



Anchoring and Risk Factors

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ABSTRACT

Profitability and investment are becoming the new focus of empirical asset pricing. We examine the extent to which their return predictability is attributable to investors' tendency to anchor on 52-week high. Based on a return decomposition methodology developed by George et al. (2014), two profitability measures (operating profitability, return on equity) and two investment measures (asset growth and investment to assets) are entirely attributable to anchoring. These results survive a battery of robustness checks and hold largely in various subsamples. The findings send a warning that these two potential risk factors could be attributed to the anchoring bias.

Keywords: Profitability, Investment, Anomaly, Anchoring, Return Decomposition

JEL Classifications: G12, G14, G18

1. INTRODUCTION

More profitable firms earn higher average future returns (Haugen and Baker, 1996; Cohen et al., 2002). Firms that invest more aggressively, however, on average earn lower returns (Fairfield et al., 2003; Titman et al., 2004; Cooper et al., 2008; Fama and French, 2008). Because these return patterns, along with many others, are not explained by asset pricing models such as the capital pricing asset model (CAPM) or the Fama and French (1993) three-factor model, they are viewed as anomalies. Fama and French (2006) interpret the investment and profitability anomalies in a dividend discount model. Studies that follow further highlight the importance of the profitability and investment anomalies as they incorporate the two anomalies into their empirical asset pricing models as factors. For example, Chen et al. (2011) model includes the market, profitability, and investment factors; Hou et al. (2015) propose a four-factor model based on the market, size, and the investment and profitability factors; Fama and French (2015) construct a five-factor model, which adds the investment and profitability factors to the market, size, and book-to-market factors as in Fama and French (1993). Thus, profitability and

investment are increasingly becoming the center stage of empirical asset pricing.

One important question is left open in the aforementioned studies: Are the profitability and investment factors proxies for rational risks or investors' irrational beliefs? In this paper we shed light on this question by examining the role of a specific type of irrational beliefs: investors' tendency to anchor on 52-week high. That is, when a stock's price is closer to its 52-week high, investors form an irrational belief that the stock price has little room to grow and thus are less likely to bid up the price, leading to underpricing and higher returns. On the other hand, when the stock price is far below its 52-week high, investors form an irrational belief that the stock price has much room to grow and thus are more likely to bid up the price, resulting in overpricing and lower returns. In this paper we examine the extent to which the return predictability of profitability and investment is attributable to anchoring.

Several motivations are behind our choice of anchoring. First, anchoring as a psychological bias is a well-documented

phenomenon in the psychology literature.¹ It is intuitively appealing for addressing the research question here, because it is hard to think of any alternative rational risk explanation for anchoring. Thus, anchoring provides a relatively clean test for investors' irrational beliefs or behavioral biases. Second, the choice is motivated by, and built upon, its recent success in explaining momentum (George and Hwang, 2004) and earnings surprise (George et al., 2014, GHJ thereafter), two of the more resilient anomalies in the literature. Notably, Lee and Piqueira (2017, 2019) show that anchoring even affects decisions of corporate insiders and short sellers, arguably the most rational and informed agents in the market.

Using a simple and intuitive methodology developed by GHJ (2014) to decompose anomaly returns, we report empirical evidence that highlights the strong impact of anchoring in both profitability and investment anomalies. Our main findings can be summarized as follows. Two profitability measures (operating profitability and return on equity) and two measures of investment (asset growth and investment to assets ratio) are entirely attributable to anchoring. These findings survive a battery of robustness checks and largely hold in various subsamples.

The paper contributes to the asset pricing literature by showing evidence of a considerable gap between theoretical and empirical asset pricing. As Fama and French (2015) put it, theoretical asset pricing models work forward and empirical asset pricing models work backward. From assumptions about investor preference and investment opportunities, theories such as those of Merton (1973) and Ross (1976) prescribe how risk should be measured and how it is related to expected return. By contrast, empirical asset pricing models take the patterns in average returns as given and propose models to capture them. Ideally, if the empirical factors are reasonable proxies for rational risk, the empirical models are well connected to theory. In reality, however, empirical models tend not to explicitly specify whether the factors are proxies for rational risk or irrational beliefs. The findings in this paper suggest that profitability (measured by operating profitability or return on equity) and investment (measured by asset growth or investment to assets ratio) are entirely attributable to investors' anchoring bias, not rational risk.

This paper adds to the growing literature on the role of anchoring in stock market (e.g. Lee and Piqueira, 2017; 2019). Our paper directly extends GHJ (2014) by applying their methodology to the profitability and investment anomalies, two of the many important

anomalies that help explain stock returns. As conjectured by GHJ (2014), the methodology is quite general and can be applied to any other anomalies. It remains to be seen in future work the extent to which the anchoring effect accounts for the various return patterns in the stock market.

After describing the data, sample, and methodology in section 2, we present the main results in section 3, followed by subsample results in section 4, and conclude in section 5.

2. SAMPLE, DATA, AND METHODOLOGY

2.1. Sample

The sample includes all NYSE/Amex/NASDAQ common stocks (share code 10 or 11) covered in CRSP/Compustat merged database from July 1963 to December 2013, a total of 606 year/month cross-sections. For the anomaly of *ROE* (return on equity, defined in Appendix A), because of data availability, the sample covers the period of July 1972 to December 2013.

We apply the standard filters: We exclude stocks whose prior month-end price is lower than \$5 and stocks with market capitalization below the first NYSE decile breakpoint. These sampling restrictions do not alter our conclusion, as shown in the robustness section. Because we examine the anomalies separately, we do not require that all anomaly variables are non-missing. Thus the average number of stocks for a monthly cross-section varies across the anomalies: 2,022 for operating profitability (*OP*), 2,076 for return on equity (*ROE*), 1,894 for asset growth ($\Delta A/A$), and 1,647 for investment to assets (*I/A*).

2.2. Data

We construct four anomaly variables as used in Chen et al. (2011), Hou et al. (2015), and Fama and French (2015), the studies that build profitability and investment factors. They include two measures for profitability (*OP*, *ROE*) and two for investment ($\Delta A/A$ and *I/A*).

The definition of operating profitability (*OP*) follows Fama and French (2015). Return on equity (*ROE*) follows Chen et al. (2011) and Hou et al. (2015). Asset growth ($\Delta A/A$) follows Hou et al. (2015) and Fama and French (2015). Investment to assets ratio (*I/A*) follows Chen et al. (2011). All data come from Compustat annual and quarterly databases. Details of the definitions are contained in Appendix A.

Except for *ROE*, which is quarterly updated, the other four measures are updated annually. *ROE* of quarter *q* predicts returns of months starting from the month after the quarter *q* earnings announcement to the month of the quarter *q*+1 earnings announcement. For annually updated variables, by June of year *t*, the variables are measured using accounting information as of or prior to the fiscal year ending in year *t*-1. The measures are used to predict returns for months from July of year *t* to June of year *t*+1.

To apply the methodology developed in George et al. (2014, GHJ thereafter), we define the nearness ratio (*NR*), following George and Hwang (2004). Specifically, the nearness ratio for stock *j* in

¹ See, e.g., Tversky and Kahneman (1974), Kahneman et al. (1982, p. 14-20), Kahneman (2001), and Ginsburgh and van Ours (2003). Besides George and Hwang (2004), there are other important studies in the finance literature that involves anchoring on 52-week high. Li and Yu (2012) show that the Dow Index returns are significantly related to the nearness of the index to its 52-week high. Baker, Pan, and Wurgler (2009) find that target shareholders anchor on 52-week high as a reference point in mergers and acquisitions. George et al (2018) find that the price-to-high variable (equivalent of the Nearness ratio (*NR*), defined in the next section) is positively correlated with the profitability and investment growth. Huddart et al. (2009) find that investors' trading decisions are influenced by 52-week high stock price. Ma et al. (2019) find that acquirer reference prices affect market reactions and merger decisions.

month t , $NR_{j,t}$ is defined in Equation (1), where $P_{j,t}$ is the price of stock j at the end of month t , and $H_{j,t-11-t}$ is the highest daily closing price over the past 12 months (or 252 trading days), including month t . The prices are adjusted for stock splits and dividends using CRSP daily price adjustment factor. NR of month $t-1$ predicts return in month $t+1$.

$$NR_{j,t} = \frac{P_{j,t}}{H_{j,t-11-t}} \quad (1)$$

We first confirm that the anomalies generate abnormal returns after accounting for known common risk factors. In our main analysis we use Fama and French (1993) three-factor regressions as the known common risks. Specifically, for each anomaly, we monthly form quintiles by NYSE breakpoints.² The time series of the equal-weighted portfolio returns for the quintiles are regressed on the Fama and French (1993) three factors. The intercepts are the abnormal returns. Results based on excess returns and/or value-weighting are qualitatively similar and thus are not reported. We also show the anomaly profit from a strategy that buys stocks in the top quintile and sells stocks in the bottom quintile. Table 1 reports the three-factor alphas for the quintiles (Q1 to Q5) and the anomaly profit (Q5–Q1) for each of the anomalies, shown in the column heading. For each of the anomalies, Table 1 reports significant abnormal returns from a strategy that buys the top quintile and sells the bottom quintile. For example, for OP , the three-factor alpha for the lowest quintile (weakest operating profitability) is -0.24% while that for the highest quintile (strongest operating profitability) is 0.10% , resulting in a profit of 0.34% ($t=3.46$). Likewise, for $\Delta A/A$, the lowest quintile (firms that grow aggressively) earns an alpha of -0.25% and the highest quintile (firms that grow conservatively) earns an alpha of 0.05% , resulting in a profit of 0.30% ($t=4.28$).

We also form NR quintiles by NYSE breakpoints and estimate the quintile returns over the subsequent month. The monthly alphas are presented in the last column of Table 1. The lowest quintile (stocks with price far below its 52-week high, or anchored low) earns an alpha of -0.73% and the highest quintile (stocks with price close to its 52-week high, or anchored high) earns an alpha of 0.35% , resulting in an anomaly profit of 1.08% ($t=6.88$).

Results in Table 1 suggest that each of the anomalies predicts stock returns in the cross-section. Therefore, based on these anomalies one could construct return series as factor-mimicking portfolios (as in Chen et al., 2011; Hou et al., 2015; and Fama and French, 2015). The last column of Table 1 suggests that nearness ratio also significantly explains the cross-section of stock returns. That is, stock returns are significantly affected by investors' tendency to anchor on 52-week high.

2 For the investment anomalies ($\Delta A/A$ and I/A), because lower investment predicts higher returns, we take the inverse of the measures to form quintiles. This way, the top quintile (lowest investment level) predicts higher returns and the bottom quintile (highest investment level) predicts lower returns. For the three profitability anomalies, higher anomaly variable values predict higher returns so we simply use the anomaly variable to form quintiles.

Table 1: Quintile returns of the anomalies and nearness ratio

Quintiles	OP	ROE	$\Delta A/A$	I/A	NR
Q1	-0.24	-0.59	-0.25	-0.27	-0.73
Q2	-0.01	-0.14	0.06	0.04	-0.01
Q3	0.03	0.02	0.10	0.10	0.15
Q4	0.03	0.20	0.10	0.14	0.23
Q5	0.10	0.40	0.05	0.08	0.35
Q5–Q1	0.34	0.98	0.30	0.35	1.08
	[3.46]	[7.93]	[4.28]	[4.98]	[6.88]

For ROE the data cover the period July 1972 to December 2013. For all others, the data cover July 1963 to December 2013. The table shows the quintile monthly alphas from Fama and French (1993) three-factor regressions. Specifically, for each anomaly, we monthly form quintiles based on NYSE breakpoints. The time series of the equal-weighted portfolio returns for the quintiles are regressed on the Fama and French (1993) three factors. The intercepts are the abnormal returns. The rows "Q5–Q1" show the profits from the anomaly strategy that buys stocks in the top quintile and sells stocks in the bottom quintile, with t -stats in brackets. For OP , ROE , and NR , the quintiles are formed on the variables directly. For $\Delta A/A$ and I/A the quintiles are formed on the negative of the variables because they are inversely related to future returns. All variables are defined in Appendix A

In this paper we examine the extent to which the return predictability of these anomalies is attributable to anchoring. To see how anchoring contributes to an anomaly's return predictability, for each of the anomalies we conduct a two-way sort analysis. For convenience we use X for a generic anomaly. We independently sort stocks monthly into quintiles on an anomaly variable X and nearness ratio NR , both by NYSE breakpoints. We then calculate their equal-weight portfolio returns for each of the 25 (5×5) portfolios and take the intercepts from the Fama and French (1993) three-factor regressions. These monthly alphas are presented in Table 2, a panel for each anomaly. We also report tests on spreads between the conditional extreme portfolios.

Panel A shows the results for OP . The last column of the Panel presents the spread (t -stats in brackets) between the two extreme NR quintiles (HNR and LNR), conditional on the OP quintiles. Clearly all five spreads are positive and significant, indicating that even after controlling for the anomaly variable OP , the nearness ratio explains the cross-section of stock returns, which later we call the pure anchoring effect. A closer look at the last column also reveals that the NR spreads are higher in the extreme OP quintiles. That is, the anchoring effect is stronger when the anomaly variable OP takes extreme values, an effect we later call the interaction effect. The last two rows list the spreads (t -stats in brackets) between the two extreme OP quintiles conditional on NR . Some of the numbers in the last two rows of Panel A are not statistically significant, indicating that the relation between OP and stock returns is no longer robust after controlling for NR .

The other panels also show signs of the anchoring effects. Throughout all panels, the most salient finding is that all NR spreads, the numbers presented in the last column are positive and significant, indicating the strength of the anchoring effect. For ROE and $\Delta A/A$, the anchoring effect is stronger when the anomaly variables take extreme values. For I/A , the anchoring effect is stronger in the two lower quintiles.

The ROE quintile spreads are positive and significant for each of the NR quintiles. The magnitude ranges from 0.62% to 0.86% ,

Table 2: Two-way sort results

Anomaly quintile	LNR	NR2	NR3	NR4	HNR	HNR-LNR
Panel A: <i>OP</i>						
Q1	-0.99	-0.05	0.13	0.12	0.17	1.16 [6.21]
Q2	-0.57	0.03	0.15	0.14	0.21	0.78 [4.68]
Q3	-0.49	0.03	0.10	0.19	0.29	0.78 [4.89]
Q4	-0.56	-0.06	0.15	0.18	0.38	0.95 [5.81]
Q5	-0.65	0.07	0.18	0.47	0.52	1.18 [7.51]
Q5-Q1	0.34 [2.57]	0.11 [1.03]	0.06 [0.51]	0.34 [3.00]	0.35 [3.13]	
Panel B: <i>ROE</i>						
Q1	-1.12	-0.31	-0.24	-0.24	-0.00	1.11 [4.67]
Q2	-0.59	0.02	0.00	-0.03	0.06	0.66 [3.48]
Q3	-0.34	-0.03	0.12	0.14	0.21	0.54 [3.07]
Q4	-0.36	0.11	0.30	0.33	0.41	0.77 [4.23]
Q5	-0.44	0.31	0.42	0.62	0.76	1.20 [6.20]
Q5-Q1	0.67 [4.32]	0.62 [4.62]	0.65 [4.64]	0.86 [6.17]	0.77 [5.20]	
Panel C: $\Delta A/A$						
Q1	-1.10	-0.22	-0.01	0.33	0.50	1.59 [9.22]
Q2	-0.52	0.08	0.17	0.21	0.34	0.86 [5.55]
Q3	-0.26	0.09	0.17	0.21	0.24	0.50 [3.06]
Q4	-0.26	0.11	0.20	0.20	0.23	0.49 [2.95]
Q5	-0.51	0.12	0.23	0.18	0.31	0.82 [4.65]
Q5-Q1	0.59 [5.38]	0.34 [3.66]	0.24 [2.66]	-0.16 [-1.66]	-0.19 [-2.11]	
Panel D: <i>I/A</i>						
Q1	-1.07	-0.27	0.00	0.24	0.41	1.48 [8.34]
Q2	-0.54	-0.01	0.17	0.29	0.41	0.95 [5.42]
Q3	-0.37	0.08	0.17	0.23	0.38	0.74 [4.24]
Q4	-0.31	0.14	0.19	0.27	0.38	0.69 [4.19]
Q5	-0.53	0.11	0.30	0.33	0.24	0.78 [4.77]
Q5-Q1	0.53 [4.73]	0.39 [4.44]	0.30 [3.20]	0.09 [1.01]	-0.17 [-1.75]	

For *ROE* the data cover the period July 1972 to December 2013. For all others, the data cover July 1963 to December 2013. The table shows the monthly alphas from Fama and French (1993) three-factor regressions for the 25 (5 × 5) portfolios formed by independent quintile sorts on an anomaly variable *X* and nearness ratio *NR*. The variable *X* is indicated in the title of each Panel. The equal-weighted portfolio returns are then regressed on a Fama and French (1993) three-factor model and the intercepts are reported in each Panel. The last column reports the spread (t-stats in brackets) between the top and bottom *NR* quintiles conditional on the anomaly quintiles. The last two rows of each Panel report the spread (with t-stats in brackets) between the extreme *X* quintiles conditional on the *NR* quintiles. For *OP*, *ROE*, and *NR*, the quintiles are formed on the variables directly. For $\Delta A/A$ and *I/A* the quintiles are formed on the negative of the variables because they are inversely related to future returns. All variables are defined in Appendix A

below the whole-sample result of 0.98%, as presented in Table 1. Thus, controlling for *NR* erodes *ROE*'s magnitude of return predictability. For $\Delta A/A$, the spreads from the extreme $\Delta A/A$ quintiles are positive and significant when the *NR* values are ranked in the bottom three quintiles but negative when the *NR* values are ranked in the top two quintiles. This result suggests that the $\Delta A/A$ anomaly is bifurcated by anchoring. The *I/A* quintile spreads are positive and significant for the three lower *NR* quintiles, positive but not significant for the fourth, and negative for the highest *NR* quintile.

To sum up, data in Table 2 suggest that anchoring potentially contributes to the return predictability of the anomalies. To see the extent to which the anomalies are attributed to anchoring, it is useful to decompose the effect purely due to the anomaly, the pure anchoring effect, and the effect that investors anchor even more when the anomaly variable takes extreme values. The return decomposition methodology developed by GHL (2014) is exactly for this purpose.

2.3. The George et al. (2014) Methodology

GHL (2014) develop the return decomposition methodology and show that the earnings surprise anomaly is entirely attributed to anchoring. The essence of the methodology is that there are two types of anchoring effect. First is the pure anchoring effect. That

is, investors simply anchor on 52-week high, regardless of whether the earnings surprise is extreme or not. The other is through interaction. That is, beyond the pure anchoring effect, investors tend to anchor even more when the earnings surprise is extreme.

The following example of stocks S1 and S2 illustrates the two effects and their difference. For stock S1, its price is near its 52-week high and there is zero earnings surprise. Investors anchoring on the 52-week high form an irrational belief that, relative to the 52-week high, the stock price does not have much room to grow. As a result, they are less likely to bid up the price, leading to underpricing. In this case, the anchoring effect is pure, in the sense that there is no role played by earnings surprise. Thus, the return for stock S1 can be modeled as $\infty + A_H$, where ∞ is the benchmark return and A_H is the pure anchoring effect when the price is anchored high.

For stock S2, the price is also near its 52-week high, but the company has just experienced an extreme positive earnings surprise. In this case, if investors underreact to the earnings surprise there is an earnings surprise effect, which we call X_{GG} , where "GG" stands for extremely good earnings news; there will be also a pure anchoring effect A_H . In addition, because of the extreme positive earnings surprise, investors anchoring on the 52-week high are unwilling to bid up the stock price after it

substantially deviates from the anchor. This resistance to further price change leaves much of the extreme positive earnings information unincorporated into the price. This effect is also due to investors' anchoring bias, but it is beyond that purely due to high price. GH (2014) model this component as the interaction effect, denoted $I_{GG,HP}$ for the interaction between extreme good earnings news (GG) and stock price anchored high (H). The return for stock S2 is thus modeled as $\infty + A_H + X_{GG} + I_{GG,HP}$

We follow the GH (2014) methodology to model the mean returns for portfolios formed by independent sorts on an anomaly X and the nearness ratio NR .³ As illustrated in the previous discussions, for convenience we borrow most of the notations from GH (2014) except that we use a generic X for an anomaly in place of their Standardized Unexpected Earnings (SUE) variable. In addition, we use HNR and LNR for the highest and lowest NR quintiles.

More formally, in addition to the benchmark return μ , there are three types of return components, X , A , and I . The X components are for the pure anomaly effects; the A components are for the pure anchoring effect; and the I components are for the interaction effect. Stocks ranked in the bottom (top) X quintile are considered having extremely bad (good) X news, represented by BB (GG). Single B and G represent the second (modestly bad) and fourth (modestly good) quintiles, respectively. The middle three NR quintiles are lumped together. Thus, by NR ranks stocks are in the H, L, and M group if their NR ranks are in the top, bottom, and middle quintiles, respectively. Stocks that are ranked neither in the extreme NR quintiles nor the extreme anomaly quintiles are treated as benchmark.

In this setting, the 15 (5×3) portfolios formed by the intersection of the anomaly X and NR have average returns as shown in Figure 1. For example, the upper-left cell of the matrix is for stocks ranked in the bottom X quintile and bottom NR quintile. These are stocks with extreme bad X news and stock price anchored low. The mean returns of these stocks, $R_{BB,L}$ have three components in addition to the benchmark μ . First is the pure anomaly effect X_{BB} , as these stocks experience the extreme bad X news; the second is the pure anchoring effect A_L , as the prices are anchored low; the last is the interaction effect $I_{BB,L}$. This interaction term captures the extra price distortion when investors anchor even more when the X news is extremely bad. Thus, we have

$$R_{BB,L} = \infty + X_{BB} + A_L + I_{BB,L} \tag{2}$$

For stocks in this portfolio, if the returns are purely due to the bad X news then X_{BB} is negative and significant; if the returns are entirely attributable to investors anchoring on 52-week high, then the combined anchoring and interaction effects ($A_L + I_{BB,L}$) is negative and significant but X_{BB} is not significant.

3 To better align with the GH methodology, one can think of a marginal investor making trading decisions based on two signals, the anomaly variable X and the price level NR . The anomaly variable could be as fresh as an earnings announcement or as stale as past asset growth or recent accounting profitability. Either way, so long as they affect investors' decision, the GH methodology is equally applicable.

Figure 1: Return decomposition matrix

Anomaly quintiles	LNR	NR2-NR4	HNR
X1	$\mu + X_{BB} + A_L + I_{BB,L}$	$\mu + X_{BB} + I_{BB,M}$	$\mu + X_{BB} + A_H$
X2	$\mu + X_B + A_L + I_{B,L}$	$\mu + X_B + I_{B,M}$	$\mu + X_B + A_H$
X3	$\mu + A_L$	μ	$\mu + A_H$
X4	$\mu + X_G + A_L$	$\mu + X_G + I_{G,M}$	$\mu + X_G + A_H + I_{G,H}$
X5	$\mu + X_{GG} + A_L$	$\mu + X_{GG} + I_{GG,M}$	$\mu + X_{GG} + A_H + I_{GG,H}$

Similarly, the lower-right cell of the matrix is for stocks experiencing extremely good X news and stock prices anchored high. Their mean returns are modeled in equation (3), where X_{GG} is the pure anomaly effect, A_H the pure anchoring effect, and $I_{GG,H}$ the interaction effect. Note that the example of stock S2 as discussed in the beginning of this section belongs to this group.

$$R_{GG,H} = \infty + X_{GG} + A_H + I_{GG,H} \tag{3}$$

Average returns of stocks in the other cells of the matrix are similarly modeled, depending on their X and NR ranks. For instance, the middle cell in the first row is for stocks with non-extreme NR but extreme negative X news. These stocks have a pure anomaly effect X_{BB} ; there is no pure anchoring effect since their NR is not extreme. Some innocuous assumptions are made. For stocks experiencing extremely or modestly bad X news ($X1$ and $X2$) there is no interaction effect if the stock prices are anchored high. Likewise, for stocks experiencing extremely or modestly good X news ($X4$ and $X5$) there is no interaction effect if the stock prices are anchored low. Stocks ranked in the middle X quintile have neither pure anomaly effect nor interaction effect. The only effect is due to pure anchoring A_L for those anchored low and A_H for those anchored high. The center cell of the matrix represents the benchmark. These stocks have neither extreme X news nor extreme NR and earn the benchmark return of ∞ .

Equations (2) and (3) suggest a return decomposition, as shown in equation (4). The left hand side of the equation (4) is the return of a strategy that trades on both the X anomaly and the nearness ratio NR . It buys stocks ranked in the top X quintile and top NR quintile and sells stocks ranked in the bottom X quintile and bottom NR quintile. For convenience we call it the enhanced strategy or enhanced profit as the strategy is based on an anomaly X but enhanced by NR . This enhanced profit comes from a pure anomaly effect ($X_{GG} - X_{BB}$), a pure anchoring effect ($A_H - A_L$), and an interaction effect ($I_{GG,H} - I_{BB,L}$).

$$R_{GG,H} - R_{BB,L} = (X_{GG} - X_{BB}) + (A_H - A_L) + (I_{GG,H} - I_{BB,L}) \tag{4}$$

$$= \text{Anomaly} + \text{Anchoring} + \text{Interaction}$$

Whether and the extent to which the anomaly X contributes to predicting returns can be tested by the statistical and economic significance of the component ($X_{GG} - X_{BB}$).

To estimate the components, GH (2014) propose to run Fama-MacBeth regressions of future returns on dummy variables for the X and NR quintiles and the piecewise interaction terms. Appendix B describes the details of deriving the individual X , A ,

and I components, the anomaly effect ($X_{GG}-X_{BB}$), the anchoring effect (A_H-A_L), and the interaction effect ($I_{GG,H}-I_{BB,L}$).

3. MAIN RESULTS

3.1. Return Decomposition for the Anomalies

Table 3 presents the return decomposition results. Each column represents an anomaly, indicated in the heading. For ease of exposition we present results based on Fama and French (1993) three-factor regressions with all months included (January included). Results for excess returns and/or with January excluded reach the same conclusions. The rows for each column are identical to those in GHJ (2014, Table 3). Panel A presents the time-series averages of the Fama and MacBeth regression coefficients. Panel B of Table 3 presents the estimates of the return components (X , A , and I), derived from the regression coefficients shown in Panel A.

For example, X_{GG} returns attributable to extremely good X news is the summation of the regression coefficients on $X5$ and on the interaction between $X5$ and LNR ; the anchoring components A_H and A_L are simply the coefficients on HNR and LNR , respectively; $I_{GG,H}$ is the difference between the coefficients on $X5*HNR$ and $X5*LNR$. These return components form the base for tests reported in Panel C.

The relevant messages from the regressions are contained in Panels B and C. We discuss them for each of the profitability and investment anomalies in turn.

3.1.1. Return decomposition for OP

For operating profitability, OP , the first column of Panel B shows no significant Fama and French (1993) three-factor alphas associated with stocks having extreme high (top quintile) or low (bottom quintile) operating profitability. These estimates indicate

Table 3: Return decomposition

Anomalies	OP	ROE	$\Delta A/A$	I/A
Panel A: Regressions				
Intercept	0.11 (2.17)	0.07 (1.11)	0.16 (3.27)	0.16 (3.47)
$X5$	0.12 (2.33)	0.39 (6.19)	0.01 (0.23)	0.10 (1.92)
$X4$	-0.03 (-0.68)	0.19 (4.13)	0.01 (0.19)	0.05 (1.19)
$X2$	-0.00 (-0.11)	-0.07 (-1.65)	-0.00 (-0.09)	-0.01 (-0.20)
$X1$	-0.05 (-0.71)	-0.33 (-3.32)	-0.14 (-2.52)	-0.17 (-2.86)
HNR	0.18 (2.19)	0.14 (1.48)	0.08 (1.05)	0.22 (2.45)
LNR	-0.60 (-5.42)	-0.41 (-3.23)	-0.42 (-3.60)	-0.52 (-4.35)
$X5*HNR$	0.11 (1.47)	0.17 (2.00)	0.06 (0.79)	-0.23 (-2.58)
$X4*HNR$	0.12 (1.80)	0.02 (0.23)	-0.02 (-0.29)	-0.04 (-0.59)
$X2*HNR$	-0.07 (-1.01)	-0.07 (-0.88)	0.11 (1.56)	0.04 (0.52)
$X1*HNR$	-0.06 (-0.77)	0.12 (1.04)	0.40 (5.48)	0.21 (2.30)
$X5*LNR$	-0.29 (-3.12)	-0.49 (-4.15)	-0.26 (-2.38)	-0.26 (-2.36)
$X4*LNR$	-0.05 (-0.57)	-0.21 (-1.85)	-0.01 (-0.06)	0.01 (0.05)
$X2*LNR$	-0.08 (-0.83)	-0.18 (-1.75)	-0.26 (-2.65)	-0.16 (-1.61)
$X1*LNR$	-0.45 (-4.36)	-0.45 (-3.60)	-0.69 (-7.14)	-0.53 (-4.88)
Panel B: Return components				
$X_{GG}=(X5+X5*LNR)$	-0.17 (-1.72)	-0.11 (-0.90)	-0.25 (-2.33)	-0.17 (-1.52)
$X_G=(X4+X4*LNR)$	-0.08 (-0.88)	-0.02 (-0.19)	0.00 (0.02)	0.06 (0.51)
$X_B=(X2+X2*HNR)$	-0.07 (-1.18)	-0.14 (-2.01)	0.11 (1.69)	0.03 (0.48)
$X_{BB}=(X1+X1*HNR)$	-0.12 (-1.30)	-0.21 (-1.55)	0.26 (3.52)	0.04 (0.42)
$A_H=HNR$	0.18 (2.19)	0.14 (1.48)	0.08 (1.05)	0.22 (2.45)
$A_L=LNR$	-0.60 (-5.42)	-0.41 (-3.23)	-0.42 (-3.60)	-0.52 (-4.35)
$I_{GGH}=(X5*HNR-X5*LNR)$	0.40 (3.63)	0.66 (4.89)	0.32 (2.50)	0.04 (0.28)
$I_{G,H}=(X4*HNR-X4*LNR)$	0.17 (1.66)	0.22 (1.86)	-0.01 (-0.13)	-0.05 (-0.40)
$I_{B,L}=(X2*LNR-X2*HNR)$	-0.01 (-0.06)	-0.11 (-0.99)	-0.36 (-3.31)	-0.20 (-1.80)
$I_{BB,L}=(X1*LNR-X1*HNR)$	-0.38 (-2.84)	-0.57 (-3.36)	-1.09 (-9.05)	-0.74 (-5.52)
Panel C: Tests				
$X_{GG}-X_G$	-0.09 (-1.01)	-0.09 (-0.72)	-0.25 (-2.42)	-0.22 (-2.11)
$X_{BB}-X_B$	-0.04 (-0.55)	-0.07 (-0.53)	0.15 (2.26)	0.01 (0.08)
X_G-X_B	-0.00 (-0.02)	0.12 (0.97)	-0.10 (-0.93)	0.02 (0.18)
$X_{GG}-X_{BB}$ (Anomaly)	-0.05 [-0.34]	0.10 [0.55]	-0.51 [-3.74]	-0.21 [-1.42]
A_H-A_L (Anchoring)	0.78 [4.89]	0.54 [3.07]	0.50 [3.06]	0.74 [4.24]
$I_{GG,H}-I_{G,H}$	0.23 (2.18)	0.44 (3.11)	0.33 (2.64)	0.09 (0.69)
$I_{BB,L}-I_{B,L}$	-0.38 (-3.18)	-0.46 (-3.03)	-0.73 (-6.96)	-0.54 (-4.56)
$I_{G,H}-I_{B,L}$	0.18 (1.03)	0.34 (1.71)	0.35 (1.85)	0.15 (0.75)
$I_{GGH}-I_{BB,L}$ (Interaction)	0.78 [3.92]	1.23 [4.94]	1.41 [6.69]	0.78 [3.46]

For ROE the data cover the period July 1972 to December 2013. For all others, the data cover July 1963 to December 2013. For each of the anomalies indicated in the column heading, Panel A shows results of the Fama and MacBeth regression coefficients from a regression specified in Appendix B. Specifically, for each cross-section, stock return of month t is regressed on an intercept, the four quintile dummies formed on the anomaly, the two quintile dummies for the extreme NR ratios, and the piecewise interaction between the two sets of dummy variables. The anomaly variable and NR are based on information available by the end of month $t-1$. The time-series of the Fama-MacBeth regression coefficients are then regressed on the Fama and French (1993) three factors to adjust for any comovement with the three risk factors. The intercepts are reported in Panel A. Panel B presents the estimates of the return components as outlined in Appendix B. Panel C reports tests on the return components. For OP , ROE , and NR , the quintiles are formed on the variables directly. For $\Delta A/A$ and I/A the quintiles are formed on the negative of the variables because they are inversely related to future returns. T -statistics are in parentheses or brackets below the coefficients. All variables are defined in Appendix A.

that the abnormal returns associated with the *OP* anomaly, shown in Table 1, are probably not attributed to operating profitability, but something else. Indeed, the two anchoring components both have the expected sign and are significant. Relative to the benchmark, stocks anchored high (with high nearness ratio) earn an average return of 0.18% ($t=2.19$) and stocks anchored low (with low nearness ratio) earn an average return of -0.60% ($t=-5.42$). In addition, the two extreme interaction terms have the expected signs and are highly significant. The interaction effect for stocks ranked in the top *OP* quintile and top *NR* quintile is 0.40% ($t=3.63$); the interaction effect for stocks ranked in the bottom *OP* quintile and bottom *NR* quintile is -0.38% ($t=-2.84$). These numbers suggest that there are significant pure anchoring and interaction effects but little is attributable to *OP* itself.

The formal tests are summarized in Panel C of Table 3. Not surprisingly, the first column in Panel C of Table 3 reports that the pure anomaly effect ($X_{GG} - X_{BB}$) for *OP* is an insignificant -0.05% ($t=-0.34$). By contrast, the anchoring effect is 0.78% ($t=4.89$) and the interaction effect is 0.78% ($t=3.92$). The return decomposition for *OP* is summarized in Equation (5).

$$R_{GG,H} - R_{BB,L} = \text{Anomaly} + \text{Anchoring} + \text{Interaction} \quad (5)$$

1.51	=	-0.05	+	0.78	+	0.78
		[-0.34]		[4.89]		[3.92]

These results indicate that the abnormal returns associated with the *OP* anomaly are due to investors' tendency to anchor on 52-week high and a stronger anchoring effect when the operating profitability of a stock is extreme.

The first column in Panel C of Table 3 also presents some additional tests. The first row $X_{GG} - X_G$ tests the different anomaly effects between extremely strong (top quintile) and mildly strong (second to top quintile) operating profitability; the second row $X_{BB} - X_B$ tests the different anomaly effect between extremely weak (bottom quintile) and mildly weak (second to bottom quintile) operating profitability; the third row $X_G - X_B$ tests the difference between the mildly strong (second to top quintile) and mildly weak (second to bottom quintile) operating profitability. For the *OP* anomaly, there are no significant results, indicating further that stock returns do not vary with *OP* per se. The structure of the decomposition methodology also allows testing the differential interaction effects between the top two *OP* quintiles for stocks that are anchored high ($I_{GG,H} - I_{G,H}$), and the differential interaction effects between the bottom two *OP* quintiles for stocks that are anchored low ($I_{BB,L} - I_{B,L}$). Following the argument in GHL (2014, pp. 14), if investors anchor more with extreme *OP* than mild *OP*, it is implied that $I_{GG,H} > I_{G,H}$ and $I_{BB,L} < I_{B,L}$. If, however, extreme *OP* helps investors correct their anchoring bias, opposite inequalities are implied: $I_{GG,H} < I_{G,H}$ and $I_{BB,L} > I_{B,L}$. Data reported in these (sixth and seventh) rows in Panel C support the former conjecture. That is, investors anchor more when *OP* is more extreme. These results provide further evidence that investors' anchoring bias is at work with the *OP* anomaly.

3.1.2. Return decomposition for ROE

Results for the *ROE* anomaly, our second profitability measure, is presented in the second column of Table 3. Based on the Fama-

MacBeth regression coefficients reported in Panel A, estimates of the return components are shown in Panel B and the relevant tests presented in Panel C. Panel B shows that the average return attributable to being ranked in the top *ROE* quintile is -0.11% ($t=-0.90$); the return is -0.21% ($t=-1.55$) for the bottom *ROE* quintile. Neither is statistically significant. By contrast, the pure anchoring effect appears much stronger. The average return attributable to being anchored high (*HNR*) is 0.14% ($t=1.48$) and -0.41% ($t=-3.23$) for being anchored low (*LNR*). Likewise, there are strong interaction effects. $I_{GG,H}$, the interaction effect for stocks ranked in the top *ROE* quintile and top *NR* quintile is 0.66% ($t=4.89$); $I_{BB,L}$, the interaction effect for stocks in the bottom *ROE* quintile with prices anchored low is -0.57% ($t=-3.36$).

The decomposition is detailed in Panel C with the main message summarized in equation (6). For the profit of 1.88% from the enhanced strategy, only 0.10% ($t=0.55$) is attributed to the anomaly, *ROE*; a much larger and more significant return of 0.54% ($t=3.07$) is due to investors' tendency to anchor, regardless of *ROE*; an even larger return of 1.23% ($t=4.94$) is attributable to the interaction effect. That is, investors anchor even more for stocks with extreme *ROEs*.

$$R_{GG,H} - R_{BB,L} = \text{Anomaly} + \text{Anchoring} + \text{Interaction} \quad (6)$$

1.88	=	0.10	+	0.54	+	1.23
		[0.55]		[3.07]		[4.94]

It is interesting to note the similarity between the return decomposition for *SUE*, the earnings surprise anomaly, as analyzed in greater detail in GHL (2014) and that for the *ROE* anomaly as discussed here.⁴ Using the return decomposition methodology, the two anomalies behave much the same way in predicting stock returns. In particular, while prima facie trading strategies based on them generate significant abnormal returns and are thus considered anomalies, the underlying force appears the same: investors' anchoring bias. That is, investors tend to anchor on 52-week high in general, and they anchor even more when the anomaly variables take more extreme values.

3.1.3. Return decomposition for $\Delta A/A$

Results for $\Delta A/A$, the asset growth anomaly and our first investment measure, is presented in the fourth column of Table 3. Just as with the profitability measures, the Fama-MacBeth regression coefficients are reported in Panel A, estimates of the return components shown in Panel B and relevant tests presented in Panel C. Because lower investment is associated with higher future returns, the quintiles are formed on the negative of $\Delta A/A$. Thus, the $\Delta A/A$ ranks reflect firms' conservatism in growth. The higher the $\Delta A/A$ ranks, the more conservative the growth strategy is.

Shown in Panel B, the average return attributable to being most conservative in growth is -0.25% ($t=-2.33$); the return is 0.26% ($t=3.52$) for the most aggressive quintile. These numbers indicate that more aggressive investment predicts higher, but not lower future returns, an exactly opposite relation to what

4 GHL (2014, p.14), for the earnings surprise anomaly *SUE*, report an insignificant anomaly effect of 0.05% ($t=0.32$), an anchoring effect of 0.49% ($t=2.81$), and an interaction effect of 0.82% ($t=3.81$).

the anomaly suggests (e.g. Fairfield et al., 2003; Titman et al., 2004; Cooper et al., 2008; Fama and French, 2006, 2008). Indeed, this reversal of relation appears driven by the pure anchoring effect and the interaction effect. Panel B shows that the anchoring components are modestly strong. Relative to the benchmark, being anchored high is associated with a return of 0.08% ($t=1.05$) and being anchored low is associated with a return of -0.42% ($t=-3.60$).

More striking is the interaction effect. Shown in Panel B, $I_{GG,HP}$ the interaction effect is a significant 0.32% ($t=2.50$) for stocks with the most conservative growth and stock prices anchored high. Even more striking, $I_{BB,L}$ the interaction effect for stocks with extremely aggressive asset growth and stock prices anchored low, is a highly significant -1.09% ($t=-9.05$). These return patterns are consistent with investors anchoring even more with extreme news. When observing aggressive asset growth by firms whose stock prices are far below their 52-week high, investors tend to form an irrational belief that the future stock price has much room to grow. As a result, they are more likely to bid up the stock prices, leading to overvaluation. When the value-relevant information eventually comes to the market, the stock prices fall.

The decomposition is detailed in Panel C and the main message summarized in equation (7). For the profits of 1.41% from taking advantage of the $\Delta A/A$ anomaly and NR , 0.50% ($t=3.06$) is attributable to the pure anchoring effect regardless of the aggressive or conservative growth; a much larger effect of 1.41% ($t=6.69$) is due to the interaction effect. That is, investors anchor more when firms invest or grow extremely aggressively or conservatively. After accounting for the anchoring effect and the interaction effect, the effect attributable to the asset growth anomaly $\Delta A/A$ is actually a negative one, -0.51% ($t=-3.74$).

$R_{GG,H} - R_{BB,L}$	=	Anomaly	+	Anchoring	+	Interaction	(7)
1.41	=	-0.51	+	0.50	+	1.41	
		[-3.74]		[3.06]		[6.69]	

3.1.4. Return decomposition for I/A

The last, but not least, column of Table 3 presents results for the I/A anomaly, our second investment measure. Though quantitatively different, Panel B shows a similar pattern of the return components for the I/A anomaly to that for $\Delta A/A$. Notably, the two extreme anomaly components (X_{GG} and X_{BB}) have signs that are exactly opposite to the expected, indicating a weak or reversed pure anomaly effect; both components for the pure anchoring effect are significant; the interaction effect for stocks with extreme aggressive investment and prices ranked low is significant.

The decomposition results are presented in Panel C and summarized in equation (8). For the enhanced profit of 1.31% that takes advantage of both I/A and NR , the pure anchoring effect is 0.74% ($t=4.24$) and the interaction effect is 0.78% ($t=3.46$), and the pure anomaly effect is -0.21% ($t=-1.42$). Thus, after accounting for the effect that investors anchor and the effect that investors anchor even more when the investment is extreme, there is a reversed

(positive) relation, though not statistically distinguishable from zero, between investment and future stock return.⁵

$R_{GG,H} - R_{BB,L}$	=	Anomaly	+	Anchoring	+	Interaction	(8)
1.31	=	-0.21	+	0.74	+	0.78	
		[-1.42]		[4.24]		[3.46]	

We highlight three main messages from Table 3. First, regardless of the anomaly variables chosen, the anchoring effect is always strong and significant, suggesting that investors' anchoring is an important and salient phenomenon in the stock market. Second, the return decomposition methodology reveals that the return predictability by two profitability measures (OP and ROE) and two investment measures ($\Delta A/A$ and I/A) is entirely attributable to investors' tendency to anchor on 52-week high. That is, investors tend to anchor on 52-week high regardless of the anomaly variable, and the anchoring effect is stronger when the anomaly variable takes extreme values. After controlling for the (combined) anchoring effect, the two investment proxies actually predict returns positively: More aggressive investment is associated with higher returns.

3.2. Robustness Checks

In this section we check the robustness of our main results. The return decomposition results for all five anomalies are presented in Table 4. Each panel represents some variation in the empirical analysis. Details shown below, all robustness checks convey the same message: There is no significant pure anomaly effect for OP , ROE , $\Delta A/A$ and I/A .

Following GHL (2014) we check robustness by using excess returns without any risk adjustment. In this setting, the components in return decomposition and the effects derived from the Fama-MacBeth regressions are all based on raw returns without any risk adjustment. Likewise, we check robustness by excluding January returns from the time series. The return decomposition results are presented in Panels A and B of Table 4. In addition, we check the robustness of our main findings by controlling for the liquidity factor developed by Pastor and Stambaugh (2002). Panel C of Table 4 presents the results.

In the main analysis our sample excludes stocks with price lower than \$5 and market capitalization below the lowest NYSE breakpoint. Such a choice is to ensure that our findings are not influenced by a large number of microcap stocks, which are economically less important. This choice, however, excludes a large number of stocks that exhibit strong anomalous returns (e.g. Zhang, 2006). To check robustness we form a more inclusive sample, in which we only require that the stock price be above \$1. The microcap stocks (market cap below the first NYSE breakpoint) are not excluded. We then run the tests as in Table 3 based on this more inclusive sample. The return decomposition results are shown in Panel D of Table 4.

5 For the investment measure as in Titman et al. (2004), we find that the decomposition equation is $1.30 = -0.06 [-0.45] + 0.88 [5.09] + 0.48 [2.39]$, indicating that the return predictability of the Titman et al. (2004) investment measure is also entirely attributable to investor anchoring.

Table 4: Robustness checks

	<i>OP</i>	<i>ROE</i>	$\Delta A/A$	<i>I/A</i>
Panel A: Excess returns				
$X_{GG} - X_{BB}$ (Anomaly)	-0.08 [-0.56]	0.10 [0.57]	-0.43 [-3.19]	-0.13 [-0.91]
$A_H - A_L$ (Anchoring)	0.43 [2.34]	0.28 [1.37]	0.12 [0.64]	0.39 [1.96]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.77 [4.05]	1.07 [4.46]	1.49 [7.27]	0.79 [3.63]
Panel B: January excluded				
$X_{GG} - X_{BB}$ (Anomaly)	0.01 [0.05]	0.12 [0.63]	-0.55 [-3.95]	-0.18 [-1.23]
$A_H - A_L$ (Anchoring)	0.66 [3.58]	0.46 [2.31]	0.35 [1.87]	0.63 [3.20]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.83 [4.19]	1.20 [4.74]	1.56 [7.30]	0.79 [3.50]
Panel C: Liquidity factor adjusted				
$X_{GG} - X_{BB}$ (Anomaly)	-0.03 [-0.21]	0.10 [0.54]	-0.52 [-3.86]	-0.20 [-1.39]
$A_H - A_L$ (Anchoring)	0.79 [5.07]	0.55 [3.18]	0.51 [3.17]	0.76 [4.43]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.78 [3.94]	1.24 [5.06]	1.42 [6.79]	0.76 [3.42]
Panel D: Inclusive sample				
$X_{GG} - X_{BB}$ (Anomaly)	-0.12 [-1.00]	0.21 [1.25]	-0.15 [-1.21]	-0.12 [-0.87]
$A_H - A_L$ (Anchoring)	0.92 [5.84]	0.36 [2.08]	0.69 [4.17]	0.70 [3.96]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.58 [3.29]	1.45 [6.38]	1.13 [5.85]	1.06 [5.22]
Panel E: Momentum factor adjusted				
$X_{GG} - X_{BB}$ (Anomaly)	0.03 [0.20]	0.15 [0.83]	-0.47 [-3.37]	-0.23 [-1.56]
$A_H - A_L$ (Anchoring)	0.14 [1.31]	-0.08 [-0.73]	-0.13 [-1.09]	0.07 [0.60]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.71 [3.46]	1.05 [4.41]	1.28 [5.64]	0.76 [3.29]
Panel F: No financials				
$X_{GG} - X_{BB}$ (Anomaly)	-0.10 [-0.66]	0.12 [0.58]	-0.65 [-4.61]	-0.19 [-1.29]
$A_H - A_L$ (Anchoring)	0.74 [4.49]	0.54 [3.05]	0.40 [2.36]	0.67 [3.90]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.83 [3.90]	1.18 [4.31]	1.67 [7.44]	0.85 [3.76]
Panel G: Non-NYSE breakpoints				
$X_{GG} - X_{BB}$ (Anomaly)	-0.06 [-0.39]	0.03 [0.13]	-0.41 [-3.05]	-0.25 [-1.69]
$A_H - A_L$ (Anchoring)	0.87 [4.92]	0.57 [2.92]	0.65 [3.88]	0.77 [4.12]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.88 [4.39]	1.43 [5.52]	1.30 [6.01]	0.99 [4.27]

The table reports robustness checks of the main results in Table 3. Each panel reflects some deviation from the base specification in Table 3. In Panel A, the results are based on excess returns instead of the Fama and French (1993) three-factor regression alphas; in Panel B, all Januaries are excluded from the time-series; in Panel C, the Pastor and Stambaugh (2002) liquidity factor is added in addition to the Fama and French (1993) three factors; in Panel D, the sample also include small and low-priced stocks; in Panel E, the momentum factor is also adjusted in addition to the three factors; in Panel F, all financial stocks (SIC codes between 6000 and 6999) are excluded from the sample; in Panel G, the quintile breakpoints are based on all (NYSE, AMEX, and NASDAQ) stocks instead of just NYSE stocks. For *ROE* the data cover the period July 1972 to December 2013. For all others, the data cover July 1963 to December 2013. For *OP*, *ROE*, and *NR*, the quintiles are formed on the variables directly. For $\Delta A/A$ and *I/A* the quintiles are formed on the negative of the variables because they are inversely related to future returns. T-statistics are in brackets below the coefficients. All variables are defined in Appendix A

GHL (2014) also examines a regression specification in which the momentum factor is controlled for. We check the robustness of our findings by regressing the time-series of the Fama-MacBeth regression coefficients on the Carhart (1997) four-factor model and keep the intercepts as abnormal returns. The return decomposition results are reported in Panel E of Table 4.

Chen et al. (2011, p.4), and Hou et al. (2015, section 2) exclude financial stocks in their factor portfolios. We check robustness by excluding financial stocks. Panel F of Table 4 reports the return decomposition results.

In our main analysis we use NYSE breakpoints to form quintiles, which is common in the literature of anomalies. This is to minimize the impact of a large number of microcap stocks in forming portfolios. For the purpose of checking robustness, we repeat our analysis by extracting the breakpoints from all (NYSE, AMEX, and NASDAQ) stocks instead of just the NYSE stocks. The return decomposition results are presented in Panel G of Table 4.

4. RESULTS ON SUBSAMPLES

So far, our analysis is based on the whole cross-sections over the whole sample period from July 1963 to December 2013 (for *ROE*, July 1972 to December 2013). Because anomalies tend to vary in

the cross-section and in time series, it is important to see how the anchoring effect and the pure anomaly effect of the anomalies vary. For this purpose, we conduct the return decomposition exercise in subsamples formed in the cross-section and in the time series.

We form cross-sectional subsamples on proxies for information uncertainty, as anomalies are stronger among stocks with greater information uncertainty (Zhang, 2006). Time-series subsamples are formed on investor sentiment (Stambaugh et al., 2012) and on time (before and after 1990).

4.1. The Role of Information Uncertainty

Before looking at the data, it is useful to first form expectations on how the anchoring effect and the pure anomaly effect should vary among subsamples formed on proxies for information uncertainty. There are two effects from information uncertainty. First, greater information uncertainty is associated with higher anomaly profits (Zhang, 2006). Second, information uncertainty also affects the extent to which investors anchor. When investors face greater information uncertainty in evaluating stocks, they are more likely to rely on easily available information, such as the 52-week high, as an anchor or reference point. Thus, it is expected that the anchoring effect (the combination of the pure anchoring effect and the interaction effect) is stronger among stocks with greater information uncertainty.

If greater information uncertainty is associated with both higher anomaly profits and a greater anchoring effect, its impact on the pure anomaly effect then becomes unclear. To see this point we rearrange the return decomposition equation by moving the pure anomaly effect to the left hand side, as shown in Equation (9).

$$\text{Anomaly} = [R_{GG,H} - R_{BB,L}] - [\text{Anchoring} + \text{Interaction}] \quad (9)$$

There are two terms on the right hand side of equation (9). The first term $R_{GG,H} - R_{BB,L}$ is the profit from the enhanced strategy, which takes advantage of both the anomaly and the nearness ratio; the second term “Anchoring+Interaction” represents the impact of investors’ tendency to anchor on 52-week high; both terms increase with information uncertainty. Thus, whether the pure anomaly effect, which is equal to the difference between the two terms on the right hand, increases or decreases with information uncertainty is undetermined ex ante and essentially an empirical question. Our discussion of the results based on subsamples primarily focuses on whether the main findings from our whole-sample analysis hold in the subsamples as well.

We follow Zhang (2006) and choose three proxies for information uncertainty: market capitalization, the number of analysts following, and idiosyncratic volatility. The first two proxies are used in GHL (2014) to form subsamples. A subsample analysis on idiosyncratic volatility directly sheds light on the issue of limits to arbitrage (e.g. Pontiff, 1996, 2006). Results based on other proxies in Zhang (2006) or proxies used in many subsequent papers (e.g. Choi and Sias, 2012) on information uncertainty are qualitatively similar.⁶

To conduct the subsample analysis on market capitalization, we first independently sort on the anomaly variable (one of the five anomalies) and nearness ratio, the same way as in Table 3. We use NYSE market capitalization median as the cutoff point to form two subsamples. Small (large) stocks have their market cap below (above) the NYSE market cap median. Within each market cap subsample we run Fama-MacBeth regressions, estimate the return components from the regression coefficients, and perform various tests as in Panel C of Table 3. For brevity, we only report the return decomposition results, which carry the main messages of the analysis. Panel A of Table 5 presents the return decomposition results for the two market cap subsamples. On the top of the results we also report the enhanced profit, $R_{GG,H} - R_{BB,L}$, the left hand side of the return decomposition equation, which is the profit from trading on both the anomaly and nearness ratio.

Consistent with Zhang (2006), Panel A of Table 5 shows that the enhanced profits for all five anomalies are higher among small stocks than large stocks. For example, for *OP*, the enhanced profit is 1.65% among small stocks and 1.20% among large stocks. The combined anchoring effect (the summation of anchoring and interaction) is also stronger among small stocks (1.74%) than among large stocks (1.13%). After accounting for the pure anchoring effect and the interaction effect, the pure anomaly effect for *OP* is -0.09% ($t=-0.53$) among small stocks and 0.07%

($t=0.36$) among large stocks. Neither is significant. Similarly, for the anomalies of *ROE*, $\Delta A/A$ and *I/A*, the pure anomaly effects are not significant, consistent with the whole-sample results. For *ROE* there is a marginally significant pure anomaly effect of 0.40% ($t=1.73$) among small stocks, but the pure anomaly effect among large stocks is -0.29% ($t=-1.10$), negative and not significant.

The second proxy for information uncertainty is the number of analysts following the stock. Due to data availability, for this analysis we use the sample from January 1980 to December 2013. We form two subsamples: stocks that are followed by few analysts (below the cross-sectional median) and stocks followed by many analysts (above the cross-sectional median). Following the same empirical procedure as in the previous panel, we run Fama-MacBeth regressions for the two subsamples, estimate the return components, and conduct the various tests. The main results are summarized in Panel B of Table 5.

In Panel B, we first confirm that the enhanced profit is higher among stocks followed by fewer analysts. This finding is consistent with the notion that anomalies are stronger among stocks with little information available. Panel B also shows that the combined anchoring effect (the pure anchoring effect plus the interaction effect) is stronger among stocks followed by fewer analysts. These patterns hold for all the five anomalies.

After accounting for the combined anchoring effects, none of the pure anomaly effects for *OP*, *ROE*, $\Delta A/A$, and *I/A* in the two subsamples has a t-statistics that is both significant and positive. The pure anomaly effect for $\Delta A/A$ among stocks followed by few analysts is actually negative and significant. The overall evidence for the subsamples formed on the number of analysts following is largely consistent with the whole-sample evidence.

The third and last proxy for information uncertainty is idiosyncratic volatility (*IVOL*), which is the standard deviation of the residuals from regressions of daily excess returns on the market, size, and book-to-market factors using the daily data over the prior month (e.g. Ang et al., 2006). Investors face greater information uncertainty when valuing stocks with higher *IVOL*. We independently sort stocks into two equal subsamples based on their past month *IVOL*. The subsequent empirical procedure is the same as in the previous two panels. The return decomposition results are presented in Panel C of Table 5. Panel C first confirms that abnormal returns from the enhanced trading strategy are higher for high *IVOL* stocks than for low *IVOL* stocks. Likewise, the combined anchoring effect is stronger among high *IVOL* stocks. After accounting for the anchoring effect, there is no significant and positive pure anomaly effect for the anomalies of *OP*, *ROE*, $\Delta A/A$ and *I/A*. The highest t-statistics for these four anomalies occurs with *ROE* among high *IVOL* stocks, which is 1.51. Thus, the evidence based on *IVOL* subsamples is largely consistent with the whole-sample evidence. That is, there is no pure anomaly effect for *OP*, *ROE*, $\Delta A/A$ and *I/A*.

4.2. The Role of Investor Sentiment

Investor sentiment affects asset prices. Baker and Wurgler (2006) argue that investor sentiment affects more on securities whose

⁶ Unreported for brevity, similar results obtain in subsamples formed on firm age, sigma, book-to-market ratio, and institutional ownership.

Table 5: Results on cross-sectional subsamples

Panel A: By size	OP	ROE	$\Delta A/A$	I/A
Small stocks				
$R_{GG,H} - R_{BB,L}$	1.65	2.18	1.51	1.53
$X_{GG} - X_{BB}$ (Anomaly)	-0.09 [-0.53]	0.40 [1.73]	-0.55 [-3.07]	-0.23 [-1.14]
$A_H - A_L$ (Anchoring)	0.95 [5.71]	0.70 [3.91]	0.62 [3.49]	0.83 [4.42]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.79 [2.99]	1.08 [3.40]	1.43 [4.98]	0.93 [2.86]
Anchoring+Interaction	1.74 [7.15]	1.78 [5.75]	2.05 [8.12]	1.76 [6.79]
Large stocks				
$R_{GG,H} - R_{BB,L}$	1.20	1.39	1.17	0.96
$X_{GG} - X_{BB}$ (Anomaly)	0.07 [0.36]	-0.29 [-1.10]	-0.32 [-1.85]	-0.03 [-0.15]
$A_H - A_L$ (Anchoring)	0.60 [3.01]	0.40 [1.70]	0.36 [1.85]	0.70 [3.25]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.53 [1.73]	1.27 [3.18]	1.13 [3.93]	0.28 [0.88]
Anchoring+Interaction	1.13 [4.10]	1.67 [4.67]	1.49 [5.50]	0.99 [3.44]
Panel B: By analysts following	OP	ROE	$\Delta A/A$	I/A
Few analysts				
$R_{GG,H} - R_{BB,L}$	1.86	2.30	1.71	1.56
$X_{GG} - X_{BB}$ (Anomaly)	-0.28 [-1.29]	0.18 [0.62]	-0.50 [-2.52]	-0.36 [-1.42]
$A_H - A_L$ (Anchoring)	0.88 [4.31]	0.65 [3.36]	0.71 [3.15]	0.93 [3.88]
$I_{GG,H} - I_{BB,L}$ (Interaction)	1.26 [3.65]	1.48 [3.63]	1.49 [4.26]	0.99 [2.39]
Anchoring+Interaction	2.15 [6.81]	2.12 [5.57]	2.21 [7.04]	1.92 [6.01]
Many analysts				
$R_{GG,H} - R_{BB,L}$	1.26	1.50	1.31	1.23
$X_{GG} - X_{BB}$ (Anomaly)	0.30 [1.16]	-0.00 [-0.01]	-0.25 [-1.12]	-0.03 [-0.14]
$A_H - A_L$ (Anchoring)	0.63 [2.48]	0.44 [1.74]	0.50 [1.89]	0.65 [2.41]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.32 [0.87]	1.07 [3.02]	1.07 [3.11]	0.61 [1.64]
Anchoring+Interaction	0.95 [2.53]	1.51 [4.15]	1.56 [4.86]	1.27 [3.79]
Panel C: By volatility	OP	ROE	$\Delta A/A$	I/A
High IVOL stocks				
$R_{GG,H} - R_{BB,L}$	1.57	2.22	1.81	1.64
$X_{GG} - X_{BB}$ (Anomaly)	0.12 [0.61]	0.40 [1.51]	-0.28 [-1.42]	-0.19 [-0.92]
$A_H - A_L$ (Anchoring)	1.22 [6.16]	0.86 [4.14]	0.84 [4.08]	0.99 [4.76]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.23 [0.77]	0.95 [2.58]	1.25 [3.81]	0.84 [2.60]
Anchoring+Interaction	1.45 [5.32]	1.82 [5.05]	2.09 [7.16]	1.82 [6.65]
Low IVOL stocks				
$R_{GG,H} - R_{BB,L}$	1.21	1.37	0.68	0.62
$X_{GG} - X_{BB}$ (Anomaly)	0.07 [0.42]	-0.08 [-0.36]	-0.68 [-4.02]	-0.01 [-0.07]
$A_H - A_L$ (Anchoring)	0.36 [2.13]	0.14 [0.68]	0.16 [0.90]	0.55 [2.92]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.78 [2.78]	1.30 [3.69]	1.20 [4.19]	0.09 [0.27]
Anchoring+Interaction	1.14 [5.03]	1.44 [4.97]	1.36 [5.95]	0.64 [2.45]

The table reports subsample results based on the whole-sample results in Table 3. The subsamples are formed on market capitalization (Panel A), number of analysts following (Panel B), and idiosyncratic volatility (Panel C). Specifically, stocks are independently sorted into quintiles on the anomaly variable X (by NYSE breakpoints), as indicated by the column heading and quintiles on the nearness ratio NR (by NYSE breakpoints). The subsamples are formed by NYSE market capitalization median (Panel A), sample medians of number of analysts following (Panel B), and sample median of idiosyncratic volatility (Panel C). For each anomaly and each subsample, we follow the procedure outlined in Appendix B and report the test results in the Panels. The row " $R_{GG,H} - R_{BB,L}$ " is the profit from a trading strategy that takes advantage of the anomaly variable and NR. The row "Anchoring+Interaction" is the summation of the two rows above it. For ROE the data cover the period July 1972 to December 2013. For all others, the data cover July 1963 to December 2013. For OP, ROE, and NR, the quintiles are formed on the variables directly. For $\Delta A/A$ and I/A the quintiles are formed on the negative of the variables because they are inversely related to future returns. T-statistics are in brackets below the coefficients. All variables are defined in Appendix A

valuations involve subjective judgment and are difficult to arbitrage. Consistent with this view, Stambaugh et al. (2012) report evidence that anomalies are more pronounced during periods of higher investor sentiment. Because both investor sentiment and anchoring reflect investors' behavioral biases, it is instructive to examine the interaction between the two. If investors rely more on 52-week high to make investment decisions during periods of high investor sentiment, we expect that the anchoring effect (the pure anchoring and interaction effects combined) in the return decomposition is stronger during periods of high investor sentiment than during periods of low investor sentiment. Following the logic in the previous section, then the relationship between investor sentiment and the pure anomaly effect is essentially an empirical question. On the other hand, if higher investor sentiment reduces investors' reliance on 52-week high price as a reference

point, then we expect a weaker anchoring effect during periods of high investor sentiment. In this case, the pure anomaly effect is stronger during periods of high investor sentiment. As both possibilities are open, our empirical analysis and the ensuing discussions focus mostly on checking whether the anchoring effect holds in periods of low and high investor sentiment.

The investor sentiment data cover the period from July 1965 to December 2010.⁷ We follow the approach in Stambaugh et al. (2012) and divide the months into two groups. The months with prior month end sentiment level below (above) the time series median form the period of low (high) investor sentiment. For

⁷ Data source: http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_v23_POST.xlsx. We thank Professor Wurgler for making the data available at his website.

each the two time-series subsamples, we follow the empirical procedure used in Table 3 and report the test results in Table 6. For convenience we also report the enhanced profit as well as the combined anchoring effect (anchoring+interaction).

Consistent with Stambaugh et al. (2012), Table 6 first confirms that anomaly returns are higher during periods of higher investor sentiment. For example, the enhanced strategy that trades on the *OP* anomaly and nearness ratio earns a monthly alpha of 1.96% during periods of higher investor sentiment but 1.11% during months of lower investor sentiment. This pattern holds for all other anomalies as well. Table 6 also shows that the combined anchoring effect (the pure anchoring effect plus the interaction effect) is also stronger during periods of high sentiment. For the *OP* anomaly, the combined anchoring effect is 2.00% (t=5.62) during periods of high investor sentiment and 1.18% (t=4.16) during periods of low investor sentiment. This pattern holds with the other anomalies as well.

The pattern of the resulted pure anomaly effects is the same as that from the whole sample. For the anomalies of *OP*, *ROE*, $\Delta A/A$ and

I/A, there is no significant positive pure anomaly effects, regardless of high or low level of investor sentiment. There is also no clear pattern between the two sentiment periods.

Overall, results in Table 6 suggest that the evidence from subsamples formed on investor sentiment is consistent with the main conclusions from the whole-period analysis.

4.3. The Role of Time

In this section we examine whether the effect of anchoring decays over time. There are potential reasons that anchoring decays over time. First is learning by investors. Investors over time learn about their tendency to anchor on 52-week high in their investment decisions and correct the bias with time. Second is the force of arbitrage. Investors aware of the bias might take advantage of the bias. Thus, this anchoring effect might go away over time. On the other hand, the force of learning and arbitrage might be limited. It is not easy for investors who suffer from the anchoring bias to attribute clearly their investment loss to the anchoring bias. In addition, there are substantial transaction costs and arbitrage costs

Table 6: Subsamples by investor sentiment

	<i>OP</i>	<i>ROE</i>	$\Delta A/A$	<i>I/A</i>
Low sentiment				
$R_{GG,H} - R_{BB,L}$	1.11	1.52	1.19	1.11
$X_{GG} - X_{BB}$ (Anomaly)	-0.07 [-0.42]	0.24 [1.01]	-0.50 [-2.65]	-0.19 [-0.98]
$A_H - A_L$ (Anchoring)	0.63 [3.05]	0.31 [1.44]	0.35 [1.62]	0.60 [2.71]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.55 [1.95]	0.97 [3.00]	1.33 [4.49]	0.70 [2.43]
Anchoring+Interaction	1.18 [4.16]	1.28 [3.68]	1.68 [5.77]	1.30 [4.49]
High sentiment				
$R_{GG,H} - R_{BB,L}$	1.96	2.23	1.66	1.56
$X_{GG} - X_{BB}$ (Anomaly)	-0.05 [-0.20]	-0.01 [-0.03]	-0.47 [-2.19]	-0.31 [-1.26]
$A_H - A_L$ (Anchoring)	0.95 [3.47]	0.66 [2.29]	0.66 [2.40]	0.82 [2.60]
$I_{GG,H} - I_{BB,L}$ (Interaction)	1.05 [3.36]	1.58 [3.95]	1.47 [4.53]	1.06 [2.73]
Anchoring+Interaction	2.00 [5.62]	2.24 [4.89]	2.13 [5.60]	1.88 [5.37]

The table reports subsample results based on the whole-sample results in Table 3. The subsamples are formed on investor sentiment. Specifically, stocks are independently sorted into quintiles on the anomaly variable *X*, as indicated by the column heading and quintiles on the nearness ratio *NR* (both by NYSE breakpoints). The months from July 1965 to December 2010 are divided in to two equal periods by the time-series median of investor sentiment as in Baker and Wurgler (2006). The period of low (high) sentiment refer to the months with investor sentiment level below (above) the time series median. For each anomaly and each sentiment subsample, we follow the procedure outlined in Appendix B and report the test results in the Panels. The row " $R_{GG,H} - R_{BB,L}$ " is the profit from a trading strategy that takes advantage of the anomaly variable and *NR*. The row "Anchoring+Interaction" is the summation of the two rows above it. Because the investor sentiment data cover the period from July 1965 to December 2010, for *ROE* the data cover the period July 1972 to December 2010. For all others, the data cover July 1965 to December 2010. For *OP*, *ROE*, and *NR*, the quintiles are formed on the variables directly. For $\Delta A/A$ and *I/A* the quintiles are formed on the negative of the variables because they are inversely related to future returns. T-statistics are in brackets below the coefficients. All variables are defined in Appendix A

Table 7: Subsamples by time

	<i>OP</i>	<i>ROE</i>	$\Delta A/A$	<i>I/A</i>
Before 1990				
$R_{GG,H} - R_{BB,L}$	1.68	2.26	1.44	1.40
$X_{GG} - X_{BB}$ (Anomaly)	0.10 [0.63]	0.45 [1.85]	-0.71 [-4.16]	-0.30 [-1.62]
$A_H - A_L$ (Anchoring)	0.81 [4.25]	0.54 [2.08]	0.44 [2.22]	0.76 [3.58]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.77 [2.93]	1.26 [3.68]	1.71 [6.38]	0.94 [3.13]
Anchoring+Interaction	1.58 [6.09]	1.80 [5.43]	2.15 [8.93]	1.70 [6.62]
After 1990				
$R_{GG,H} - R_{BB,L}$	1.52	1.77	1.38	1.23
$X_{GG} - X_{BB}$ (Anomaly)	-0.08 [-0.38]	0.03 [0.11]	-0.37 [-1.83]	-0.13 [-0.59]
$A_H - A_L$ (Anchoring)	0.75 [3.08]	0.54 [2.47]	0.59 [2.45]	0.79 [3.17]
$I_{GG,H} - I_{BB,L}$ (Interaction)	0.85 [2.82]	1.20 [3.60]	1.16 [3.64]	0.57 [1.77]
Anchoring+Interaction	1.60 [5.00]	1.75 [4.52]	1.75 [4.89]	1.36 [4.11]

The table reports subsample results based on the whole-sample results in Table 3. Specifically, stocks are independently sorted into quintiles on the anomaly variable *X*, as indicated by the column heading and quintiles on the nearness ratio *NR* (both by NYSE breakpoints). The period of "before 1990" refers to the months before (not including) January 1990, and the period of "after 1990" refers to the months after (including) January 1990. For each anomaly and each time subsample, we follow the procedure outlined in Appendix B and report the test results in the Panels. The row " $R_{GG,H} - R_{BB,L}$ " is the profit from a trading strategy that takes advantage of the anomaly variable and *NR*. The row "Anchoring+Interaction" is the summation of the two rows above it. For *ROE* the data cover the period July 1972 to December 2013. For all others, the data cover July 1963 to December 2013. For *OP*, *ROE*, and *NR*, the quintiles are formed on the variables directly. For $\Delta A/A$ and *I/A* the quintiles are formed on the negative of the variables because they are inversely related to future returns. T-statistics are in brackets below the coefficients. All variables are defined in Appendix A

involved in arbitrage strategies (e.g. Pontiff, 1996, 2006; McLean and Pontiff, 2016). So the force of arbitrage might be limited as well. Thus, how the impact of anchoring bias on return anomalies evolve over time is an empirical question. Our investigation in this regard mostly focuses on checking the robustness over the sub periods.

For simplicity we divide our sample into two: Before 1990 and after (and including) 1990. The year of 1990 is approximately in the middle of our sample period. Table 7 reports the return decomposition results. The combined anchoring effect (anchoring+interaction), however, exhibits no clear pattern between the two periods. Thus, there is no evidence that the anchoring effect decays over time. Regarding the pure anomaly effect, the main conclusions in the whole sample largely hold in the two subsamples. The only marginal exception is *ROE* for the period before 1990, where there is a weakly significant pure anomaly effect of 0.45% ($t=1.85$). This marginally significant pure anomaly effect for *ROE* before 1990, however, disappears after 1990.

5. CONCLUSION

Recently empirical asset pricing focuses on the role of profitability and investment in explaining stock returns. Whether the return predictability of profitability and investment is due to rational risk or investors' irrational beliefs, however, is an open question. In this paper we examine the role of a particular type of irrational beliefs in the return predictability of profitability and investment: investors' tendency to anchor on 52-week high. Based on a return decomposition methodology recently developed by George et al. (2014), we find that the return predictability of two profitability measures (operating profitability and return on equity) and two investment measures (asset growth and investment to assets) is entirely attributable to anchoring. These main findings survive a battery of robustness checks and hold largely in cross-sectional and time-series subsamples.

Examining the nature of the asset pricing factors is important as it helps understand the connection between empirical and theoretical asset pricing. Asset pricing theory such as Merton's (1973) intertemporal capital asset pricing model and Ross's (1977) arbitrage pricing theory prescribes how risk should be measured and is related to expected return. Empirical efforts take the return patterns as given and propose models to capture them. Doing so, empirical asset pricing leaves an open question whether the factors in the empirical models are rational risk or irrational beliefs (Fama and French, 2006). This paper contributes by sending a warning that the potential risk factors based on profitability and investment might actually reflect investors' behavioral bias.

This paper joins the research effort pioneered by George and Hwang (2004) and George et al. (2014) that highlights the role of anchoring in the stock market. These studies combined, the following anomalies can be attributed entirely to anchoring: momentum, earnings surprise, operating profitability, return on equity, asset growth, and investment to asset. With the simple and intuitive methodology developed by George et al. (2014), it

remains to be seen the extent to which many other return anomalies are attributable to anchoring.

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APPENDIXES

Appendix A: Variable definitions

Except for *ROE*, which is quarterly updated, the other four anomalies (*OP*, $\Delta A/A$, and *I/A*) are updated annually. By June of year t , the variables are measured using accounting information as of and/or prior to the fiscal year ending in year $t-1$. The measures are used to predict returns for months starting from July of year t to June of year $t+1$.

Operating profitability (*OP*): Sales (Compustat annual item SALE) minus cost of goods sold (COGS), interest expense (XINT), and selling, general, and administrative expenses (XSGA), all as of year $t-1$, then divided by book equity at the end of year $t-1$. Book equity is total assets (AT), minus total liabilities (LT), plus balance sheet deferred taxes and investment tax credit (TXDITC) if available, minus preferred stock liquidating value (PSTKL) if available, or redemption value (PSTKRQ) if available, or caring value (PSTK). *OP* is annually updated.

Return on equity (*ROE*): It is income before extraordinary items (Compustat quarterly item IBQ) divided by prior-quarter book equity. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (TXDITCQ) if available, minus the book value of preferred stock. Shareholders' equity is stockholders' equity (SEQQ), or common equity (CEQQ) plus

the carrying value of preferred stock (PSTKQ), or total assets (ATQ) minus total liabilities (LTQ) in that order, depending on availability. We use redemption value (item PSTKRQ) if available, or carrying value (PSTKRQ) for the book value of preferred stock. This *ROE* is applied to predict returns for months starting from the month after the current quarter earnings announcement (so that the quarterly earnings information is available by portfolio formation) up to the month of the next earnings announcement.

Asset growth ($\Delta A/A$): The annual change in total assets (AT) divided by lagged total assets.

Investment to assets (*I/A*): The annual change in gross property, plant, and equipment (PPEGT) plus annual change in inventories (INVT) divided by lagged book value of assets (AT).

Nearness ratio (*NR*): The nearness ratio for stock j in month t is equal to $\frac{P_{j,t}}{H_{j,t-11-t}}$, where $P_{j,t}$ is the price of stock j at the end of

month t , and $H_{j,t-11-t}$ is the highest daily closing price over the past 12 months (or 252 trading days), including month t . The prices are adjusted for stock splits and stock dividends using CRSP daily price adjustment factor. We use *NR* of month $t-1$ to predict stock return in month $t+1$.

Idiosyncratic volatility (IVOL): The standard deviation of the residuals from regressions of daily excess returns on the market, size, and book-to-market factors using the daily data over the prior month.

Appendix B: The George et al. (2014) methodology of return decomposition

The Fama-MacBeth regression is specified as follows.

$$R_{i,t} = b_{0,t} + b_{1,t} * X5_{i,t-1} + b_{2,t} * X4_{i,t-1} + b_{3,t} * X2_{i,t-1} + b_{4,t} * X1_{i,t-1} + b_{5,t} * HNR_{i,t-2} + b_{6,t} * LNR_{i,t-2} + b_{7,t} * (X5_{i,t-1} * HNR_{i,t-2}) + b_{8,t} * (X4_{i,t-1} * HNR_{i,t-2}) + b_{9,t} * (X2_{i,t-1} * HNR_{i,t-2}) + b_{10,t} * (X1_{i,t-1} * HNR_{i,t-2}) + b_{11,t} * (X5_{i,t-1} * LNR_{i,t-2}) + b_{12,t} * (X4_{i,t-1} * LNR_{i,t-2}) + b_{13,t} * (X2_{i,t-1} * LNR_{i,t-2}) + b_{14,t} * (X1_{i,t-1} * LNR_{i,t-2}) + \epsilon_{i,t}$$

$X5$, $X4$, $X2$ and $X1$ are dummy variables for stocks ranked into the corresponding quintiles on anomaly X . HNR (LNR) is equal to one if the stock is ranked in the top (bottom) NR quintile, and zero otherwise.

In a two-way independent sort of stocks on an anomaly (X) into quintiles and five quintiles on NR (the middle three quintiles are then lumped together), both by NYSE breakpoints, the average return of the 5x3 intersection portfolios can be derived from the Fama-MacBeth regression coefficients, shown below in Table A-1.

Table A-1

	<i>LNR</i>	<i>NR2-NR4</i>	<i>HNR</i>
$X1$	$b_0 + b_4 + b_6 + b_{14}$	$b_0 + b_4$	$b_0 + b_4 + b_3 + b_{10}$
$X2$	$b_0 + b_3 + b_6 + b_{13}$	$b_0 + b_3$	$b_0 + b_3 + b_5 + b_9$
$X3$	$b_0 + b_6$	b_0	$b_0 + b_5$
$X4$	$b_0 + b_2 + b_6 + b_{12}$	$b_0 + b_2$	$b_0 + b_2 + b_5 + b_8$
$X5$	$b_0 + b_1 + b_6 + b_{11}$	$b_0 + b_1$	$b_0 + b_1 + b_5 + b_7$

The decompositions for each of the 5x3 cells suggest that the mean returns of the intersection portfolios are shown in Table A-2, in the form of the return components.

Table A-2

Anomaly quintiles	<i>LNR</i>	<i>NR2-NR4</i>	<i>HNR</i>
$X1$	$\mu + X_{BB} + A_L + I_{BB,L}$	$\mu + X_{BB} + I_{BB,M}$	$\mu + X_{BB} + A_H$
$X2$	$\mu + X_B + A_L + I_{B,L}$	$\mu + X_B + I_{B,M}$	$\mu + X_B + A_H$
$X3$	$\mu + A_L$	μ	$\mu + A_H$
$X4$	$\mu + X_G + A_L$	$\mu + X_G + I_{G,M}$	$\mu + X_G + A_H + I_{G,H}$
$X5$	$\mu + X_{GG} + A_L$	$\mu + X_{GG} + I_{GG,M}$	$\mu + X_{GG} + A_H + I_{GG,H}$

George et al. (2014) show that the equations are uniquely identified. The individual components are then solved as follows.

$\mu = b_0$	$A_H = b_5$	$A_L = b_6$	
$X_{GG} = b_1 + b_{11}$	$X_G = b_2 + b_{12}$	$X_B = b_3 + b_9$	$X_{BB} = b_4 + b_{10}$
$I_{GG,H} = b_7 - b_{11}$	$I_{G,H} = b_8 - b_{12}$	$I_{B,L} = b_{13} - b_9$	$I_{BB,L} = b_{14} - b_{10}$
$I_{GG,M} = -b_{11}$	$I_{G,M} = -b_{12}$	$I_{B,M} = -b_9$	$I_{BB,M} = -b_{10}$