55 (4.93)	0.26	7.87	10.18	12.45	33.86
I/A	10.58 (4.92)	0.47	7.89	10.23	12.52	33.86
AC	10.45 (4.89)	0.47	7.76	10.08	12.39	33.86
SUE	9.67 (3.78)	1.07	7.31	9.58	11.82	31.97
FP	10.28 (5.04)	0.88	7.52	9.89	12.24	38.23
ROA	10.64 (5.11)	1.15	7.85	10.22	12.58	36.61
MOM	10.33 (3.93)	1.26	7.95	10.31	12.55	33.84

Table IV. 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, we sort all NYSE stocks on B/M, size (ME), CI, NSI, AI, AG, I/A, and total 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 6-month returns (MOM) and earnings surprises (SUE), and use the NYSE breakpoints to split all stocks into quintiles. We hold the portfolios for 6 months and calculate value-weighted returns. Each month, we use NYSE-AMEX-NASDAQ breakpoints to sort all stocks on Campbell, Hilscher, and Szilagyi's (2008) FP into quintiles and calculate 1-year value-weighted returns for each portfolio. Each month, we also use NYSE breakpoints to sort all stocks on quarterly 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 Appendix A1 for detailed variable definitions. "H − L" is the high-minus-low portfolios and "[t]" is heteroskedasticity-and-autocorrelation-consistent t-statistics testing a given H − L moment is zero. 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	11.7	8.6	7.1	7.5	15.6	12.7	11.0	11.3	14.5	10.4	10.1	10.6	15.3	10.3	9.5	10.1
3	13.7	10.9	10.1	10.8	14.5	11.1	10.0	10.5	12.6	9.8	9.1	9.5	13.0	9.8	9.1	9.6
High	16.5	15.2	16.0	17.0	12.0	9.6	8.8	9.5	10.2	10.4	9.2	10.0	8.2	10.1	8.8	9.5
H–L	4.8	6.6	8.9	9.5	−3.5	−3.1	−2.2	−1.9	−4.3	0.0	−0.9	−0.7	−7.1	−0.2	−0.6	−0.6
[t]	2.6	15.5	8.5	8.1	−1.3	−9.9	−6.5	−5.9	−3.9	−0.2	−3.0	−2.2	−3.9	−1.1	−2.1	−2.7
	Panel E: AI				Panel F: AG				Panel G: I/A				Panel H: AC			
Low	15.1	10.1	8.9	9.3	15.8	10.4	9.4	9.8	13.6	10.4	9.6	10.0	13.3	9.8	9.1	9.3
3	13.6	9.8	9.5	10.2	12.6	9.7	9.6	10.1	13.0	9.7	9.2	9.7	13.9	9.8	9.1	9.5
High	10.4	9.9	8.1	9.0	10.5	9.7	8.2	8.6	10.5	10.0	8.8	9.2	9.1	9.9	8.4	8.9
H–L	−4.7	−0.2	−0.8	−0.3	−5.3	−0.7	−1.2	−1.1	−3.1	−0.5	−0.8	−0.8	−4.2	0.0	−0.7	−0.4
[t]	−3.9	−0.9	−2.0	−0.7	−3.5	−3.6	−4.3	−4.0	−2.2	−3.0	−4.0	−4.1	−3.8	0.3	−3.1	−2.4
	Panel I: SUE				Panel J: FP				Panel K: ROA				Panel L: MOM			
Low	9.3	10.1	9.2	9.9	12.9	9.2	7.9	8.3	6.4	10.9	9.7	10.6	7.5	11.2	9.9	10.6
3	11.3	10.1	8.8	9.4	11.5	11.1	9.9	10.5	11.2	10.4	10.0	10.3	11.8	10.1	9.0	9.6
High	13.8	10.0	8.2	8.8	5.2	13.1	10.8	11.8	12.8	9.4	7.8	8.1	14.1	9.7	7.7	8.3
H–L	4.5	−0.1	−1.0	−1.1	−7.7	3.8	2.8	3.5	6.4	−1.6	−1.8	−2.5	6.6	−1.5	−2.2	−2.3
[t]	4.7	−3.2	−19.9	−20.2	−4.6	36.7	18.5	23.6	3.4	−22.0	−16.1	−32.0	3.3	−16.4	−24.5	−23.9

earns a higher expected return than the growth quintile: 15.2% versus 8.6% per annum. The spread of 6.6% is more than 15 standard errors from zero. This expected return spread is close to the average return spread of 4.8% 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 2.6 standard errors from zero.

In the two modified GLS procedures, the estimates of the expected value premium are 8.9 and 9.5% per annum, which are larger than the average return. Both estimates are more than 8 standard errors from zero. From Panel B, the expected returns of the small-minus-big quintile range from 1.9% to 3.1% per annum, which are close to the average return of 3.5%. Although the average return is insignificant, the expected returns are all more than 5.5 standard errors from zero.

The similarity between average return and expected return estimates ceases to exist for the remaining anomalies. From Panel C, the high-minus-low *CI* quintile earns an average return of −4.3% per annum, which is more than 3.5 standard errors from zero. In contrast, the expected return estimates are substantially lower in magnitude, ranging from −0.0% to −0.9%. 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. All 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 −7.1% per annum ($t = -3.9$). In contrast, the expected return estimates of this zero-investment quintile range from −0.2% to −0.6%. From Panel E, the high-minus-low *AI* quintile earns an average return of −4.7%, which is more than 3.5 standard errors from zero. However, the expected return estimates of this long–short quintile range from −0.2% to −0.8%, and two of three estimates are within 1 standard error of zero.

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 −5.3% per annum, which is 3.5 standard errors from zero. However, the expected return estimates range from −0.7% to −1.2%, albeit significant. Panel G shows that the average return of the high-minus-low I/A quintile is −3.1% ($t = -2.2$). In contrast, the expected return estimates only fall in the range between −0.5% and −0.8%, 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 −4.2% ($t = -3.8$). The baseline GLS procedure yields a zero expected return estimate. The two modified procedures yield expected return estimates of

−0.7% and −0.4%. Although significant, these estimates are substantially lower in magnitude than the average return estimate.[3]

The remaining four panels report that the expected return estimates for the high-minus-low quintiles formed on earnings surprises, failure probability, *ROA*, and *MOM* 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 4.5% per annum, which is 4.7 standard errors from zero. In contrast, the expected return estimates range from −0.1% to −1.1%, and are all significant. The average return of the high-minus-low failure probability quintile is −7.7%, which is 4.6 standard errors from zero. However, its expected return estimates are significantly positive with 3.8, 2.8, and 3.5%, respectively.

From Panel K, the high-minus-low *ROA* quintile earns an average return of 6.4% per annum, which is 3.4 standard errors from zero. In contrast, the expected return estimate from the baseline procedure is −1.6%, and the estimates from the two modified procedures are −1.8 and −2.5%. Finally, Panel L shows that the winner-minus-loser quintile earns an average return of 6.6% ($t = 3.3$). In contrast, its expected return estimates range from −1.5% to −2.3%.

The key message from Table IV is clear. The average returns and the expected returns are dramatically different across the testing portfolios, except for the value and the size premiums. A secondary point is that 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.

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. Although 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. The fixed 12-year forecasting horizon might be too short for some growth firms. In particular, many bio-technology firms are loss firms that

3 Wu, Zhang, and Zhang (2010) also document that the expected return spread across the extreme *AC* quintiles is too small in magnitude relative to the average return spread. Their estimates are based only on the baseline GLS estimation. We show that the expected return estimates from the modified procedures are largely similar, meaning that bias in analyst forecasts does not affect the expected return estimates of the *AC* portfolios.

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 analyst 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.

Table V 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 insignificant.

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 returns 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, 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 and the size premiums are again the only exceptions with consistent signs and magnitude between average realized returns and expected 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. These methods are proposed by Easton *et al.* (2002, ETSS hereafter), Easton (2006), and Easton and Sommers (2007). As noted, the GLS procedures estimate the expected return at the firm level and then aggregate to the portfolio level. In contrast, the alternative procedures estimate the expected return and the expected growth at the portfolio level.

Table V. 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: B/M, size (ME), CI, NSI, AI, AG, I/A, and total 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 6-month returns (MOM), earnings surprises (SUE), and ROA and the NYSE–AMEX–NASDAQ breakpoints of FP to split the stocks into quintiles each month. We calculate 6-month value-weighted returns for the MOM, SUE, and ROA portfolios and 1-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 heteroskedasticity-and-autocorrelation-consistent t-statistics. The sample periods are described in Table I. Implied costs of equity are in annualized percent.

		Low Ltg		2		High Ltg	
		H–L	[t]	H–L	[t]	H–L	[t]
B/M	$A[R]$	3.1	1.4	3.5	1.4	6.9	3.0
	$E_0[R]$	7.5	8.9	6.0	12.2	6.6	11.8
	$E_1[R]$	8.2	6.4	5.7	11.1	8.1	8.9
	$E_2[R]$	9.0	5.3	6.6	10.4	8.2	10.4
ME	$A[R]$	−2.5	−0.9	−4.3	−1.4	−2.6	−0.6
	$E_0[R]$	−2.8	−5.4	−3.4	−7.5	−3.5	−12.3
	$E_1[R]$	−2.5	−4.8	−2.6	−7.7	−2.6	−12.3
	$E_2[R]$	−1.8	−4.2	−2.4	−5.5	−2.5	−11.4
CI	$A[R]$	−0.8	−0.5	−6.2	−3.0	−10.0	−5.2
	$E_0[R]$	0.3	1.1	0.6	2.0	0.1	0.3
	$E_1[R]$	0.3	1.1	0.1	0.4	−0.9	−2.8
	$E_2[R]$	0.5	1.2	0.1	0.3	−0.1	−0.3
NSI	$A[R]$	−4.2	−2.5	−5.9	−3.2	−8.5	−3.2
	$E_0[R]$	−0.5	−2.4	0.3	1.3	−0.7	−2.7
	$E_1[R]$	0.2	0.6	0.0	0.0	−1.0	−7.0
	$E_2[R]$	0.6	1.7	0.0	0.0	−1.1	−5.7
AI	$A[R]$	−3.6	−2.2	−1.9	−1.4	−3.9	−1.3
	$E_0[R]$	0.7	3.1	0.4	1.5	−0.5	−1.9
	$E_1[R]$	0.9	2.3	−0.3	−0.7	−1.1	−2.8
	$E_2[R]$	1.1	2.7	0.4	0.9	−0.8	−2.2
AG	$A[R]$	−1.1	−0.7	−6.6	−3.3	−6.5	−1.4
	$E_0[R]$	−0.2	−1.4	−0.3	−1.0	−1.4	−5.2
	$E_1[R]$	0.2	0.7	−0.7	−2.9	−1.6	−5.2
	$E_2[R]$	0.2	0.8	−0.7	−3.0	−1.6	−5.0

		Low Ltg		2		High Ltg	
		H–L	[t]	H–L	[t]	H–L	[t]
I/A	$A[R]$	−1.8	−0.7	−2.3	−1.2	−4.5	−1.5
	$E_0[R]$	0.1	0.4	−0.1	−0.9	−1.1	−5.5
	$E_1[R]$	0.6	2.2	−0.2	−1.4	−1.6	−7.0
	$E_2[R]$	0.7	1.9	−0.3	−1.2	−1.6	−4.7
AC	$A[R]$	1.1	0.4	−5.3	−2.4	−6.8	−2.6
	$E_0[R]$	0.3	1.2	0.1	0.4	0.4	1.7
	$E_1[R]$	−0.2	−0.7	−0.4	−1.9	−0.3	−1.5
	$E_2[R]$	0.0	0.0	−0.1	−0.5	−0.1	−0.7
SUE	$A[R]$	3.7	2.7	3.4	2.5	4.9	3.0
	$E_0[R]$	−0.2	−3.5	−0.3	−4.0	0.1	1.0
	$E_1[R]$	−1.3	−21.2	−0.9	−12.9	−0.8	−8.9
	$E_2[R]$	−1.3	−21.1	−0.8	−12.3	−0.8	−9.7
FP	$A[R]$	−2.1	−1.1	−5.0	−2.4	−9.4	−4.4
	$E_0[R]$	3.4	21.0	3.6	26.7	3.5	29.6
	$E_1[R]$	2.6	9.8	3.2	18.4	2.5	14.2
	$E_2[R]$	3.5	16.6	3.7	21.0	2.8	17.8
ROA	$A[R]$	3.4	1.4	4.2	1.7	9.0	3.4
	$E_0[R]$	−1.9	−20.0	−1.9	−21.7	−0.9	−5.9
	$E_1[R]$	−1.0	−5.1	−1.8	−14.5	−2.0	−11.9
	$E_2[R]$	−2.1	−13.5	−2.5	−26.9	−2.3	−15.2
MOM	$A[R]$	2.7	1.0	5.4	2.2	11.5	4.2
	$E_0[R]$	−1.3	−9.2	−1.4	−13.3	−1.7	−18.6
	$E_1[R]$	−2.3	−17.9	−1.9	−20.1	−2.3	−22.6
	$E_2[R]$	−2.3	−17.4	−2.0	−19.0	−2.4	−23.9

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 EPS, and r_i is the cost of equity.

4.1.a *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 grow perpetually at a constant annual rate of g_i. This assumption means that we can reformulate Equation (3) as:

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

in which P_{it} is price per share of firm i at time t, $Y_{\mathrm{it+1}}^{\mathrm{IBES}}$ 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 $P_{\mathrm{it}} - B_{\mathrm{it}}$ and the present value of the infinite residual income stream. Some algebra shows that Equation (4) is equivalent to:

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

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

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

in which $\gamma_0 = g$ 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.

4.1.b *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 1-year ahead *ROE* from the Fama-French (2006) *ROE* forecasting regressions. Doing so includes the sample observations not covered by analysts. In this modified ETSS estimation, we use the forecasted *ROE* from the full Fama-French profitability regressions (using the simplified specification yields largely similar results).

4.1.c *The O'Hanlon-Steele estimation*

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

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

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:

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

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

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

in which $\delta_0 = r$, r is the portfolio-level expected return, $\delta_1 = (r - g')/(1 + g')$, and g' is the expected growth rate for the portfolio. We estimate annual Fama-MacBeth (1973) cross-sectional regressions in each period using the Weighted Least Squares with the weights given by market capitalization. We use the value weights to ease comparison with the results from the GLS procedures (that use value weights to aggregate firm-level expected returns to portfolio-level estimates).

We implement the estimation procedures for all testing quintile portfolios. To test whether a given high-minus-low quintile has an expected return of zero, we estimate the cross-sectional regressions for the two extreme quintiles simultaneously, 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 expected growth rate of zero is analogous.

4.2 EXPECTED RETURN ESTIMATES FROM THE ETSS PROCEDURES

Panel A of Table VI describes 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 3,101, 1,710, and 1,807, 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 2,887, 1,537, and 1,882, respectively. Panel C describes the sample for the O'Hanlon-Steele estimation. Since 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 for the B/M, CI, and AI quintiles increase to 3,472, 1,829, and 2,058, respectively.

More important, Table VII reports expected returns from the ETSS methods that estimate expected returns and growth rates simultaneously. The expected return estimates diverge from those obtained from the GLS procedure as well as those from the average returns. From Panel A, the average return of the high-minus-low B/M quintile is 3.9% 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: −1.5% ($t = -0.8$) from the baseline ETSS estimation, −12.7% ($t = -13.5$) from the modified ETSS estimation, and −9.8% ($t = -6.8$) from the O'Hanlon–Steele estimation. Panel B shows that the average return of the small-minus-big quintile is 2.6% per annum, which is within 1 standard error of zero. In contrast, the expected return estimates from the baseline and modified ETSS procedures are −6.7% and −8.2%, respectively, which are both more than 6 standard errors from zero. The estimate from the O'Hanlon-Steele procedure is −13.0%, which is more than 5 standard errors from zero.

Similarly large differences between average returns and expected returns are also evident for the CI, NSI, AI, AG, I/A, and AC quintiles. Panel C shows that although the average return of the high-minus-low CI quintile is significantly negative, −3.5%, the expected return estimate from the baseline ETSS procedure is significantly positive, 5.0%, which is more than 3 standard errors from zero. The modified ETSS procedure and the O'Hanlon-Steele procedure provide expected return estimates of −1.9 and −3.0%, both of which are at least 2.5 standard errors from zero. From Panel D, the high-minus-low NSI quintile earns an average return of −7.1% ($t = -2.9$). The expected return estimates from the three ETSS procedures again differ greatly, ranging from −1.9% to 1.3% and two out of the three estimates are insignificant.

Table VI. Descriptive statistics, samples for estimating expected returns, and expected growth rates simultaneously

We winsorize each sample at 0.5 and 99.5 percentiles to control for extreme outliers. "# Firms" is the average number of firms in a given sample. *B*/*M* is book-to-*ME*. *ME* is market capitalization in millions of dollars. *CI* is composite issuance. *NSI* is net stock issues. *AI* is abnormal investment. *AG* is asset growth. *I*/*A* is investment to assets. *AC* is total *AC*. *SUE* is standardized unexpected earnings. *FP* (in percent) is failure probability calculated as in Campbell, Hilscher, and Szilagyi (2008). *ROA* is return on assets. *MOM* is prior 6-month returns. See Appendix A1 for detailed variable definitions.

	Sample	# Firms	Mean (SD)	Min	25%	50%	75%	Max
			Panel A: the baseline ETSS estimation					
B/*M*	80–11	3,101	1.56 (6.33)	0.04	0.37	0.63	1.00	75.37
ME	80–11	3,101	2,056.78 (6,102.77)	8.96	131.78	387.18	1281.89	56311.69
CI	80–11	1,710	0.02 (0.43)	−1.71	−0.19	−0.03	0.18	1.85
NSI	80–11	2,861	0.05 (0.12)	−0.21	0.00	0.01	0.04	0.79
AI	80–11	1,807	0.31 (0.58)	−1.13	0.05	0.21	0.42	4.36
AG	80–11	2,359	0.21 (0.46)	−0.43	0.01	0.10	0.24	3.62
I/*A*	80–11	2,482	0.11 (0.19)	−0.36	0.02	0.07	0.14	1.35
AC	80–11	2,118	−0.03 (0.09)	−0.33	−0.07	−0.04	0.01	0.32
SUE	80–11	2,484	−0.07 (2.05)	−13.05	−0.62	0.05	0.66	7.20
FP	80–11	2,286	0.07 (0.16)	0.01	0.03	0.04	0.07	3.54
ROA	80–11	2,647	0.01 (0.04)	−0.21	0.00	0.01	0.02	0.10
MOM	80–11	2,734	0.09 (0.36)	−0.81	−0.11	0.05	0.22	4.81
			Panel B: the modified ETSS estimation (the full Fama-French *ROE* forecasting regression)					
B/*M*	75–11	2,887	1.42 (3.62)	0.10	0.47	0.78	1.24	39.13
ME	75–11	2,887	1,104.55 (2,896.39)	2.83	51.21	185.84	736.92	23189.90
CI	75–11	1,537	−0.04 (0.46)	−1.89	−0.22	−0.06	0.14	1.77
NSI	75–11	2,886	0.04 (0.11)	−0.23	0.00	0.01	0.04	0.77
AI	75–11	1,882	0.26 (0.53)	−0.91	0.02	0.17	0.37	3.92
AG	75–11	2,887	0.16 (0.35)	−0.39	0.00	0.08	0.21	2.35
I/*A*	75–11	2,859	0.10 (0.17)	−0.39	0.02	0.07	0.14	1.14
AC	75–11	2,687	−0.03 (0.09)	−0.34	−0.07	−0.03	0.01	0.33
SUE	77–11	2,586	−0.05 (1.92)	−11.78	−0.60	0.06	0.67	6.84
FP	75–11	2,359	0.09 (0.19)	0.01	0.03	0.04	0.08	3.71
ROA	77–11	2,571	0.00 (0.04)	−0.23	0.00	0.01	0.02	0.10
MOM	75–11	2,800	0.09 (0.37)	−0.79	−0.12	0.04	0.23	4.81
			Panel C: the O'Hanlon-Steele estimation					
B/*M*	65–11	3,472	1.56 (5.16)	0.04	0.47	0.79	1.22	64.25
ME	65–11	3,472	1,153.94 (3,612.54)	1.68	44.05	162.20	661.12	32414.09
CI	65–11	1,829	−0.04 (0.42)	−1.66	−0.22	−0.07	0.13	1.69
NSI	65–11	3,472	0.04 (0.12)	−0.23	0.00	0.01	0.03	0.90
AI	65–11	2,058	0.24 (0.47)	−1.08	0.03	0.17	0.34	3.53
AG	65–11	2,892	0.16 (0.39)	−0.50	0.00	0.08	0.21	3.26
I/*A*	65–11	3,047	0.10 (0.19)	−0.47	0.01	0.06	0.14	1.50
AC	70–11	2,501	−0.03 (0.09)	−0.40	−0.07	−0.03	0.02	0.37
SUE	77–11	3,333	−0.04 (1.96)	−12.07	−0.60	0.07	0.68	7.07
FP	75–11	3,024	0.09 (0.20)	0.01	0.03	0.04	0.08	4.00
ROA	77–11	3,330	0.00 (0.04)	−0.26	0.00	0.01	0.02	0.10
MOM	65–11	3,233	0.08 (0.35)	−0.77	−0.12	0.04	0.21	5.37

Table VII. 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, we sort all NYSE stocks on B/M, size (ME), CI, NSI, AI, AG, I/A, and total 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 6-month returns (MOM) and earnings surprises (SUE), and use the NYSE breakpoints to split all stocks into quintiles. We hold the portfolios for 6 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) FP into quintiles and calculate 1-year value-weighted returns for each portfolio. Each month, we also use NYSE breakpoints to sort all stocks on quarterly 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 Appendix A1 for detailed variable definitions. "H − L" is the high-minus-low portfolios and "[t]" is heteroskedasticity-and-autocorrelation-consistent t-statistics testing a given H − L moment is zero. The sample periods are in Table VI. 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	12.2	10.1	18.5	20.1	15.0	4.5	4.7	4.3	14.7	7.8	12.5	15.3	16.1	10.1	12.4	13.2
3	14.2	9.7	11.6	11.4	14.2	12.7	10.7	12.4	13.2	10.4	12.2	12.4	13.7	9.3	11.6	13.7
High	16.1	8.6	5.8	7.8	12.4	11.2	12.9	16.8	11.2	12.7	10.6	13.6	9.0	11.4	10.5	14.2
H−L	3.9	−1.5	−12.7	−9.8	−2.6	6.7	8.2	13.0	−3.5	5.0	−1.9	−3.0	−7.1	1.3	−1.9	−0.8
[t]	1.7	−0.8	−13.5	−6.8	−0.8	6.2	6.1	5.2	−2.5	3.1	−2.6	−2.5	−2.9	1.2	−3.2	−0.9
	Panel E: AI				Panel F: AG				Panel G: I/A				Panel H: AC			
Low	15.1	12.2	6.9	6.7	15.6	10.9	7.3	6.1	13.6	10.8	9.0	10.7	13.6	14.0	10.4	11.2
3	13.5	10.3	12.0	12.3	13.4	11.0	12.9	13.1	13.3	10.7	12.8	14.3	14.4	12.7	12.2	14.1
High	11.7	11.1	14.0	20.5	11.3	16.1	13.2	20.1	11.4	14.9	12.7	17.6	10.1	10.9	13.5	18.7
H − L	−3.4	−1.1	7.0	12.6	−4.3	5.1	5.9	13.3	−2.2	4.1	3.7	6.4	−3.5	−3.1	3.1	7.7
[t]	−2.1	−0.4	7.0	10.1	−2.5	2.4	6.1	10.1	−1.2	1.8	6.6	7.8	−3.7	−1.2	5.3	7.6
	Panel I: SUE				Panel J: FP				Panel K: ROA				Panel L: MOM			
Low	9.9	13.7	17.0	17.1	13.3	14.7	17.1	19.7	7.2	6.0	6.1	6.2	8.1	13.5	13.8	13.4
3	11.5	16.0	14.3	13.3	11.6	15.3	12.8	14.0	11.3	13.7	13.4	12.2	11.9	15.4	15.5	14.4
High	14.0	16.6	14.5	14.8	6.3	−10.3	−7.3	−5.1	13.2	19.0	20.2	21.3	14.6	16.0	13.7	14.5
H−L	4.1	2.9	−2.5	−2.3	−7.0	−25.1	−24.4	−24.8	6.0	12.9	14.1	15.1	6.6	2.5	0.0	1.1
[t]	4.6	9.2	−17.3	−8.9	−4.3	−18.4	−16.3	−19.2	3.3	21.4	33.1	27.0	3.2	7.8	−0.1	4.0

The high-minus-low AI, AG, and AC quintiles all earn significantly negative average returns, −3.4%, − 4.3%, and −3.5%, which are at least 2.1 standard errors from zero, respectively. However, the modified ETSS procedure produces significantly positive expected return estimates, 7.0, 5.9, and 3.1%, respectively. The O'Hanlon-Steele procedure produces even larger positive expected return estimates, 12.6, 13.3, and 7.7%, respectively, all of which are more than 7.5 standard errors from zero. The baseline ETSS procedure produces insignificantly negative expected return estimates for the high-minus-low AI and AC quintiles but significantly positive high-minus-low AG quintile.

The high-minus-low I/A quintile earns an insignificant average return of −2.2% ($t = -1.2$). The baseline ETSS procedure produces an insignificantly positive average return of 4.1%. The modified ETSS procedure and the O'Hanlon-Steele procedure offer estimates of 3.7 and 6.4%, respectively, both of which are more than 6.5 standard errors from zero.

Panels I–L report that the average return estimates also diverge from the expected return estimates for the remaining anomaly variables. From Panel I, the high-minus-low SUE quintile earns an average return of 4.1% ($t = 4.6$). The baseline ETSS estimate of the expected return is close at 2.9%. However, both modified ETSS estimate and the O'Hanlon-Steele estimate are significantly negative, −2.5% and −2.3%, which are at least 8.5 standard errors from zero.

Panel J shows that the high-minus-low FP quintile earns an average return of −7.0% ($t = -4.3$). Although the sign is consistent, the expected return estimates from the ETSS procedures are more than three times larger in magnitude, ranging from −24.4% to −25.1%, which are more than 16 standard errors from zero. From Panel K, the high-minus-low ROA quintile earns an average return of 6.0% ($t = 3.3$). The expected return estimates from the ETSS procedures have the same positive sign, but are more than twice as large as the average return. Finally, Panel L shows that the high-minus-low MOM quintile earns an average return of 6.6%, which is more than 3 standard errors from zero. In contrast, the estimates from the ETSS procedures range from 0% to 2.5%.

4.3 ETSS VERSUS GLS

Why do the expected return estimates from the ETSS procedures differ from those based on the GLS procedures? We note that the ETSS procedures contain a few specification errors that are absent in the GLS procedures, errors that are the likely culprits for the differences.

For instance, the cross-sectional regression in Equation (6) is derived under strong assumptions. There are measurement errors in $Y_{\text{it}+1}^{\text{IBES}}$ and $P_{\text{it}}/B_{\text{it}}$ 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, $P_{\text{it}}/B_{\text{it}}$ 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, and specification errors can arise from three sources. First, the residual earnings might not be a perpetuity that grows at a constant rate. Second, $(P_{\text{it}} - B_{\text{it}})/B_{\text{it}-1}$ and $(r_i - g_i')/(1 + g_i')$ might be correlated cross-sectionally, meaning 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 $(r_i - g_i')/(1 + g_i')$ cannot be replaced with $(r - g')/(1 + g')$. O'Hanlon and Steele (2000) assume that all these errors have a mean of zero to allow the transformation of Equation (8) into the cross-sectional regression in Equation (9).

5. Summary and Interpretation

We use valuation models to estimate expected returns to anomalies-based trading strategies, including those formed on B/M, size, CI, NSI, AI, AG, I/A, AC, SUE, FP, ROA, and short-term prior returns. The key finding is that except for the value and the size premiums, expected return estimates differ drastically from average realized returns. We interpret this evidence in two ways: mispricing and measurement errors in expected returns.

5.1 MISPRICING

There exist both behavioral and rational explanations for anomalies. Behavioral finance argues that investors make systematic mistakes in pricing assets, and that these mistakes produce predictable pricing errors manifested as anomalies. In particular, behavioral models typically assume a constant discount rate. As such, in these models, the anomalous returns are unexpected, and the average returns to anomalies-based trading strategies should equal their average unexpected returns.

For instance, in Daniel, Hirshleifer, and Subrahmanyam (1998) investors exhibit overconfidence in overestimating 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.

In another example, Barberis, Shleifer, and Vishny (1998) argue that 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 leads to investors' underreaction to news, generating return continuation over short horizons between 1 and 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 is consistent with the overreaction evidence that stocks that have had a long record of good news tend to become overpriced and have low average returns.

At the other extreme, rational models shut down predictable unexpected returns and interpret anomalies as the correlations between expected returns and firm characteristics. The assumption of rational expectations in these models means that the market's forecasting errors (such as pricing errors) are not forecastable (e.g., Muth, 1961). As such, in these models, returns to zero-cost strategies are expected and their average returns should equal expected returns. For instance, 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. Since value firms have less profitable assets than growth firms, value firms want to disinvest more, especially in recessions. Since 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.

More generally, Liu, Whited, and Zhang (2009) and Hou, Xue, and Zhang (2012) argue that expected returns are linked to expected marginal benefits of investment divided by marginal costs of investment. Stocks with high B/M, low I/A, low equity issues, and low AG earn higher expected returns because their low investment levels imply low marginal costs of investment. Intuitively, firms with low discount rates have more projects with positive net present value and invest more than those with high discount rates. In addition, stocks with high earnings surprises, high short-term prior returns, low financial distress, and high ROA have higher expected marginal benefits of investment and subsequently earn higher expected returns.

Both the Daniel, Hirshleifer, and Subrahmanyam (1998) and the Barberis, Shleifer, and Vishny (1998) models assume a constant discount rate (expected return) across all firms. As such, the average returns to zero-cost strategies are due to predictable variations in unexpected returns. To the extent that accounting-based costs of capital provide reasonable proxies for expected returns, our key finding suggests that mispricing is the main driving force of anomalies. In contrast, the rational models all predict that average returns of anomalies strategies equal their expected returns (with zero average unexpected returns). As such, our key finding that the average returns differ drastically from the expected returns for most anomalies is inconsistent with rational models.

However, it should be emphasized that behavioral biases might also cause expected returns to vary across firms, once these biases are modeled carefully in an equilibrium framework (e.g., Barberis, Huang, and Santos, 2001). By attributing only unexpected returns to behavioral biases, our empirical design has the caveat of ruling out this possibility. In particular, our expected return estimates are built on an accounting identity, the residual income model. A discounting formula is potentially consistent with both behavioral and rational pricing (e.g., Fama and French, 2006).

Unfortunately, testing formal behavioral equilibrium theories via structural estimation is a more ambitious goal than what we set out to do. Our objective is more modest, focusing on a common prediction across Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). In the anomalies literature, these models provide leading behavioral explanations for capital markets anomalies. These models all assume a constant discount rate for all firms. As such, the average returns of the zero-cost portfolios formed on anomaly variables are all driven by differences in unexpected returns. As noted, it is not inconceivable that behavioral biases can potentially cause expected returns to vary across firms. However, this channel is ruled out by the leading behavioral models in order to focus on predictable unexpected returns.

5.2 MEASUREMENT ERRORS IN EXPECTED RETURNS

The mispricing interpretation depends on the quality of implied costs of equity as proxies for expected returns. Since no expected return measures are perfect, the interpretation is subject to Fama's (1998) joint hypothesis problem. As standard in the anomalies literature, we can only test whether anomalies are consistent with the market's expectations in a given expected return model.

Although we have tried to address some of the caveats in the expected return estimates derived from imperfect growth forecasts, several other issues can induce measurement errors in the expected returns. Most important, the implied costs of capital, calculated as the internal rates of returns, are proxies for the expected returns in the long term. The long-term expected returns can differ from the 1-month- or the 1-year-ahead expected returns after the portfolio formation. For all the anomalies strategies that we consider, the holding period is no longer than 1 year and is sometimes as short as 1 month. The horizon difference between the long-term nature of implied costs of capital and the short-term nature of average returns can potentially explain our key finding.

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, as well as cash flow growth and leverage (see also Lambert, 2009). Unfortunately, given the tightly parameterized structure in Hughes *et al.*, it is not clear how to estimate these differences in the data. To what extent these measurement errors can account for the striking inconsistencies between expected returns and average realized returns for anomalies-based trading strategies remains an interesting open question.

Appendix A1: Variable Definitions

B/M is the book equity at the fiscal year-end divided by the ME 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 postretirement 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 *ME* is price per share times shares outstanding from CRSP.

The *CI* measure from Daniel and Titman (2006) is:

$$\iota(t-\tau) = \log\left(\frac{\mathrm{ME}_t}{\mathrm{ME}_{t-\tau}}\right) - r(t-\tau, t), \tag{A1}$$

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 ($\mathrm{ME}_{t-\tau}$) is total *ME* 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 *ME* 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 *CI*. In contrast, repurchase activities such as open market share repurchases, dividends, or any other action that pays cash out of a firm decrease the *CI*.

The *NSIs* 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 *NSI* 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 *NSI* 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 *AI*, which applies for the portfolio formation year t, as:

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

in which CE_{t-1} is capital expenditure (Compustat annual item CAPX) scaled by its sales (item SALE) in year $t-1$. The last 3-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. *AG* for the portfolio formation year t is 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 AC for the last fiscal year ending in calendar year $t-1$ as changes in noncash 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 noncash working capital is the change in noncash current assets minus the change in current liabilities less short-term debt and taxes payable.

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

in which ΔCA is the change in current assets (item ACT), ΔCASH 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 the depreciation and amortization expense (item DP).

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

$$\begin{aligned}\mathrm{Distress}_t = &-9.164 - 20.264\,\mathrm{NIMTAAVG}_t + 1.416\,\mathrm{TLMTA}_t \\ &- 7.129\,\mathrm{EXRETAG}_t + 1.411\,\mathrm{SIGMA}_\mathrm{t} - 0.045\,\mathrm{RSIZE}_t \\ &- 2.132\,\mathrm{CASHMTA}_t + 0.075\,\mathrm{MB}_t - 0.058\,\mathrm{PRICE}_t\end{aligned}$$

where

$$\mathrm{NIMTAAVG}_{t-1,\,t-12} \equiv \frac{1-\phi^3}{1-\phi^{12}}(\mathrm{NIMTA}_{t-1,\,t-3} + \ldots + \phi^9\mathrm{NIMTA}_{t-10,\,t-12})$$

$$\mathrm{EXRETAVG}_{t-1,\,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}(\mathrm{EXRET}_{t-1} + \ldots + \phi^{11}\mathrm{EXRET}_{t-12})$$

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 ME 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. $\mathrm{EXRET} = \log(1+R_{it}) - \log(1+R_{S\,\&\,P\,500,\,t})$ 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 ME and total liabilities. SIGMA is the volatility of each firm's daily stock return over the past 3 months. RSIZE is the relative size of each firm measured as the log ratio of its *ME* 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 *ME* 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.

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