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Investor and price response to patterns in earnings surprises

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Abstract

As part of their model to explain short-term positive and long-term negative auto-correlation in stock returns, Barberis, Shleifer, and Vishny [1998. A model of investor sentiment. Journal of Finance 49, 307–345] suggest that investors may extrapolate trends in earnings performance. I test this portion of their model by examining investor trading patterns in firms that experience consecutive same-sign earnings surprises. Consistent with their model, after controlling for regularities in trading activity, I find that the net buying of small investors increases with the number of consecutive positive earnings surprises. I further find that purchasing activity of small investors subsequent to consecutive positive surprises is significantly negatively correlated with returns throughout the remainder of the year. These results suggest that such investors are not simply rationally updating after public news announcements. My results are robust to controlling for auto-correlation in earnings surprises.

JEL classification: G14

In recent years, traditional risk-based asset pricing models such as the Capital Asset Pricing Model and the Arbitrage Pricing Theory have faced significant challenges in fully explaining regularities in security returns, in particular short-run positive auto-correlation and long run reversal (DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993, 2001, among others). Based on psychology literature that suggests individuals are subject to cognitive and motivational errors, Barberis, Shleifer, and Vishny (1998) develop a model to

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explain these phenomena of momentum and reversal.[1] Underlying their model is the assumption that earnings surprises follow a random walk, but investors believe that the earnings process is either "trending" or "mean-reverting". To motivate their model, Barberis, Shleifer, and Vishny (1998) introduce extrapolation bias which suggests that, in analyzing the history of earnings performance, investors may be insensitive to the likelihood of prior outcomes and may draw strong inferences from small samples in order to determine whether earnings are determined by the trending or mean-reverting regime. Indeed, Tversky and Kahneman (1974) find that individuals believe they see patterns in random sequences.

Despite its significance in the finance literature and its ability to explain empirical regularities, the Barberis, Shleifer, and Vishny (1998) model has been criticized based on the notion that, after aggregating trading activity, the actions of individual investors may simply "cancel out" (Rubenstein, 2001). Further, the evidence supporting a role for psychology in financial markets is mixed. For example, Chan, Frankel, and Kothari (2004) find that small trader biases do not affect post-earnings announcement returns. Battalio and Mendenhall (2005), however, evaluate small trader behavior following earnings surprises for Nasdaq stocks and find that investors placing small trades are influenced by seasonal random walk forecast errors and, further, have some impact on stock prices. In support of Barberis, Shleifer, and Vishny (1998), Bloomfield and Hales (2002) show that experimental subjects make decisions based on historical "patterns;" however, Durham, Hertzel, and Martin (2005) examine the football wagering market, and find little evidence that investors behave according to the model.[2]

To shed light on the important two-part debate in the previous paragraph, I first test whether, in aggregate, small investors behave in a manner consistent with the extrapolation portion of the Barberis, Shleifer, and Vishny (1998) model. I then examine whether their trading behavior is enough to impact subsequent returns. To test whether individuals extrapolate, I analyze aggregate order imbalances (OIB) following consecutive positive (or negative) earnings surprises. OIB (studied extensively in a series of papers by Chordia, Roll, and Subrahmanyam) is roughly the number of shares purchased less the number of shares sold by buyers and sellers who place market orders. Thus, analyzing OIB as a measure of trading activity is a direct way to provide evidence of biases of traders who initiate orders.[3] Because this OIB measure is based on number of trades rather than on trading volume, it also tends to capture the behavior of the more numerous small investors. Finally, Chordia, Roll, and Subrahmanyam (2002, 2005) have shown that daily order imbalances (which are serially correlated) do not map one-to-one with daily returns (which are not serially correlated); therefore, I also investigate whether there is a link between trading patterns and returns.[4]

I find that small investors initiating market orders extrapolate past trends in earnings performance, which is consistent with the Barberis, Shleifer, and Vishny (1998) prediction. Specifically, after controlling for regularities in trading activity, the net buying of small

[1]Empirical evidence suggests that individual investors invest in a manner that is inconsistent with the rational paradigm (e.g., Benartzi and Thaler, 2001; Odean, 1998, 1999).

[2]While Hertzel, and Martin (2005) find that gamblers believe a short "streak" may continue, betting behavior suggests these individuals believe that longer streaks will end.

[3]Details on how OIB is measured are presented in Section 2.1.

[4]Hvidkjaer (2005), Coval and Shmnway (2005), Massa and Simonov (2005), Chan, Chen, and Lakonishok (2002), and Bloomfield, Libby, and Nelson (2003), among others, are related papers.

investors (measured by aggregate OIB) increases with the number of consecutive positive quarterly earnings surprises. Further, purchasing activity in the quarter following a string of consecutive positive surprises is significantly negatively correlated with returns throughout the remainder of the year, indicating that trading activity following strings of positive earnings surprises is not justified by future price performance. According to my results, an investor who conditions on strings of consecutive positive surprises and purchases those stocks in the lowest buy-imbalance decile and shorts those in the largest buy-imbalance decile can outperform an investor who does not use a conditioning strategy by approximately 5% (annually). My results are robust to controlling for auto-correlation in earnings surprises.

I also uncover evidence that those stocks with especially high OIB following strings of positive surprises tend to be growth stocks. Indeed, the fact that there is greater uncertainty surrounding growth stocks and that OIB is higher for these stocks is consistent with Einhorn, 1980, viz., that biases are more severe for tasks requiring more subjective judgment than for more concrete tasks. Though I find that, even after controlling for book-to-market, low OIB stocks outperform those with high OIB, the fact that high OIB stocks tend to be growth stocks accords with the notion put forth by Lakonishok, Shleifer, and Vishny (1994) that naïve investors extrapolate past earnings growth too far into the future. Overall, while the relation I uncover between OIB and subsequent returns is statistically significant, it is unlikely that it is economically significant enough to explain the perceived patterns of short-run positive auto-correlation and long-run reversal that Barberis, Shleifer, and Vishny (1998) set out to explain. At the same time, institutions with low transaction costs might improve their performance by overweighting those stocks with low OIB following strings and selling those with high OIB.

The remainder of the paper proceeds as follows. Section 1 introduces extrapolation bias and delineates the hypotheses. Section 2 discusses the data and method. Empirical results and a sensitivity analysis are presented in Section 3, and Section 4 concludes.

1. Extrapolation bias and hypotheses

1.1. Extrapolation bias

Tversky and Kahneman (1974) show that subjects use heuristics to reduce mental effort in decision making. Barberis, Shleifer, and Vishny (1998) incorporate this finding in a model that makes use of extrapolation bias and conservatism to explain documented patterns of short-run positive and long-run negative auto-correlation in stock returns. Because of its ability to accommodate empirical testing, I test the extrapolation bias (one manifestation of the representativeness heuristic) which leads subjects to generalize about a population of future outcomes after observing only a small sample. In particular, subjects who have viewed only one or two event outcomes often conclude that these are representative of future outcomes. Barberis, Shleifer, and Vishny (1998) write:

> When a company has a consistent history of earnings growth over several years... investors might conclude that the past history is representative of an underlying earnings growth potential. While a consistent pattern of high growth may be nothing more than a random draw for a few lucky firms, investors... infer from

> the in-sample growth path that the firm belongs to a small and distinct population of firms whose earnings just keep growing (p. 316).

Despite previous evidence that might moderate beliefs, "extrapolators" place unfounded emphasis on recent trends. My analysis tests for evidence that, after aggregating trading activity, financial market agents exhibit the extrapolation bias. I use earnings history (described in the next section) as the stimulus to examine the trading activity of these investors.

1.2. Hypotheses

Investors who extrapolate typically allocate too much weight to recent trends given the probability of the trends occurring in the population.[5] Small investors, for example, might suffer from this bias because it is costly for them to analyze the quality of each firm. To test the extrapolation heuristic, I begin by considering net buying activity in a portfolio of stocks that experience strings of consecutive same-sign (positive or negative) quarterly earnings surprises (announced earnings less the mean analyst forecast). Since earnings surprises should not be auto-correlated in a rational market, the number of consecutive same-sign surprises should not influence order imbalances (OIB) unless a stock's subsequent performance is expected to be correlated with the number of surprises in the string. I also address the relation between OIB and returns. I pool observations of firms with x consecutive positive (negative) surprises (where $2 \leqslant x \leqslant 5$) and test whether the occurrence of a string of consecutive same-sign surprises has implications for OIB and returns. Specifically, I measure a string's effect on OIB by controlling first for daily and seasonal regularities as well as for lagged effects of OIB and returns and, later, for average market OIB (details are presented in Section 2). This method allows me to determine whether strings have any incremental influence on OIB.

According to Barberis, Shleifer, and Vishny (1998), some investors might think a trend in earnings surprises (or prices) will continue while others believe it will terminate. Hypothesis 1 is based on the premise that, on average, investors may be more likely to surmise the continuation than the reversal of a string of consecutive positive (or negative) earnings surprises. This is because, after a string of consecutive positive (negative) surprises, investors revise their expectations to believe the firm is more likely to be of high (low) quality. Any post-earnings drift would also suggest the group believing in the trend dominates.[6]

Hypothesis 1. Given a string of consecutive positive (negative) earnings surprises,

$$\mathrm{H}_0\colon\ \overline{\mu_{\mathrm{s}}} = \overline{\mu_{\mathrm{n}}},$$

$$\mathrm{H}_\mathrm{A}\colon\ \overline{\mu_{\mathrm{s}}} < (>) \overline{\mu_{\mathrm{n}}},$$

where $\overline{\mu_{\mathrm{s}}}$ is the mean daily average OIB innovation in the quarter following the last announcement in the string for the group of stocks that experiences a string of consecutive

[5] Because they use only a subset of available information, extrapolators are not Bayesian.

[6] While a potential explanation for the apparent domination of the "trending" group is that the group of investors who purchase after a string of positive announcements is composed of both extrapolators *and* Bayesians (whose rational revision in beliefs also predicts continuation), systematic underperformance following strings would suggest investor irrationality. I test this with Hypothesis 2.

same-sign surprises, and $\overline{\mu_{\mathrm{n}}}$ represents the same OIB measure but for a group of firms experiencing an isolated positive (negative) surprise.[7] I examine OIB in the quarter subsequent to the surprise (henceforth, period 1) and, later in the paper, confirm the results are similar using a shorter event-time window (7 days around the surprise).

Hypothesis 1 tests whether small investors extrapolate on a string of positive (negative) earnings surprises and buy (sell) more after a string than after any single positive (negative) surprise.[8] Note that a test of Hypothesis I examines whether trading activity at the aggregate level supports the idea that agents extrapolate trends, independent of whether such behavior is rational. For example, there could be higher serial correlation in earnings surprises in groups of firms that experience strings. Investors could rationally expect this and tilt their orders accordingly. Or, analysts may be biased in such a way that makes strings of consecutive same-sign surprises (in either direction) more likely in some industries than in others. I address such issues in Section 3.

Although those who believe that earnings follow a ‘‘trending’’ regime may dominate for the reasons provided above, neither trading interest nor buying activity will be uniform within the group of stocks experiencing a string of x consecutive same-sign surprises. In other words, because of cross-sectional differences in characteristics of the stocks in the sample, some stocks within a given string-length group will be purchased more aggressively than others. For example, according to Lakonishok, Shleifer, and Vishny (1994), investors may select stocks based on growth versus value considerations. This notion of heterogeneous buying within groups coupled with the idea that more ‘‘sophisticated’’ traders take countering positions, especially when the imbalance becomes excessive, implies that the stocks in which extrapolators buy (sell) relatively aggressively in period 1 may subsequently underperform those stocks that have less imbalance. Based on Coval and Shmnway (2005) who find that the average investor turns his stocks over every 250 days, I test whether the average OIB innovation in period 1 is correlated with return performance in the subsequent three quarters (henceforth, period 2).

Hypothesis 2. Given a string of consecutive same-sign earnings surprises,

(A) $$\mathrm{H_0}:\ \rho_{\mu_{\mathrm{s}},r} = 0,$$

$$\mathrm{H_A}:\ \rho_{\mu_{\mathrm{s}},r} < 0.$$

(B) $$\mathrm{H_0}:\ |\rho_{\mu_{\mathrm{s}},r}| = |\rho_{\mu_{\mathrm{n}},r}|,$$

$$\mathrm{H_A}:\ |\rho_{\mu_{\mathrm{s}},r}| > |\rho_{\mu_{\mathrm{n}},r}|,$$

where μ_{s} and μ_{n} are defined as in Hypothesis 1, r is equal to the buy-and-hold return for the respective stock in period 2, and ρ represents the correlation. Note that part A of Hypothesis 2 tests that the correlation is less than 0 for the sample of firms experiencing strings but part B tests whether the *magnitude* of this (potentially negative) correlation is larger for the sample (‘‘string’’) groups than for the group of firms with isolated surprises.

[7] By construction, this OIB residual is mean zero in the full sample.

[8] I use the term ‘‘small’’ investor because I analyze OIB measured in terms of number of transactions (see Section 2.1 for a brief discussion on small versus large traders).

2. Data and method

2.1. Data

Return, price, and share volume data are obtained from the daily and monthly files provided by the Center for Research in Security Prices (CRSP). I match these data with daily order imbalance (OIB) data (on signed *market* orders) for New York Stock Exchange securities. The OIB data originate from the Institute for the Study of Security Markets (ISSM) database (1988–1992) and the New York Stock Exchange Trades and Automated Quotations (TAQ) database (1993–1998). Details on the OIB database can be found in Chordia, Roll, and Subrahmanyam (2001), but a few points are worth considering: the Lee and Ready (1991) algorithm classifies a market order (and a marketable limit order) as buyer- or seller-initiated based on whether the trade is executed closer to the ask or bid of the prevailing quote. Thus, the algorithm estimates imbalances based on the *sign* of the orders placed by traders who demand immediacy (liquidity demanders).[9] This is distinct from the notion that there is a buyer for every seller so the sum of all trades is equal to zero: if, on average, specialists maintain constant inventories, any imbalance will be absorbed by standing-order and limit-order traders (liquidity suppliers). I make the distinction between the liquidity demander and liquidity supplier based on the standard assumption that it is costly to place and monitor a limit order: for those with a longer investment horizon, outside opportunities may make the cost of monitoring limit orders high. Thus, this trader would not bother with monitoring intraday limit orders and, instead, would be more likely to issue a market order. The OIB dataset allows us to understand the behavior of this type of investor.

I begin the analysis by examining OIB measured in terms of number of transactions, defined as the *number* of buyer-initiated trades less the *number* of seller-initiated trades on day t, standardized by the sum of buyer- and seller-initiated trades for a given stock on a given day. This variable gives equal weight to small and large orders. The database, however, also includes OIB in terms of dollar value, which accounts for both the trade size and frequency. In Section 3.3, I consider the dollar value measure of imbalances, defined as the *dollar amount* of buyer-initiated trades less that of seller-initiated trades, standardized by the total dollar volume of all trades in the relevant stock. Because this variable gives relatively larger traders more weight, comparing the results using these two measures allows me to draw inferences about the behavior of small versus large traders.[10] Summary statistics on the OIB data are provided in Table 1. On average, OIB appear to be tilted toward the buy-side, as indicated by a positive mean value of 6.48 for OIB_{num}, the unscaled imbalance. Furthermore, $\text{OIB}_{\text{numst}}$, which is OIB_{num} standardized by the number of trades in the relevant stock on the relevant day, has a slightly negative mean, which suggests that days with large buying pressure are often days with more trading activity.

I match the OIB data with data from the Institutional Brokers Estimate System (I/B/E/S) U.S. Summary History dataset on quarterly earnings. The Summary History dataset contains summary statistics on earnings announcements and analyst forecasts. Because forecasts are revised frequently for a given stock in a given period, the mean is calculated

[9] Market orders are executed immediately at the best available price whereas limit orders are executed as prices move to the level specified in the order.

[10] Currently, approximately 10 percent of market orders (share-weighted) in listed stocks are placed by individual investors in accounts managed themselves (information from Paul Bennett, NYSE).

Table 1
Summary statistics

Table 1 presents summary statistics for the order imbalance and earnings data. OIB_{num} represents order imbalance measured in terms of the number of transactions and OIB_{numst} is OIB_{num} standardized by the number of transactions for a given stock on a given day. Error is calculated as Actual–Estimate, where Actual signifies the announced EPS, and Estimate represents the mean forecast of earnings per share (EPS) for a given firm-quarter for the firms on which I have OIB data. Analyst refers to the number of analysts following the stock. In the lower portion of this table, I present the correlation (ρ) between the forecast error (Error) and lagged values of the forecast error. The lagged variables are the 1st, 2nd, 3rd, and 4th lags of Error, respectively. ** Indicates significance at 5%. The sample period is 1988–1998, inclusive.

Variable	*N*	Mean	StDev	Skewness	Kurtosis
OIB_{num}	3,609,754	6.48	59.94	35.35	3101.64
OIB_{numst}	3,609,754	−0.02	0.35	−0.25	0.93
Error	25,082	−0.22	2.96	−25.02	1628.20
Analyst	25,082	6.58	4.52	1.92	4.34
Variable	Error	Lag1	Lag2	Lag3	Lag4
ρ	1.000	0.080**	0.041**	0.018**	0.001

by averaging the most recent forecast received from each analyst, eliminating the problem of having to adjust for uneven time periods between forecast and announcement dates. From this dataset, I obtain the mean forecast of earnings per share (EPS), actual EPS, and the earnings report date.[11] For each quarterly announcement, I measure an earnings surprise as the difference between actual earnings announced on day t and the average forecast for the period corresponding to the announcement. I require that price and return data be present for the announcement day and surrounding days. To capture expectations, and therefore surprises, I examine the results for earnings surprises based on the analyst model of earnings expectations rather than on the seasonal random walk model (which is used in Battalio and Mendenhall, 2005). The analyst model is appropriate because earnings surprises as determined by analyst forecast errors are disseminated to investors via brokerage houses.[12]

Summary statistics on the earnings data are also presented in Table 1, Panel A. The average number of estimates for a given firm/quarter in the entire sample is 6.58. Given the auto-correlation results of Bernard and Thomas (1990), in Panel B I report correlation coefficients in earnings forecast errors up to four lags. While there is evidence of serial correlation in forecast errors (the largest correlation of 0.08 is at the first lag) none of the correlations are as large as those found in Bernard and Thomas (1990), and there is no evidence of reversal over the sample period.

[11]EPS is calculated as the net income from continuing operations divided by the number of shares outstanding. Earnings forecasts are made on a continuing operations basis, after backing out discontinued operations, extra-ordinary changes, and other non-operating items. With regard to the number of shares outstanding, measured in millions, I/B/E/S computes a weighted average of the number of shares outstanding for a given year. Values are adjusted for stock splits. Since I/B/E/S attempts to report actual earnings as soon as they are released, earnings reports are taken directly from the news wires.

[12]Though I focus on the analyst model of earnings, my results are qualitatively unchanged if I define an earnings surprise using the naïve expectations model, which classifies a surprise as positive if announced earnings are larger than they were in the same quarter of the previous year and negative if they are smaller. Unreported results are consistent with Battalio and Mendenhall (2005).

2.2. Method

Chordia, Roll, and Subrahmanyam (2005) find that OIB are auto-correlated, depend on lagged market returns, and are subject to calendar effects. Foster and Viswanathan (1990) document daily regularities in trading volume that would be reflected in OIB data. Consequently, when attempting to measure an OIB innovation, it is necessary to consider variables that are known to make OIB predictable. I therefore adjust the OIB data to account for calendar effects. In line with Gallant, Rossi, and Tanehen (1992), I remove calendar effects from the mean and then from the variance of the OIB series. I employ day-of-the-week and monthly dummy variables (one for each day: Monday through Thursday and one for each month: February through December) and, for each stock in the sample, I regress the OIB series on the set of dummy variables to obtain the following mean equation:

$$\omega = x'\beta + \varepsilon,$$

where ω represents the OIB series and x contains the adjustment regressors. I then standardize the residuals from the above equation to construct the following variance equation:

$$\log(\varepsilon^2) = x'\gamma + \eta.$$

To ensure comparable magnitudes for the adjusted and unadjusted series, I calculate an adjusted series:

$$\omega_{\text{adj}} = \alpha + \delta(\hat{\varepsilon}/\exp(x'\gamma/2)),$$

where α and δ are chosen such that the sample means and variances of ω and ω_{adj} are equivalent.[13]

Additionally, microstructure effects like transaction costs, which may instigate traders to split orders, and inventory carrying costs, which may cause the market maker to implement a pricing scheme that is based on current inventory levels, suggest serial dependencies in OIB (see Hasbrouck, 1991; Madhavan and Smidt, 1991, among others). I address these issues with an autoregressive (AR) model that also helps disentangle new information from beliefs. In particular, I specify the following equation for the adjusted order imbalance series, denoted in the below equation by OIB_t:

$$\text{OIB}_t = \gamma + \alpha_1 r_{t-1} + \alpha_2 r_{t-2} + \cdots + \beta_1\,\text{OIB}_{t-1} + \beta_2\,\text{OIB}_{t-2} + \cdots + \eta_t, \tag{1}$$

where γ is the constant, the α's and β's are the coefficients, and η_t is the disturbance.[14] I assume that OIB is a stable function of past returns and, to alleviate concerns about

[13]Though papers like Rozeff and Kinney (1976), among others, find systematic calendar effects on returns, I do not adjust these data because daily returns are serially uncorrelated (Chordia, Roll, and Subrahmanyam, 2001). Also, for brevity, I do not present results from these regressions.

[14]This structure allows a causality from returns to imbalances, but does not allow for contemporaneous causality; because x_t precedes r_t, it is not necessary to include r_t to back out the innovation. Though a misspecified model may contaminate the innovations, the disturbance, η_t, is uncorrelated with the regressors, and the estimates are consistent. I back out η_t on a firm-by-firm basis, making possible event clustering immaterial. Unreported results (available upon request) suggest that order imbalances load negatively on previous returns, but positively on past imbalances. Finally, the model is motivated by the findings in Chordia, Roll, and Subrahmanyam (2002). One may wonder how it is the case that OIB are auto-correlated and cross-correlated with returns, yet returns are serially uncorrelated; the model in Chordia and Subrahmanyam (2004) provides an explanation.

bid-ask bounce, I use midpoint returns: $\mathrm{midpt}_t - \mathrm{midpt}_{t-1}/\mathrm{midpt}_{t-1}$, where midpt_t is the midpoint between the bid and ask quotes just prior to the last transaction on day t.[15] I explain the residual (η_t) from the AR model as the unanticipated portion of OIB (the innovation), and I interpret part of this residual as corresponding to an innovation in beliefs. Because the residual could include an unexpected liquidity trade, it may not perfectly represent a change in beliefs. Nonetheless, the part unrelated to beliefs is white noise and should not contaminate the results. Obtaining the OIB innovation allows me to examine the incremental amount of OIB that results from the event (a string of consecutive same-sign surprises) as compared to OIB on any given trading day.

While the purpose of the above adjustments is to examine the effect that a string of consecutive signed surprises has on *innovations* in OIB, and these adjustments are important and appropriate for the analysis that focuses on a short event window, I am initially interested in OIB in the quarter following the sequence of surprises, so there may be a concern that such high-frequency adjustments are inappropriate. Therefore, in Section 3.2, I repeat my basic analyses using a market-adjusted OIB, which is the simplest measure that minimizes any cross-sectional dependence that would appear if events cluster in time or if there is time variation in market OIB. Specifically, I measure the market-adjusted OIB as raw OIB for each stock on day t less the average market OIB on day t. I proceed by testing Hypotheses 1 and 2 separately for positive and negative cases. Results are presented in the next section.

3. Results

3.1. Order imbalances

Table 2 indicates that small investors trade in a manner consistent with extrapolation (Hypothesis 1). While the average OIB residual over the entire sample is zero by construction, Panel A shows that the mean OIB innovation in the quarter following a string of 2 positive announcements is 0.166, which is significantly different from zero ($t = 2.05$). The average residual increases almost monotonically up to 0.723 ($t = 4.17$) for a string of 5 consecutive positive earnings surprises.

Consistent with Barberis, Shleifer, and Vishny (1998), small investors buy significantly more after strings of positive surprises. Since it is possible that small investors purchase after *any* positive surprise, I compare these numbers to those for the group of firms that experiences only a *single* positive earnings surprise. The mean residual for this "No-string" group is −0.205.[16] A Satterthwaite difference in means test that accommodates unequal variances confirms that I can reject the null of Hypothesis 1. Results are presented in the rightmost column of Panel A. There is a significant difference between the mean daily OIB residual of each sample group and that of the "No-string" group. t-Statistics ranging from 3.91 to 6.41 are all significant at the 1% level, according with the notion that individuals extrapolate past trends. It appears

[15] I do not employ a VAR system because there is negligible serial dependence in returns (see, for example, Chordia, Roll, and Subrahmanyam, 2005).

[16] Examining firms that experience strings of positive surprises might induce a survival bias on the sample, and if the "No-string" group consists of all isolated positive surprises, results will be biased in my favor. Therefore, I also create a different "No-string" group using data from only those firms that are present for at least 40 announcements (10 years). Results remain qualitatively unchanged.

Table 2
Evidence on extrapolation

In Table 2, data for groups of firms experiencing strings of consecutive positive and negative surprises are given in Panels A and B, respectively. $\overline{\mathrm{OIB}}_{(1,63)}$ is the average daily order imbalance and $\mathrm{RET}_{(1,63)}$ is the buy-and-hold return in the quarter following the last announcement in a string of X ($2 \leqslant X \leqslant 5$) consecutive same-sign surprises for those portfolios of firms that experience the string. Day zero is the day on which the Xth surprise occurred; the subscripts on OIB and RET denote the days following. $\mathrm{SD}_{\mathrm{oib}}$, $\mathrm{SD}_{\mathrm{ret1}}$, and $\mathrm{SD}_{\mathrm{ret2}}$ each refer to the standard deviations of the variable to its immediate left. The t-statistics indicate whether the relevant variables are significantly different from 0. N refers to the number of firms experiencing the relevant string over the sample period, 1988–1998. In the penultimate column denoted $\overline{\mathrm{Size}}$, I offer the mean size of the firms experiencing the string of the respective length: I determine the average size for a firm in a given year and then take the mean size of firms at the time they experience the string. In the rightmost columns (labeled T_{DM}), I present the t-statistics from differences in means tests between $\overline{\mathrm{OIB}}$ in the relevant sample group and the "No-string" group (in the bottom row). This tests Hypothesis 1 that a string of consecutive same-sign surprises has an incremental impact on OIB, different from that of an isolated surprise. ** And * respectively indicate significance at 5% and 10%. Note that means and standard deviations of the OIB terms are multiplied by 100.

Length	$\overline{\mathrm{OIB}}_{(1,63)}$	$\mathrm{SD}_{\mathrm{oib}}$	T_{oib}	$\mathrm{RET}_{(1,63)}$	$\mathrm{SD}_{\mathrm{ret1}}$	T_{ret1}	$\mathrm{RET}_{(64,252)}$	$\mathrm{SD}_{\mathrm{ret2}}$	T_{ret2}	N	$\overline{\mathrm{Size}}$	T_{DM}
Panel A: Positive strings												
2	0.166	3.698	2.05**	0.043	0.172	11.40**	0.039	0.323	5.50**	2078	5278.21	3.91**
3	0.329	3.839	2.93**	0.025	0.235	3.64**	0.039	0.305	4.37**	1169	5501.10	4.34**
4	0.768	3.666	5.35**	0.028	0.177	4.04**	0.029	0.295	2.51**	652	5113.98	6.41**
5	0.723	3.612	4.17**	0.022	0.182	2.52**	0.027	0.309	1.82*	434	5564.98	5.15**
$\text{No-string}_{\text{pos}}$	−0.205	3.952	−4.15**	0.051	0.172	23.73**	0.081	0.678	9.56**	6407	5312.08	
Panel B: Negative strings												
2	−0.589	4.316	−2.30**	−0.034	0.213	−2.69**	0.025	0.722	0.58	284	1254.90	−2.35**
3	−0.614	4.373	−1.71*	−0.037	0.256	−1.76*	0.076	0.793	1.17	149	1128.91	−1.77**
4	−0.525	4.182	−1.15	0.016	0.605	0.24	0.002	0.486	0.04	84	1269.99	−1.20
5	−0.029	3.920	−0.05	−0.074	0.223	−2.27**	0.098	0.444	1.51	47	1295.59	−0.10
$\text{No-string}_{\text{neg}}$	0.027	4.648	0.48	−0.036	0.188	−15.97**	0.030	0.418	5.98**	6953	4986.81	

that the belief of small investors in the earnings trend becomes stronger with multiple consecutive positive surprises. This is evident through the OIB residual, which is increasingly tilted toward the buy-side. Also consistent with Barberis, Shleifer, and Vishny (1998), Barth, Elliott, and Finn (1999) find that, after controlling for level of growth, investors value firms that grow steadily more than they do firms that grow erratically.[17]

Though the mean OIB innovation appears related to strings of consecutive positive surprises, Table 2 suggests that the return over the quarter following the last announcement in the string does not increase with string-length. For positive strings, the buy-and-hold return is much lower for longer strings, consistent with the idea that more sophisticated limit-order traders (whose trades are not reflected in the OIB database) are taking countering positions. Despite the fact that OIB becomes more heavily tilted in the direction of the string, even in the immediate future, it does not appear that firms experiencing positive strings perform better as string-length increases. These results indicate that the relationship between OIB and returns might be more complicated than casual intuition would suggest.

[17]See also Shanthikumar (2005).

The results for negative strings are given in Panel B. Though there is no pattern in absolute size, the mean residual is always negative. By looking at the group of firms that experience only a single negative earnings surprise, however, the OIB residual is *positive* (0.027). This is greater than in the negative string cases, but as can be seen in the difference in means tests presented in the rightmost column of the table, the difference between the two is only statistically significant in the cases of string-lengths 2 and 3. The lack of significance is consistent with the notions that individuals are reluctant to realize losses and the risks involved in short-selling can be prohibitively high. It is not consistent, however, with Barberis, Shleifer, and Vishny (1998). Some may argue that it is not surprising that the extrapolation phenomenon does not occur after negative strings, which occur relatively infrequently. Accounting conservatism (the tendency for firms to recognize losses more quickly than gains) and managerial bath-taking incentives, for example, suggest that negative earnings will be much less frequent and larger in absolute value than positive earnings. Thus, according to these principles, firms will infrequently report strings of negative earnings. Although additional results for negative strings are available upon request, for brevity, I continue by examining whether extrapolation bias following positive strings has predictive power for subsequent returns.

3.2. Subsequent returns

In the previous section, I provide evidence in accordance with Barberis, Shleifer, and Vishny (1998) that, even after aggregating, investors appear to extrapolate following strings of consecutive positive earnings surprises. At the same time, one might notice from the sample sizes of the different string-length groups that the conditional probabilities of another positive surprise occurring increase monotonically from 26% after a non-positive surprise to 67% after 4 consecutive positive surprises. Thus, an alternative interpretation is that traders are rationally updating their beliefs and are buying more when the string-length is longer. Another possibility is that there is a slow diffusion of information: consecutive positive earnings could easily bring increased press coverage, and as small investors become aware of the firm, they buy more. To shed light on such possibilities, it is important to examine subsequent returns. If agents are acting rationally or if information is being only slowly incorporated into price, one would expect a non-negative correlation between period 1 buying activity and period 2 returns.

I now consider the correlation between period 1 OIB and period 2 returns *within* groups of firms experiencing strings.[18] Though I focus on correlations within groups rather than across groups, the (unreported) cross-correlation suggests a negative correlation between period 2 returns and period 1 OIB. Hypothesis 2 is concerned with the relation between returns in period 2 and the OIB innovation in period 1 following strings of consecutive same-sign surprises. Table 3, Panel A shows that, in all cases, the correlations between the average daily residual OIB in period 1 ($\overline{\text{OIB}}_{(1,63)}$) and the period 2 buy-and-hold return ($\text{RET}_{(64,252)}$) are *negative* and significantly different from zero.[19] The correlation is the

[18]Even *across* strings, period 2 returns are negatively correlated with period 1 OIB, though not with period 1 returns. This, too, accords with the idea that the stocks being aggressively purchased by extrapolators are underperforming those that appear to have less naïve-buyer interest.

[19]Though unreported, respective p-values for strings of 2–5 consecutive positive surprises are 0.000, 0.000, 0.005, and 0.010. Additionally, using the Spearman rank correlation coefficient, a nonparametric rank statistic, yields consistent results, and the significance remains for all cases.

Table 3
Correlation coefficients, positive strings

Table 3, Panel A gives the correlation matrices for the average daily OIB residual in period 1 ($\overline{\text{OIB}}_{(1,63)}$), the average daily OIB residual in period 2 ($\overline{\text{OIB}}_{(64,252)}$), the buy-and-hold return in period 1 ($\text{RET}_{(1,63)}$), and the buy-and-hold return in period 2 ($\text{RET}_{(64,252)}$) for the groups of firms that experience a string of consecutive same-sign surprises. Day zero is the day on which the Xth ($2 \leqslant X \leqslant 5$) surprise occurred; the subscripts on OIB and RET denote the days following. The length and the direction of the string are given at the top of each matrix. Panel B gives t-statistics from differences in correlation tests between the relevant sample group and the ''No-string'' group for positive strings using both buy-and-hold and average daily returns (top and bottom rows, respectively). This table gives results to respective tests of Hypotheses 2A and 2B (whether there is a correlation between residual OIB and subsequent returns following a string of consecutive same-sign earnings surprises and if this correlation is significantly different from the ''No-string'' group). ** Indicates significance at 5%. The sample period is 1988–1998, inclusive.

	$\overline{\text{OIB}}_{(1,63)}$	$\overline{\text{OIB}}_{(64,252)}$	$\text{RET}_{(1,63)}$
Panel A: Buy-and-hold			
		2 Positive surprises	
$\overline{\text{OIB}}_{(64,252)}$	0.259**		
$\text{RET}_{(1,63)}$	0.118**	−0.024	
$\text{RET}_{(64,252)}$	−0.134**	−0.054**	−0.106**
		3 Positive surprises	
$\overline{\text{OIB}}_{(64,252)}$	0.259**		
$\text{RET}_{(1,63)}$	0.058**	−0.025	
$\text{RET}_{(64,252)}$	−0.138**	0.068**	−0.076**
		4 Positive surprises	
$\overline{\text{OIB}}_{(64,252)}$	0.208**		
$\text{RET}_{(1,63)}$	0.106**	−0.149**	
$\text{RET}_{(64,252)}$	−0.106**	−0.068**	0.008
		5 Positive surprises	
$\overline{\text{OIB}}_{(64,252)}$	0.237**		
$\text{RET}_{(1,63)}$	0.102**	0.002	
$\text{RET}_{(64,252)}$	−0.143**	0.068	-0.170**
		Positive no-string	
$\overline{\text{OIB}}_{(64,252)}$	0.250**		
$\text{RET}_{(1,63)}$	0.182**	−0.012	
$\text{RET}_{(64,252)}$	0.005	−0.015	−0.053**

	2	3	4	5
Panel B: Differences in correlations, positive strings				
b&h	−3.77**	−3.48**	−2.28**	−2.74**
ave	−2.34**	−2.60**	−2.00**	−2.00**

strongest for string-length 5, consistent with the notion of irrational buying in period 1 due to extrapolation. Correlation coefficients higher than 0.13 in magnitude are surprising. Note that, as anticipated, in the ''No-string'' group the correlation is not significantly different from zero. One interpretation is that I am simply capturing initial underreaction in the ''No-string'' (or benchmark) case. Even though for this group there is positive correlation in buying activity between period 1 and period 2, underreaction is unlikely because the return correlation in the two periods for this group is actually negative. Further, there is no correlation between OIB in period 1 and return in period 2. The results indicate that excessive period 1 buying following strings is followed by underperformance. Similar (unreported) results are obtained using an average daily return. My results do not suggest these firms experience negative abnormal stock returns in period 2; rather, for high OIB firms, period 2 performance following strings of surprises is relatively lower than for low OIB firms.[20]

Results for Hypothesis 2B (viz., that the correlation is different and, in fact, stronger after strings of consecutive positive earnings surprises than after an isolated surprise) are presented in Table 3, Panel B. Tests examining the difference in correlations between the "No-string" group and the string samples yield significant t-statistics ranging from -2.28 to -3.77 for the groups of firms with strings of consecutive positive surprises. Thus, I reject the null hypothesis that the correlation coefficients between the sample groups and the "No-string" sample are equivalent.

One might also notice that the negative correlation between the OIB innovation and returns in the following period is stronger than that between returns in the two periods. Two points are worth noting in this regard. First, individual stock returns are influenced by trading activity as well as the arrival of public information. The variation induced by the latter may attenuate the return correlation across the two periods. Second, the variable I use from the OIB database neglects the size of the trade. Therefore, the relative weight of larger traders, who display less evidence of psychological biases, is reduced. Regardless, the negative correlations suggest that the people in the imbalance database who appear to be trading most aggressively according to the extrapolation heuristic are designing perverse trading strategies.

In line with White (1980), I present t-statistics calculated using asymptotically consistent standard errors from regressing the buy-and-hold return in period 2 on the average OIB innovation in period 1 for the groups of firms experiencing positive strings. Table 4, Panel A shows the coefficients are significant (evidenced by t-statistics ranging from -2.56 to -5.46). Moreover, the coefficient for the "No-string" group is not only smaller (in magnitude) than that in any of the above cases, but it is also insignificant ($t = 0.18$).[21] Results using returns adjusted according to the market model are qualitatively similar and can be found in Table 4, Panel B. One explanation for this result is that stocks with relatively high average OIB in period 1 earn relatively lower subsequent returns when compared to those with lower mean OIB because they have lower exposure to systematic risk. I therefore compare the second period market betas of those stocks with high average OIB to those with low average OIB. Unreported results suggest not only that the average market betas for the higher OIB groups are statistically indistinguishable from those for the lower OIB groups, but also that there is no significant change in market betas from the one-year window before the last surprise in a string to the 1-year window after the last surprise in a string for any of the string-length groups. Thus, shifting allocations based on changing risk does not seem to account for the results. (I use market beta rather than total

[20]Even if I alter the window to begin one or two trading days later, the results still obtain. This suggests that, if one wishes to make a case that rebalancing is done as a result of a change in the risk-expected return tradeoff, there is still the issue that agents are slow to make this adjustment.

[21]Results using average daily returns or returns that are adjusted according to the Fama and French (1993) 3-factor model are qualitatively unchanged and are available upon request.

Table 4
Regression results I

Table 1 reports regression results for the sample of firms experiencing strings of consecutive positive surprises. In Panel A, I provide intercept and coefficient estimates from regressing the buy-and-hold return in period 2 ($\mathrm{RET}_{(64,252)}$) on the average daily OIB residual in period 1 ($\overline{\mathrm{OIB}}_{(1,63)}$) following strings of X consecutive positive surprises ($2 \leqslant X \leqslant 5$). Day zero is the day on which the Xth surprise occurred; the subscripts on OIB and RET denote the days following. The relevant equation is

$$\mathrm{RET}_{(64,252)} = \alpha + \beta\,\overline{\mathrm{OIB}}_{(1,63)} + \varepsilon.$$

In Panel B, I use the risk-adjusted buy-and-hold return (returns are adjusted according to the market model). In Panel C, I perform OLS while controlling for book-to-market effects, defined as the book value of equity divided by the market value of equity for a given quarter. t-Statistics are presented below the point estimates. * And ** indicate significance at 10% and 5%, respectively.

	2	3	4	5	No-string$_{\mathrm{pos}}$
Panel A: Buy-and-hold returns					
Intercept[a]	4.11	4.11	3.46	3.64	8.10
t-stat	5.19**	4.32**	2.80**	2.24**	4.66**
Beta[b]	−11.64	−11.00	−8.66	−12.41	0.79
t-stat	−5.46**	−4.44**	−2.56**	−2.78**	0.18
R^2(%)	1.79	1.91	1.11	2.05	0.07
Panel B: Risk-adjusted returns					
Intercept[a]	−9.84	−11.48	−10.59	−11.26	−5.38
t-stat	−13.94**	−12.68**	−8.97**	−8.23**	−2.95**
Beta[b]	−1.86	−2.43	−2.52	−2.36	−1.10
t-stat	−3.20**	−3.11**	−2.40**	−1.89*	−0.87
R^2(%)	0.56	0.83	0.87	0.87	0.18

	2	3	4	5
Panel C: Value v. growth				
Intercept[b]	1.56	1.39	0.16	0.59
t-stat	8.14**	6.69**	4.63**	3.17**
Beta$_{\mathrm{OIB}}$	−1.23	−1.28	−0.95	−1.04
t-stat	−4.32**	−4.33**	−4.40**	−3.94**
Beta$_{\mathrm{BTM}}$[b]	−1.22	−1.45	−0.80	−0.77
t-stat	−3.48**	−3.69**	−2.74**	−2.14**
R^2(%)	2.98	3.47	1.85	1.86

[a]Point estimate is multiplied by 100.
[b]Point estimate is multiplied by 10.

volatility because of the usual argument that idiosyncratic risk is diversifiable. Nonetheless, unreported estimates from a GARCH(1,1) model are largely consistent with the market beta results. (Results from the GARCH model are available upon request.))

Even if investors use the extrapolation heuristic to choose which stocks to consider as Barberis, Shleifer, and Vishny (1998) suggest, that their trades consistently yield inferior subsequent performance is inconsistent with the rational paradigm, unless there is a correlation between buying activity and some risk factor. For example, maybe it is the string of positive surprises in conjunction with some other cross-sectional attribute that excites these traders who intensively purchase some stocks over others. To test this, I explore the relationship between book-to-market and period 1 OIB (Fama and French, 1993; Lakonishok, Shleifer, and Vishny, 1994). I find that low OIB firms tend to have high book-to-market values, compared to firms with relatively larger OIB. This result suggests that traders initiating market orders have a propensity toward growth stocks; it is also consistent with Lakonishok, Shleifer, and Vishny (1994) who find evidence that investors rely too heavily on the past growth rates for such firms. Additionally, the results relating OIB to subsequent returns further support the notion of extrapolation, and the story postulated in Lakonishok, Shleifer, and Vishny (1994): buying pressure in period 1 bids up the price of growth stocks relative to their fundamental value, which leads to subsequent underperformance. Nonetheless, even *after* controlling for book-to-market, my regression results still obtain (Table 4, Panel C). This result suggests that there is a statistically significant incremental effect beyond that of growth stocks underperforming value stocks in post-portfolio formation periods. As another possibility, I consider the model of Cooper, Gutierrez, and Hameed (2004) that postulates that conditioning on whether the market is in a "UP or DOWN" state (measured by previous 12-month market excess return) may make investor biases more prevalent. While I find that investors extrapolate more in up markets (i.e., when strings of earnings surprises are accompanied by up markets, average net buying increases), I do not find any difference in the effect of buying activity on subsequent returns when I account for market state.

Overall, even though it appears that the OIB residual is greater, on average, after strings of consecutive positive surprises, returns are not superior in the subsequent period. The fact that the average OIB residual in period 1 (which is positive after positive strings) is positively correlated with OIB in period 2 indicates that there is a group of extrapolators who continue to purchase in period 2. Yet, the negative correlation between OIB in period 1 and returns in period 2 indicates that the more investors buy a stock in period 1, the lower are its subsequent returns.[22] To explain this, I suggest that more sophisticated investors (whose offsetting trades are masked in my database) cause negative price-pressure, while small traders are purchasing stocks that have already appreciated. The larger traders enter in period 2, after there is a significant enough run-up in prices to justify short sale constraints.

In order to gain a better appreciation of the economic significance of the post-string negative correlation between OIB and subsequent returns, I sort firms according to the average daily OIB residual in period 1 and examine the difference in returns in period 2 for each group. I measure high versus low OIB stocks by ranking stocks based on the average residual OIB in the quarter following the announcement and sorting the sample into thirds. Stocks that fall into the upper and lower thirds are denoted high and low OIB stocks, respectively. As can be seen in Fig. 1, the group with the low average OIB residual (group 1) has a significantly higher return in period 2 than does the group of firms with high average residual OIB (group 3) for all string groups. As an example, the average difference in daily returns between group 1 and group 3 for the firms experiencing a string of 3 positive announcements is 0.057% per day. The annual return difference

[22] Hirshleifer, Myers, Myers, and Teoh (2004) find similar results in that individual buying is related to negative returns.

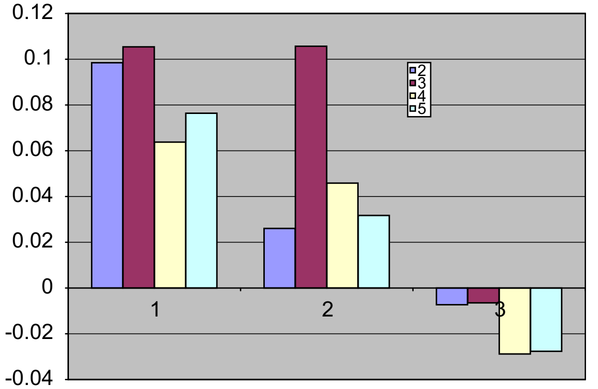

Fig. 1. Graphs the period 2 buy-and-hold return for firms sorted according to period 1 OIB. Groups 1-3 on the *X*-axis refer to the respective groups sorted by low, medium, and high OIB for the indicated string-length. (A stock is designated as high, medium, or low OIB if it falls in the top, middle, or bottom third of the sample when sorted according to OIB during the quarter following the announcement.) The period 2 return is plotted on the *Y*-axis.

approximates 15.4%, which on a risk-adjusted basis roughly corresponds to 12.3%. This is modestly greater than the average return on the market over the same period. Unreported results suggest that if I split the sample into deciles based on period 1 OIB the average annual return across the groups of firms experiencing 2 through 5 consecutive surprises is 16.68%, almost 5% higher than it is for the "No-string" group. Sharpe ratios of zero-cost portfolios formed by purchasing the stocks in the low OIB group and shorting those in the high OIB group over period 2 throughout the sample period range from 0.45 to 0.72 for the groups of firms experiencing 2 through 5 consecutive positive surprises. My results indicate that institutions with low transactions costs could improve their performance by overweighting those stocks with low OIB following strings and selling those with high OIB. At the same time, it does not appear that my results are fully able to explain documented patterns of short-run positive auto-correlation and long-run reversal.

As indicated in Section 2.2, I repeat the primary analyses above using a less complex adjustment to the OIB series. In the exercise that follows, I measure "market-adjusted OIB" as each stock's raw OIB on day t (i.e., the number of buys less the number of sells divided by the total number of transactions) less the average market OIB on day t (i.e., the equal-weighted average OIB over the stocks in my sample). This alternative adjustment simply eliminates any time series variation that may arise in market OIB from the OIB of the sample stocks. Results using this variable are presented in Table 5 where, for each string-length group and the "No-string" group, I show the average OIB over period 1, the correlation between period 1 OIB and period 2 returns, and the coefficients from the regressions that relate period 2 returns to period 1 OIB. Panels A and B, which respectively give results for positive and negative strings, indicate that my primary results are essentially unchanged. In particular, for positive strings, average market-adjusted OIB is monotonically increasing in string-length (from 0.021 for the stocks that experience 2 consecutive surprises to 0.050 for those that experience 5 consecutive positive surprises), but there is no pattern for negative strings. Additionally, for positive surprises, p-values ranging from 0.006 to 0.044 suggest significantly negative correlations between period 1 OIB and period 2 returns for each of the string-length groups, but not for the "No-string"

Table 5
Market adjusted OIB

Table 5 reports the primary results of Tables 2–4 using an alternative measure of OIB. Here, OIB is measured as number of buys less number of sells divided by total number of transactions for a given stock on a given day (i.e., raw OIB), less the market average OIB on that same day. As in Table 2, average period 1 OIB is presented, and t-statistics that test whether these estimates are significantly different from zero are given in parentheses below. The correlation coefficient between period 1 OIB and period 2 returns (as in Table 3) is presented and p-values (indicating significance) are given in parentheses below. Finally, the Betas from Table 4 are given, with t-statistics in parentheses below. All results are provided for string-length X, where $2 \leqslant X \leqslant 5$, as well as for the "No-string" group. Panel A gives results for positive strings and Panel B shows results for negative strings.

	2	3	4	5	No-string_{pos}
Panel A: Positive strings					
$\overline{\text{OIB}}_{(1,63)}$	0.0208	0.0258	0.0309	0.0497	−0.0049
	(8.43)	(8.45)	(8.20)	(10.35)	(−0.88)
$\text{Corr}_{\text{OIB,RET}}$	−0.061	−0.060	−0.087	−0.091	−0.009
	(0.006)	(0.032)	(0.015)	(0.044)	(0.836)
$\text{Beta}_{\text{OIB}}{}^{\text{a}}$	−1.55	−1.63	−2.41	−2.41	−0.25
	(−2.75)	(−2.14)	(−2.44)	(−2.02)	(−0.21)
Panel B: Negative strings					
$\overline{\text{OIB}}_{(1,63)}$	0.0214	0.0186	0.0068	0.0138	0.0010
	(8.44)	(5.39)	(1.48)	(2.36)	(0.16)
$\text{Corr}_{\text{OIB,RET}}$	−0.068	−0.029	−0.059	−0.074	0.001
	(0.002)	(0.316)	(0.128)	(0.135)	(0.979)
$\text{Beta}_{\text{OIB}}{}^{\text{a}}$	−2.06	−0.81	−4.93	−1.92	0.03
	(−3.06)	(−1.00)	(−1.52)	(−1.50)	(0.03)

[a]Point estimate is multiplied by 100.

group. Finally, the "OIB β's" are also significantly negative for each of the positive string-length groups, though this is not the case for the "No-string" group (or for any of the negative groups with string-length greater than 2).

I have thus far focused on a one-year period subsequent to returns, but have not examined whether my results have any implications for a shorter event window. I therefore analyze order imbalances and market-adjusted returns in the 3 days before and after the last surprise in the earnings string.[23] The short-term results mirror those of the longer-term. In particular, after strings of positive surprises, there is strong buying activity both before and after the announcement. This buying activity increases with string-length. As shown in Table 6, Panel A, on all days surrounding the event of positive surprises, there is significantly more buying activity for longer strings. For all days in the event window, the t-statistic testing for a difference in means between the sample of firms experiencing five consecutive surprises and that experiencing only one is significantly positive (see column labeled T_{DMret}). For negative strings, prior to the surprise, there is significantly more selling after the 5th consecutive negative surprise than after an isolated negative surprise. However, this effect largely dissipates after the earnings announcement. This result suggests that perhaps people are responding to rumors of a negative surprise before the event and that this effect is stronger for more consecutive negative surprises. Yet,

[23]In this analysis, I return to the OIB series described in Section 2.2, which is adjusted for calendar regularities and seasonal effects.

Table 6
Short term results

Table 6 reports averages for daily OIB and the S & P adjusted daily return for strings of length 5 and length 1. t-Statistics to the right of each variable test whether the relevant variable is significantly different from zero. t-Statistics to a difference in means test between the two string groups are shown under the columns labeled T_{DM} for OIB and returns, respectively. Day 0 is the day of the last surprise in the string. ** Indicates significance at 5%.

Day	OIB_5	T_{oib5}	OIB_1	T_{oib1}	T_{DMoib}	RET_5	T_{ret5}	RET_1	T_{ret1}	T_{DMret}
Panel A: Positive strings										
−3	0.032	6.26**	−0.031	−7.90**	9.78**	0.001	1.68	−0.000	−1.19	2.06**
−2	0.027	5.18**	−0.018	−4.57**	6.89**	0.001	1.58	−0.000	−0.53	1.56
−1	0.025	4.91**	−0.036	−9.35**	9.60**	0.002	5.19**	0.001	3.53**	2.22**
0	0.038	7.92**	0.004	0.95	5.70**	0.004	9.99**	0.003	9.33**	3.04**
1	0.031	6.13**	−0.016	−3.93**	6.56**	−0.001	−1.58	0.001	2.65**	2.73**
2	0.037	7.43**	−0.009	−2.39**	7.32**	0.001	1.45	0.000	0.91	0.73
3	0.029	5.97**	0.002	0.64	4.27**	0.000	0.02	0.000	0.70	−0.36
Panel B: Negative strings										
−3	−0.053	−6.47**	−0.032	−7.92**	−2.25**	−0.003	−4.51**	−0.001	−2.22**	−3.30**
−2	−0.047	−5.84**	−0.023	−5.70**	−2.72**	−0.001	−1.61	−0.001	−2.75**	−0.35
−1	−0.052	−6.56**	−0.023	−5.71**	−3.31**	−0.000	−0.65	0.000	1.21	−1.07
0	−0.020	−2.45**	0.008	2.12**	−3.21**	0.002	3.10**	0.002	5.66**	0.80
1	−0.010	−1.20	−0.019	−4.77**	1.06	0.002	3.09**	−0.000	−0.50	3.05**
2	−0.028	−3.46**	0.001	0.22	−3.20**	−0.001	−1.43	−0.001	−3.36**	−0.22
3	−0.009	−1.10	−0.009	−2.22**	−0.02	−0.001	−1.45	−0.002	−5.78**	0.89

consistent with the idea that investors hold on to loser stocks and are reluctant to realize losses (Odean, 1998), people are less eager to sell after the negative event is realized. Results are given in Panel B.

When I examine the effects of buying and selling activity on returns (given in the right hand side of the table), for strings of positive surprises, there is a significantly positive effect on returns on the day of and the day before the event. However, as was the case for the longer term results, the relationship becomes negative the day after.[24] Further, there is no consistent effect of OIB on returns following negative surprises.

3.3. Sensitivity analyses

A primary concern is that while controlling for seasonalities and other short-term dependencies in modeling stock-by-stock imbalances, I may be taking away power from the test since strings of earnings surprises are low-frequency events. Thus, in Table 7, I provide the means and correlations for the groups of positive and negative strings *without* making any adjustment to the OIB series. Though in previous tables I analyze OIB and returns over a fixed time period (i.e., period 1 was represented by the 63 days after an announcement), in this table, I account for the fact that announcements may not be separated by exactly 63 days. Nonetheless, the results are qualitatively similar to those presented in Tables 2 and 3. For positive string groups, OIB over period 1 increases from

[24]The fact that these results are so consistent with the longer term results raises the issue of whether the long-run effect is primarily due to what happens in the first couple of days surrounding the announcement. However, per footnote 21, altering the trading window to begin a couple of days later does not qualitatively affect my results.

Table 7
Summary statistics and correlation coefficients, raw OIB series
Table 7 provides summary statistics for the unadjusted OIB in the period after a string of a given length before the next earnings surprise, including a t-statistic testing whether the value is significantly different from zero. It also shows summary statistics for the holding period return in the period which begins on the date of the next earnings announcement after the string until the end of the year. The correlation coefficient between period 1 OIB and period 2 returns is given in the right hand column of each matrix, and p-values for the correlation are given below. Bold p-values indicate a significance level greater than 10%. PSURX (NSURX) denotes a string of X consecutive positive (negative) surprises, where $2 \leqslant X \leqslant 5$. The sample period is 1988–1998, inclusive.

	N	Mean	STD	t-stat	Corr		N	Mean	STD	t-stat	Corr
PSUR2						NSUR2					
OIB_1	7641	0.0202	0.1153	15.31	−0.0919	OIB_1	5743	0.0058	0.1342	3.28	−0.0482
RET_2	5807	0.0511	0.3399	11.46	**0.0001**	RET_2	4462	0.0314	0.3276	6.40	**0.0013**
PSUR3						NSUR3					
OIB_1	4529	0.0281	0.1103	17.14	−0.1148	OIB_1	3119	0.0075	0.1352	3.10	−0.0529
RET_2	3407	0.0349	0.3457	5.89	**0.0001**	RET_2	2412	0.0370	0.3396	5.35	**0.0094**
PSUR4						NSUR4					
OIB_1	2785	0.0370	0.1051	18.58	−0.1257	OIB_1	1782	0.0085	0.1338	2.68	−0.0576
RET_2	2064	0.0247	0.3522	3.19	**0.0001**	RET_2	1378	0.0441	0.3341	4.90	**0.0325**
PSUR5						NSUR5					
OIB_1	1775	0.0460	0.0991	19.56	−0.1408	OIB_1	1069	0.0054	0.1343	1.31	−0.0608
RET_2	1287	0.0221	0.3588	2.21	**0.0001**	RET_2	832	0.0603	0.3414	5.09	**0.0795**

0.020 to 0.046 as firms experience from 2 to 5 consecutive positive surprises. The difference in these means is statistically significant ($t = 9.57$). Further, for positive strings, the negative correlations between period 1 OIB and period 2 returns increase in magnitude from −0.09 to −0.14 as the string-length increases from 2 to 5. As before, there is no monotonic pattern in buying activity after negative strings.

There may be some concern that a contemporaneous overlap in firms experiencing strings of consecutive same-sign surprises could drive the results. Indeed, many of the strings occur during the Internet boom. However, the sample comes from NYSE firms, making it unlikely that the bubble in the technology sector is responsible for this result. Regardless, event-time imbalances may not be independent, invalidating the above t-statistics. To correct for possible clustering, I perform the following Fama and MacBeth (1973) style regression:

$$R_{j,t} = \alpha_t + \beta_1 \,\text{sizeret}_{j,t} + \beta_2 \,\text{indret}_{j,t} + \beta_3 \,\text{string}\, X_{j,t} + \beta_4 \,\overline{\text{OIB}}_{j,t} \,\text{string}\, X_{j,t} + \varepsilon_t,$$

where $R_{j,t}$ is the return for firm j in month t, $\text{sizeret}_{j,t}$ is the return of the size decile to which firm j belongs in month t, $\text{indret}_{j,t}$ is the month t return of the industry portfolio to which firm j belongs, $\text{string}\, X_{j,t}$ is a dummy variable that takes on the value 1 if a firm experiences the Xth ($2 \leqslant X \leqslant 5$) surprise in a string of consecutive positive surprises in the quarter prior to month t, and $\text{OIB}_{j,t}\, \text{string}\, X_{j,t}$ is an interaction variable between the dummy variable $\text{string}\, X_{j,t}$ and average past OIB.

Results that shed light on potential horizon effects are presented in Table 8. Panel A shows the number of strings of a given length in a given year and Panel B presents results using past 3-month average residual OIB. Consistent with Bernard and Thomas (1989) and indicated by t-statistics ranging from 4.98 to 9.24, returns tend to be high in the period

Table 8
Monthly return regressions
Table 8, Panel A provides the number of strings of a given length in the designated year (left hand column). Panel B reports the results from the following Fama-MacBeth regression:

$$R_{j,t} = \alpha_t + \beta_1\,\text{sizeret}_{j,t} + \beta_2\,\text{indret}_{j,t} + \beta_3\,\text{string}\,X_{j,t} + \beta_4\,\overline{\text{OIB}}_{j,t}\,\text{string}\,X_{j,t} + \varepsilon_t,$$

where $R_{j,t}$ is the return for firm j in month t, $\text{sizeret}_{j,t}$ is the return of the size decile to which firm j belongs in month t, $\text{indret}_{j,t}$ is the month t return of the industry portfolio to which firm j belongs, string $X_{j,t}$ is a dummy variable that takes on the value 1 if a firm experiences the Xth consecutive positive surprise in the quarter prior to month t, and $\overline{\text{OIB}}_{j,t}$ string $X_{j,t}$ is an interaction variable between the dummy variable, string $X_{j,t}$, and past 3-month OIB ($2 \leqslant X \leqslant 5$). I give the mean coefficient for each string-length, including results using a dummy variable that takes on the value 1 for an isolated positive surprise (iso). For brevity, I do not report the intercept or the coefficients for the other independent variables, though they are available upon request. The sample period is 1988–1998, inclusive. N is the number of months, and ** indicates significance at 5%.

Year	string2	string3	string4	string5
Panel A: Distribution of strings across years				
1988	169	99	75	21
1989	182	87	45	54
1990	151	68	27	17
1991	134	62	33	19
1992	141	76	54	26
1993	181	90	40	32
1994	223	137	67	52
1995	241	146	83	49
1996	283	166	87	48
1997	233	153	92	74
1998	140	85	49	42
Total	2078	1169	652	434

	iso	2	3	4	5
Panel B: Regression coefficients					
string X	0.84	1.08	0.95	1.23	1.01
t-stat	4.98**	9.24**	6.29**	7.39**	5.13**
OIB string X	−3.97	−10.47	−12.23	−18.55	−13.54
t-stat	−0.73	−4.52**	−4.08**	−4.95**	−2.87**

following any positive surprise (whether isolated or in a string). More relevant to this study, however, is that in the positive string cases, the coefficients on the interaction terms, which account for past 3-month OIB, are significantly negative: the t-statistics associated with these coefficients range from −2.87 to −4.95. Note that the negative return correlation between OIB and subsequent returns is absent following isolated surprises ($t = -0.73$). Again, these results are consistent with the notion that individuals extrapolate trends of performance and, according to subsequent returns, purchase too aggressively. In particular, the negative correlation between OIB and subsequent returns is consistent with investor overreaction.[25] As another possibility, extreme observations in my moderately-sized sample could potentially impact the OLS estimation. Thus, I also present results from

[25] I also perform the original OLS analysis using clustered standard errors. The results are qualitatively unchanged and are available upon request.

Table 9
Regression results II
Table 9 reports regression results for the sample of firms experiencing strings of consecutive positive surprises. In this table, the Reweighted Least Squares/Least Trimmed Squares (RLS/LTS) method of Rousseeuw (1984) and Rousseeuw and Leroy (1987) is used for estimation. In Panel A, I provide intercept and coefficient estimates from regressing the buy-and-hold return in period 2 ($RET_{(64,252)}$) on the average daily OIB residual in period 1 ($\overline{OIB}_{(1,63)}$) following strings of X consecutive positive surprises ($2 \leqslant X \leqslant 5$). Day zero is the day on which the Xth surprise occurred; the subscripts on OIB and RET denote the days following. The relevant equation is

$$RET_{(64,252)} = \alpha + \beta\,\overline{OIB}_{(1,63)} + \varepsilon.$$

In Panel B, risk-adjusted returns are obtained from the market model. * And ** indicate significance at 10% and 5%, respectively.

	2	3	4	5
Panel A: Buy-and-hold returns				
Intercept[a]	2.54	2.13	1.55	2.03
t-stat	4.34**	2.75**	1.56	1.76*
Beta[b]	−1.25	−1.26	−2.04	−1.99
t-stat	−2.59**	−1.91*	−2.30**	−1.88*
F-stat	6.72**	3.65*	5.28**	3.52*
Panel B: Risk-adjusted returns				
Intercept[a]	−7.59	−8.90	−10.55	−8.23
t-stat	−13.55**	−12.21**	−10.85**	−8.31**
Beta[b]	−0.76	−1.26	−2.70	−1.86
t-stat	−1.67*	−2.05**	−3.11**	−2.04**
F-stat	2.78*	4.19**	9.69**	4.17**

[a]Point estimate is multiplied by 100.
[b]Point estimate is multiplied by 10.

the robust regression technique of reweighted least squares/least trimmed squares (RLS/LTS), developed by Rousseeuw (1984) and Rousseeuw and Leroy (1987).[26] As can be seen from Table 9, my results are robust to this procedure.

As mentioned in Section 2.1, it is well-documented that there is auto-correlation in forecast errors. Chan, Frankel, and Kothari (2004) suggest that, in recent years, analysts have manipulated their forecasts toward positive surprises because they face severe conflicts of interest, and earnings disappointments represent particularly bad news (which may dampen clients' interest in stocks). Because errors are significantly auto-correlated up to the third lag, I correct for serial correlation in positive surprises by examining strings of consecutive positive surprises wherein each *actual* earnings surprise in the string is greater than that predicted by an AR(3) model. That is, on a firm-by-firm basis, I account for the predictable portion of the forecast error, and then examine whether the residual is positive or negative. If the residual is greater than zero, then the surprise is positive. This leaves us with a drastically altered sample size (3166 and 842 firms in the respective samples of string-lengths 2 and 5, for example). In the case of longer strings, the average residual OIB in period 1 is statistically different from that of the ''No-string'' group. *t*-statistics for the

[26]LTS estimation consists of minimizing the h smallest squared residuals, where $h = (N + n + 1)/2$, N and n being the numbers of observations and regressors, respectively.

Table 10

Summary statistics and correlations, auto-correlation in surprises

Table 10 shows data for groups of firms experiencing strings of positive surprises, after accounting for auto-correlation in earnings surprises. $\overline{\text{OIB}}_{(1,63)}$ is the average daily order imbalance in the quarter following the last announcement in a string of X $(2 \leqslant X \leqslant 5)$ consecutive positive surprises for those portfolios of firms that experience the string. $\text{RET}_{(1,63)}$ is the buy-and-hold return over the same period. Day zero is the day on which the Xth surprise occurred; the subscripts on OIB and RET denote the days following. SD_{oib} and SD_{ret} refer to the standard deviation of $\text{OIB}_{(1,63)}$ and $\text{RET}_{(1,63)}$, respectively. t-Statistics to the right of the standard deviations test whether the relevant estimates are significantly different from zero. N refers to the number of firms experiencing the relevant string over the sample period, 1988–1998. In the penultimate column, denoted $\overline{\text{Size}}$, I offer the mean size of the firms experiencing the string of the respective length: I determine the average size for a firm in a given year and then take the mean size of firms at the time they experience the string. In the column labeled T_{DM}, I present the t-statistics from differences in means tests between OIB in the relevant sample group (in the respective row) and the "No-string" group (in the bottom row). In the rightmost column labeled ρ, I present the correlation coefficient between period 1 OIB and period 2 returns. Means and standard deviations of OIB are multiplied by 100. ** Indicates significance at 5%.

String-length	$\overline{\text{OIB}}_{(1,63)}$	SD_{oib}	T_{oib}	$\overline{\text{RET}}_{(1,63)}$	SD_{ret}	T_{ret}	N	T_{DM}	ρ
2	−0.073	3.905	−0.89	0.026	0.185	6.67**	3166.0	39	−0.131**
3	−0.108	3.021	−1.17	0.012	0.195	2.01**	2253	1.00	−0.129**
4	0.348	3.526	2.86**	0.012	0.188	1.85	1066	3.76**	−0.077**
5	0.531	3.612	10.22**	0.023	0.166	9.63**	842	4.69**	−0.112**
$\text{No-string}_{\text{pos}}$	−0.107	3.863	−0.00	0.033	0.192	0.00	4830		−0.030

difference in means tests are, respectively, 0.39, 1.00, 3.76, and 4.69 for string-lengths 2–5. These results suggest that, *after* taking into account the positive auto-correlation in forecast errors, small investors buy relatively more following longer strings of consecutive positive surprises. As can be seen in Table 10, correlation coefficients between average residual OIB over period 1 and period 2 buy-and-hold returns range from −0.08 to −0.13, all of which are significantly different from zero. Given that analysts might "manage" earnings, a surprise that "just beats" earnings forecasts may not be equivalent to a larger surprise. However, in another study, I examine the size of surprise relative to buying and selling pressure. While a larger surprise (in magnitude) induces more trading activity, it does not affect the relationship between post-surprise OIB and subsequent returns, thus implying that the results of this paper would be unchanged if I were to eliminate negligible forecast errors.

Since it may be costly for individuals to gather information about the firms in which they might invest, I also analyze whether the correlation results are more prevalent in firms wherein less information is readily available (see, for instance, Chen, Hong, and Stein, 2002). To do this, I sort the sample by analyst following and size. Unreported results suggest the average number of analysts following a stock is increasing with string-length. The results also suggest that the negative correlations between OIB and subsequent returns are, in fact, stronger for the group of firms with lower analyst following, supporting the notion that biases are seen more in trading stocks surrounded by greater uncertainty (see, also, Hong, Lim, and Stein, 2000; Einhorn, 1980). Splitting the sample into relatively large and small firms provides somewhat surprising results. Overall, the negative correlation seems stronger for bigger firms. I believe this result is an artifact of the sample, which is composed of large NYSE firms. If there were a greater discrepancy between the size of small and large firms in the sample, I would expect different results. Further unreported results show that no discernable pattern emerges after splitting the sample according to turnover, which suggests that turnover (volume) does not drive the results.

Finally, because of the difference in how OIB measured in dollar value treats large trades relative to OIB determined by number of transactions, I also examine the hypotheses using the former OIB variable. This variable places relatively more weight on larger trades than does OIB measured by number of transactions (OIB_{numst}). To maintain consistency, I scale the dollar value of OIB by the dollar volume traded in the relevant stock on the relevant day. OIB measured in dollars yields results that look quite different from OIB measured in number of transactions. Specifically, larger traders do *not* buy significantly more following a string compared to after an isolated positive surprise. These unreported results imply that larger traders do not extrapolate in the way that smaller traders do and that larger traders are more sophisticated in that their trades do not lead to relatively lower subsequent returns.

4. Concluding remarks

A growing literature addresses how investor biases can affect asset prices. I contribute to this literature by presenting evidence on the direct manifestation of extrapolation bias in trading activity, which has a prominent role in the Barberis, Shleifer, and Vishny (1998) model. Consistent with Barberis, Shleifer, and Vishny (1998), which suggests that investors may perceive patterns in random sequences, my results imply that individuals extrapolate past strings of positive news (measured by the number of consecutive positive earnings surprises that a firm experiences). The fact that investors are less likely to extrapolate negative news is in accordance with both a disposition effect, wherein agents are loath to sell stocks that have experienced negative strings and concomitant downward price moves, and the idea that short sale constraints make it difficult to sell un-owned stocks following strings of negative earnings performance. I also find that stocks with relatively lower OIB outperform and tend to have higher book-to-market ratios than stocks with relatively higher OIB, especially following strings of consecutive positive earnings surprises. These results are consistent with the extrapolation hypothesis of Lakonishok, Shleifer, and Vishny (1994) (see also Skinner and Sloan, 2002). Though the relation I uncover between OIB and subsequent returns is statistically significant, it is unlikely that its economic significance can justify the perceived patterns of short-run positive auto-correlation and long-run reversal that Barberis, Shleifer, and Vishny (1998) set out to explain. At the same time, institutions with low transactions costs might improve their performance by overweighting those stocks with low OIB following strings and selling those with high OIB.

I find that trading behavior (measured by OIB) depends on the history of quarterly earnings surprises. Some of the results may be consistent with a rational framework. In isolation, the hypotheses that people buy (sell) more after positive (negative) news do not imply irrational behavior. Such behavior may be predicted by a rational model wherein agents update their conditional expected return and rebalance their portfolios. In particular, Brav and Heaton (2002) warn that, empirically, drift caused by an uncertain investor subject to "rational learning" may appear similar to one caused by an extrapolative investor. Moreover, papers such as Cochrane, Longstaff, and Santa-Clara (2003) predict risk and return changes after informational events. Nonetheless, both types of papers are silent regarding my finding that net order flow after long strings is negatively correlated with subsequent returns; i.e., these models do not address why stocks would be more prone to such negative correlation as string-length increases. Finally, the equilibrium results of such models are achieved by way of a Walrasian market clearing condition and, thus, do not disentangle buyer-initiated trades from sell-initiated ones. While my results do not appear to be driven by changes in risk, it would be interesting to study whether there is a change in risk perception of the investors in the given OIB groups or whether ‘‘strings’’ bring new investors to the market. I leave this for another paper.

Another point worth considering is that Hvidkjaer (2005) finds that with a short formation period, initial selling pressure of winners is followed by delayed buying pressure. As the formation period is lengthened, however, initial selling pressure disappears. Since increasing string-length is similar to increasing the formation period of a momentum portfolio, it would be interesting to explore whether my results are driven by a delayed response to surprises earlier in the string. At the same time, the correlation between OIB in period 1 and returns in period 2 is negative, casting doubt on whether individuals underreact (see, for example, Bernard and Thomas, 1989). Instead, the negative correlation between OIB and subsequent returns combined with the positive correlation between period 1 and period 2 OIB suggests that there is persistence in buying after a string of positive surprises, according with the idea that small investors extrapolate to the point that they overreact.

For future research, a decomposition of earnings errors into accruals and cash flows and further relating my findings to other heuristic-based biases such as anchoring and conservatism should prove to be useful exercises. Disaggregated data on individuals and institutions also would provide a greater understanding of the identity of agents that exhibit biased investing behavior. Finally, one might compare the results presented in this paper with results obtained from analyzing other sequences of earnings surprises.

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