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A Closer Look at Analyst Expectations: Stickiness and Confirmation Bias

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Abstract

This paper provides a closer look at the expectation formation process of individual analyst. Using a detailed analyst earnings forecasts dataset, we document the existence of stickiness and confirmatory bias in individual analyst expectations. When the latest signal about firm fundamentals is inconsistent with prior belief, analysts are subject to confirmation bias, and tend to be stickier to their previous earnings forecasts. Confirmation bias is more serve in the case of positive priors. Besides, we find significant economical evidences in the stock market. Profitability anomalies are stronger for firms which are followed by analysts with serious stickiness and confirmatory bias in expectations.

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1. Introduction

Analysts are one of the key participants in financial markets. Their forecasts are often perceived as proxies for market expectations and differences in opinions. When updating the forecasts, analysts are likely to deviate from rationality, and might over-react or under-react to new information, leading to predictable forecast errors. How would various psychological biases influence the predictions of analysts? This paper examines the combining impact of stickiness and confirmation bias on individual analysts' forecasts.

Bouchaud et al. (2018) document that analysts are sticky to their expectations, and model the forecasts to be determined by previous expectations and contemporary rational expectation. Building on the framework of Bouchaud et al. (2018) that analyze the slow updating process of consensus forecasts, we extend the model into individual analyst level. We are curious about whether the feature of stickiness also exist in individual expectations, which will contribute to reveal the source of stickiness in consensus forecasts. In addition, we establish the linkage between sticky expectation and confirmatory bias. Pouget, Sauvagnat, and Villeneuve (2017) argue that individual analysts are prone to confirmatory bias. Information that is inconsistent with their prior opinions would be ignored. As a result, the next forecasts of biased analysts are less likely to be in the same direction with the new information. Literature has proved that both confirmatory bias and stickiness deliver significant impact on analysts' forecasts, but how they interact with each other and jointly affect analysts' forecasts remain unknown. We find that the combined effects from stickiness and confirmation bias deserve careful exploration and show that stock portfolio returns significantly respond to them.

Let us consider that an analyst initially holds positive view about an asset's future cash flows. If subsequent information is negative, analyst who is subject to both confirmation bias and stickiness, would be more likely to neglect the inconsistent new information, and become stickier to his or her prior opinions. However, if the new information is also positive, then analyst is away from confirmation bias, and only updates the forecasts slowly. Following Bouchaud et al. (2018), we can measure the total effect of the two biases on analysts expectations by regressing the forecasts on the prior beliefs and previous forecasts.

We test the hypotheses using observed earnings per share (EPS) forecasts from I/B/E/S. Consistent with the literature, we make the assumption that analysts' views are representative of investors' expectations. First, empirical tests provide support for the existence of stickiness at individual level. Second, a larger value of stickiness parameter in the case of inconsistent information demonstrates that confirmatory bias strengthens stickiness. Third, we find that only when previous belief is positive, analysts are significantly affected by confirmation bias. The impact of confirmation bias cannot be identified when the previous belief is negative. This finding is also intuitive. Literature points out that agents sometimes are over-optimistic (Drake and Myers (2011), Ackert and Athanassakos (1997)). If over-optimistic analysts hold positive attitudes at the beginning, they will be more reluctant to accept subsequent contrary information, especially the negative information. Over-optimism can also explain the phenomenon when previous beliefs are negative. Analysts are more willing to adjust to the direction of good news even if their prior views are negative, thus weakening the influence of confirmation bias.

Some economical predictions can be derived from our setup. As analysts update their forecasts about future cash flows slower if the latest signal does not confirm their prior beliefs, which means a higher degree of under-reaction, then earnings momentum and returns momentum are supposed to be stronger. Momentum strategies sorted by the degree of stickiness and confirmation bias certify the predictions.

This paper is closest related to the behavior finance literature, which has studied various patterns of analyst forecasts. Abarbanell and Bernard (1992) document that analysts underreact to past earnings. Ali, Klein and Rosenfeld (1992) show a similar result in annual earnings forecasts. Bouchaud et al. (2018) offer a model in which expectations under-react to news. In contrast, there are some papers arguing overreaction of analysts forecasts (see for Debondt and Thaler (1985), Lakonishok et al. (1994)). Bordalo et al. (2018) propose a new model based on a portable formalization of representativeness heuristic, and suggest that analysts overreact to news by exaggerating the probability of states that have become objectively more likely. Landier, Ma, and Thesmar (2017) measure belief formation in an experimental setting. They conclude that both extrapolation and stickiness exist in the data, but extrapolation quantitatively dominates. Du, Shen, and Wei (2015) provide further evidences for the confirmatory bias in analysts expectations by showing that analysts with higher expectations on average revise their forecasts higher for next period than their peers following the same firm.

Several studies relate the behavioral bias in belief formation process to stylized facts in security market. Excess trading volume, excess return volatility and momentum have been explained by overconfidence coupled with self-attribution bias (see for Daniel, Hirshleifer, and Subrahmanyam (1998), and Odean (1998)), gradual information flow and limited attention (Hong and Stein (2007)), and confirmation bias (Pouget, Sauvagnat, and Villeneuve (2017)). Bouchaud et al. (2018) also argue that sticky expectations can explain momentum and quality anomaly. We complement the literature by exploring the relationship between stock anomalies and analysts' behavioral bias in a more specific framework.

The contribution of the paper is threefold. First, we propose a dynamic expectation process which is driven by the interaction of two biases that are well grounded in psychology. Second, we show that consensus stickiness comes from the stickiness at individual level, confirming the hypothesis in the literature. Third, we deliver evidences in the data for novel empirical predictions, and explain the stock market anomalies.

The remainder of the paper is organized as follows. Section 2 lays out research designs. Section 3 describes the data. Section 4 gathers our empirical results. Section 5 concludes.

2. Research Design

This section introduces our specification, which nests rationality, stickiness and confirmation bias. Let us first describe how stickiness affects individual analyst expectations across fiscal quarters. The basic model is in line with Bouchaud et al. (2018), except some changes about the notations. We denote $F_{j,Q}^{i}\pi_t$ as the forecasts formed at fiscal quarter Q by analyst i about the profits of firm j at current fiscal year t. $E_{j,Q}^{i}\pi_t$ stands for rational expectation of firm's profit π_t. Then, expectations are assumed to be updated according to the following process:

$$F_{j,Q}^{i}\pi_t = (1-\lambda_i)E_{j,Q}^{i}\pi_t + \lambda_i F_{j,Q-1}^{i}\pi_t \tag{1}$$

where λ_i measures the degree of expectation stickiness of analyst i. Bouchaud et al. (2018) apply such structure to consensus forecasts, and their empirical results also favor this type of expectation formation process at individual level. Here, we provide a direct examination about the stickiness at individual level. As noted by Bouchaud et al. (2018), when $\lambda_i = 0$, expectations are rational. When $\lambda_i > 0$ ($\lambda_i < 0$), the analysts under-react (over-react) to the new information. A large positive value of λ_i indicates a large degree of stickiness.

Next, we define confirmation bias and link it with stickiness in a unified specification. If the latest signal is not consistent with prior belief, the analyst is less willing to accept the new information, and more likely to stick to his own previous views. Thus, less information is incorporated into his next forecast. We expect that stickiness becomes larger in this circumstance. In other words, confirmation bias strengthens sticky expectations.

To illustrate the confirmation bias clearly, we employ some measures based on earlier work (see for, Hirsheleifer, Lim, and Teoh (2009), Pouget, Sauvagnat, and Villeneuve (2017)). We use quarterly unexpected earnings ($SUE_{j,Q}$) as a proxy for the arrival of public news, and use analyst annual forecast revision $Rev_{i,j,Q}$ as a proxy for prior beliefs. Then, we construct a dummy variable $D_{i,j,Q}$ to measure whether the newly released information is consistent with analyst's prior belief. It equals one if analyst i's annual earnings forecast revision $Rev_{i,j,Q}$ for firm j, if any, made between the announcement dates of the Q-1 and Q quarterly earnings has different sign from $SUE_{j,Q}$, which indicates that there is confirmation bias, and zero, otherwise.

Returning to the belief formation process, we model the combining effect of sticky expectation and confirmation bias as follows:

$$\begin{aligned} F_{i,Q,post}\pi_{j,t} &= \left(1-\lambda_{i,1}D_{i,j,Q}-\lambda_{i,2}\left(1-D_{i,j,Q}\right)\right)E_{i,Q}\pi_{j,t} \\ &+\lambda_{i,1}D_{i,j,Q}\times F_{i,Q,pre}\pi_{j,t}+\lambda_{i,2}\left(1-D_{i,j,Q}\right)\times F_{i,Q,pre}\pi_{j,t} \end{aligned} \tag{2}$$

where $F_{i,Q,post}\pi_{j,t}$ ($F_{i,Q,pre}\pi_{j,t}$) stands for the annual earnings forecast of firm j at fiscal year t, which is made by analyst i after (before) the announcement of Q quarterly earnings. $D_{i,j,Q}$ is the dummy variable indicating whether the information is consistent with previous opinions. $\lambda_{i,1}$ measures the stickiness level when analysts are not subject to confirmation bias, and $\lambda_{i,2}$ measures the stickiness level when there is confirmation bias. According to our analysis, both $\lambda_{i,1}$ and $\lambda_{i,2}$ should be positive, and the value of $\lambda_{i,2}$ is expected to be larger and more significant than $\lambda_{i,1}$.

In the next step, we transform the structure in Equation (2) to straightforward testable predictions that forecast errors could be predicted by past revisions and signals:

$$E_{i,Q}\left(\pi_{j,t} - F_{i,Q,post}\pi_{j,t}\right) = \frac{\lambda_{i,1}D_{i,j,Q}}{1-\lambda_{i,1}D_{i,j,Q}-\lambda_{i,2}\left(1-D_{i,j,Q}\right)} \times \left(F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}\right) + \frac{\lambda_{i,2}\left(1-D_{i,j,Q}\right)}{1-\lambda_{i,1}D_{i,j,Q}-\lambda_{i,2}\left(1-D_{i,j,Q}\right)} \times \left(F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}\right) \tag{3}$$

As $D_{i,j,Q}$ is a dummy, we can write it in a simpler form:

$$E_{i,Q}\left(\pi_{j,t} - F_{i,Q,post}\pi_{j,t}\right) = \frac{\lambda_{i,1}D_{i,j,Q}}{1-\lambda_{i,1}} \times \left(F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}\right) + \frac{\lambda_{i,2}\left(1-D_{i,j,Q}\right)}{1-\lambda_{i,2}} \times \left(F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}\right) \tag{4}$$

When the expectations are sticky, information is slowly incorporated in forecast, thus positive information should generate positive forecast revisions, and generate momentum in forecasts. We can further infer that momentum is stronger for firms whose analysts are significantly affected by stickiness and confirmatory bias.

3. Data Construction

The sample consists of all analyst-stock-year-quarter observations for which we have information on quarterly earnings announcements and analysts' earnings forecasts. We use analysts' annual earnings forecasts from the Intitutional Brokers Estimates System (I/B/E/S) database. Quarterly and annual earnings data and other firm-level accounting variables are obtained from Compustat database. Return and trading data are from CRSP database.[2] Our full sample covers the period from

[2] We link CRSP and Compustat using WRDS ccmxpf_linktable, and link CRSP and I/B/E/S using iclink.

January 1982 to December 2018.

It needs to be cautious when matching actual earnings from Compustat with the EPS forecasts from I/B/E/S. Problems can arise due to stock splits occurring between the EPS forecast and the actual earnings announcement. If there is a stock split event between the date of analyst's forecast and the actual earnings announcement, the forecast and the actual EPS value might be based on different number of shares outstanding. Following prior research, we use the CRSP cumulative adjustment factors to put the forecasts from the unadjusted detail history and the actual EPS from Compustat on the same share basis. We focus on companies' ordinary stocks traded on NYSE, AMEX, and NASDAQ[3], and exclude observations for which the stock price is less than 5 dollars.

The commonly used measure of earnings surprises is standardized unexpected earnings ($SUE_{j,Q}$) (Bernard and Thomas (1989)). SUE for stock j in quarter Q is defined as $(E_{j,Q} - E_{j,Q-4} - c_{j,Q})/\sigma_{j,Q}$, where $E_{j,Q}$ is the quarterly earnings per share in year-quarter Q, $E_{j,Q-4}$ is the quarterly earnings four quarters ago, $c_{j,Q}$ and $\sigma_{j,Q}$ are the average and standard deviation, respectively, of $(E_{j,Q} - E_{j,Q-4})$ over the previous eight quarters. The earnings per share in Compustat database are also split-adjusted.

$D_{i,j,Q}$ is a dummy which has been defined in Section 2. It equals to one if the latest signal proxied by $SUE_{j,Q}$ is consistent with the prior belief of analyst proxied by $Rev_{i,j,Q}$, and 0, otherwise. Following Pouget, Sauvagnat, and Villeneuve (2017), individual revisions $Rev_{i,j,Q}$ are computed as the difference between the last annual earnings forecast made between the announcement dates of the $Q-1$ and Q quarterly earnings and the last forecast, if any, made before the announcement date of the $Q-1$ quarterly earnings.

Table 1 reports summary statistics about the variables of interest. There are 1,206,927 (requiring no missing observations of $Rev_{i,j,Q}$, $SUE_{j,Q}$ and $D_{i,j,Q}$) analyst-stock-year-quarter observations, 8611 unique firms and 17985 analysts. The mean and median of $D_{i,j,Q}$ is above 0.5, which indicates that the quarterly earnings announcement is consistent with analysts previous forecast revisions in more than half of the cases.

[3] CRSP share codes 10 or 11; exchange codes1, 2 or 3.

Table 1: Summary statistics

	N	Mean	Std	Min	P25	P50	P75	Max
$(\pi_{j,t} - F_{i,Q,post}\pi_{j,t})/P_{j,t-1}$	1,206,927	-0.013	0.031	-0.185	-0.024	-0.002	0.002	0.153
$(F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t})/P_{j,t-1}$	1,206,927	-0.001	0.006	-0.030	-0.003	0.000	0.002	0.020
$(\pi_{j,t-1} - \pi_{j,t-2})/P_{j,t-1}$	504,09	0.004	0.052	-0.178	-0.012	0.003	0.018	0.229
$SUE_{j,Q}$	249,420	-0.033	0.963	-2.475	-0.622	-0.004	0.586	2.474
$SignSUE_{j,Q}$	1,206,927	0.488	0.498	0.000	0.000	0.000	1.000	1.000
$SignRev_{i,j,Q}$	1,206,927	0.509	0.500	0.000	0.000	1.000	1.000	1.000
$D_{i,j,Q}$	1,206,927	0.598	0.493	0.000	0.000	1.000	1.000	1.000

4. Empirical Results

4.1 Regression analysis

We test our hypothesis by estimating Equation (4) which links forecast errors with past forecast revisions and signals. We normalize the variables in Equation (4) by the stock price of last fiscal year end $t-1$. The regression is as follows:

$$\frac{\pi_{j,t} - F_{i,Q,post}\pi_{j,t}}{P_{j,t-1}} = a + b \times D_{i,j,Q} \times \frac{F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}}{P_{j,t-1}}$$
$$+c\left(1 - D_{i,j,Q}\right) \times \frac{F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}}{P_{j,t-1}} + \mathrm{d}\frac{\pi_{j,t-1} - \pi_{j,t-2}}{P_{j,t-1}} + \varepsilon_{i,j,Q} \qquad (5)$$

Comparing Equation (4) and Equation (5), the coefficient b equals $\frac{\lambda_{i,1}}{1-\lambda_{i,1}}$, and c equals $\frac{\lambda_{i,2}}{1-\lambda_{i,2}}$. If the confirmatory bias we proposed and sticky expectation exist at individual level, the value of c should be positive and larger than the value of b. To control for extrapolation bias, we add $\frac{\pi_{j,t-1}-\pi_{j,t-2}}{P_{j,t-1}}$ into the equation. When we do not consider confirmation bias, the equation changes into the following form which directly tests the existence of stickiness at individual level.

$$\frac{\pi_{j,t} - F_{i,Q,post}\pi_{j,t}}{P_{j,t-1}} = a + b \times \frac{F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}}{P_{j,t-1}} + \mathrm{d}\frac{\pi_{j,t-1} - \pi_{j,t-2}}{P_{j,t-1}} + \varepsilon_{i,j,Q} \qquad (6)$$

Table 2: Regression results

	(1)	(2)	(3)	(4)	(5) $Rev_{i,j,Q}$>0	(6) $Rev_{i,j,Q}$<0
Intercept	-0.003***	-0.003***	-0.003***	-0.003***	-0.001***	-0.004***
	(-6.04)	**(-5.37)**	**(-5.73)**	**(-5.40)**	**(-3.81)**	**(-6.58)**
$(F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t})/P_{j,t-1}$	0.095***	0.113***				
	(3.75)	**(4.19)**				
$D_{i,j,Q} \times (F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t})/P_{j,t-1}$			0.058**	0.065**	0.054	0.118***
			(2.18)	**(2.38)**	**(1.48)**	**(3.93)**
$(1 - D_{i,j,Q}) \times (F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t})/P_{j,t-1}$			0.165***	0.174***	0.213***	0.027
			(6.26)	**(6.52)**	**(8.15)**	**(0.84)**
$(\pi_{j,t-1} - \pi_{j,t-2})/P_{j,t-1}$		0.015**		0.016**	0.009*	0.021**
		(2.28)		**(2.41)**	**(1.73)**	**(2.55)**
Obs.	1,153,153	1,047,825	989,953	940,200	510,873	429,327
R^2	0.24%	0.47%	0.46%	0.67%	0.26%	0.98%

Table 2 reports the regression results. In Model (1), we set $d = 0$ and estimate Equation (6). The estimated value of b is 0.095, which means $\lambda = 0.087$. Though much smaller than the estimated value of λ in Bouchaud et al. (2018)[4], it is significant at 1% level. The second column confirms the finding. After controlling extrapolation bias, there is still strong stickiness in individual analyst forecasts. Parameter d is significantly positive, implying that individual analysts do not overreact much across quarters and there is no extrapolation bias. Thus, from the first two columns in Table 2, we can infer that the stickiness in consensus forecasts documented by Bouchaud et al. (2018) is likely to come from the stickiness at individual level, though the extent of stickiness is smaller, which might be due to more heterogeneity or volatility across analysts. In later section, we will show that the stickiness at individual level is still strongly linked with stock market.

Next, we turn to the third and the fourth column. We care about the relative magnitude of the coefficient b and c. In model (3), both b and c are significantly positive, corresponding to sticky expectation. The value of b is much larger and more significant than c, which means that analysts become stickier to their previous beliefs when the latest signal is inconsistent with priors, supporting confirmation bias. In model (4), the results still hold with extrapolation bias controlled.

It might be necessary to check whether the strength of confirmation bias is affected by the sign of prior belief. For optimistic agent, positive attitude might be more

[4] Bouchaud et al. (2018) estimate λ using consensus forecasts, and find $\lambda = 0.14$ based on yearly frequency, $\lambda = 0.6$ based on quarterly frequency.

difficult to be changed by an opposite signal. We conduct a subsample test. Model (5) and Model (6) display the estimated parameters under positive and negative previous forecasts revisions, respectively. It is interesting to find that the results are quite different in the two circumstances. For analysts whose previous revisions are positive, b is insignificant and c is much larger as well as more significant than b. This results support our main argument that the extent of stickiness is higher when analysts are subjected to confirmation bias. However, for analysts whose previous revision is negative, b becomes larger and more significant than c. Confirmation bias does not enhance stickiness.

These different results are not that strange. Analysts are less willing to accept the bad information when they initially expect that the firm's future cash flow will increase, thus are affected by confirmation bias more heavily, and sticker to their positive views. In contrast, good news is more easily to change the negative attitude of the analysts than bad news. The heterogeneity of confirmation bias might derive from over-optimism or other psychological factors which deserves more exploration.

For robustness, we change the proxy of signal by replacing IBES-based earnings surprises with the standard earnings surprises in Pouget, Sauvagnat, and Villeneuve (2017), and conduct the above regressions. The calculation of IBES-based measure is similar to the standard earnings surprises, except that $E_{j,Q-4}$ and $E_{j,Q}$ are replaced by analyst's expectations and IBES reported actual earnings, respectively. Analysts' expectation is defined as the median of latest individual analyst forecasts issued within the 90 days prior to the date of earnings announcement. Regression results are reported in Table 3. They still support the three findings that individual analyst is sticky, and confirmation bias could enhance stickiness, but the such interaction is only significant when the previous beliefs are positive.

Table 3: Regression results

	(1)	**(2)**	**(3) $\boldsymbol{Rev_{i,j,Q}}$>0**	**(4) $\boldsymbol{Rev_{i,j,Q}}$<0**
Intercept	-0.003***	-0.003***	-0.001***	-0.004***
	(-5.32)	**(-5.24)**	**(-3.82)**	**(-6.44)**
$D_{i,j,Q} \times (F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t})/P_{j,t-1}$	0.049**	0.049*	0.044	0.163***
	(1.98)	**(1.95)**	**(1.14)**	**(5.94)**
$(1 - D_{i,j,Q}) \times (F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t})/P_{j,t-1}$	0.137***	0.137***	0.115***	-0.001
	(5.07)	**(5.07)**	**(4.49)**	**(-0.03)**
$(\pi_{j,t-1} - \pi_{j,t-2})/P_{j,t-1}$		0.003	0.002	0.004
		(0.79)	**(0.57)**	**(0.76)**
Obs.	989,953	940,200	510,873	429,327
R^2	0.46%	0.67%	0.26%	0.98%

4.2 Stock market anomalies

In this section, we link behavioral bias in analyst expectations with stock prices. Bouchaud et al. (2018) point out that profitability anomalies are stronger for stocks that are followed by stickier analysts, which is a direct test for our argument. If confirmation bias enhances the extent of stickiness, stock anomalies are supposed to be stronger. We compute signals for profitability, and price momentum in our sample:

Cash flows *(cf)* have been founded to be a strong predictor of returns. It is the net cash flow from the firm's operating activities normalized by total assets, calculated as the ratio of Compustat items *oancfy* and *atq*.

Momentum *(mom)* is the cumulative firm-level return between months t-12 and t-2 as in Jegadeesh and Titman (1993).

In line with the literature, we assume accounting data to be available after recorded earnings announcement which is obtained from Compustat quarterly. Accounting profitability signals are updated in the month following a firm's fiscal quarter earnings announcement, and remain valid until the month of the firm's next fiscal quarter earnings announcement.

First, we show that the anomalies are indeed present in our sample. Then, we measure the level of stickiness using the coefficient in front of forecast revisions without (with) confirmation bias, and examine the link between the degree of stickiness/confirmation bias and the strength of anomalies.

4.2.1 Anomalies in the full sample

We sort stocks each month into quintiles of the signal, and then compute the returns of equally weighted portfolios for each of the five quintile portfolios, and the long-short portfolio. Table 4 displays the earnings and return momentum in our sample. Excess returns, CAPM adjusted alpha, Fama-French three factors adjusted alpha, and Carhart four factors adjusted alpha of the portfolios are presented in Panel A, Panel B, Panel C, and Panel D, respectively. Portfolio returns of momentum strategy are not adjusted by Carhart four factors, as a momentum risk factor has already been included in the factors.

Table 4: Anomalies in the full sample

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q5-Q1**
Panel A. Excess returns						
Cash flow	1.27%***	1.27%***	1.33%***	1.51%***	1.64%***	0.37%***
	(4.96)	(5.48)	(5.73)	(6.55)	(7.23)	(3.54)
Past return	0.66%**	1.04%***	1.12%***	1.25%***	1.49%***	0.84%***
	(2.09)	(4.43)	(5.46)	(5.95)	(5.17)	(3.74)
Panel B. CAPM						
Cash flow	0.51%***	0.56%***	0.62%***	0.81%***	0.95%***	0.43%***
	(3.99)	(4.96)	(5.34)	(7.17)	(8.17)	(3.56)
Past return	-0.24%	0.34%***	0.50%***	0.62%***	0.69%***	0.93%***
	(-1.64)	(2.71)	(4.48)	(5.38)	(3.99)	(4.25)
Panel C. Fama-French three factors (1993)						
Cash flow	0.47%***	0.45%***	0.53%***	0.73%***	0.88%***	0.41%***
	(6.02)	(7.13)	(7.66)	(10.54)	(11.58)	(3.49)
Past return	-0.33%***	0.20%**	0.37%***	0.52%***	0.71%***	1.05%***
	(-2.60)	(2.37)	(5.57)	(8.36)	(6.17)	(4.86)
Panel D. Carhart four factors (1997)						
Cash flow	0.53%***	0.49%***	0.59%***	0.77%***	0.92%***	0.39%***
	(6.25)	(7.75)	(9.01)	(11.78)	(11.28)	(3.10)

Consistent with prior studies, there indeed exist substantial long-short returns. Risk-adjusted alphas are also significant. In Panel D, the monthly four-factor alpha of long-short portfolio using cash flow strategy is 0.39%, and significant at 1% level. In Panel C, the monthly three-factor alpha of momentum strategy is 1.05%, significantly at 1% level.

4.2.2 Linkage between individual analysts' stickiness and stock returns

In this subsection, we do not consider confirmation bias, and focus on the relationship between pure stickiness at individual level and anomalies. The prediction is that anomalies are stronger when firms are followed by stickier analysts. To test this, we first use all observations that are available for a given firm to estimate the firm-level stickiness. More specifically, we estimate the equation as follows, and obtain the firm-level stickiness using the transformation $\lambda_j = b_j/(1 + b_j)$.

$$\frac{\pi_{j,t} - F_{i,Q,post}\pi_{j,t}}{P_{j,t-1}} = a_j + b_j \times \frac{F_{i,Q,post}\pi_{j,t} - F_{i,Q,pre}\pi_{j,t}}{P_{j,t-1}} + \varepsilon_{i,j,Q} \quad (7)$$

Next, we conduct portfolio analysis. We sort stocks into terciles of the firm-level stickiness parameter λ_j. With a tercile of λ_j, we sort firms into quintiles of profitability *(cf)*, or return momentum *(mom)* at each month. Then we compute equally weighted returns of these double sorted portfolios and adjust them for risk using standard asset pricing techniques. This portfolio analysis is different from Bouchaud et al. (2018). We estimate firm-level stickiness using individual analyst forecasts, whereas Bouchaud et al. (2018) use census forecasts to estimate the stickiness parameter. Table 5 reports our results.

Table 5: Linkage between stickiness and stock returns

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A. Cash flows						
P1	0.62%***	0.63%***	0.67%***	0.68%***	0.89%***	0.27%
	(5.21)	(6.95)	(8.13)	(8.11)	(7.69)	(1.38)
P2	0.49%***	0.48%***	0.48%***	0.73%***	0.97%***	0.48%**
	(3.34)	(4.76)	(6.07)	(9.24)	(7.15)	(2.05)
P3	0.21%	0.16%	0.35%***	0.52%***	1.14%***	0.93%***
	(1.19)	(1.26)	(3.80)	(7.11)	(8.42)	(3.48)
P3-P1	-0.41%***	-0.47%***	-0.34%***	-0.17%**	0.24%**	0.65%***
	(-3.37)	(-4.94)	(-3.79)	(-2.14)	(2.22)	(4.05)
Panel B. Momentum						
P1	0.16%	0.51%***	0.63%***	0.61%***	0.74%***	0.58%***
	(1.29)	(5.74)	(7.71)	(7.45)	(6.25)	(2.94)
P2	0.00%	0.31%***	0.40%***	0.66%***	0.81%***	0.81%***
	(0.02)	(3.22)	(5.42)	(8.26)	(5.78)	(3.44)
P3	-0.42%**	-0.07%	0.22%**	0.39%***	0.97%***	1.38%***
	(2.50)	(-0.62)	(2.39)	(5.41)	(7.06)	(5.37)
P3-P1	-0.58%***	-0.57%***	-0.42%***	-0.23%***	0.21%*	0.79%***
	(-4.52)	(-6.21)	(-4.68)	(-2.81)	(1.94)	(4.76)

In Panel A, we use the Carhart four factors to adjust the portfolio returns that are double sorted on firm-level stickiness and cash flows. In Panel B, we use the Fama-French threes factors to adjust the portfolio returns that are double sorted on stickiness and past returns. Our target is to examine whether the risk-adjusted alpha of the long-short portfolio in the highest λ_j tercile (P3) is larger than that in the lowest tercile (P1).

As shown in Table 5, monthly alpha of the long-short cash flow strategy is 0.93% among the stickiest firms and significant at 1%. By contrast, the risk-adjusted alpha is only 0.27% among the least sticky firms, and not significant. The difference between the two groups yields substantial monthly profit of 0.65%, with t-statistic of 4.05. These findings confirm the conclusion in Bouchaud et al. (2018) that the long-short strategy is significantly stronger for the stickiest stocks. In addition, we show that the stickiness measured by individual analyst forecasts also contribute to explain stock market anomalies. We could further infer that stickiness in consensus forecasts might stem from under-reaction at the individual level. The pattern in Panel B of Table 5 is similar to Panel A. Risk-adjusted alpha of long-short momentum strategy is the largest and most significant in the highest λ_j. The monthly difference (P3-P1) is 0.79% with t-statistic of 4.76.

A potential concern of above analysis is look-forward bias, which arises from the fact that we use the full time series of analysts forecast to estimate the firm-level stickiness. It is hard to avoid in the empirical design of Bouchaud et al. (2018). However, in our setup, we can keep away from look-forward bias by extrapolating the boosting effect of confirmation bias on stickiness which is illustrated in Section 4.2.3.

4.2.3 Linkage between confirmation bias and stock returns

The regression results have shown that confirmation bias enhances the degree of stickiness. Analysts tend to be stickier to their previous belief when receiving an unfavorable signal, thus we expect that stock market anomalies are stronger when analysts are subject to confirmation bias.

At each month, we first divide firms into two groups according to the level of confirmation bias. For a given firm, if the average value of the dummy variable $D_{i,j,Q}$ ($avgD_{j,Q}$) is less than 0.5, which means that, on average, the latest information is inconsistent with the priors of the analysts who are following the firm, we infer that the firm is more affected by confirmation bias. Otherwise, the firm is perceived to be less affected by confirmation bias if the average value of $D_{i,j,Q}$ ($avgD_{j,Q}$) is more than 0.5[5].

In a second step, within each group, we sort firms into quintiles of profitability *(cf)*, or return momentum *(mom)* at each month, and compute equally weighted returns of these double sorted portfolios. Risk-adjusted alphas of portfolio returns are reported in Table 6.

[5] The results are similar if we employ the median value of $D_{i,j,Q}$ to conduct double sort.

Table 6: Linkage between confirmation bias and stock returns

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q5-Q1**
Panel A. Cash flows						
$avgD_{j,Q} = 1$	0.54%***	0.41%***	0.52%***	0.73%***	0.84%***	0.30%**
	(5.89)	(5.99)	(6.60)	(9.86)	(10.38)	(2.19)
$avgD_{j,Q} = 0$	0.40%***	0.49%***	0.53%***	0.71%***	0.93%***	0.53%***
	(5.74)	(7.08)	(7.80)	(9.06)	(11.69)	(4.73)
Diff	-0.15%**	0.08%	0.01%	-0.02%	0.09%	0.23%**
	(-2.47)	(1.50)	(0.28)	(-0.28)	(1.67)	(2.56)
Panel B. Momentum						
$avgD_{j,Q} = 1$	-0.16%	0.23%***	0.31%***	0.36%***	0.69%***	0.85%***
	(-1.52)	(2.86)	(4.31)	(5.45)	(8.28)	(5.34)
$avgD_{j,Q} = 0$	-0.18%*	0.21%***	0.23%***	0.36%***	0.75%***	0.93%***
	(-1.68)	(2.63)	(3.06)	(5.70)	(6.09)	(4.73)
Diff	-0.02%	-0.02%	-0.08%	0.00%	0.07%	0.08%
	(-0.32)	(-0.34)	(-1.23)	(0.00)	(0.94)	(0.75)

The cash flow strategy in Panel A confirms our expectation that the long-short portfolio return is higher when the firms are followed by analysts who are subject to confirmation bias. Monthly return difference between groups of high and low confirmation bias is 0.23%, and significant at 5%, demonstrating that confirmation bias indeed influence the reaction speed of analysts and further affect stock returns. However, momentum strategy in Panel B does not provide desirable evidences. The long-short portfolio return of firms of high confirmation bias is only 0.08% higher than firms of low confirmation bias and the difference is not significant. The results are not as convincing as the findings in Section 4.2.2, which might be due to the heterogeneity of confirmation bias. We have shown that confirmation bias works more significantly when the previous forecast revisions are positive in Section 4.1. Along this line, we continue to test the effect of confirmation bias on stock returns under different sign of previous forecast revisions.

The procedures of triple sort are similar with above analysis. The rank variable is the sign of mean forecast revision ($avgRev_{j,Q}$) in the first step, and $avgD_{j,Q}$ in the second step, and cash flow or past return in the third step. Risk-adjusted alphas of portfolio returns are reported in Table 7. We focus on the issue whether anomalies are stronger in firms of high confirmation bias when the previous forecast revisions are positive.

Table 7: Linkage between confirmation bias and stock returns

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A. $avgRev_{j,Q} > 0$, cash flows						
$avgD_{j,Q} = 1$	0.48%***	0.41%***	0.47%***	0.70%***	0.74%***	0.27%*
	(4.66)	(4.75)	(5.23)	(7.13)	(7.91)	(1.76)
$avgD_{j,Q} = 0$	0.44%***	0.57%***	0.51%***	0.81%***	1.03%***	0.58%***
	(5.63)	(6.50)	(6.64)	(9.36)	(10.09)	(4.26)
Diff	-0.04%	0.16%*	0.03%	0.12%	0.28%***	0.31%***
	(-0.39)	(1.74)	(0.27)	(1.33)	(3.04)	(3.17)
Panel B. $avgRev_{j,Q} < 0$, cash flows						
$avgD_{j,Q} = 1$	0.33%***	0.55%***	0.44%***	0.58%***	0.84%***	0.51%***
	(4.25)	(6.72)	(5.44)	(6.97)	(8.12)	(3.88)
$avgD_{j,Q} = 0$	0.60%***	0.52%***	0.56%***	0.79%***	0.88%***	0.30%***
	(6.53)	(6.08)	(5.87)	(9.80)	(9.42)	(2.41)
Diff	0.27%**	-0.02%	0.12%	0.20%**	0.04%	-0.22%
	(2.19)	(-0.30)	(1.46)	(2.49)	(0.39)	(-1.58)
Panel C. $avgRev_{j,Q} > 0$, momentum						
$avgD_{j,Q} = 1$	-0.11%	0.22%**	0.40%***	0.39%***	0.75%***	0.87%***
	(-0.96)	(2.39)	(4.76)	(4.92)	(7.89)	(5.12)
$avgD_{j,Q} = 0$	-0.37%***	0.11%	0.09%	0.25%***	0.67%***	1.06%***
	(-2.76)	(1.18)	(1.04)	(3.32)	(5.92)	(5.30)
Diff	-0.26%	-0.12%	-0.31%**	-0.14%***	-0.07%*	0.19%**
	(-1.53)	(-0.67)	(-1.96)	(-3.19)	(-1.77)	(2.49)
Panel D. $avgRev_{j,Q} < 0$, momentum						
$avgD_{j,Q} = 1$	0.04%	0.33%***	0.41%***	0.47%***	0.78%***	0.76%***
	(0.34)	(3.55)	(4.59)	(5.23)	(5.53)	(3.68)
$avgD_{j,Q} = 0$	-0.13%	0.21%**	0.21%**	0.31%***	0.61%***	0.74%***
	(-1.10)	(2.50)	(2.25)	(3.79)	(5.86)	(3.81)
Diff	-0.16%*	-0.12%*	-0.20%**	-0.16%**	-0.17%*	-0.01%
	(-1.74)	(-1.87)	(-2.57)	(-1.97)	(-1.80)	(-0.06)

Panel A of Table 7 displays the cash flow strategy in the group of observations where the average analysts forecast revision ($avgRev_{j,Q}$) is positive. Within each sub group, high level of cash flows predicts high stock returns. Especially, the cash flow strategy generates larger and more significant long-short returns in the case of $avgD_{j,Q} = 0$. The difference between firms of high confirmation bias ($avgD_{j,Q} = 0$) and low confirmation bias ($avgD_{j,Q} = 1$) is 0.31%, and significant at 1%, which implies that when the latest information is different from the average analyst' previous belief, in other words, when average analyst is subject to confirmation bias and becomes stickier, cash flow anomaly delivers stronger performance. However, when $avgRev_{j,Q}$ is negative, profits from Q5-Q1 is smaller in the case of inconsistent signal. Cash flow anomaly is less pronounced when average analyst has confirmation bias. The opposite pattern in Panel A and Panel B is consistent with the regression results of Model (5) and Model (6) in Table 2, turning out that confirmation bias is more significant when analyst's prior is negative. Momentum strategies in Panel C and Panel D also show supportive results.

5. Conclusion

This paper provides detailed investigations about individual analyst's belief formation process. We find empirical evidences for sticky expectation at individual level, which sheds some light on the speculation that stickiness in consensus forecasts comes from stickiness in individual forecasts. The stickiness at individual level also contributes to explain stock anomalies, including cash flow and momentum strategy. The most interesting finding is the interaction between confirmation bias and stickiness in individual analyst expectations. When the sign of latest earnings surprise is different from the direction of the analyst's previous forecast revision, the analyst will be subject to confirmation bias, and update his expectation more slowly, and thus stock anomalies are more pronounced in this case. Further exploration shows that confirmation bias only significantly enhances stickiness when the prior view is positive.

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