The Role of Anchoring Bias in the Equity Market: Evidence from Analysts' Earnings Forecasts and Stock Returns

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The Role of Anchoring Bias in the Equity Market: Evidence from Analysts' Earnings Forecasts and Stock Returns

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Abstract

We test the implications of anchoring bias associated with forecast earnings per share (FEPS) for forecast errors, earnings surprises, stock returns, and stock splits. We find that analysts make optimistic (pessimistic) forecasts when a firm's FEPS is lower (higher) than the industry median. Further, firms with FEPS greater (lower) than the industry median experience abnormally high (low) future stock returns, particularly around subsequent earnings announcement dates. These firms are also more likely to engage in stock splits. Finally, split firms experience more positive forecast revisions, more negative forecast errors, and more negative earnings surprises after stock splits.

I. Introduction

Analysts are key financial market participants. Researchers often use analysts' earnings forecasts as proxies for market expectations and differences in opinions. In addition, analysts' earnings forecasts are one of the rare settings for which researchers have a large natural data set (individual analysts' actual decisions) and for which the biases in decision making can be observed and verified

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ex post. Not surprisingly, the activities of analysts have been fertile ground for behavioral research. However, prior studies have shown that analysts often suffer from a number of biases. The implications of these potential cognitive biases for investors and, even more so, for managers are less understood.

This study considers the behavior of financial market participants from a perspective different from that studied in previous research. It focuses on anchoring bias, a topic that has been characterized by Hirshleifer (2001) as an important part of "dynamic psychology-based asset-pricing theory in its infancy" (p. 1535). "Anchoring" describes the fact that, in forming numerical estimates of uncertain quantities, adjustments in assessments away from some initial value (called the "anchor") are often insufficient. One of the first studies of this cognitive bias is the seminal experiment by Tversky and Kahneman (1974). These authors report that estimates of the percentage of African nations in the United Nations were affected by a number between 0 and 100 that was determined by spinning a wheel of fortune in the subjects' presence. Subsequent research has confirmed the generality and the robustness of this cognitive bias.

We hypothesize that market participants such as sell-side analysts and investors may also be affected by such anchoring bias when they estimate the future profitability of a firm. This estimation is a complex task and involves a high degree of uncertainty, suggesting that market participants may anchor on salient but irrelevant information. Our discussions with financial analysts suggest that earnings forecasts for a specific firm are likely to be affected by the *levels* of forecast earnings per share (FEPS) of its industry peers. One analyst pointed out in an interview that analysts "are reluctant to make earnings forecasts that further deviate from the current industry 'norm' (a historically stable range of FEPS within the industry)." Specifically, when a company's current FEPS is already much higher (lower) than those of its industry peers, analysts appear to make insufficient upward (downward) adjustments even if such adjustments are well supported by fundamental information. We describe this observation as the analysts' anchoring bias toward the industry norm. To capture this intuition, we construct a measure of cross-sectional anchoring in FEPS (CAF) as the difference between the firm's FEPS (F_FEPS) and the industry median FEPS (I_FEPS), scaled by the absolute value of the latter. With this measure of CAF, we generate the following hypotheses.

First, if analysts anchor on the industry norm, their forecasts will be too close to this number. As a result, analysts are likely to underestimate (overestimate) the future earnings of firms with their F_FEPS above (below) the I_FEPS. In other words, analysts give more pessimistic earnings forecasts for firms with a high FEPS than for similar firms in the same industry but with a low FEPS. Therefore, earnings forecast errors should be higher for high-FEPS firms than for low-FEPS firms in the same industry.

If investors are affected by biased analysts' earnings forecasts, their expectations of a firm's future profitability should be similarly biased. Firms with a high FEPS relative to their industry peers should suffer from low expectations regarding their future profits. Conversely, firms with a low FEPS relative to their industry peers should enjoy unduly high expectations regarding their future profits. If this is the case, stocks forecasted to have high *levels* of earnings per share

(EPS) should significantly outperform similar stocks in the same industry forecasted to have low *levels* of EPS when the firms' true profitability is subsequently revealed, for example, around subsequent earnings announcement dates.

We generate empirical results consistent with all the hypotheses suggested by the cross-sectional anchoring bias. Using U.S. data from 1983 to 2005, we find that analysts' earnings forecasts for firms with a high CAF are more pessimistic than the forecasts for similar firms but with a low CAF. This result is consistent with the hypothesis that analysts anchor their forecasts on the industry norm. We further find that stock returns are significantly higher for firms with a high CAF than for similar firms in the same industry but with a low CAF. The positive relation between firm CAF and future stock returns cannot be explained by known risk factors, book-to-market (BM) ratios, earnings-to-price (EP) ratios, fundamental value-to-price (VP) ratios, accounting accruals, price momentum, earnings momentum, post loss/profit announcement drifts, or the nominal price per share. Moreover, earnings surprises are relatively more positive for firms with a high CAF than for firms with a low CAF. These results are consistent with the notion that investors are also affected by the cross-sectional anchoring bias. All of these results are stronger when the industry norm is more stable or when market participants are less sophisticated. We also find that the likelihood of a stock split within a year is greater when the CAF is high. This is consistent with the idea that managers realize the existence of anchoring in the financial markets and adjust their behavior to take advantage of this cognitive bias.

Finally, our results indicate that the effects of stock splits are consistent with the presence of cross-sectional anchoring. Split firms experience more positive forecast revisions, more negative forecast errors, and more negative earnings surprises after stock splits compared with those that do not split their stocks. In addition, firms whose CAF was positive prior to stock splits but negative afterward experience a change from positive to negative in forecast errors, abnormal returns, and earnings surprises. By contrast, firms that maintain a positive CAF after stock splits continue to display positive forecast errors, abnormal returns, and earnings surprises. Last, the split ratio (i.e., the change in the number of shares) is negatively related to the change in forecast errors, stock returns, and earnings surprises from the pre- to the post-split periods.

As with any new asset pricing anomalies, more work is required to ensure that the effect that we document cannot be explained by some other unspecified phenomenon. However, our empirical results consistently support the idea that anchoring, a significant cognitive bias in the psychology literature, affects the decision making of individuals in an important economic setting. This large-sample test complements the previous research, which was largely based on small-sample experimental work. To the best of our knowledge, this study is the first to use a large-sample archival approach to understand the implications of the cross-sectional anchoring effect in a finance setting. Although we focus on analysts' earnings forecasts and price behavior in order to take advantage of a particularly rich data set, we expect that our results can be generalized in other finance settings as well.

The results of this study also enhance our understanding of the financial markets by providing a new understanding of analyst and investor behavior. Our results suggest that understanding this cognitive bias may yield a trading strategy that generates significant abnormal returns. Specifically, our results suggest that a hedge portfolio that goes long on firms with a high CAF and short on firms with a low CAF could, over the period studied, have generated a risk-adjusted return (α) of 0.71% per month, or 8.52% per year. The profitability of such a trading strategy remains significant for investment horizons that span at least 12 months. Finally, our results suggest a corporate strategy based on stock splits for managers of firms with a high level of FEPS. Such a strategy can mitigate undervaluation and sometimes generate overvaluation by influencing analysts' earnings forecasts or revisions.

In addition, our study complements previous studies on nominal stock prices. Weld, Michaely, Thaler, and Benartzi (2009) find that the cross-sectional distribution of nominal stock prices per share in the United States has been very stable, with the median hovering around $30 since early in the last century. We show that a similar effect exists for FEPS: The median nominal FEPS has been hovering around $1.50 since analysts' earnings forecasts became available. Baker, Greenwood, and Wurgler (2009) suggest that managers split shares driven by "small-cap premiums" to cater to investors' preference. However, the source of this higher valuation for low-price firms remains unclear. We consider the possibility that these low-price firms are overvalued because of the anchoring bias of market participants. Consistent with this view, our results suggest that low-FEPS stocks (relative to their industry peers) are indeed overpriced.

The remainder of this paper is organized as follows: In Section II, we review the previous studies on anchoring bias. In Section III, we develop our research hypotheses. In Section IV, we describe our research design. Section V discusses our sample and descriptive statistics, while Section VI presents our main empirical results. Section VII presents a few additional empirical tests, and we conclude the study in Section VIII.

II. Prior Research on Anchoring

The results of prior research (Tversky and Kahneman (1974)) suggest that individuals use cognitively tractable decision strategies, known as heuristics, to cope with complex and uncertain situations. These heuristics reduce complex inference tasks to relatively simple cognitive operations. Although these "mental shortcuts" help individuals in dealing with complex and uncertain situations, they may also lead to systematically skewed outcomes. The anchoring effect is one of the most studied cognitive biases that lead individuals to make suboptimal decisions. In their classic study, Tversky and Kahneman explore the idea that individuals frequently form estimates by starting with an easily available reference value and then adjusting from this value. Although this approach may not be problematic per se, research has shown that individuals typically fail to properly adjust their final estimates away from the salient but overemphasized starting point (the "anchor").

Tversky and Kahneman's (1974) seminal example involves spinning a wheel of fortune in front of the subjects to generate a number between 0 and 100. They asked the subjects for their best estimates of the percentage of African nations in the United Nations. The obviously irrelevant random number generated from the wheel of fortune generates systematic bias in the estimations. For example, the average estimate from subjects who observed the number 10 was 25%. By contrast, the average estimate from subjects who observed the number 65 was 45%. This result has been replicated in many other experimental settings. For example, Tversky and Kahneman asked half of their subjects to estimate the value of $1 \times 2 \times 3 \times 4 \times 5 \times 6 \times 7 \times 8$ and asked the other half to estimate the value of $8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1$ within 5 seconds. The average answers from the 2 groups were 512 and 2,250, respectively. Russo and Schoemaker (1989) provided an anchor to subjects based on a constant (varying from 400 to 1,200) plus the last 3 digits of the subject's phone number. The two researchers then asked for an estimate of the year in which Attila the Hun was finally defeated. Estimates were positively and significantly correlated with the anchor. More recently, Qu, Zhou, and Luo (2008) provide physiological evidence of the anchoring process based on event-related potential techniques (i.e., techniques that measure the brain responses stimulated by a thought or a perception).

Previous research has also suggested that it is particularly difficult to correct anchoring bias. Consistent with this view, Northcraft and Neale ((1987), p. 95) conclude that "(1) experts are susceptible to decision bias, even in the confines of their 'home' decision setting, and (2) experts are less likely than amateurs to admit to (or perhaps understand) their use of heuristics in producing biased judgments." Plous (1989) shows that task familiarity is not sufficient for avoiding anchoring bias. In addition, the effects of anchoring bias are not significantly influenced by the ease with which respondents can imagine the outcome (outcome availability), by asking the respondents to list the most likely path to the outcome (path availability), or by casting the problem in terms of avoidance (rather than occurrence). Plous also mentions that anchoring bias exists even after correcting for various social demand biases (i.e., the existence of expert opinion running against the initial anchor). Wright and Anderson (1989) consider the effect of situational familiarity on anchoring. They conclude (p. 68), "The anchoring effect is so dominant that increasing situational familiarity did not result in decreased anchoring." Instead they find that monetary incentives can reduce anchoring, but the effect is only marginal in its statistical significance. By contrast, Tversky and Kahneman (1974) find that payoffs for accuracy do not reduce the anchoring effect. Furthermore, Brewer, Chapman, Schwartz, and Bergus (2007) report that accountability does not reduce anchoring bias in doctors' predictions of infection. Whyte and Sebenius (1997) provide results suggesting that groups do not "de-bias" individual judgments.

III. Hypotheses Development

Given the documented robustness of anchoring bias, we hypothesize that market participants such as sell-side analysts and investors would also be affected by anchoring heuristics when they estimate the future profitability of a firm. This estimation is a complex task and involves a high degree of uncertainty, such that market participants will naturally anchor on salient information in their decision making. Prior research (Chapman and Johnson (2002)) suggests that anchors are most influential if they are expressed on the same response scale as the items being estimated (i.e., dollars for dollars rather than percentage when estimating dollars) and if they represent the same underlying dimension (width for width rather than length when estimating width). The popular financial Web site Investopedia.com notes, "Earnings per share is generally considered to be the single most important variable in determining a share's price."[1] Tversky and Kahneman (1974) show in an experimental setting that subjects primed with the median of other subjects' estimates anchor on this median. A natural candidate for possible anchors in our setting is thus the industry median FEPS (a good representation of industry norms).[2] Since an analyst usually covers a group of firms within the same industry, this number is readily available and is naturally associated with the task at hand. For example, Zacks Investment Research states in the 1st line of a recent analyst report that "median EPS is projected to drop 21.2%."[3]

To validate the plausibility that analysts do anchor on the industry norm, we interviewed 6 stock analysts from leading investment banks. First, we described 2 hypothetical stocks (Stock A and Stock B) with identical business and firm characteristics (e.g., firm size, firm performance, market power, corporate governance structure, and so forth). Second, we told our interviewees that the *only* differences between Stock A and Stock B were the level of EPS and the number of shares outstanding: Stock A has an EPS of $0.10 with 100,000 shares outstanding, and Stock B has an EPS of $10.00 with 1,000 shares outstanding. Third, we showed our interviewees a hypothetical figure of the industry cross-sectional distribution of FEPS (similar to Figure 2 in our study) with the industry median FEPS hovering around $1.50. Finally, we asked them which of the stocks is more likely to double its EPS next year (i.e., from $0.10 to $0.20 per share for Stock A, and from $10 to $20 per share for Stock B). Five out of the 6 interviewed analysts picked Stock A. When we asked them which stock is more likely to halve its EPS next year (i.e., from $0.10 to $0.05 per share for Stock A, and from $10 to $5 per share for Stock B), these 5 analysts chose Stock B instead. In a follow-up discussion, analysts admitted that their estimations were obviously affected by the industry media FEPS, especially when it is stable over time.

If participants indeed anchor on the industry norm (proxied by the industry median FEPS in our study), this should have important implications for the behavior of analysts, investors, and the managers of publicly traded companies. First, if analysts anchor on the industry norm of forecast EPS, their forecasts would be closer to this number than they should be. As a result, they would underestimate the future earnings growth of firms with a high FEPS. In other words, analysts would give more optimistic (pessimistic) earnings forecasts for firms with a low (high) FEPS, relative to the industry median, than for similar firms in the same industry. Thus, signed earnings forecast errors would be smaller for

[1] See http://www.investopedia.com/terms/e/eps.asp

[2] We do not argue here that the industry median FEPS is the only possible anchor that leads to behavioral bias. Instead, we argue that it can be an important one, particularly in explaining the empirical patterns documented in this study. We will discuss alternative anchors, including time-series anchoring, in Section VII.B.

[3] See http://www.reuters.com/article/pressRelease/idUS213655+25-Jun-2009+BW20090625

a low-FEPS firm than for a high-FEPS firm in the same industry. This motivates our 1st hypothesis.

Hypothesis 1. Analyst forecasts are more optimistic (indicated by lower signed forecast errors in our study) for firms with a low FEPS relative to their industry median FEPS than for firms with a high FEPS relative to their industry median FEPS.

If investors are affected by biased analysts' earnings forecasts, their expectations of future earnings should also be biased. Firms with a high FEPS relative to their industry norm should suffer from low expectations regarding their future profits. The reverse is true for firms with a low FEPS relative to their industry norm. If this is the case, stocks with a high FEPS should significantly outperform similar stocks in the same industry that have a low FEPS once the true earnings are revealed. This motivates our 2nd hypothesis.

Hypothesis 2. Controlling for risk factors, future stock returns for firms with a high FEPS relative to their industry median FEPS are higher than for firms with a low FEPS relative to their industry median FEPS.

This prediction should be particularly true around subsequent earnings announcement dates when the correction of mispricing is most likely to happen.

If managers expect such biases among analysts and investors, they may be tempted to manage their EPS forecasts so that they are low relative to those for other similar firms. One natural way to achieve this would be to split the shares. We expect that firms with a high FEPS relative to other firms in the industry would be more likely to engage in stock splits to lower their FEPS.[4] This motivates our 3rd hypothesis.

Hypothesis 3. The probability of a stock split is higher for firms with a high FEPS relative to their industry median than for firms with a low FEPS relative to their industry median.

If this strategy is successful, both analysts and investors are affected. In particular, split firms should, on average, experience larger positive revisions in their earnings forecasts, greater negative forecast errors, and larger negative changes in earnings surprises after a stock split than should no-split firms.

IV. The Research Design

We apply 2 basic approaches to test our hypotheses: regression analyses and portfolio sorts. The regression approach allows us to control easily for a host of potentially confounding effects. The portfolio approach allows us to address econometric issues such as overlapping observations and nonlinearities more easily than a regression framework. It also allows us to deal more easily with the "bad model issue" discussed by Fama (1998) and Mitchell and Stafford (2000).

[4]The idea here is similar to the catering theory of share prices suggested by Baker et al. (2009). However, our tests of anchoring bias in stock splits mainly focus on analysts' response instead of the impact on investors.

A. Regression Analysis

The following cross-sectional and time-series model is used to test our hypotheses:

$$\text{(1)} \qquad \text{DEP\_VAR}_{i,t} = \alpha + \beta\,\text{CAF}_{i,t-1} + \gamma^K X^K_{i,t-1} + \varepsilon_{i,t},$$

where $\text{DEP\_VAR}_{i,t}$ represents the value of the dependent variable for firm i in period t. To test Hypothesis 1, we make analysts' forecast error (FE) the dependent variable. Following Ramnath (2002), for each month, the FE is computed as the difference between the actual EPS announced at the end of the fiscal year and the current monthly consensus EPS forecast, scaled by the stock price when the consensus EPS is released.[5] The consensus EPS forecast is the mean of 1-year-ahead EPS forecast in the previous month from the unadjusted summary historical file of the Institutional Brokers' Estimate System (IBES). The actual EPS is reported in the IBES actual file.

To test Hypothesis 2, we define two dependent variables: $\text{BHAR}_{0,1}$ is the cumulative buy-and-hold raw return for firm i in the current month, t; and ECAR is the sum of the 3-day, risk-adjusted, cumulative abnormal returns around the earnings announcements over the next 12 months after the end of calendar month $t-1$. To test Hypothesis 3, SPLIT is the dependent variable. SPLIT is an indicator variable that equals 1 if the firm carries out a significant stock split (i.e., 1 share is split into 1.5 or more shares) in the month, and 0 otherwise.

The main treatment variable, CAF, measures cross-sectional anchoring bias. $\text{CAF}_{i,t-1}$ is defined as the difference between the FEPS for firm i (F_FEPS) in month $t-1$ and the industry median FEPS (I_FEPS) in the same month, scaled by the absolute value of the latter. Following Bhojraj and Lee (2002), we define industries by their Standard Industrial Classification (SIC) 2-digit codes. Various other CAF specifications and industry definitions are tested, but the results remain quantitatively and qualitatively similar.[6] Two interesting features of this variable are that i) a firm can choose its preferred value of CAF through a stock split (or a reverse stock split), and ii) a firm can also affect the value of CAF for other firms in the same industry by engaging in a stock split.[7] The fact that economically

[5] FE = [(ACTUAL_EPS − F_FEPS) × 100]/PRICE, where F_FEPS represents a firm's consensus *forecasted* EPS, ACTUAL_EPS is its actual EPS that is announced at the end of the fiscal year, and PRICE is the stock price when the F_FEPS is reported. Following Diether, Malloy, and Scherbina (2002), we do not distinguish between firms with different fiscal year-ends for the forecast errors. The untabulated result indicates that there is no statistical difference for our results between firms with a December fiscal year-end and firms with a non-December fiscal year-end.

[6] For example, we define $\text{CAF}_{i,t-1}$ as the difference between firm i's FEPS and I_FEPS, scaled by the standard deviation of the former within each industry. We have also defined the industries using the Fama-French (1997) 48 industry classifications. Our conclusions are unaffected.

[7] Suppose that Firm X (the firm for which the analyst is forecasting) has an EPS forecast of \$2.00. Firm Y is the only other firm in the industry, and its total forecasted earnings are \$2,100, and it has 1,000 common shares outstanding. Thus, Firm Y's forecasted EPS is \$2.10. So, the industry median forecasted EPS is \$2.05. The CAF for firm X is (\$2.00 − \$2.05) ÷ |\$2.05| = −0.02. Reconsider the above example, but now Firm Y has 2,000 shares outstanding. Firm Y's forecasted EPS is \$2,100 ÷ 2,000 = \$1.05. The industry median is now \$1.525, and CAF for firm X is (\$2.00 − \$1.525) ÷ |\$1.525| = 0.31. Note that the stability of the anchor (i.e., the industry median FEPS) also significantly affects the anchoring bias. We provide more detailed discussions in Section VII.A.

irrelevant decisions (such as stock splits) can affect the value of CAF mitigates the risk that CAF proxies for some omitted risk factor.

Aside from including a constant (untabulated), a vector of K control variables (X^K) is included in the regression. Specifically, X^K_{it-1} includes the logarithm of firm i's market capitalization (SIZE) at the end of month $t-1$,[8] the logarithm of its BM ratio, its accounting accruals (ACCRUAL), and the 3-day abnormal return around its most recent earnings announcement before the beginning of month t ($\text{ES}_{\text{RECENT}}$). The lagged information is used for all of the control variables to ensure that the values of these variables are known by investors at the beginning of month t to avoid any look-ahead bias. We also control for past returns in our specifications. When either FE or ECAR is the dependent variable, we simply use the 6-month buy-and-hold return in the prior 6 months ($\text{RET}_{-6:0}$). However, when $\text{BHAR}_{0,1}$ is the dependent variable, we control for a 1-month lag in the buy-and-hold return of the past 6 months ($\text{RET}_{-7:-1}$) and the return in the past 1 month ($\text{RET}_{-1:0}$), because previous research has shown the importance of intermediate-term momentum and short-term reversal (Jegadeesh and Titman (1993), (2001)). In addition, we control for the following 3 additional variables when FE is the dependent variable: EXPERIENCE (the natural logarithm of 1 plus the average number of months current analysts have been following the firm), BREADTH (the natural logarithm of the average number of stocks followed by current analysts), and HORIZON (the natural logarithm of 1 plus the number of months before firm i's next earnings announcement). The detailed definitions of these variables are given in the Appendix.

If Hypothesis 1 is correct, the coefficient of CAF should be positive when FE is the dependent variable. In essence, when F_FEPS is high relative to I_FEPS, analysts may anchor on I_FEPS and issue overpessimistic forecasts. This would lead to high subsequent stock returns as market participants gradually revise and correct their optimism. Then we would expect positive earnings surprises when the true earnings are announced. Therefore, if Hypothesis 2 is correct, we would expect the coefficient of CAF to be positive when $\text{BHAR}_{0,1}$ is the dependent variable. We would also expect the coefficient of CAF to be positive when ECAR is the dependent variable, as investors realize their initial mistake when subsequent earnings are released. If Hypothesis 3 is correct, the coefficient of CAF should be positive when SPLIT is the dependent variable. In other words, the managers would prefer to reduce the FEPS by splitting their stocks to avoid pessimistic earnings forecasts from analysts and undervaluation from investors. We use the Fama-MacBeth (1973) procedure to estimate equation (1) when the dependent variable is continuous (FE, $\text{BHAR}_{0,1}$, or ECAR). The Newey-West (1987) heteroskedasticity- and autocorrelation-adjusted estimates of standard errors are used to compute the t-statistics on the estimated coefficients. When the dependent variable is SPLIT, the panel logit regression is used to estimate equation (1), and the clustered standard errors at both the firm level and the time (year) level are used to compute the z-statistics.

[8]Using 9 decile indicator variables instead of a continuous variable does not affect our conclusions.

B. Portfolio Sorts

Our 2nd approach is based on portfolio sorts. At the end of each calendar month, we first rank all firms in the sample and group them into quintiles (G1–G5) according to their market capitalization (SIZE). Within each SIZE group, we further sort all firms into 5 subgroups (E1–E5) based on their CAF measures. We then analyze the behavior of different variables across all 25 portfolios. To test Hypothesis 1, we consider FE as the dependent variable.

To test Hypothesis 2, we consider α and ECAR. Alpha is the intercept from a time-series regression based on the Fama and French (1993) 3-factor model plus a Carhart (1997) momentum factor described as

$$(2) \qquad R_{p,t} - R_{f,t} = \alpha_p + \beta_p^M(\mathrm{MKT}_t - R_{f,t}) + \beta_p^S \mathrm{SMB}_t + \beta_p^H \mathrm{HML}_t + \beta_p^U \mathrm{UMD}_t + \varepsilon_{i,t},$$

where R_p is the monthly return on portfolio p, MKT is the monthly return on the market portfolio, and R_f is the monthly risk-free rate. Here, MKT – R_f, SMB, and HML are returns on the market, size, and BM factors, respectively, as constructed by Fama and French (1993); UMD is Carhart's momentum factor; R_f is proxied by the 1-month U.S. T-bill rate; HML (high minus low) is the difference between the return on a portfolio of high (the top 30%) BM stocks and the return on a portfolio of low (the bottom 30%) BM stocks; SMB (small minus big) is the difference between the return on a portfolio of small (the bottom 50%) stocks and the return on a portfolio of large (the top 50%) stocks; and UMD is the difference between the return on a portfolio of stocks with high (the top 50%) prior-year returns and the return on a portfolio of stocks with low (the bottom 50%) prior-year returns, skipping the return in the formation month. Factor returns and the risk-free rates are from Kenneth French's Web site.[9] We estimate the intercept (α) for each of the 25 portfolios.

To test our different hypotheses, we form a hedge portfolio that longs stocks in the highest CAF group and shorts stocks in the lowest CAF group. We then test the statistical significance of FE, α, and ECAR in each of the hedge portfolios.

V. Sample and Descriptive Statistics

A. Sample Selection

Our basic sample consists of all NYSE, AMEX, and NASDAQ-listed common stocks in the intersection of i) the Center for Research in Security Prices (CRSP) stock file, ii) the merged Compustat annual industrial file, and iii) the unadjusted summary historical file of IBES for the period from Jan. 1983 to Dec. 2005.[10] To be included in the sample for a given month, t, a stock must

[9] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[10] Although IBES provides data starting from 1976, we restrict our sample period to Jan. 1983 to Dec. 2005 for two reasons. First, before Jan. 1983, the coverage of stocks by IBES was limited, which would reduce the power of our tests. Second, the IBES detailed unadjusted historical file begins in 1983. Hence, we can only conduct robustness checks on the results with the detailed file after 1983. Extending the sample period to 1976 does not materially change our results.

satisfy the following 5 criteria: First, the mean of analysts' forecasts (i.e., the consensus forecast) of the 1-year-ahead (FY1) EPS in the previous month, $t-1$, is available from the IBES unadjusted summary historical file. Second, its returns in the current month, t, and the previous 7 months, $t-7$ to $t-1$, are available from CRSP, and sufficient data are available to obtain market capitalization and stock prices in the previous month, $t-1$. Third, sufficient data from CRSP and Compustat are available to compute the Fama and French (1992), (1993) BM ratio as of December of the previous year. Fourth, stocks priced below $5 at the end of the previous month, $t-1$, are excluded, as are stocks for which Compustat reports a negative book value of stockholders' equity (Compustat item 60) as of the previous month, $t-1$. Finally, to ensure that the CAF measure is economically meaningful, an industry (based on the SIC 2-digit codes) must have at least 5 firms if it is to be included in our sample. This screening process yields 709,605 stock-month observations or an average of 2,571 stocks per month.[11]

B. Sample Characteristics

Table 1 provides summary statistics describing our sample. All of the independent variables, as mentioned above, are either lagged by 1 month or computed based on public information as of the previous month, $t-1$, in order to ensure that they were already available to investors at the beginning of each month and can be used to execute our trading strategies. Table 1 reports the time-series averages

TABLE 1

Summary Statistics

Table 1 reports descriptive statistics for the final sample during the period Jan. 1983–Dec. 2005. The sample includes all stocks listed on the NYSE, AMEX, and NASDAQ, excluding stocks priced below $5 at the end of the previous month. A stock is eligible to be included only if there are sufficient data in the CRSP, Compustat, and IBES databases to compute the firm characteristics defined in the Appendix. In addition, we require that each industry-year, as defined by the 2-digit SIC industry codes, must have 5 or more firms to be included in our sample. The time-series averages of common statistics for the major dependent and independent variables are reported.

Variables	Mean	Median	Standard Deviation	Skewness	10th Percentile	90th Percentile
CAF	0.132	0.000	2.059	1.209	−0.912	1.445
F_FEPS ($)	1.592	1.328	1.531	1.111	0.156	3.421
FE (%)	−1.538	−0.081	5.994	−5.993	−4.183	0.716
$\text{BHAR}_{0,1}$ (%)	1.191	0.723	11.725	0.637	−11.520	14.265
ECAR (%)	0.122	0.044	6.917	0.165	−6.947	7.356
SPLIT	0.008	0.000	0.088	12.404	0.000	0.000
SIZE ($B)	2.019	0.351	6.237	5.820	0.060	4.087
BM	0.688	0.599	0.465	1.710	0.213	1.243
$\text{RET}_{-6:0}$ (%)	10.827	6.962	31.392	1.186	−22.080	46.148
ACCRUAL	−0.027	−0.034	0.086	0.575	−0.116	0.071
$\text{ES}_{\text{RECENT}}$ (%)	0.296	0.114	6.890	0.412	−6.734	7.579
EP_{t-1}	0.043	0.058	0.090	−2.871	−0.034	0.114

[11]Following previous studies (e.g., Jegadeesh and Titman (2001)), we remove stocks with prices under $5 because such stocks not only have few analysts following them, but they also incur large transaction costs due to their poor market liquidity (thin trading and large bid-ask spreads), which could distort the feasibility of any trading strategy. We also remove stocks with a negative book value of stockholders' equity simply to make sure that our results are not driven by financially distressed firms. Including these observations leads to (untabulated) results that are economically and statistically more significant.

of the cross-sectional means, medians, standard deviations, and other statistics. It can be seen that all of the variables exhibit substantial variation, suggesting that portfolio sorting strategies based on these firm characteristics can offer reasonable statistical power for our tests. The mean and median of firm size (SIZE) are \$2.02 billion and \$0.35 billion, respectively, values that are much larger than the corresponding values for all CRSP stocks (an untabulated result). This reflects the fact that the sample of firms covered by IBES omits many small stocks. Since the return anomaly reported in this study is stronger for small stocks, our sample selection criteria are actually biased against finding significant results.

Table 2 reports the univariate correlations among these variables. Here, CAF is significantly and positively correlated with F_FEPS, SIZE, FE, and EP_{t-1}, and CAF is also positively correlated with $BHAR_{0,1}$ and ECAR, albeit statistically insignificantly. The correlations among control variables are generally low, suggesting that multicollinearity is not a big concern in the regressions.

TABLE 2

Correlations among Major Variables

Table 2 reports the correlation coefficients between major dependent and independent variables. The final sample covers Jan. 1983–Dec. 2005. The sample includes all stocks listed on the NYSE, AMEX, and NASDAQ, excluding stocks priced below \$5 at the end of the previous month. To be included in the sample, a stock must have sufficient data in the CRSP, Compustat, and IBES databases to compute the firm characteristics defined in the Appendix. In addition, we require that each industry-year, as defined by the 2-digit SIC industry codes, must have 5 or more firms to be included in our sample. Time-series average correlation coefficients are reported in this table. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	CAF	F_FEPS	FE	$BHAR_{0,1}$	ECAR	SPLIT	SIZE	BM	$RET_{-6:0}$	ACCRUAL	ES_{RECENT}	EP_{t-1}
F_FEPS	0.722***	1.000										
FE	0.113**	0.146**	1.000									
$BHAR_{0,1}$	0.020	0.031	0.110**	1.000								
ECAR	0.014	0.021	0.107**	0.177**	1.000							
SPLIT	0.054	0.066	0.022	0.022	0.005	1.000						
SIZE	0.304***	0.355***	0.067**	0.001	0.005	0.017	1.000					
BM	−0.055	0.063	−0.056	0.025	0.019	−0.030	−0.081**	1.000				
$RET_{-6:0}$	0.034	0.048*	0.178***	0.021	0.025	0.077**	0.019	0.083	1.000			
ACCRUAL	−0.001	−0.020	−0.033	−0.024	−0.016	0.003	−0.068*	−0.116*	−0.070	1.000		
ES_{RECENT}	0.022	0.023	0.094**	0.032	0.024	0.025	0.008	0.024	0.236***	−0.020	1.000	
EP_{t-1}	0.321***	0.425***	0.141**	0.022	0.011	0.016	0.056	0.050*	−0.019*	0.112*	−0.004	1.000

VI. Empirical Results

A. Anchoring and Forecast Errors

Results from regressions testing Hypothesis 1 are reported in Panel A of Table 3. Three different models with an increasing number of control variables are considered. The 1st column reports the results of a model that controls for log(SIZE), log(BM), and $RET_{-6:0}$. In the 2nd column, ACCRUAL and ES_{RECENT} are added as control variables. In the last column, results including EP and 3 other control variables specific to the FE regressions (EXPERIENCE, BREADTH, and HORIZON) are reported. Consistent with Hypothesis 1, the coefficient of CAF is significant and positive in all 3 models. The effect is statistically significant, with t-statistics ranging from 4.01 (Model 3) to 5.23 (Model 1). The effect is also economically significant. For example, an increase of CAF by 1 standard deviation increases FE by approximately 20% of the absolute level of its mean.[12]

TABLE 3

Forecast Errors and Anchoring

Table 3 reports the results from the Fama-MacBeth (1973) regressions to test the incremental role of CAF in explaining the cross section of forecast errors. The dependent variable is the forecast error (FE), defined as FE = [(ACTUAL − FEPS) × 100]/PRICE. The explanatory variables include a constant (not reported), the cross-sectional anchoring measure of FEPS (CAF), log(SIZE), log(BM), $RET_{-6:-0}$, ACCRUAL, ES_{RECENT}, EP_{t-1}, EXPERIENCE, BREADTH, and HORIZON. Their detailed definitions are provided in the Appendix. In Panel A, the regressions are estimated each month from Feb. 1983 to Dec. 2005, and the means of the monthly estimates are reported. Stocks priced below $5 are excluded from the sample. For all the dependent and explanatory variables, values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. Panel B reports the time-series averages of forecast errors (FE) for 5 × 5 SIZE- and CAF-sorted portfolios. The portfolios are constructed as follows: At the beginning of each month, all stocks are sorted into 5 groups (G1–G5) based on their SIZE at the end of the previous month. The stocks in each SIZE group are then further sorted into 5 quintiles (E1–E5) based on their CAF in the previous month. The t-statistics reported in parentheses are adjusted for serial correlation and heteroskedasticity based on Newey and West (1987). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Results from the Fama-MacBeth Regressions of Forecast Errors

Independent Variables	1	2	3
CAF	0.272***	0.272***	0.150***
	(5.23)	(5.19)	(4.01)
log(SIZE)	0.391***	0.384***	0.393***
	(11.18)	(10.98)	(12.09)
log(BM)	−0.252***	−0.277***	−0.299***
	(−3.46)	(−4.79)	(−3.77)
$RET_{-6,0}$	0.037***	0.035***	0.037***
	(6.87)	(6.54)	(6.69)
ACCRUAL		−0.797***	−1.783***
		(−3.77)	(−5.50)
ES_{RECENT}		0.043***	0.045***
		(6.18)	(6.82)
EP_{t-1}			9.042***
			(6.57)
EXPERIENCE			−0.112**
			(−2.48)
BREADTH			0.127***
			(3.19)
HORIZON			−0.965***
			(−10.51)
Avg. adj. R^2	0.066	0.072	0.102
Avg. N	1,448	1,446	1,441

Panel B. Forecast Errors (%) for SIZE- and CAF-Sorted Portfolios

	Size Quintiles					
CAF Quintiles	G1 (small)	G2	G3	G4	G5 (large)	All Stocks
E1 (low)	−5.299	−3.936	−2.868	−1.637	−0.885	−2.925
E2	−3.137	−2.039	−1.206	−0.659	−0.369	−1.482
E3	−2.611	−1.492	−0.845	−0.526	−0.301	−1.155
E4	−2.404	−1.446	−0.764	−0.549	−0.323	−1.097
E5 (high)	−2.293	−1.285	−0.756	−0.545	−0.279	−1.032
E5 − E1	3.006***	2.651***	2.112***	1.092***	0.606***	1.893***
t-statistic	(6.00)	(5.21)	(6.40)	(5.24)	(4.58)	(6.09)

Panel B of Table 3 provides the results of portfolio sorts based on size (from G1 to G5) and CAF (from E1 to E5). The last column of the panel reports the

[12]We estimate the effect as the product of 0.150 (from Column 3 in Panel A of Table 3) and 2.059 (from Table 1) divided by 1.538 (from Table 1), which equals 0.201.

results of the partitions based on CAF for firms of all sizes pooled together. As can be seen, the mean values of FE are negative for all 25 portfolios, suggesting that analyst forecasts in our sample are on average too optimistic. As we go from E1 (the portfolio of firms with the lowest CAF) to E5 (the portfolio of firms with the highest CAF), the average value of FE increases monotonically. The difference in the average value of FE between E5 and E1 is positive and statistically significant with a t-statistic of 6.09. The other 5 columns report the mean values of FE for different portfolios based on size and CAF. For all levels of CAF, the mean value of FE decreases as firm size decreases. More importantly, FE increases in all size groups as CAF increases. However, the magnitude of the difference in FE between firms with a high CAF and firms with a low CAF monotonically decreases as firm size increases. For example, the magnitude of the difference in FE between high- and low-CAF firms decreases from 3.006 to 0.606 as firm size increases. Similarly, the t-statistic of the difference decreases from 6.00 to 4.58 as firm size increases from G1 to G5. The results from portfolio sorts are also consistent with the prediction of Hypothesis 1.

B. Anchoring and Future Stock Returns

Panel A of Table 4 presents the results of regressions of a 1-month ahead return ($BHAR_{0,1}$) on CAF and our control variables designed to test Hypothesis 2. For all 3 models, the coefficient of CAF is significant and positive, with t-statistics ranging from 2.65 (Model 3) to 2.95 (Model 2). The economic effect is such that increasing CAF by 1 standard deviation increases $BHAR_{0,1}$ by approximately 15% of its mean value.[13]

Panel B of Table 4 provides the results of portfolio sorts based on size (from G1 to G5) and CAF (from E1 to E5). For each portfolio, we estimate a time-series regression based on the Fama-French (1993) and Carhart (1997) 4-factor model for each portfolio. The intercepts (αs) of the test portfolios are reported in Panel B of Table 4. The last column of the panel reports the results of the partitions based on CAF for firms of all sizes pooled together. As we go from E1 to E5, the value of α increases monotonically. The difference in α between E5 and E1 (i.e., the hedge portfolio) is 0.71% per month, or 8.52% per year, and is statistically significant with a t-statistic of 4.05. The other 5 columns report the intercepts for different hedge portfolios based on size and CAF. The average values of the abnormal returns (αs) are positive and significant for all levels of firm size. However, both the magnitude and the statistical significance monotonically decrease as firm size increases.

Table 4 focuses on the 1-month-ahead return. However, the effect of CAF on future stock returns is not only limited to a 1-month horizon. Figure 1 plots the average cumulative raw returns at monthly intervals of the trading strategy that buys the highest-CAF decile portfolio and sells the lowest-CAF decile portfolio. It appears that the returns on the hedge portfolio using this CAF strategy grow consistently, at least in the first 12 months after portfolio formation. To formally

[13]We estimate the effect as the product of 0.085 (from Column 3 of Table 4) and 2.059 (from Table 1) scaled by 1.191 (from Table 1), which equals 0.147.

TABLE 4

The Cross Section of Stock Returns and Anchoring

Panel A of Table 4 reports the results from the Fama-MacBeth (1973) regressions to test the incremental role of CAF in explaining the cross section of stock returns. The dependent variable is the 1-month raw return ($BHAR_{0,1}$) in the current month, t. The explanatory variables include a constant (not reported), the cross-sectional anchoring measure of FEPS (CAF), log(SIZE), log(BM), $RET_{-7:-1}$, $RET_{-1:0}$, ACCRUAL, ES_{RECENT}, and EP_{t-1}. Detailed definitions are provided in the Appendix. Panel B reports the risk-adjusted returns (i.e., α) for equal-weighted portfolios based on SIZE and CAF sorting. Alpha is the intercept term from the time-series regression based on the Fama and French (1993) plus Carhart (1997) 4-factor model described in equation (2). The portfolios are constructed as follows: At the beginning of each month, stocks are sorted into 5 groups (G1–G5) based on their market capitalization (SIZE) at the end of the previous month, and the stocks in each SIZE group are further sorted into 5 quintiles (E1–E5) based on their CAF in the previous month. Stocks priced below $5 are excluded from the sample. For all the dependent and explanatory variables (except for stock returns), values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. The t-statistics reported in parentheses are adjusted for serial correlation and heteroskedasticity using the Newey and West (1987) procedure. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Results from the Fama-MacBeth Regressions of Stock Returns

Independent Variables	1	2	3
CAF	0.109***	0.110***	0.085***
	(2.91)	(2.95)	(2.65)
log(SIZE)	−0.049	−0.070	−0.070
	(−0.99)	(−1.43)	(−1.42)
log(BM)	0.229*	0.176	0.169
	(1.78)	(1.40)	(1.34)
$RET_{-7:-1}$	0.010***	0.008***	0.008***
	(3.63)	(2.79)	(2.92)
$RET_{-1:0}$	−0.028***	−0.034***	−0.035***
	(−5.06)	(−6.09)	(−6.15)
ACCRUAL		−2.396***	−2.658***
		(−6.31)	(−7.06)
ES_{RECENT}		0.057***	0.057***
		(12.78)	(12.94)
EP_{t-1}			1.637***
			(3.21)
Avg. adj. R^2	0.043	0.046	0.048
Avg. N	1,889	1,887	1,886

Panel B. Alphas Based on the Fama-French and Carhart 4-Factor Model for SIZE- and CAF-Sorted Portfolios

	Size Quintiles					
CAF Quintiles	G1 (small)	G2	G3	G4	G5 (large)	All Stocks
E1 (low)	−0.802	−0.474	−0.394	−0.322	−0.171	−0.433
E2	−0.150	−0.049	−0.111	−0.056	−0.031	−0.079
E3	0.054	0.238	0.244	−0.003	0.108	0.128
E4	0.421	0.152	0.173	0.042	0.006	0.159
E5 (high)	0.573	0.360	0.196	0.150	0.121	0.280
E5 – E1	1.375***	0.834***	0.590**	0.473**	0.292*	0.713***
t-statistic	(6.51)	(3.42)	(2.49)	(2.24)	(1.70)	(4.05)

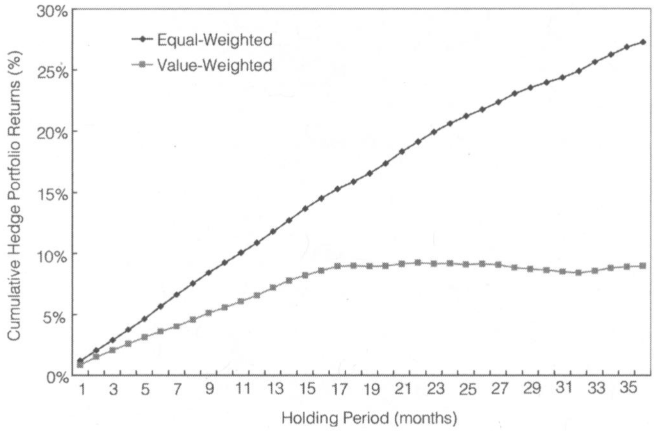
investigate the CAF effect beyond the 1-month horizon, we reestimate a model similar to the one reported in the last column of Panel A of Table 4 using returns cumulated over 3, 6, and 12 months after portfolio formation. The coefficients of CAF are 0.135, 0.219, and 0.442, with t-statistics of 2.25, 2.42, and 2.39, respectively, suggesting a persistent impact of CAF on long-run returns. Although the cumulative returns grow at a decreasing rate, they do not show any reversal over the next 36 months, whereas Jegadeesh and Titman (2001) find a dramatic reversal of returns to the momentum strategy after 1 year. This distinguishes the CAF effect from the price momentum effect.

To put these profits into a practical perspective, we consider the effect of transaction costs using the model proposed by Keim and Madhavan (1997) (also

FIGURE 1

The Cumulative (Buy-and-Hold) Returns to a Hedging Strategy of Buying the Highest CAF Stocks and Selling the Lowest CAF Stocks

At the beginning of each month from Feb. 1983 to Dec. 2003, all stocks are ranked into deciles based on their CAF in the previous month. Ten CAF-sorted portfolios are formed and held for 36 months, and the portfolio returns are equal-weighted as well as value-weighted. Figure 1 plots the difference in mean cumulative return between the highest CAF decile portfolio and the lowest CAF decile portfolio.



used by Barber, Lehavy, McNichols, and Trueman (2001) and Bushee and Raedy (2006)).[14] Untabulated results indicate that the mean of the 12-month cumulative raw returns associated with the CAF hedge portfolio is 8.44% for the whole sample, while the mean of the corresponding estimated trading costs for this portfolio is 3.84%. The cumulative hedge portfolio returns vary from 11.69% to 4.53% for the different size quintiles, while the estimated corresponding transaction costs vary from 6.67% to 1.21%. These results suggest that our CAF trading strategies are still profitable even after taking transaction costs into account.

C. Anchoring and Market Reactions around Earnings Announcements

Having found that future returns and CAF are positively related, we focus next on returns around earnings announcements. Panel A of Table 5 presents the results of regressions of the earnings announcement return (ECAR) against CAF and other control variables. Here, ECAR is the 3-day accumulative abnormal return relative to the CRSP value-weighted index surrounding the subsequent earnings announcement date after portfolio formation. For all 3 models, the coefficient of CAF is significantly positive with t-statistics ranging from 3.72 (Model 1) to 3.82 (Model 2). The economic effect is such that increasing CAF

[14]To obtain conservative estimates, we use the 99th percentile of the distribution of trade dollar size for the month under consideration (from the Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases), and we assume that the cost of shorting low-CAF stocks is twice as much as that of shorting high-CAF stocks.

by 1 standard deviation increases ECAR by approximately 89.45% of its mean value.[15]

TABLE 5

Ex Post Earnings Announcement Returns and Anchoring

Panel A of Table 5 reports the results from the Fama-MacBeth (1973) regressions to test the incremental role of CAF in explaining the cross section of ex post earnings announcement returns. The dependent variable is the earnings announcement return (ECAR), which is defined as the cumulative 3-day abnormal return relative to the CRSP value-weighted index surrounding the next earnings announcement date after portfolio formation over the next 12 months. The explanatory variables include a constant (not reported), the cross-sectional anchoring measure of FEPS (CAF), log(SIZE), log(BM), $\mathrm{RET}_{-6:-0}$, ACCRUAL, $\mathrm{ES}_{\mathrm{RECENT}}$, EP_{t-1}, and the time-series anchoring measure of FEPS (TAF). Their detailed definitions are provided in the Appendix. For all dependent and explanatory variables (except for stock returns), values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. Panel B reports the time-series averages of the means of ECAR for the 5×5 SIZE- and CAF-sorted portfolios. At the beginning of each month, all stocks are sorted into 5 groups (G1–G5) based on their market capitalization (SIZE) at the end of the previous month. Stocks in each SIZE group are further sorted into 5 quintiles (E1–E5) based on their CAF in the previous month. The portfolios are held for 12 months after formation. Stocks priced below $5 are excluded from the sample. The *t*-statistics reported in parentheses are adjusted for serial correlation and heteroskedasticity using the Newey and West (1987) procedure. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Results from the Fama-MacBeth Regressions of ECAR

Independent Variables	1	2	3
CAF	0.049***	0.050***	0.053***
	(3.72)	(3.82)	(3.79)
log(SIZE)	0.033**	0.026	0.026
	(2.02)	(1.61)	(1.60)
log(BM)	0.207***	0.186***	0.187***
	(6.71)	(6.33)	(6.37)
$\mathrm{RET}_{-6:-0}$	0.005***	0.004***	0.004***
	(4.32)	(3.87)	(3.85)
ACCRUAL		−0.928***	−0.950***
		(−3.99)	(−4.00)
$\mathrm{ES}_{\mathrm{RECENT}}$		0.017***	0.017***
		(3.97)	(3.93)
EP_{t-1}			−0.048
			(−0.20)
Avg. adj. R^2	0.004	0.005	0.005
Avg. *N*	1,900	1,898	1,896

Panel B. Ex Post Earnings Announcement Effects (ECAR) for SIZE- and CAF-Sorted Portfolios

	Size Quintiles					
CAF Quintiles	G1 (small)	G2	G3	G4	G5 (large)	All Stocks
E1 (low)	−0.270	−0.460	−0.207	0.055	0.106	−0.155
E2	0.061	−0.002	0.025	0.217	0.205	0.101
E3	0.140	0.116	0.223	0.226	0.242	0.189
E4	0.335	0.162	0.232	0.301	0.213	0.249
E5 (high)	0.276	0.212	0.162	0.278	0.181	0.222
E5 − E1	0.546***	0.672***	0.369***	0.223*	0.075	0.377***
t-statistic	(4.51)	(5.00)	(3.18)	(1.71)	(1.11)	(5.13)

Panel B of Table 5 provides the results of ECAR for portfolios sorted based on size (from G1 to G5) and CAF (from E1 to E5). For each portfolio, we estimate the average of the 3-day cumulative abnormal returns surrounding the subsequent earnings announcement dates after portfolio formation. The last column of the panel reports the results of the partitions based on CAF for firms of all sizes pooled together. As we go from E1 (the portfolio of firms with the

[15]We estimate the effect as the product of 0.053 (from Column 3 in Panel A of Table 5) and 2.059 (from Table 1) scaled by 0.122 (from Table 1), which equals 89.45%.

lowest CAF) to E5 (the portfolio of firms with the highest CAF), the average value of earnings surprises increases. The average return of the hedge portfolio (long E5 and short E1) is 0.38% over the 3-day period around the subsequent earnings announcement and is statistically significant with a t-statistic of 5.13.

In addition, the returns of the hedge portfolios are positive for all size groups. However, both the magnitude and the statistical significance decrease as firm size increases. For example, the magnitude of the difference in 3-day earnings surprises decreases from 0.55% to 0.08% from G1 to G5. Similarly, the t-statistic for the difference also decreases from 4.51 to 1.11 as firm size increases. Overall, the returns of the hedge portfolios surrounding earnings announcements are significant for the 3 smallest size quintiles. The results in Table 5 indicate that a substantial part of the CAF effect is concentrated around the earnings announcement dates. Based on a 1-year holding horizon, on average, such returns account for approximately 18% of the CAF effect, even though the trading days around earnings announcements account for less than 5% of the total trading dates.[16] The results also suggest that the CAF effect cannot be reconciled by any obvious risk-based explanation. If the significant excess returns from the CAF strategy are generated because of benchmarking errors from any asset pricing model, they would be expected to accrue relatively smoothly over the year, not clustered around earnings announcements.[17]

D. Anchoring and the Decision for Stock Splits

Before testing Hypothesis 3, we examine the time-series behavior of FEPS and aggregate earnings. Figure 2 indicates a stable pattern in the cross-sectional distribution of the forecasts of nominal EPS. Untabulated results indicate that such a pattern also exists in realized nominal EPS. The cross-sectional median of FEPS rarely deviates from a small range bounded by \$1 and \$2 in our sample period covering 1983–2005. In contrast, the median of total forecast earnings (TFE) in the cross section almost triples from US\$14 million to US\$37 million during the same period.

Panel A of Table 6 presents the results of logit regressions of SPLIT against CAF and the control variables. In all 3 models, the coefficient of CAF is significant and positive, with t-statistics ranging from 2.40 in Model 1 to 2.95 in Model 3. The economic effect is such that increasing CAF by 1 standard deviation increases the odds of a stock split by approximately 5%. We also find that large and growth firms are more likely to engage in a stock split, as reflected by

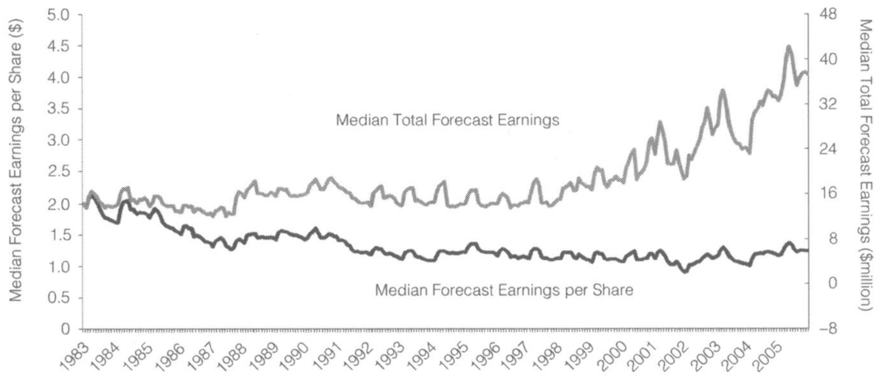
[16]The average 3-day announcement return for the hedge portfolio is 0.38% per quarter, and the average annualized hedge portfolio return is 8.4%. Thus, the hedge portfolio return surrounding the earnings announcement period accounts for $(0.38\% \times 4) \div 8.4\% = 18.10\%$ of the overall portfolio return, even though the trading days around earnings announcements account for only $(3 \times 4) \div 250 = 4.8\%$ of the total number of trading days in the year.

[17]This methodology, initially proposed by Chopra, Lakonishok, and Ritter (1992) to study overreaction, has been applied in several studies to test for the possibility that investors have biased expectations. For example, La Porta, Lakonishok, Shleifer, and Vishny (1997) study stock price reactions around earnings announcements to examine whether the superior returns on value stocks result from investors' expectations biases. Titman, Wei, and Xie (2004) apply this approach to study whether the negative relation between capital investment and subsequent stock returns is attributed to mispricing.

FIGURE 2

Median F_FEPS and Median TFE in the Cross Section

The solid line is the median of forecast earnings per share (F_FEPS) ($) in the cross section, and the shadowed line is the median of total forecast earnings (TFE) (in million $) from Feb. 1983 to Dec. 2005. The value of TFE is presented on the y-axis on the right, while the value of F_FEPS is on the y-axis on the left.



a positive and significant coefficient on log(SIZE) and a negative and significant coefficient on log(BM), where BM is an inverse measure of growth opportunities. As the stock price (PRICE) is an important motivation to split shares, we control for it by including either the decile indicator variables or log(PRICE) in

TABLE 6

Stock Splits and Anchoring

Panel A of Table 6 reports the results from the panel logit regressions testing the likelihood of a stock split. The dependent variable is a dummy variable that equals 1 if a firm carries out a significant stock split in month t, and 0 otherwise. The explanatory variables include a constant (not reported), the cross-sectional anchoring measure of FEPS (CAF), log(SIZE), log(BM), $\text{RET}_{-6:-0}$, ACCRUAL, $\text{ES}_{\text{RECENT}}$, and EP_{t-1}. Their detailed definitions are provided in the Appendix. The z-statistics reported in parentheses have been adjusted for clustered standard errors at both the firm level and the time (year) level. Panel B reports the time-series averages of stock split ratios (SSR) for 5 × 5 SIZE- and CAF-sorted portfolios. At the beginning of each month, all stocks are sorted into 5 groups (G1–G5) based on their market capitalization (SIZE) at the end of the previous month. The stocks in each SIZE group are further sorted into 5 quintiles (E1–E5) based on their CAF in the previous month. The portfolios are held for 12 months after formation. SSR is defined as the change in the cumulative stock-split-driven factor used to adjust shares outstanding in the following 12 months. Stocks priced below $5 are excluded from the sample. The t-statistics reported in parentheses are adjusted for serial correlation and heteroskedasticity using the Newey and West (1987) procedure. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Results from the Likelihood Logit Regressions of a Stock Split

Independent Variables	1	2	3
CAF	0.007**	0.007***	0.006***
	(2.40)	(2.65)	(2.95)
log(SIZE)	0.052***	0.082***	0.073***
	(4.33)	(5.67)	(4.95)
log(BM)	−0.175***	−0.225***	−0.237***
	(−8.76)	(−9.46)	(−9.86)
$\text{RET}_{-6:-0}$	0.008***	0.008***	0.008***
	(6.67)	(6.21)	(5.96)
$\text{ES}_{\text{RECENT}}$		0.016***	0.017***
		(9.56)	(9.83)
ACCRUAL		1.159***	0.940***
		(6.81)	(5.39)
EP_{t-1}			2.321***
			(7.68)
Pseudo R^2	0.027	0.035	0.037

(continued on next page)

TABLE 6 (continued)

Stock Splits and Anchoring

Panel B. SSRs for SIZE- and CAF-Sorted Portfolios

	Size Quintiles					
CAF Quintiles	G1 (small)	G2	G3	G4	G5 (large)	All Stocks
E1 (low)	1.011	1.017	1.027	1.054	1.077	1.037
E2	1.021	1.033	1.052	1.073	1.070	1.050
E3	1.034	1.058	1.081	1.092	1.115	1.076
E4	1.052	1.082	1.121	1.144	1.168	1.113
E5 (high)	1.100	1.139	1.169	1.181	1.239	1.166
E5 − E1	0.090***	0.122***	0.142***	0.127***	0.162***	0.129***
t-statistic	(11.34)	(14.67)	(12.58)	(9.96)	(9.08)	(12.72)

the regression. The untabulated results indicate that our conclusions are similar to those drawn from Panel A.

Panel B of Table 6 reports the average stock split ratio (SSR) of the portfolios sorted based on SIZE (from G1 to G5) and CAF (from E1 to E5). The last column of the panel reports the results of the partitions based on CAF for firms of all sizes pooled together. As we go from E1 to E5, the average value of SSR increases monotonically. The difference in the average value of SSR between E5 and E1 is positive and statistically significant with a t-statistic of 12.72 in the pooled sample. The results also indicate that the difference in SSR between E1 and E5 is significant in all size groups. In addition, the magnitude of the difference in SSR between high- and low-CAF firms increases as firm size increases. For example, the magnitude of the difference increases from 0.090 to 0.162 as firm size increases from G1 to G5. All of these results are consistent with those reported in Panel A of Table 6. When firm size is replaced by the stock price as the partitioning variable, our untabulated results indicate that our conclusions are similar to those drawn from Panel B.

E. Anchoring and Consequences of Stock Splits

Hypothesis 3 relies on the notion that stock splits are motivated, at least in part, by the desire of managers to benefit from the anchoring biases of market participants. The empirical results discussed below suggest that this strategy is successful and works in the way the cross-sectional anchoring bias predicts. First, untabulated results indicate that firms engaging in a stock split experience more positive earnings forecast revisions, more negative forecast errors, and more negative earnings surprises after the split.

Second, we focus on the stock splits of firms with an ex ante level of FEPS higher than the industry median.[18] We then consider the behavior of our key variables. Since many factors may affect the firm immediately after a stock split, we focus on the adjusted values of FE (ADJ_FE), $BHAR_{0,1}$ ($ADJ\_BHAR_{0,1}$), and

[18]We do not consider firms that performed a reverse stock split, because most of these firms had shares priced below $5 before the split. In fact, we can identify only 17 cases of reverse stock splits that meet our data requirements. We thank an anonymous referee for suggesting this research design.

ECAR (ADJ_ECAR) rather than on the unadjusted values.[19] In addition, the unadjusted FE tends to be negative, since analysts on average are optimistic; the unadjusted $\mathrm{BHAR}_{0,1}$ tends to be positive, since the average raw returns are positive during our study period. Here, ADJ_$\mathrm{BHAR}_{0,1}$ is the difference in $\mathrm{BHAR}_{0,1}$ between an individual firm and an equal-weighted portfolio of benchmark firms based on similar SIZE, BM, and $R_{-6,0}$, following Daniel, Grinblatt, Titman, and Wermers (1997); ADJ_FE and ADJ_ECAR are defined similarly. We exclude the 3 months immediately before and after the stock split where confounding factors may play a significant role. We regress ADJ_FE, ADJ_$\mathrm{BHAR}_{0,1}$, or ADJ_ECAR in the post-split period ($t + 4$ to $t + 15$, where t is the split month) on an indicator variable that takes the value of 1 if CAF is negative and 0 if CAF is positive in that period. We control for the level of CAF, ADJ_FE, ADJ_$\mathrm{BHAR}_{0,1}$, and ADJ_ECAR in the pre-split period ($t - 15$ to $t - 4$). Consistent with our predictions, the results reported in Panel A of Table 7 indicate that the coefficient of the indicator variable is negative and significant at the 5% level in all 3 cases.

Third, we consider a matched sample design that matches the pre-split CAF levels of the post-split CAF > 0 subgroup with those of the post-split CAF $<$ 0 subgroup.[20] More specifically, we start with the firms that have a negative CAF after the stock split (the "base sample"). We match each observation in this base sample with an observation in the group of firms with post-split CAF > 0 (the "matched sample") that has the closest pre-split CAF. We then consider the difference in the means of ADJ_FE, ADJ_$\mathrm{BHAR}_{0,1}$, and ADJ_ECAR between the 2 samples. Panel B of Table 7 reports the results. The left-hand side of the panel reports the results in the pre-split period ($t - 15 : t - 4$). By construction, there is no difference in the pre-split CAF between the 2 samples. The differences in the means of pre-split ADJ_FE and ADJ_$\mathrm{BHAR}_{0,1}$ between the 2 samples are also insignificant, while the difference in ADJ_ECAR is statistically significant only at the 10% level.

The right-hand side of the panel in Table 7 reports the results in the post-split period ($t + 4 : t + 15$). The differences in the mean values of post-split ADJ_FE, ADJ_$\mathrm{BHAR}_{0,1}$, and ADJ_ECAR between the 2 samples are all significantly positive. In addition, the mean values of post-split ADJ_FE, ADJ_$\mathrm{BHAR}_{0,1}$, and ADJ_ECAR all have the predicted signs: negative in the base sample and positive in the matched sample. The mean values are significantly different from 0 in all 3 cases in the base sample but only in 1 case in the matched sample. The lack of significance in the 2 remaining cases in the matched sample is expected and is due to the low statistical power of this test. Indeed, the matching process forces us to drop numerous firms in the post-split CAF > 0 sample that have a high post-split CAF (from 2,188 to 751), resulting in a close-to-zero mean value of

[19]For example, a stock split may affect the liquidity of the stock (e.g., Brennan and Copeland (1988)) and investors' expectations of its future earnings growth (e.g., McNichols and Dravid (1990)). However, our unreported results show that the results in Table 7 based on unadjusted values of FE, $\mathrm{BHAR}_{0,1}$, and ECAR are also consistent with the cross-sectional anchoring theory, but the significance levels are weaker. The results are available from the authors.

[20]Note that our regression design in Panel A of Table 7 to include the level of pre-split CAF in the regressions explicitly serves this purpose.

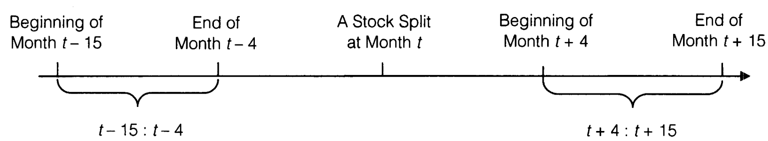
post-split CAF (0.248) in the matched sample. Therefore, this matching process leads to a small and even undetectable CAF effect on the matched sample.

To alleviate the problem of the low test power associated with the matched sample approach, we perform a 4th test using an unmatched sample design. Specifically, we partition all stock-split firms in this subsample based on the post-split CAF level into 4 groups: i) significantly positive (CAF > 0, High), ii) marginally positive (CAF > 0, Low), iii) marginally negative (CAF < 0, Low), and iv) significantly negative (CAF < 0, High). We then compare our key variables before and after stock splits for the 4 groups. The results presented in Panel C of Table 7 are consistent with our predictions. In the pre-split period, the mean values

TABLE 7

Forecast Errors, Stock Returns, and Ex Post Earnings Announcement Returns Before and After Stock Splits

Panel A of Table 7 reports the regression results on the adjusted values of forecast errors (ADJ_FE), 1-month stock returns (ADJ_BHAR$_{0,1}$), and ex post earnings announcement returns (ADJ_ECAR) in the post-split period. Panels B and C reports the average values of these variables in the period before and the period after major stock splits. When a stock split occurs at month t, $t-15:t-4$ represents a 12-month period from the beginning of month $t-15$ to the end of month $t-4$, and $t+4:t+15$ represents a 12-month period from the beginning of month $t+4$ to the end of month $t+15$ (as shown below). Here, ADJ_BHAR$_{0,1}$ is the difference in BHAR$_{0,1}$ between an individual firm and an equal-weighted portfolio of benchmark firms based on similar SIZE, BM, and $R_{-6,0}$ following Daniel et al. (1997), and ADJ_FE and ADJ_ECAR are defined similarly.



Stocks priced below $5, whether before stock splits or after stock splits, are excluded from the sample. We require that there are no other stock splits for the same company in a 15-month period before or after each stock split in our sample. We also require that all stock-split firms must have their FEPS higher than the industry median before the stock splits (at the beginning of month t). In Panel A, dependent variables are ADJ_FE, ADJ_BHAR$_{0:1}$, and ADJ_ECAR after the stock splits. The key independent variable is a dummy variable that equals 1 if the post-split CAF is negative, and 0 otherwise. Other control variables include ADJ_FE, ADJ_BHAR$_{0:1}$, and ADJ_ECAR prior to the stock splits. In Panel B, we carry out a matched sample design as follows: We start with the firms in the post-split CAF < 0 subgroup (denoted as "Base sample"). We match each observation in this base sample with an observation in the group of firms with the post-split CAF > 0 ("Matched sample") that has the closest pre-split CAF. The first 2 columns report the mean values of ADJ_FE, ADJ_BHAR$_{0:1}$, and ADJ_ECAR for both samples, while the 3rd column reports the differences between the 2 samples. In Panel C, all split firms are divided into 2 groups according to the after-split FEPS level, that is, whether the after-split FEPS (at the end of month t) is higher or lower than the industry median. Industries are defined by 2-digit SIC codes. "All" is for all split firms that meet our screening criteria. "Low" is the subsample with CAF below the median value of each subgroup (firms with CAF> 0 or firms with CAF< 0 after splits), while "High" is the subsample with CAF above the median value of each subgroup (firms with CAF> 0 or firms with CAF< 0 after splits). Average values of ADJ_FE, ADJ_BHAR$_{0:1}$, and ADJ_ECAR before and after the stock splits are reported in the panel. The t-statistics are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Results from the Regressions on the Post-Split CAF Indicator

Independent Variables	ADJ_FE ($t+4$, $t+15$)	ADJ_BHAR$_{0:1}$ ($t+4$, $t+15$)	ADJ_ECAR ($t+4$, $t+15$)
Post-split CAF indicator < 0	−0.565***	−0.810***	−0.300**
	(−4.93)	(−6.19)	(−2.07)
Pre-split CAF level	−0.005	0.025	0.016
	(−0.25)	(1.18)	(0.69)
ADJ_FE ($t-15$, $t-4$)	0.317***	0.010	0.055
	(11.98)	(0.33)	(1.64)
ADJ_BHAR$_{0:1}$ ($t-15$, $t-4$)	−0.063***	−0.081***	−0.105***
	(−3.70)	(−4.18)	(−4.88)
ADJ_ECAR ($t-15$, $t-4$)	0.031*	0.025	0.126***
	(1.79)	(1.26)	(5.69)
Adj. R^2	0.057	0.021	0.016
N	2,869	2,869	2,869

(continued on next page)

TABLE 7 (continued)

Forecast Errors, Stock Returns, and Ex Post Earnings Announcement Returns Before and After Stock Splits

Panel B. Mean Values of ADJ_FE, ADJ_BHAR$_{0:1}$, and ADJ_ECAR before and after Stock Splits with Matching

	$t-15:t-4$			$t+4:t+15$		
Variables	Test Sample Post CAF < 0	Matched Sample Post CAF > 0	Difference	Test Sample Post CAF < 0	Matched Sample Post CAF > 0	Difference
CAF	0.389	0.389	0.000	−0.244	0.248	−0.492
ADJ_FE	0.658***	0.654***	0.004	−0.205*	0.447***	−1.343***
	(10.16)	(13.65)	(0.82)	(−1.84)	(6.49)	(−3.89)
ADJ_BHAR$_{0,1}$	1.211***	1.309***	−0.088	−0.516***	0.129	−0.645***
	(11.73)	(10.85)	(−1.60)	(−4.51)	(1.08)	(−3.86)
ADJ_ECAR	0.748***	1.048***	−0.300*	−0.219*	0.110	−0.329*
	(7.08)	(12.87)	(−1.75)	(−1.76)	(0.86)	(−1.89)

Panel C. Mean Values of ADJ_FE, ADJ_BHAR$_{0:1}$, and ADJ_ECAR before and after Stock Splits without Matching

	$t-15:t-4$			$t+4:t+15$		
Variables	All	Low	High	All	Low	High
C1. Firms with CAF > 0 after Stock Splits						
CAF	1.452	0.689	2.214	0.797	0.287	1.307
ADJ_FE	0.723***	0.687***	0.759***	0.462***	0.416***	0.507***
	(31.65)	(22.13)	(22.66)	(16.38)	(9.69)	(13.92)
ADJ_BHAR$_{0:1}$	1.596***	1.411***	1.781***	0.482***	0.314***	0.649***
	(27.06)	(18.97)	(19.52)	(9.65)	(4.53)	(9.08)
ADJ_ECAR	0.977***	0.778***	1.175***	0.300***	0.206**	0.394***
	(14.46)	(9.36)	(11.07)	(4.48)	(2.31)	(3.94)
N	2,118	1,059	1,059	2,118	1,059	1,059
C2. Firms with CAF < 0 after Stock Split						
CAF	0.389	0.284	0.495	−0.244	−0.414	−0.074
ADJ_FE	0.658***	0.562***	0.755***	−0.205*	−0.353**	−0.057
	(10.16)	(5.10)	(11.19)	(−1.84)	(−1.96)	(−0.98)
ADJ_BHAR$_{0:1}$	1.211***	1.072***	1.350***	−0.516***	−0.598***	−0.432***
	(11.73)	(7.01)	(9.76)	(−4.51)	(−3.41)	(−2.95)
ADJ_ECAR	0.748***	0.594***	0.902***	−0.219*	−0.300***	−0.137
	(7.08)	(3.78)	(6.40)	(−1.76)	(−2.72)	(−0.78)
N	751	376	375	751	376	375

of ADJ_FE, ADJ_BHAR$_{0,1}$, and ADJ_ECAR are all significantly positive in all groups. More importantly, in the post-split period, all the mean values of ADJ_FE, ADJ_BHAR$_{0,1}$, and ADJ_ECAR in the 2 extreme subgroups (firms with either a significantly positive CAF or a significantly negative CAF in the post-split period) are statistically different from 0 in the predicted directions (i.e., positive for firms with CAF $>$ 0 and negative for firms with CAF $<$ 0). As expected, the mean values of ADJ_FE, ADJ_BHAR$_{0,1}$, and ADJ_ECAR in the 2 marginal groups have the predicted signs but lower point estimates and lower statistical significance levels than in the extreme groups.

In the 5th test, we estimate the effect of the split ratio on the change in the key variables. The new dependent variables are the changes in the mean values of ADJ_FE, ADJ_BHAR$_{0,1}$, and ADJ_ECAR from the pre-split period to the post-split period (i.e., ΔADJ_FE, ΔADJ_BHAR$_{0,1}$, and ΔADJ_ECAR). For each observation (i.e., each stock split in month t), we calculate the post-split value as the average from month $t+4$ to $t+15$. Similarly, we calculate the pre-split value as the average from month $t-15$ to $t-4$. The control variables are the change in log(SIZE), log(BM), ACCRUAL, and EP_{t-1}. Our key independent variable is log(SSR), which is the natural logarithm of the split ratio (observed at month t). Untabulated results indicate that log(SSR) significantly affects the changes in the mean values of ADJ_FE, $ADJ\_BHAR_{0,1}$, and ADJ_ECAR. More specifically, the estimated coefficients of log(SSR) are all negative, and the corresponding t-statistics are -2.16, -2.37, and -3.87 for ΔADJ_FE, $\Delta ADJ\_BHAR_{0,1}$, and ΔADJ_ECAR, respectively. These findings also support our anchoring hypothesis.

VII. Additional Analysis

A. Cross-Sectional Partitions

Taken together, the above results suggest that analysts and investors anchor on the industry norm. It seems reasonable that any anchoring effect should be stronger when the anchor is more stable. To test this conjecture, we reestimate the models from Panel A of Tables 3–5 by splitting the entire sample into 2 subgroups based on the stability of the anchor. We use the full specification reported in the last column of each table. The stability of the anchor is measured in terms of the coefficient of variation (CV) of I_FEPS corresponding to a period covering the previous 24 months. A lower CV indicates a more stable anchor. Untabulated results indicate that the coefficient of CAF is statistically more significant in the subsamples with more stable anchors, and the difference in coefficients between the stable and unstable subsamples is significant at the 1%, 5%, or 10% levels, depending on the variables of interest.

We next examine the effect of analyst/investor sophistication on anchoring bias. To do so, we split the entire sample into 2 subgroups based on the sophistication of the market participants. For analyst sophistication, the size of their employers is used as a proxy. Prior work (Hong and Kubik (2003)) suggests that analysts working for large brokers produce more informative forecasts. Prior research also confirms that institutional investors are more sophisticated than retail investors (Bartov, Radhakrishnan, and Krinsky (2000), Bhushan (1994)). Therefore, investor sophistication is proxied by the percentage of institutional ownership. The untabulated results indicate that the effect of anchoring is weaker when market participants are sophisticated than when they are not. The effect is economically and statistically more significant in the subsamples dominated by unsophisticated participants. The difference between the coefficients of CAF across the subsamples is significant at the 5% level or better.

B. Alternative Anchors

As we discuss in Section II, anchoring is a well-established principle in the psychology literature, and we believe that the anchoring bias is relevant for understanding the financial markets. However, what is less clear is precisely which anchors are relevant. As we explain in Section III, our discussions with analysts have led us to believe that the industry median FEPS is a good proxy for the industry norm of FEPS. We do not argue that this is the *only* possible proxy. We do, however, believe that it is an intuitive one. Naturally, all variables that are closely related to the industry norm of FEPS, such as the mean, the mode, or even median realized earnings, should give empirical results that are very similar to those documented in this study. In untabulated tests, we find that this is indeed true.

We also investigate in greater detail the effect of 2 alternative candidates. First, we construct a measure of cross-sectional anchoring based on the stock price per share (PRICE). Specifically, we define CAP, the analog of CAF, as the difference between the PRICE of a firm and the industry median PRICE, scaled by the value of the latter. Second, we consider the role of time-series anchoring by constructing TAF,[21] defined as the difference between firm i's FEPS and its most recently announced EPS, scaled by the absolute value of the latter. We add CAP or TAF as additional independent variables in our baseline regressions (similar to those reported in Tables 3–5). Untabulated results indicate that the inclusion of alternative anchoring measures does not significantly weaken the explanatory power of CAF in any of these regressions. To further ensure that the CAF effect is not driven by the price level, we form 1,375 subgroups based on the time period and the price level (275 months multiplied by 5 different price levels). We estimate our baseline model (similar to those reported in Tables 3–5) in each subgroup. We then calculate the overall t-statistics by taking the mean and the standard deviation of the estimated coefficients across all subgroups. Our conclusions are not affected.

Finally, we consider a portfolio trading strategy similar to the one used in Panel B of Table 4, but we focus on CAP or TAF (instead of CAF). Panel A of Table 8 presents the results for the partitions based on CAP. In sharp contrast with the strong return predictability of CAF, the CAP measure cannot predict future 1-month returns at all. The 4-factor adjusted αs do not increase or decrease monotonically as CAP increases within each size group. Further, the hedge portfolios (i.e., E5 – E1) based on the CAP measure in all size groups exhibit no significant abnormal returns (i.e., αs). Partitions based on dividend per share or the book value of equity per share yield a similar lack of predictive power. In other words, our results do not generalize to any "per share" variables.

Panel B of Table 8 presents the results for the partitions based on TAF. Results indicate that CAF has a much stronger return predictive power than TAF. The average 1-month hedge portfolio return (obtained by longing the highest TAF quintile and shorting the lowest TAF quintile simultaneously) based on TAF is 0.21%, which is less than ⅓ of that based on CAF (0.71%). More importantly, CAF is able to generate significant hedge portfolio returns in all size groups, while TAF only has predictive power in the 2 smallest size quintiles. In addition, CAF has a reasonably symmetric effect between the long and short portfolios, while the effect of TAF, if there is any, is only concentrated on the short portfolios.

[21]There is some limited research on the time-series anchoring bias in financial markets. George and Hwang (2004) propose that investors are reluctant to set a higher bid price when a stock price is at or near its highest historical value, which generates 52-week high momentum. Campbell and Sharpe (2009) show that professional forecasters anchor their predictions of macroeconomic data on previous values, which leads to systematic and sizeable forecast errors. Baker, Pan, and Wurgler (2009) suggest that anchoring bias also affects corporate acquisitions. By contrast, we focus on cross-sectional anchoring bias.

TABLE 8

Robustness Checks with Alternative Anchors

Panel A (Panel B) of Table 8 reports the risk-adjusted returns (i.e., α) for equal-weighted portfolios based on SIZE and CAP (TAF). Here, CAP is the industry (i.e., SIC 2-digit industry codes) cross-sectional anchoring measure of stock price, defined as the difference between the price level of a firm (F_PRICE) and the industry median price level (I_PRICE), scaled by the latter; TAF is the time-series anchoring measure of forecast EPS, defined as the difference between the forecast EPS of a firm (F_FEPS) and the most recently announced actual EPS, scaled by the absolute value of the latter; and α is the intercept term from the time-series regression based on the Fama and French (1993) plus Carhart (1997) 4-factor model as described in equation (2). The portfolios are constructed as follows: At the beginning of each month, stocks are sorted into 5 groups (G1–G5) based on their market capitalization (SIZE) at the end of the previous month, and the stocks in each SIZE group are further sorted into 5 quintiles (E1–E5) based on their CAP (TAF) in the previous month. Stocks priced below $5 are excluded from the sample. The t-statistics reported in parentheses are adjusted for serial correlation and heteroskedasticity using the Newey and West (1987) procedure. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Size Quintiles					
	G1 (small)	G2	G3	G4	G5 (large)	All Stocks
Panel A. CAP Quintiles						
E1 (low)	−0.043	0.032	−0.100	0.049	0.093	0.006
E2	−0.026	0.195	0.162	−0.025	−0.025	0.056
E3	−0.090	−0.010	0.022	−0.055	0.020	−0.023
E4	0.102	−0.075	0.042	−0.076	−0.083	−0.018
E5 (high)	0.153	0.088	−0.018	−0.082	0.036	0.035
E5 − E1	0.196	0.056	0.082	−0.130	−0.058	0.029
t-statistic	(1.04)	(0.34)	(0.57)	(−0.91)	(−0.41)	(0.30)
Panel B. TAF Quintiles						
E1 (low)	−0.609	−0.282	−0.023	0.010	0.043	−0.172
E2	0.024	0.029	0.149	0.020	0.109	0.066
E3	0.301	0.150	0.070	−0.011	−0.005	0.101
E4	0.319	0.173	−0.009	−0.052	−0.089	0.068
E5 (high)	0.195	0.163	−0.095	−0.055	−0.037	0.034
E5 − E1	0.804***	0.445***	−0.073	−0.065	−0.079	0.206**
t-statistic	(5.40)	(2.91)	(−0.45)	(−0.38)	(−0.50)	(1.99)

C. Cross-Sectional Anchoring and Known Earnings-Related Anomalies

To ensure that the CAF effect is not simply a recasting of previously known earnings-related asset pricing anomalies, we control for the impacts of the post-earnings announcement drift (ES_{RECENT}), the accounting accruals (ACCRUAL), and the earnings-to-price ratios (EP_{t-1}) in all test specifications. In an untabulated test, we repeat all Fama-MacBeth (1973) regressions in Tables 3–5 by replacing the EP ratio with the VP ratio defined by Frankel and Lee (1998) or the scaled earnings level (ETA) defined by Balakrishnan, Bartov, and Faurel (2010). Here, ETA is the quarterly earnings before extraordinary items and discontinued operations scaled by the beginning-of-quarter total assets, and VP is the fundamental value-to-price ratio, where the fundamental value is estimated from a residual income model based on the current stock price and analysts' earnings forecasts. Our conclusions are not affected. Our results suggest that the CAF effect documented in this study is quite different from the asset pricing anomalies based on earnings information in the existing literature.

VIII. Conclusion

The effect of anchoring bias on market participants such as sell-side analysts and investors has not been extensively investigated previously. This study tests the proposition that market participants are affected by anchoring bias when they estimate the future profitability of a firm. The empirical results are consistent with this hypothesis. We find that analysts' earnings forecasts for firms with low forecast EPS relative to their corresponding industry median are indeed more optimistic than forecasts for similar firms that have high forecast EPS. This is consistent with the hypothesis that analysts anchor their forecasts on the industry norm. In addition, future stock returns are significantly higher for firms with EPS forecasts that are high relative to the industry median than for similar firms whose EPS forecasts are relatively low. The positive relation between FEPS and future stock returns cannot be explained by risk factors and known anomalies.

In addition, earnings surprises are more positive for firms with high EPS forecasts relative to the industry median. All of these results are stronger when the industry median is more stable or when market participants are less sophisticated. Finally, the likelihood of a stock split within a year increases when a firm's EPS forecast is high relative to the industry median. Stock-split firms experience more positive forecast revisions, more negative forecast errors, and more negative earnings surprises after a stock split compared with those that do not split their stocks. All of these results support the existence of a cross-sectional anchoring bias among market participants and are robust to many alternative specifications.

Appendix. Definitions of Major Dependent and Independent Variables

ACCRUAL: Total accruals scaled by average total assets $= ((\Delta\text{CA} - \Delta\text{CASH}) - (\Delta\text{CL} - \Delta\text{STD} - \Delta\text{TP}) - \text{DEP})/\text{TA}$, as defined in Sloan (1996), where ΔCA = change in current assets (Compustat item 4), ΔCASH = change in cash and cash equivalents (Compustat item 1), ΔCL = change in current liabilities (Compustat item 5), ΔSTD = change in debt included in current liabilities (Compustat item 34), ΔTP = change in income taxes payable (Compustat item 71), DEP = depreciation and amortization expense (Compustat item 14), and TA is the average of the beginning-of-year and end-of-year book values of total assets (Compustat item 6). Data source: Compustat.

$\text{BHAR}_{0,1}$: One-month buy-and-hold return after portfolio formation. Data source: CRSP.

BM: The Fama and French (1992) book-to-market ratio, where the value for July of year y to June of year $y+1$ is computed using the book value of equity for the fiscal year-end in calendar year $y-1$ from Compustat and the market value of equity at the end of December of year $y-1$ from CRSP. Data sources: CRSP and Compustat.

BREADTH: The natural logarithm of the average number of stocks followed by the current analysts. Data source: IBES.

CAF: The industry cross-sectional anchoring measure of forecast earnings per share (FEPS). CAF = (F_FEPS – I_FEPS)/|I_FEPS|, where F_FEPS presents an individual firm's FEPS and I_FEPS represents the industry median FEPS. Industries are defined by the SIC 2-digit codes. Data sources: IBES and Compustat.

CAP: The industry cross-sectional anchoring measure of price levels. CAP = (F_PRICE – I_PRICE)/|I_PRICE|, where F_PRICE represents an individual firm's price level, and I_PRICE represents the industry median of price levels. Industries are defined by the SIC 2-digit codes. Data source: CRSP and Compustat.

ECAR: The 3-day (day -1 to day $+1$) cumulative abnormal return relative to the CRSP value-weighted index surrounding the next earnings announcement date after portfolio formation over the next 12 months. Data sources: CRSP and IBES.

EP_{t-1}: The historical earnings-to-price ratio calculated as follows: First, net income before extraordinary items (Compustat item 237) for the most recently announced fiscal year-end (IBES Item FY0EDATS) is divided by the number of shares outstanding to obtain the historical earnings per share (E) for month $t-1$. E is then divided by the stock price (P) on the same day to obtain EP_{t-1}. Data sources: Compustat, CRSP, and IBES.

ES_{RECENT}: The 3-day (day -1 to day $+1$) cumulative abnormal return relative to the CRSP value-weighted index surrounding the most recent earnings announcement date up to the beginning of month t. Data sources: CRSP and IBES.

ETA: The ETA ratio, as defined by Balakrishnan et al. (2010), is the quarterly earnings before extraordinary items and discontinued operations scaled by the beginning-of-quarter total assets. Data sources: Compustat and IBES.

EXPERIENCE: The natural logarithm of 1 plus the average number of months that the current group of analysts has been following the firm. Data source: IBES.

FE: Forecast error in percentage. FE = [(ACTUAL_EPS – F_FEPS) $\times$ 100]/PRICE, where F_FEPS represents a firm's FEPS, ACTUAL_EPS is its actual EPS announced at the end of the fiscal year, and PRICE is the stock price when F_FEPS is reported. Data sources: IBES and CRSP.

F_FEPS: Mean of an individual firm's forecast 1-year-ahead earnings per share in the previous month from the unadjusted summary historical file of the IBES. It is also called the consensus EPS forecast. Data source: IBES.

HORIZON: The natural logarithm of 1 plus the number of months before the next earnings announcement. Data source: IBES.

INST_HOLDING: The percentage of institutional ownership at the end of the previous quarter. Data source: Thomson Reuters Institutional (13f) Holdings.

$RET_{-1:0}$: The past-1-month return. Data source: CRSP.

$RET_{-6:0}$: Buy-and-hold return over the past 6 months as of the previous month. Data source: CRSP.

$RET_{-7:-1}$: A 1-month lag of the past-6-month buy-and-hold return. Data source: CRSP.

SIZE: The market value of a firm's equity at the end of the previous month. Data source: CRSP.

SPLIT: A dummy variable that equals 1 if this firm carries out a significant stock split (i.e., 1 share is split into 1.5 or more shares) in the month, and 0 otherwise. Data source: CRSP.

TAF: The time-series anchoring measure of FEPS based on the most recently announced EPS. TAF = (F_FEPS $-$ LAST_EPS)/|LAST_EPS|, where F_FEPS represents an individual firm's FEPS, and LAST_EPS represents its most recently announced EPS. Data source: IBES.

TFE: Total forecast earnings = F_FEPS $\times$ number of shares outstanding. Data sources: CRSP and IBES.

References

Baker, M.; R. Greenwood; and J. Wurgler. "Catering through Nominal Share Prices." *Journal of Finance,* 64 (2009), 2559–2590.

Baker, M.; X. Pan; and J. Wurgler. "The Effect of Reference Point Prices on Mergers and Acquisitions." *Journal of Financial Economics,* 106 (2012), 49–71.

Balakrishnan, K.; E. Bartov; and L. Faurel. "Post Loss/Profit Announcement Drift." *Journal of Accounting and Economics*, 50 (2010), 20–41.

Barber, B.; R. Lehavy; M. McNichols; and B. Trueman. "Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns." *Journal of Finance*, 56 (2001), 531–563.

Bartov, E.; S. Radhakrishnan; and I. Krinsky. "Investor Sophistication and Patterns in Stock Returns After Earnings Announcements." *Accounting Review*, 75 (2000), 43–63.

Bhojraj, S., and C. M. C. Lee. "Who Is My Peer? A Valuation-Based Approach to the Selection of Comparable Firms." *Journal of Accounting Research*, 40 (2002), 407–439.

Bhushan, R. "An Informational Efficiency Perspective on the Post-Earnings-Announcement Drift." *Journal of Accounting and Economics*, 18 (1994), 45–65.

Brennan, M. J., and T. E. Copeland. "Stock Splits, Stock-Prices, and Transaction Costs." *Journal of Financial Economics*, 22 (1988), 83–101.

Brewer, N. T.; G. B. Chapman; J. A. Schwartz; and G. R. Bergus. "The Influence of Irrelevant Anchors on the Judgments and Choices of Doctors and Patients." *Medical Decision Making*, 27 (2007), 203–211.

Bushee, B., and J. S. Raedy. "Factors Affecting the Implementability of Stock Market Trading Strategies." Working Paper, University of Pennsylvania (2006).

Campbell, S. D., and S. A. Sharpe. "Anchoring Bias in Consensus Forecasts and Its Effect on Market Prices." *Journal of Financial and Quantitative Analysis*, 44 (2009), 369–390.

Carhart, M. M. "On Persistence in Mutual Fund Performance." *Journal of Finance*, 52 (1997), 57–82.

Chapman, G. B., and E. J. Johnson. "Incorporating the Irrelevant: Anchors in Judgments of Belief and Value." In *Heuristics and Biases: The Psychology of Judgment*, T. Gilovich, D. W. Griffin, and D. Kahneman, eds. Cambridge, UK: Cambridge University Press (2002).

Chopra, N.; J. Lakonishok; and J. R. Ritter. "Measuring Abnormal Performance: Do Stocks Overreact?" *Journal of Financial Economics*, 31 (1992), 235–268.

Daniel, K.; M. Grinblatt; S. Titman; and R. Wermers. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance*, 52 (1997), 1035–1058.

Diether, K. B.; C. J. Malloy; and A. Scherbina. "Difference of Opinion and the Cross Section of Stock Returns." *Journal of Finance*, 57 (2002), 2113–2141.

Fama, E. F. "Market Efficiency, Long-Term Returns, and Behavioral Finance." *Journal of Financial Economics*, 49 (1998), 283–306.

Fama, E. F., and K. R. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47 (1992), 427–465.

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E. F., and K. R. French. "Industry Costs of Equity." *Journal of Financial Economics*, 43 (1997), 153–193.

Fama, E. F., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.

Frankel, R., and C. M. Lee. "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns." *Journal of Accounting and Economics*, 25 (1998), 283–319.

George, T. J., and C. Hwang. "The 52-Week High and Momentum Investing." *Journal of Finance*, 59 (2004), 2145–2176.

Hirshleifer, D. "Investment Psychology and Asset Pricing." *Journal of Finance*, 56 (2001), 1533–1597.

Hong, H., and J. D. Kubik. "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts." *Journal of Finance*, 58 (2003), 313–351.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48 (1993), 65–91.

Jegadeesh, N., and S. Titman. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance*, 56 (2001), 699–720.

Keim, D. B., and A. Madhavan. "Transaction Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades." *Journal of Financial Economics*, 46 (1997), 265–292.

La Porta, R.; J. Lakonishok; A. Shleifer; and R. W. Vishny. "Good News for Value Stocks: Further Evidence on Market Efficiency." *Journal of Finance*, 52 (1997), 859–874.

McNichols, M., and A. Dravid. "Stock Dividends, Stock Splits, and Signaling." *Journal of Finance*, 45 (1990), 857–879.

Mitchell, M, L., and E. Stafford. "Managerial Decisions and Long-Term Stock Price Performance." *Journal of Business*, 73 (2000), 287–329.

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.

Northcraft, G. B., and M. A. Neale. "Experts, Amateurs and Real Estate: An Anchoring-and-Adjustment Perspective on Property Pricing Decisions." *Organizational Behavior and Human Decision Processes*, 39 (1987), 84–97.

Plous, S. "Thinking the Unthinkable: The Effects of Anchoring on Likelihood Estimates of Nuclear War." *Journal of Applied Social Psychology*, 19 (1989), 67–91.

Qu, C.; L. Zhou; and Y. Luo. "Electrophysiological Correlates of Adjustment Process in Anchoring Effects." *Neuroscience Letters*, 445 (2008), 199–203.

Ramnath, S. "Investor and Analyst Reactions to Earnings Announcements of Related Firms: An Empirical Analysis." *Journal of Accounting Research*, 40 (2002), 1351–1376

Russo, J. E., and P. J. H. Schoemaker. *Decision Traps: Ten Barriers to Brilliant Decision Making and How to Overcome Them.* New York, NY: Simon & Schuster (1989).

Sloan, R. G. "Do Stock Prices Fully Reflect Information in Cash Flows and Accruals about Future Earnings?" *Accounting Review*, 71 (1996), 289–315.

Titman, S.; K. C. J. Wei; and F. Xie. "Capital Investments and Stock Returns." *Journal of Financial and Quantitative Analysis*, 39 (2004), 677–700.

Tversky, A., and D. Kahneman. "Judgment under Uncertainty: Heuristics and Biases." *Science*, 185 (1974), 1124–1131.

Weld, W. C.; R. Michaely; R. H. Thaler; and S. Benartzi. "The Nominal Share Price Puzzle." *Journal of Economic Perspectives*, 23 (2009), 121–142.

Whyte, G., and J. K. Sebenius. "The Effect of Multiple Anchors on Anchoring in Individual and Group Judgment." *Organizational Behavior and Human Decision Processes*, 69 (1997), 75–85.

Wright, W. F., and U. Anderson. "Effects of Situation Familiarity and Financial Incentives on Use of the Anchoring and Adjustment Heuristic for Probability Assessment." *Organizational Behavior and Human Decision Processes*, 44 (1989), 68–82.