The Role of Anchoring Bias in the Equity Market

Journal and Quantitative Analysis, Vol 48, Cambridge University Press

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❖ ABSTRACT:

Prior studies have shown that analysts often suffer from a number of biases. This study considers the

behavior of financial market participants from a persperctive different that studied in previous

research. It focuses on anchoring bias describe as an important part of « dynamic psychology based

asset pricing theory int its infancy ».

We test the implications of anchoring bias associated with forecast earnings per share (FEPS) for

forecast errors, earning suprises, stock returns, and stock splits.

❖ DATA SOURCE :

U.S data from 1983 to 2005, the sample includes all stocks listed on the NYSE, AMEX, and

NASDAQ (data from Center for Reseach in Security Prices CRSP).

• Compustat.

• IBES: Institutional Brokers Estimate System.

❖ MOTIVATION OF THE STUDY:

This study is based on empirical results consistent with all the hypothesis suggested by the cross-

sectional anchoring bias. Formula : CAF = (F_FEPS - I_FEPS) / |I_FEPS|

Where F PEPS presents an individual firm's FEPS (Forecast Earning Per Share) and I FEPS represents

the industry median FEPS. Industries are defined by the SIC 2-digit codes. 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.

High CAF if (F_FEPS>I_FEPS) => analysts underestimate the future earning. (pessimistic view).

Else Low CAF if (F_FEPS<I_FEPS) => analysts overestimate the future earning. (optimistic view).

Furthermore they find that stocks returns, earning surprises and the likelihood of a stock split (within

a year) are significantly higher for firms with a High CAF than for similar firms in the same industry but

with a low CAF. These empirical results made it possible to identify three hypothèses tested in this

study.

❖ RESEARCH HYPOTHESES:

Hypothesis 1: Analyst forecast are more optimistic 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.

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

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.

RESEARCH DESIGN :

Here they apply two basic approches to test their hypotheses:

- Regression analyses
- Portfolio sorts

❖ METHODS:

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

DEP_VAR_{i,t} =
$$\alpha + \beta \operatorname{CAF}_{i,t-1} + \gamma^{K} X_{i,t-1}^{K} + \varepsilon_{i,t}$$
,

Where $DEP_VAR(i,t)$ represents the value of the dependent variable for firm i in period t.

- *CAF (i, t-1)* is defined as the difference between the FEPS for firm i in month t-1 and the industry median FEPS in the same month, scaled by the absolute value of the latter. (See motivation study section).
- Aside from including a constant a vector of K control variables (X^k) is included in the regression. It includes the logarithm of firms i market capitalization (SIZE) at the end of month t-1, the logarithm of its BM ratio, it's accounting accruals (ACCRUAL), and the 3-day abdnormal return around its most recent earnings annoucement before the beginning of month t (ESrecent).
- The lagged information is used for all of the control variables to ensure that the values of these variables are know by investors at the beginning of month t.

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

Portfolio Sorts:

The 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.

$$\begin{aligned} R_{p,t} - R_{f,t} &= \alpha_p + \beta_p^M (\text{MKT}_t - R_{f,t}) + \beta_p^S \text{SMB}_t \\ &+ \beta_p^H \text{HML}_t + \beta_p^U \text{UMD}_t + \varepsilon_{i,t}, \end{aligned}$$

Where Rp is the monthly return on portfolio p, MKT is the monthly return on the market portfolio, and Rf is the monthly risk-free rate. Here, MKT - Rf, 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; Rf 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 format

❖ TESTS ON HYPOTHESES

Regression Analysis:

Hypothesis 1: To test it, we make analysts forecast error (FE) the dependant variable $DEP_VAR = FE$. FE: Forecast error in percentage. $FE = [(ACTUAL_EPS - F_FEPS) *100]/PRICE$, where F_FEPS represents a firm 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.

Hypothesis 2: We define two dependent variables: BHAR and ECAR.

BHAR (0,1): One month buy and hold return after portfolio formation.

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.

Hypothesis 3: SPLIT is the dependant variable. 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.

Portfolio Sorts:

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, a, and ECAR in each of the hedge.

EXPECTATIONS:

If *Hypothesis 1* is correct, the coefficient of CAF should be positive when FE is the DEP_VAR.

If *Hypothesis 2* is correct, we would expect the coefficient of CAF to be positive when BHAR is the DEP_VAR. We would also expect the coefficient CAF to be positive when ECAR is the DEP_VAR.

If *Hypothesis 3* is correct, the coefficient CAF should be positive when SPLIT is the DEP_VAR.

❖ 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 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
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
$RET_{-6:0}$ (%)	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
ESRECENT (%)	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

RESULTS AND ANALYSIS:

A. Anchoring and Forecast Errors (Hypothesis 1)

Regression analysis:

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. In the 2nd column, ACCRUAL and ESrecent 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 restatistics 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.

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

Independent Variables	1	2	3
CAF	0.272*** (5.23)	0.272*** (5.19)	0.150*** (4.01)
log(SIZE)	0.391*** (11.18)	0.384*** (10.98)	0.393*** (12.09)
log(BM)	-0.252*** (-3.46)	-0.277*** (-4.79)	-0.299*** (-3.77)
RET_6,0	0.037*** (6.87)	0.035*** (6.54)	0.037*** (6.69)
ACCRUAL		-0.797*** (-3.77)	-1.783*** (-5.50)
ESRECENT		0.043*** (6.18)	0.045*** (6.82)
EP _{I-1}			9.042*** (6.57)
EXPERIENCE			-0.112** (-2.48)
BREADTH			0.127*** (3.19)
HORIZON			-0.965*** (-10.51)
Avg. adj. <i>R</i> ² Avg. <i>N</i>	0.066 1,448	0.072 1,446	0.102 1,441
Panel B. Forecast Errors (%) for	SIZE- and CAF-Sorted Portfolios		

Sorts portfolio:

	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 t-statistic	3.006***	2.651***	2.112***	1.092*** (5.24)	0.606***	1.893***

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 (Hypothesis 2) Regression analysis:

The following table presents the results of regressions of a 1 -month ahead return (BHAR) on CAF and our control variables designed to test Hypothesis 2. For all three models, the coefficient of CAF is significant and positive, with ř-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 by approximately 15% of its mean value.

Independent Variables	1	2	3
CAF	0.109*** (2.91)	0.110*** (2.95)	0.085*** (2.65)
log(SIZE)	-0.049 (-0.99)	-0.070 (-1.43)	-0.070 (-1.42)
log(BM)	0.229* (1.78)	0.176 (1.40)	0.169 (1.34)
RET_7:-1	0.010*** (3.63)	0.008*** (2.79)	0.008*** (2.92)
RET_1:0	-0.028*** (-5.06)	-0.034*** (-6.09)	-0.035*** (-6.15)
ACCRUAL		-2.396*** (-6.31)	-2.658*** (-7.06)
ESRECENT		0.057*** (12.78)	0.057*** (12.94)
EP ₁₋₁			1.637*** (3.21)
Avg. adj. R ² Avg. N	0.043 1,889	0.046 1,887	0.048 1,886

Sorts portfolio:

	OLO WORKER					
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 t-statistic	1.375*** (6.51)	0.834***	0.590**	0.473** (2.24)	0.292* (1.70)	0.713*** (4.05)

This Table focuses on the 1-month-ahead return. However, the effect of CAF on future stock returns is not only limited to a 1-month. The coefficients of CAF are 0.135, 0.219, and 0.442 for 3, 6 and 12 months. With a t-statistics of 2.25, 2.42, and 2.39, respectively, suggesting a persistent impact of CAF on long-run returns.

To put these profits into a practical perspective we will use a momentum strategy in order to prove that we can have long term returns knowing the CAF data.

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%.

These results suggest that our CAF trading strategies are still profitable even after taking transaction costs into account. These results are also consistent with the prediction of *Hypothesis 2*.

C. 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. 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.

❖ CONCLUSION:

This study tests the proposition that market participants are affected by anchoring bias when 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.