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Streaks in Earnings Surprises and the Cross-Section of Stock Returns

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The gambler's fallacy [Rabin, M. 2002. Inference by believers in the law of small numbers. *Quart. J. Econom.* **117**(3) 775–816] predicts that trends bias investor expectations. Consistent with this prediction, we find that investors underreact to streaks of consecutive earnings surprises with the same sign. When the most recent earnings surprise extends a streak, post-earnings-announcement drift is strong and significant. In contrast, the drift is negligible following the termination of a streak. Indeed, streaks explain about half of the post-earnings-announcement drift in our sample. Our results are robust to more general definitions of trends than streaks and a battery of control variables including the magnitude of earnings surprises and their autocorrelation. Overall, post-earnings-announcement drift has a significant time-series component that is consistent with the gambler's fallacy.

Key words: trends; streaks; gambler's fallacy; post-earnings-announcement drift
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1. Introduction

The quasi-Bayesian model of Rabin (2002) demonstrates that the order in which prior information is received can influence investor expectations. In particular, Rabin (2002) predicts that investors underreact to trends as a result of the gambler's fallacy. A classic example of this fallacy is when gamblers at a roulette wheel incorrectly believe that black is more likely to occur than red following a string of red draws. Intuitively, the gambler's fallacy is the belief that trends require immediate "balancing" by the opposite outcome. The justification for such balancing is to ensure the distribution of prior outcomes reverts toward a more symmetric distribution that conforms to one's prior beliefs.

Durham et al. (2005) report evidence of the gambler's fallacy in their study of college football wagers. In an experimental setting, Asparouhova et al. (2009) find stronger support for Rabin's (2002) gambler's fallacy than the representativeness bias assumed by Barberis et al. (1998; abbreviated BSV hereafter). Whereas the gambler's fallacy predicts an underreaction to trends, the representativeness bias results in the incorrect belief that trends will continue, with this extrapolation resulting in an overreaction to trends. This paper uses past earnings surprises (SURPs) to test the conflicting predictions of the gambler's fallacy and representativeness. To our knowledge, we are the first to employ earnings surprises to evaluate these theories. The frequency and salience of quarterly earnings surprises provides an ideal setting to test whether trends bias investor expectations. Indeed, BSV illustrate their model by conditioning investor expectations on prior earnings surprises.

Our main definition for a trend is a streak of consecutive earnings surprises with the same sign. Our first trading strategy ignores the magnitude of earnings surprises and buys stocks with positive streaks while selling stocks with negative streaks. This strategy is also implemented for reversals, which occur when the most recent earnings surprise is of the opposite sign as the preceding streak. Thus, reversals signify the termination of streaks. Over a six-month holding period, a four-factor alpha of 0.603% per month is obtained from buying stocks with positive streaks and selling stocks with negative streaks, where the respective streak lengths are at least two. In contrast, the returns from conditioning on reversals are insignificant. The economically and statistically significant risk-adjusted return from conditioning on streaks is available despite our sample consisting of relatively large stocks with analyst coverage. Furthermore, the positive risk-adjusted return from this trading strategy supports the gambler's fallacy because investors appear to underreact to streaks. Underreaction coefficients that compare announcement period returns with returns over a longer subsequent horizon (Cohen and Frazzini 2008, DellaVigna and Pollet 2009) provide further evidence that investors underreact to streaks.

Our second trading strategy accounts for the magnitude of the most recent earnings surprise. The return difference between stocks with extremely high and stocks with extremely low earnings surprises in the most recent quarter is known as post-earnings-announcement drift (PEAD) in the return anomalies literature. After sorting firms into quintiles according to the magnitude of their most recent earnings surprise, we further subdivide these quintiles into subportfolios of streaks and reversals. We then buy stocks with positive streaks in the highest quintile and sell stocks with negative streaks in the lowest quintile. This strategy yields a four-factor adjusted return of 0.882% per month. Once again, an insignificant return is obtained from conditioning on reversals (0.044%). The return difference between conditioning on streaks and reversals is 0.838% ($t = 5.75$). Fama–MacBeth regressions confirm the marginal return predictability of streaks after accounting for a battery of control variables that include lagged earnings surprises. Therefore, the greater return predictability of streaks relative to reversals is not attributable to the return continuation induced by same-signed earnings surprises before the most recent quarter.

We also examine conditional sorts to determine whether the magnitude of earnings surprises within streaks and reversals have different return implications. After forming streak and reversal portfolios, we sort stocks into quintiles according to the magnitude of their most recent earnings surprise. This conditional double sort reveals that PEAD is concentrated within streaks. We find no evidence that PEAD is significant within the reversal portfolio. We also examine the impact of streaks on the time-series dynamics of PEAD by constructing a streak factor from the returns of our first trading strategy that buys stocks with positive streaks and sells those with negative streaks. This streak factor accounts for the majority of PEAD's four-factor alpha. A more broadly defined factor, which is not limited to positive and negative streaks, that buys all stocks with positive earnings surprises and sells those with negative earnings surprises in the most recent quarter explains a similar portion of PEAD's four-factor alpha. Therefore, the sign of the most recent earnings surprise is only relevant to PEAD when it identifies a prevailing streak.

The existing literature has examined the contemporaneous impact of streaks on stock prices. Barth et al. (1999) as well as Myers et al. (2007) document that firms with increasing earnings have higher valuations but large price reversals following the termination of earnings increases. Ke et al. (2003) report that insiders and institutions anticipate the termination of streaks. However, these studies focus on the contemporaneous implications of streaks. In contrast, our investigation focuses on future returns by implementing calendar-time trading strategies that capture return predictability. Results in the existing literature that find greater contemporaneous price reactions to reversals than streaks are consistent with the gambler's fallacy because the underreactions to trends predicted by the gambler's fallacy imply muted contemporaneous price reactions followed by a subsequent drift in prices. Our paper is further distinguished from the existing literature given our focus on analyst-based earnings surprises that account for earnings predictability. Chan et al. (2004) confine their study to streaks consisting of four consecutive quarters of above-median (below-median) earnings growth relative to the entire cross-section of firms. In contrast, our use of analyst-based earnings surprises better conforms to the assumptions underlying the theories of BSV and Rabin (2002). Another related branch of literature explores the relationship between streaks and order flow. Frieder (2008) concludes that positive earnings streaks lead to the initiation of small buy trades. However, Battalio and Mendenhall (2005) report limited success at explaining PEAD using small trades, whereas Shanthikumar (2009) reports that large trades are not initiated by streaks. Instead of examining the microstructure implications of streaks, our paper examines their implications for return predictability.

An alternative interpretation of our findings is that earnings surprises are positively autocorrelated, and investors underestimate this autocorrelation. Bernard and Thomas (1990) hypothesize that PEAD is caused by investors underestimating the autocorrelation in realized earnings changes. Our analyst-based earnings surprises are less autocorrelated than earnings surprises defined by realized earnings changes because analysts can incorporate earnings predictability into their forecasts. Nonetheless, we test this alternative explanation by examining whether streaks predict returns better than reversals for firms that have autocorrelated earnings surprises. Autocorrelation is assessed using the runs test as well as an autoregressive model with four lags. After classifying firms into subsamples depending on whether their earnings surprises are autocorrelated or independent, we find that investors underreact more to streaks than reversals in both subsets. Thus, the gambler's fallacy, rather than autocorrelation, is driving the return predictability of streaks.[1]

Besides streaks, we also examine a more general definition of trends that relies on consistency within the sign of prior earnings surprises. Under the consistency criteria, a trend occurs when the most recent

[1] Rabin and Vayanos (2010) demonstrate that the gambler's fallacy can induce an underreaction to trends within autocorrelated signals.

quarterly earnings surprise has the same sign as the majority of prior earnings surprises. Thus, when the majority of a firm's prior earnings surprises are positive, a positive earnings surprise produces a positive trend, whereas a negative earnings surprise produces a negative reversal. We examine imbalances defined by the majority (50%) of earnings surprises over several horizons. Imbalances proxy for the likelihood functions underlying the quasi-Bayesian theories that motivate our empirical tests.[2] We continue to find that trends predict returns significantly better than reversals using the consistency-based definition of trends.

Finally, we also examine whether the gambler's fallacy is unconditionally weaker for long streaks. Rabin (2002) predicts the gambler's fallacy is undermined by the hot-hands phenomenon when investors update their beliefs after observing a long streak. However, we find no unconditional evidence of the hot-hands phenomenon. Intuitively, investors do not appear to update their beliefs regarding future earnings growth after observing long streaks. This property is consistent with investors having strong prior beliefs that earnings growth will mean revert in the long term. We also examine whether the gambler's fallacy is conditionally weaker for long streaks when investors have diffuse priors regarding future earnings. We proxy for such diffuse priors using high earnings volatility and high analyst forecast dispersion. As predicted by Rabin (2002), we find weaker evidence of the gambler's fallacy following long streaks in the subset of firms with high earnings volatility and high forecast dispersion.

The remainder of this paper begins in §2 with a discussion of the relevant theory. Section 3 then describes the data underlying our empirical tests. The results of these empirical tests are contained in §4, and §5 details their robustness. Section 6 contains our conclusions.

2. Motivation

Rabin (2002) and BSV assume that the interpretation of a signal is influenced by the sign of previous signals. In our empirical study, an underreaction to a trend has investors discounting the most recent earnings surprise's importance to future earnings, whereas an overreaction to a trend has investors magnifying its importance to future earnings.

The gambler's fallacy in Rabin (2002) posits an underreaction to trends. This fallacy arises from an informative prior regarding the likelihood of positive and negative signals, such as the belief that the long-term distribution is 50% positive and 50% negative. The gambler's fallacy causes Rabin's (2002) investor to expect a trend to reverse rather than continue. The resulting underreaction to trends yields the empirical prediction of more pronounced drifts after trends than after reversals. Intuitively, Rabin's (2002) investor believes that trends require immediate "balancing" by future signals of the opposite sign. Although this belief is correct when the number of signals is large, it does not necessarily hold true for a small number of signals. Indeed, the gambler's fallacy is also known as the law of small numbers.

In contrast to Rabin (2002), BSV assume that representativeness causes investors to expect a continuation of trends. This extrapolation induces an overreaction to trends that differs from Rabin's (2002) prediction. To ensure that stock prices eventually converge to their true value, the return implications of trends and reversals are equal in absolute magnitude but of the opposite sign in BSV's model. In contrast, long-term returns reversals are not required to correct mispricings attributable to investors underreactions. Asparouhova et al. (2009) emphasize the disparity between the empirical predictions of the gambler's fallacy and representativeness. Although the empirical market in Bloomfield and Hales (2002) provides empirical support for BSV's predictions, the Asparouhova et al. (2009) revised experiment supports the predictions of Rabin (2002).

Quarterly earnings surprises provide an ideal proxy for public signals. Indeed, these signals motivate BSV's theoretical model. Furthermore, earnings surprises defined by analyst forecasts are less autocorrelated than earnings surprises defined by realized earnings because earnings predictability can be incorporated into analyst forecasts.

3. Data

Our sample of quarterly earnings forecasts is from Thomson Financial's Institutional Brokers Estimate System (I/B/E/S) U.S. file from 1984 to 2009. Instead of using the standard adjusted summary file, we split-adjust the unadjusted file ourselves using the I/B/E/S adjustment factors. This mitigates the problem of imprecise forecasts caused by I/B/E/S's practice of rounding to the nearest cent when adjusting historical consensus forecasts after stock splits (as documented by Diether et al. 2002). Our procedure ensures that the actual earnings and the consensus forecasts are on the same per-share basis for each forecasting firm-quarter and are comparable over time for a firm.

Monthly returns are obtained from the Center for Research in Security Prices (CRSP) for stocks

[2] The consistency definition encompasses streaks as a special case. For example, a streak of four consecutive positive surprises requires the most recent surprise to be positive while also requiring the positive imbalance in the prior three surprises to equal its maximum of 100%. In contrast, the consistency definition does not require the signs of the most recent and the second most recent earnings surprise to be identical.

classified as ordinary shares (share codes 10 or 11). Delisting returns are added from the CRSP delisting file. When the delisting return is missing, we adopt the convention used by Shumway (1997) and use −30% if the corresponding delisting code is performance related. Firms in the sample are required to have a nonnegative book-to-market (BM) ratio. Book equity is calculated following Fama and French (2006). A firm's BM ratio is updated every 12 months beginning in July, where B denotes its book equity for the fiscal year ending in the preceding calendar year and M denotes its December-end market capitalization from the preceding calendar year. SURPs are computed as actual quarterly earnings minus the most recent mean consensus forecast of analysts for that quarter. This difference is then normalized by the firm's stock price on CRSP at the end of the prior month. We adjust the CRSP stock price to ensure that it is on the same per-share basis as the SURP. Actual earnings are from I/B/E/S. Our primary definition for a trend is a streak of at least two consecutive earnings surprises with the same sign while a reversal occurs upon the termination of a streak of at least two. A more general definition for trends involving the imbalance between positive and negative prior earnings surprises is evaluated in a later robustness test.

Panel A of Table 1 describes our sample. The average SURP in our 1984 to 2009 sample period is −0.052. When classifying SURPs as a streak or reversal, our sample begins in 1987 to obtain three years of prior earnings surprises. Differences in the book-to-market, size, and past returns (PRET) between streaks and reversals are reported in Panel B. PRET denotes the buy-and-hold returns over the past 12 months after omitting the most recent month. Additional firm characteristics include Amihud's (2002) illiquidity measure, percentage of institutional ownership (IO) defined by a firm's most recent quarterly 13F filing, and turnover. Amihud's (2002) illiquidity measure is computed in the month prior to portfolio formation as a firm's average daily absolute return divided by the dollar volume (in millions). Turnover is defined as the average daily number of shares traded normalized by the number of shares outstanding and is also computed in the month before portfolio formation. For NASDAQ firms, volume is adjusted to account for interdealer double counting as in Gao and Ritter (2010). The firm characteristics are computed as Fama–MacBeth averages. Specifically, the characteristics within each portfolio are averaged each month before computing the time-series averages of each portfolio. Although differences between the firm characteristics of streaks and reversals are statistically significant, several of these differences are unlikely to have economic consequences. Nonetheless, for completeness, we control for the firm characteristics in Panel B of Table 1 in later cross-sectional regressions.

After sorting stocks into quintiles according the magnitude of their most recent earnings surprise, stocks are then separated into subportfolios containing streaks and reversals. For each subportfolio, Panel A of Table 2 reports the number of positive versus negative SURPs, and Panel B reports the average SURP magnitude within each quintile. In general, positive streaks (reversals) occur more frequently than negative streaks (reversals) according to Panel A. However, Panel B indicates that negative SURPs are larger in absolute value than positive SURPs, a property that is consistent with the average SURP in Panel A of Table 1 being negative.

4. Empirical Results

This section reports the calendar-time returns from two trading strategies. The first is derived exclusively from the sign of prior earnings surprises, whereas the second also conditions on the magnitude of the most recent earnings surprise. We then use Fama–MacBeth regressions involving individual firm returns and characteristics to reexamine the portfolio-level results from these trading strategies.

4.1. Streaks

We begin by examining the returns following streaks in earnings surprises of various lengths and their subsequent reversals. A streak is defined by earnings surprises having the same sign in consecutive quarters. An earnings surprise that equals zero is classified as being negative. An alternative threshold using the median SURP to determine the signs of surprises is examined in the next section. Equally weighted monthly returns following positive streaks and negative streaks are first computed over six-month holding periods. The time-series averages of these returns are then recorded along with the returns following positive reversals and negative reversals that occur when the most recent earnings surprise is of the opposite sign as the prevailing streak. As in the existing literature, our trading strategies exclude firms whose lagged stock prices are below five dollars to guard against microstructure complications such as bid-ask bounce. To benchmark the returns from our trading strategies, we compute risk-adjusted returns using the three-factor (Fama and French 1993) and four-factor models as well as the characteristic portfolio procedure of Daniel et al. (1997; abbreviated DGTW). [3]

[3] To form DGTW portfolios, every July, firms are first sorted into quintiles based on their market capitalization on June 30th of each year using New York Stock Exchange break points. Second, within each size portfolio, firms are then sorted into quintiles according to their BM ratios. Third, firms within each double-sorted size–BM portfolio are sorted once more into momentum quintiles every month based on their buy-and-hold return over the prior 12 months

Table 1 Summary Statistics for Earnings Surprises

Panel A: Average firm characteristics by year

Year	Number of firms	Number of firm-months	SURP	Beta	BM	Size	Number of streaks	Percentage of streaks
1984	941	1,675	−0.014	1.09	0.79	1,045	—	—
1985	1,364	12,813	−0.049	1.14	0.84	1,086	—	—
1986	1,472	14,304	−0.054	1.23	0.79	1,331	—	—
1987	1,689	15,635	−0.043	1.11	0.71	1,564	8,982	0.57
1988	1,761	15,590	−0.028	1.14	0.74	1,614	8,958	0.57
1989	2,144	19,633	−0.069	1.15	0.77	1,374	11,297	0.58
1990	2,220	20,463	−0.028	1.14	0.71	1,508	12,159	0.59
1991	2,278	21,674	−0.062	1.19	0.79	1,555	12,899	0.60
1992	2,500	23,825	−0.053	1.20	0.82	1,579	14,418	0.61
1993	2,872	26,642	−0.072	1.30	0.66	1,649	16,375	0.61
1994	3,406	31,021	−0.056	1.25	0.58	1,555	18,910	0.61
1995	3,724	34,603	−0.030	1.17	0.59	1,572	21,565	0.62
1996	4,048	37,588	−0.003	1.09	0.58	1,818	22,875	0.61
1997	4,435	40,167	−0.027	1.12	0.53	2,197	24,997	0.62
1998	4,463	39,942	−0.021	1.01	0.49	2,831	24,442	0.61
1999	4,202	37,939	−0.023	1.14	0.51	3,647	23,900	0.63
2000	4,075	35,049	0.016	1.10	0.55	4,590	22,121	0.63
2001	3,426	30,785	0.019	1.02	0.63	5,155	18,537	0.60
2002	3,175	29,439	−0.001	0.92	0.64	4,622	17,834	0.61
2003	3,105	29,772	−0.081	1.03	0.65	4,153	18,154	0.61
2004	3,258	32,133	−0.025	1.14	0.61	4,247	19,288	0.60
2005	3,250	31,885	−0.001	1.16	0.49	4,725	18,810	0.59
2006	3,325	32,742	0.000	1.45	0.49	4,899	19,535	0.60
2007	3,313	32,509	−0.598	1.51	0.48	5,480	19,235	0.59
2008	3,055	29,229	−0.003	1.25	0.52	5,975	17,435	0.60
2009	2,732	25,849	−0.004	1.10	0.76	5,114	15,567	0.60
Overall	9,706	702,906	−0.052	1.16	0.61	3,245	408,293	0.61

Panel B: Average firm characteristics for streaks and reversals

	SURP	Size	BM	PRET	IO	Amihud	Turnover
Streaks	−0.037	3,304	0.61	0.185	0.531	0.50	0.561
Reversals	−0.003	3,023	0.63	0.164	0.512	0.63	0.535
Difference	−0.034***	281***	−0.02***	0.021***	0.019***	−0.13***	0.026***

Notes. This table describes our sample of earnings surprises as well as the streaks defined by these surprises. SURP is the firm's quarterly earnings surprise defined as I/B/E/S actual earnings minus the most recent mean consensus estimate, scaled by the stock price. Streaks occur when the two most recent quarterly SURPs are of the same sign. Reversals occur when such a streak has ended. For each year in our 1984 to 2009 sample period, the average SURP is reported in Panel A along with the average market beta, BM ratio, and size (millions of dollars) of the firms in our sample. The number and percentage of streaks are also reported in Panel A. Streaks are defined beginning in 1987 to obtain an initial history of prior SURPs. An extended set of firm characteristics are summarized (as Fama–MacBeth averages) in Panel B for streaks and reversals. These characteristics include returns over the past 12 months while omitting the most recent month (PRET), IO, Amihud's (2002) illiquidity measure (Amihud), and turnover.

*10%, **5%, and ***1% statistical significance of the difference in the time-series average of the firm characteristic.

The main results of our paper are summarized in Table 3. Panel A reports a cross-sectional four-factor alpha of 0.322% ($t = 4.32$) per month from buying stocks with positive streaks and a negligible 0.080% ($t = 1.21$) from buying stocks with positive reversals. The difference of 0.242% is statistically significant ($t = 3.97$). Similarly, the four-factor alpha following negative streaks exceeds that of negative reversals by −0.362% ($t = 6.34$).[4] Taken together, a trading strategy that is long positive streaks and short negative streaks earns a four-factor alpha of 0.603% per month, whereas applying the same strategy to reversals earns

while omitting the most recent month (Jegadeesh and Titman 1993). Therefore, the size and BM rankings are updated annually, whereas the momentum rankings are updated monthly. Finally, equally weighted monthly returns are computed within each characteristic portfolio.

[4] Excluding firms that are delisted during the holding period results in a negligible reduction in the number of stocks contained in the short portfolio as well as the long portfolio, and does not alter their risk-adjusted returns. Therefore, delistings are not driving the return predictability of negative streaks.

Table 2 Summary Statistics for Streaks and Reversals

Panel A: Number of observations

	SURP sign		SURP quintile				
Streak length	Negative	Positive	Smallest	2	3	4	Largest
2	72,760	74,533	29,625	24,488	33,846	28,983	30,351
3	43,477	44,507	19,013	13,993	19,362	17,825	17,791
4	26,750	27,677	12,221	8,196	11,936	11,362	10,712
5	17,398	18,905	7,911	5,441	8,001	7,693	7,257
6	11,592	12,898	5,228	3,542	5,620	5,584	4,516
7	7,584	8,917	3,345	2,398	3,784	3,848	3,126
8	5,017	5,992	2,195	1,525	2,815	2,551	1,923
9	3,363	4,273	1,525	937	1,935	1,861	1,378
≥10	8,326	11,255	3,316	2,460	5,683	4,676	3,446
All Streaks	196,267	208,957	84,379	62,980	92,982	84,383	80,500
Reversals	72,113	75,823	23,881	26,796	38,271	28,305	30,683

Panel B: Average SURP magnitude (×100)

	SURP sign		SURP quintile				
Streak length	Negative	Positive	Smallest	2	3	4	Largest
2	−1.31	0.53	−3.13	−0.10	0.02	0.13	1.16
3	−1.97	0.44	−4.44	−0.10	0.02	0.13	0.94
4	−1.65	0.44	−3.55	−0.10	0.02	0.13	0.97
5	−3.21	0.44	−6.99	−0.10	0.02	0.13	0.99
6	−4.28	0.35	−9.43	−0.10	0.02	0.13	0.81
7	−2.27	0.34	−5.07	−0.10	0.02	0.13	0.78
8	−2.43	0.31	−5.49	−0.10	0.02	0.13	0.75
9	−1.45	0.30	−3.14	−0.10	0.02	0.13	0.74
≥10	−1.63	0.27	−4.03	−0.09	0.02	0.13	0.68
All Streaks	−1.93	0.45	−4.41	−0.10	0.02	0.13	1.00
Reversals	−1.15	0.65	−3.36	−0.10	0.02	0.13	1.48

Notes. This table reports the frequency of streaks and reversals during our 1987 to 2009 sample period. Firms are sorted into quintiles each month based on their most recent SURP. A quarterly SURP denotes a firm's quarterly earnings surprise, defined as I/B/E/S actual earnings minus the most recent mean consensus estimate of analysts, scaled by its stock price. Streaks occur when the two most recent quarterly SURPs are of the same sign. Reversals occur when such a streak has ended. Panel A reports the number of observations, and Panel B the average SURP (multiplied by 100). All SURPs are winsorized at the extreme 0.1 percentiles for each monthly cross-section. SURPs greater than zero are classified as positive, whereas values equaling zero or below zero are classified as negative.

−0.001%. This difference in return predictability is statistically significant with a t-statistic of 5.66. Similar risk adjusted returns are reported for the three-factor model and the DGTW risk adjustment. This evidence strongly supports the gambler's fallacy, which predicts that investors underreact to trends but not to reversals. This result is also consistent with the conclusion by Chan et al. (1996) that earnings momentum is the result of investor underreaction.

The return difference between portfolios containing stocks with extremely high and extremely low past earnings surprise is referred to as PEAD. To evaluate the contribution of streaks to PEAD, we first sort stocks into quintiles according to the magnitude of their most recent SURP.[5] Streak and reversal subportfolios within each earnings surprise quintile are then formed. The risk-adjusted returns of these calendar-time portfolios are reported in Panel B of Table 3. A trading strategy that buys stocks with positive streaks in the largest SURP quintile and sells stocks with negative streaks in the smallest SURP quintile yields a four-factor alpha of 0.882% per month. In contrast, conditioning on reversals leads to an insignificant risk-adjusted return of 0.044% ($t = 0.48$). The difference in return predictability between streaks and reversals is large and significant (0.838%, $t = 5.75$). Panel B indicates that differences in the three-factor and four-factor alphas following streaks and reversals are significant in every SURP quintile except for the middle quintile.[6] These risk-adjusted returns are also symmetric (in absolute

[5] The middle quintile contains more stocks than adjacent quintiles because of the large number of SURPs that are zero.

[6] Another procedure matched the magnitude of the most recent SURP within streaks and reversals. This procedure ensures the streak and reversal portfolios contain an equal number of stocks. In unreported results, the results from this procedure are nearly identical to those in Table 3. Therefore, the greater return predictability of streaks in comparison to reversals is not attributable to differences in the magnitude of earnings surprises.

Table 3 Trading Strategies Using Streaks and Reversals

	Panel A: SURP Signs			Panel B: SURP quintiles					
	Negative	Positive	Spread	Smallest	2	3	4	Largest	Spread
				Four-factor alphas					
Streaks	−0.280***	0.322***	0.603***	−0.444***	−0.157*	0.071	0.263***	0.438***	0.8826***
	(−3.78)	(4.32)	(8.12)	(−5.23)	(−1.79)	(0.88)	(2.95)	(5.41)	(8.92)
Reversals	0.081	0.080	−0.001	0.056	0.097	0.118	0.068	0.101	0.044
	(1.14)	(1.21)	(−0.01)	(0.72)	(1.20)	(1.28)	(0.78)	(1.19)	(0.48)
Difference	−0.362***	0.242***	0.603***	−0.500***	−0.254***	−0.047	0.194**	0.337***	0.838***
	(−6.34)	(3.97)	(5.66)	(−5.83)	(−3.66)	(−0.86)	(2.57)	(3.99)	(5.75)
				Fama–French (1993) three-factor alphas					
Streaks	−0.375***	0.287***	0.663***	−0.561***	−0.242***	0.036	0.224**	0.397***	0.957***
	(−4.69)	(3.86)	(8.73)	(−6.05)	(−2.65)	(0.45)	(2.54)	(4.91)	(9.51)
Reversals	−0.020	0.059	0.078	−0.070	0.028	0.052	0.032	0.087	0.158
	(−0.25)	(0.89)	(1.26)	(−0.79)	(0.34)	(0.56)	(0.37)	(1.05)	(1.59)
Difference	−0.356***	0.229***	0.584***	−0.491***	−0.270***	−0.016	0.192**	0.309***	0.800***
	(−6.34)	(3.81)	(5.56)	(−5.81)	(−3.95)	(−0.29)	(2.58)	(3.70)	(5.56)
				DGTW-adjusted average returns					
Streaks	−0.239***	0.144***	0.383***	−0.391***	−0.129**	0.011	0.078	0.236***	0.627***
	(−3.87)	(3.01)	(5.74)	(−4.86)	(−2.16)	(0.21)	(1.46)	(3.46)	(6.52)
Reversals	−0.033	0.035	0.068	−0.064	−0.011	0.021	0.013	0.056	0.120
	(−0.66)	(0.64)	(1.28)	(−0.91)	(−0.20)	(0.35)	(0.19)	(0.72)	(1.39)
Difference	−0.206***	0.109**	0.315***	−0.328***	−0.118**	−0.010	0.065	0.179**	0.507***
	(−3.98)	(1.98)	(3.28)	(−4.12)	(−1.98)	(−0.21)	(0.97)	(2.17)	(3.70)
				Average number of stocks per month					
Streaks	1,132	1,202		572	478	704	624	546	
Reversals	664	654		197	251	342	249	273	

Notes. This table reports the returns from calendar-time trading strategies involving streaks and reversals in earnings surprises from 1987 to 2009. SURP is the firm's quarterly earnings surprise defined as I/B/E/S actual earnings minus the most recent mean consensus estimate, scaled by its stock price. Each month, based on the most recent SURP, firms are sorted into SURP portfolios according to the sign (Panel A) of its SURP or its quintile rank (Panel B). Stocks having streaks whose length is at least two are also independently separated into streak portfolios and reversal portfolios. Stocks remain in the relevant portfolio for six months, although stocks with lagged prices below five dollars are excluded from our trading strategies. Equally weighted returns are computed each month, and the time series of these monthly returns less the risk-free rate are regressed on the three-factor or four-factor models to obtain alpha estimates that are reported as percentages. DGTW-adjusted returns are also reported using the methodology in Daniel et al. (1997).

*10%, **5%, and ***1% statistical significance of the abnormal returns, with the associated *t*-statistics in parentheses.

value) across the SURP quintiles, although negative streaks are generally associated with slightly stronger return predictability. In summary, the results from Table 3 support the gambler's fallacy because investors appear to underreact to streaks.

To complement our study of monthly holding-period returns, we examine the immediate reaction of investors to earnings announcements by estimating underreaction coefficients. These coefficients are also estimated by Cohen and Frazzini (2008) and DellaVigna and Pollet (2009). Underreaction coefficients involve cumulative abnormal returns over a three-day horizon (*CARs*) and risk-adjusted returns over a longer six-month horizon (*Drift*). These returns yield an underreaction coefficient defined as

$$R = \frac{CARs}{CARs + Drift}, \tag{1}$$

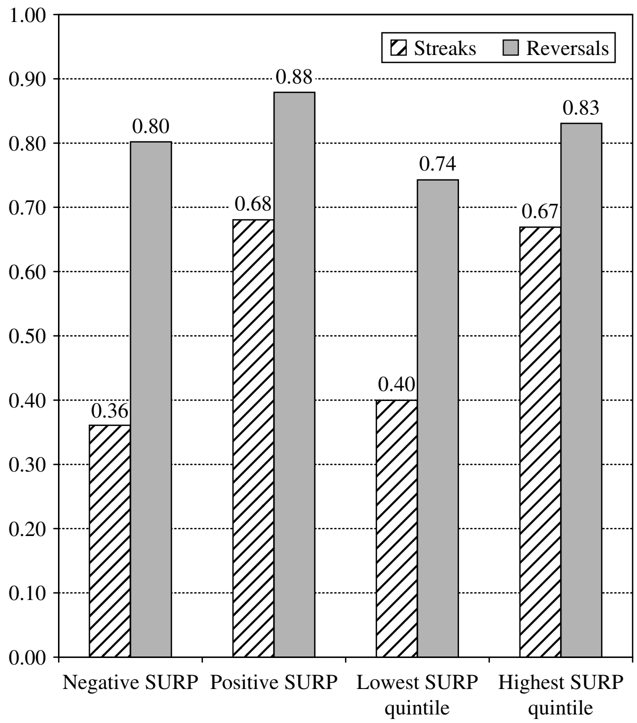
for an individual firm's quarterly earnings announcement. Provided the *CARs* and *Drift* following an earnings announcement have the same sign, a ratio $R < 1$ is evidence of investor underreaction, whereas $R > 1$ is evidence of investor overreaction. Moreover, a lower R ratio indicates a greater underreaction by investors, because less information is immediately incorporated into prices.

Figure 1 reports the underreaction coefficient for streaks as well as reversals. We compute Fama–MacBeth averages for the *CARs* and *Drift* variables for firms within a specific portfolio and then graph R using these averages. For positive SURPs, the R coefficient for streaks is 68%, compared to 88% for reversals. By implication, there is greater underreaction to streaks than to reversals. We find similar evidence for negative SURPs as well as for stocks in the lowest and highest SURP quintiles. Hence, the evidence in Figure 1 supports our earlier finding that streaks induce a greater underreaction than reversals.

4.2. Streak Length

According to Rabin (2002), if investors are uncertain about the distribution of future signals, the hot-hands phenomenon can undermine the gambler's

Figure 1 **Underreaction Coefficients for Streaks and Reversals**



Notes. These average coefficients are specified in terms of the sign and magnitude of a firm's most recent earnings surprise. A quarterly SURP is defined as the I/B/E/S actual earnings for a particular quarter minus the mean consensus analyst earnnigs forecast for that quarter, scaled by the stock price. For each month from 1987 to 2009, based on the most recent SURP, firms are sorted into SURP quintiles as well as positive SURP and negative SURP portfolios. The underreaction coefficients are defined using cumulative abnormal returns following a three-day horizon (*CARs*) following quarterly earnings announcements and risk-adjusted returns over a longer six-month horizon (*Drift*) as follows: $R = CARs/(CARs + Drift)$. The averages are computed using a Fama–MacBeth approach. First, quarterly cross-sectional average *CARs* and *Drifts* are computed, with the time-series averages of these cross-sectional averages defined as the underreaction coefficient R. A lower R ratio is evidence of a greater underreaction by investors because less information is immediately incorporated into prices.

fallacy. The hot-hands effect implies that investors overinfer after observing a long streak and expect the streak's continuation. However, we show in Table 4 that longer streaks induce stronger rather than weaker underreaction.[7] These results are consistent with investors having strong prior beliefs regarding the long-term distribution of earnings surprises that prevent the gambler's fallacy from being undermined by the hot-hands phenomenon. Indeed, after observing the continuation of a streak, investors appear to remain confident in its subsequent reversal.

The lack of empirical support for the hot-hands phenomenon may stem from competition between firms, because the entrance and exit of firms from a competitive industry leads to mean reversion in long-term earnings growth at the firm level. The empirical evidence in Chan et al. (2003) confirms that high long-term earnings growth is unlikely to persist. Therefore, informative priors regarding long-term earnings growth are justified by the belief that a firm's competitive advantage is temporary. Moreover, analysts can adjust their earnings forecasts to mitigate predictability in SURPs and therefore limit the continuation of streaks.

Although the hot-hands phenomenon is not detected in our study, it may explain flows into funds that outperform their peers provided investors chase fund performance. Jagannathan et al. (2010) find evidence of persistence among superior hedge funds. Intuitively, if the long-term investment skill of fund managers is believed to be more persistent than the long-term earnings growth of individual firms, then the hot-hands phenomenon is more likely to be detected in fund flows than in stock returns.[8]

4.3. Streaks vs. the Magnitude of Earnings Surprises

This subsection alters the double sort underlying our second trading strategy to investigate the return predictability of large earnings surprises within streaks and reversals. Within the streak and reversal portfolios, we sort stocks in quintiles according to the magnitude of their most recent SURP. As reported in Panel A of Table 5, after controlling for streaks, cross-sectional differences across the magnitude of the most recent quarter's SURP generate cross-sectional return variation in all quintiles except the middle (third) quintile. The significant four-factor alpha in the second and fourth quintiles indicate that the magnitude of the most recent SURP is relatively less important than streaks.

We also show that the ability of large earnings surprises to influence future returns is limited to streaks. In particular, within the reversal portfolio, the magnitude of a firm's most recent SURP does not impact future returns, because neither the smallest nor largest earnings surprises are associated with risk-adjusted holding-period returns.

We further examine the influence of streaks on PEAD, which is defined as the hedged portfolio return from buying stocks in Quintile 5 and selling those in Quintile 1 across the universe of stocks. We construct a streak factor defined as the monthly

[7] Compared to streaks whose length is between six and nine quarters, the slightly weaker return predictability following streaks longer than 10 consecutive quarters is driven by relatively few stocks.

[8] Dorsey-Palmer and Smith (2004) find evidence of hot hands in bowling and argue that Tversky and Gilovich (1989a, b) fail to find hot hands in basketball because of competitive reactions to recent success. In particular, unlike bowling, opposing players in basketball can alter their defensive strategy against "hot" players.

Table 4 Returns Based on Streak Length

	SURP quintiles					
	Smallest	2	3	4	Largest	Spread
	Abnormal returns based on streak length					
Streaks of 2 to 3	−0.325***	−0.095	0.105	0.197**	0.454***	0.780***
	(−3.70)	(−1.06)	(1.22)	(2.28)	(5.91)	(8.53)
Streaks of 4 to 5	−0.537***	−0.302***	−0.026	0.254**	0.383***	0.920***
	(−4.93)	(−2.74)	(−0.26)	(2.38)	(3.51)	(6.29)
Streaks of 6 to 9	−0.760***	−0.190	0.053	0.358***	0.426***	1.186***
	(−5.62)	(−1.35)	(0.50)	(2.67)	(2.86)	(5.58)
Streaks $\geq$ 10	−0.670***	−0.274	0.127	0.654***	0.450*	1.120***
	(−2.99)	(−1.36)	(0.85)	(3.22)	(1.76)	(3.49)
Reversals	0.056	0.098	0.118	0.068	0.101	0.044
	(0.72)	(1.21)	(1.28)	(0.78)	(1.19)	(0.48)
	Difference between streaks and reversals					
Streaks of 2 to 3	−0.382***	−0.193***	−0.013	0.129*	0.354***	0.735***
	(−4.45)	(−2.88)	(−0.23)	(1.80)	(4.80)	(5.54)
Streaks of 4 to 5	−0.593***	−0.400***	−0.144*	0.186*	0.283**	0.876***
	(−5.36)	(−3.93)	(−1.75)	(1.90)	(2.41)	(4.71)
Streaks of 6 to 9	−0.816***	−0.288**	−0.065	0.290**	0.326**	1.142***
	(−5.88)	(−2.15)	(−0.71)	(2.37)	(2.13)	(4.69)
Streaks $\geq$ 10	−0.727***	−0.372*	0.009	0.586***	0.349	1.076***
	(−2.33)	(−1.52)	(−0.88)	(1.64)	(2.46)	(3.32)
	Average number of stocks per month					
Streaks of 2 to 3	363	320	433	373	363	
Streaks of 4 to 5	164	117	175	167	144	
Streaks of 6 to 9	94	66	117	112	81	
Streaks $\geq$ 10	26	18	45	41	25	
Reversals	197	251	342	249	273	

Notes. This table reports the returns from calendar-time trading strategies involving streaks, and reversals in earnings surprises from 1987 to 2009. Streak lengths are determined by consecutive same-signed SURPs over 2 to 3, 4 to 5, 6 to 9, or greater than 10 quarters, respectively. A reversal occurs when a streak whose length is at least two ends. SURP denotes a firm's quarterly earnings surprise defined as the I/B/E/S actual earnings minus the most recent mean consensus estimate, scaled by its stock price. Each month, based on the most recent SURP, firms are sorted into SURP quintiles according to their most recent SURP. Stocks are also independently separated into streak-length portfolios and reversal portfolios. The stock remains in the relevant portfolio for six months, and stocks with lagged prices below five dollars are excluded from the holding-period returns. Equally weighted returns are computed each month and the time series of these monthly returns less the risk-free rate are regressed on the four-factor model to obtain alpha estimates that are reported as a percentages.

*10%, **5%, and ***1% statistical significance, with the associated t-statistics in parentheses.

long minus short return of our first trading strategy in Table 3, Panel A, that buys stocks with positive streaks and sells stocks with negative streaks. Model 1 in Panel B of Table 5 reports that PEAD's four-factor alpha equals 0.648% per month. According to Model 2, the streak factor can explain 70% of this alpha, which is reduced to 0.196% per month after its inclusion.

One concern is that the streak factor's success at explaining PEAD may simply result from the sign of the most recent SURP. If this were the case, a factor that does not include streaks but conditions on the sign of SURPs in the most recent quarter would have similar success at reducing PEAD's alpha. However, Model 3 demonstrates that this SURP-sign factor explains only 13% of PEAD's alpha. Furthermore, the inclusion of both the streak factor and the SURP-sign factor in Model 4 explains 76% of PEAD's four-factor alpha, which is not a large improvement over the streak factor's 70%. We also orthogonalize the streak factor against the SURP-sign factor in Model 5. This purged streak factor continues to remove 54% of PEAD's four-factor alpha. Thus, the majority of PEAD is attributable to streaks.[9]

[9] An alternative interpretation of the results in Panel B of Table 5 can be obtained from a broadly defined factor that buys all stocks with positive earnings surprises and sells those with negative earnings surprises in the most recent quarter. Although its ability to explain PEAD is marginally better than the streak factor's, the ability of this positive-minus-negative SURP factor to reduce PEAD's alpha is primarily due to the subset of streaks. Overall, although the signs of earnings surprises are crucial to return predictability, their ability to explain PEAD requires further conditioning on the signs of earnings surprises before the most recent quarter. Consequently, the interaction between the sign of the most recent SURP and the presence of a streak is responsible for PEAD.

Table 5 Magnitude of Earnings Surprises within Streaks and Reversals

Panel A: Four-factor alphas

	SURP quintiles sorted within streaks or reversals					
	Smallest	2	3	4	Largest	Spread
Streaks	−0.500***	−0.180**	0.027	0.224**	0.433***	0.934***
	(−6.01)	(−2.23)	(0.33)	(2.57)	(5.53)	(9.37)
Reversals	0.042	0.105	0.128	0.043	0.103	0.061
	(0.61)	(1.20)	(1.38)	(0.55)	(1.23)	(0.68)
Difference	−0.543***	−0.284***	−0.100	0.181**	0.330***	0.873***
	(−6.56)	(−3.95)	(−1.40)	(2.58)	(4.00)	(6.21)
	Average number of stocks per month					
Streaks	564	618	652	625	567	
Reversals	269	275	309	282	269	

Panel B: Time-series regressions

Model	Four-factor alpha	Reduction in alpha (%)	MrkRf	SMB	HML	UMD	Streak factor	SURP-sign factor	Purged streak factor
1	0.648***	NA	0.065***	−0.129***	−0.080***	0.088***			
	(9.35)		(4.01)	(−6.07)	(−3.38)	(6.28)			
2	0.196***	70	0.008	−0.025*	0.100***	0.035***	0.751***		
	(4.25)		(0.79)	(−1.88)	(6.14)	(4.05)	(22.18)		
3	0.567***	13	0.053***	−0.133***	−0.081***	0.055***		0.579***	
	(8.21)		(3.35)	(−6.50)	(−3.56)	(3.59)		(4.70)	
4	0.154***	76	0.002	−0.031**	0.094***	0.015	0.731***	0.383***	
	(3.44)		(0.16)	(−2.39)	(6.04)	(1.59)	(22.45)	(5.22)	
5	0.298***	54	0.022*	−0.032**	0.083***	0.064***			0.677***
	(5.76)		(1.92)	(−2.08)	(4.43)	(6.55)			(17.41)

Notes. This table reports the returns associated with the magnitude of earnings surprises within streaks and reversals over the 1987 to 2009 sample period. SURP denotes a firm's quarterly earnings surprise defined as I/B/E/S actual earnings minus the most recent mean consensus estimate, scaled by its stock price. Stocks are first separated into streaks whose length is at least two, and reversals occur when a streak ends. Second, within each streak or reversal portfolio, firms are further sorted into SURP quintiles every month based on the magnitude of their most recent SURP. The stock remains in the relevant portfolio for six months, and stocks with lagged prices below five dollars are excluded from our trading strategies. Equally weighted returns are computed each month, and the time series of these monthly returns less the risk-free rate are regressed on the four-factor model to obtain alpha estimates that are reported as percentages in Panel B. In Panel B, the time series of monthly portfolio returns from the hedged SURP 5–1 portfolio are regressed on excess market returns (MrkRf), size (SMB), value (HML), and momentum (UMD) factors as well as a streak factor. The streak factor is defined as the monthly returns from the trading strategy in Panel A of Table 3. The SURP-sign factor is long stocks with positive earnings surprises that are not in the streak portfolio and short stocks with negative earnings surprises that are also not in the streak portfolio. The purged streak factor is the original streak factor orthogonalized against this SURP-sign factor.

*10%, **5%, and ***1% statistical significance levels of abnormal returns, with the associated t-statistics in parentheses.

4.4. Alternative Trend Definition

Besides streaks of consecutive earnings surprises with the same sign, we also examine trends that arise from *consistency* within the sign of prior earnings surprises. A trend occurs when the sign of the most recent quarterly earnings surprise is the same sign as the majority (50%) of prior earnings surprises. When exactly half a firm's prior earnings surprises are nonpositive, its imbalance is also classified as negative. These imbalances proxy for the likelihood functions underlying the quasi-Bayesian theories that motivate our empirical tests. Intuitively, when the majority of a firm's prior earnings surprises are positive, a positive earnings surprise produces a positive trend, whereas a negative earnings surprise produces a negative reversal. The following diagrams illustrate a positive trend and a negative reversal, respectively:

$$\overbrace{++-++++++-++}^{\text{Positive imbalance}}\underbrace{+}_{\text{Most recent}} \longrightarrow \text{positive trend;}$$

$$\overbrace{++-++++++-++}^{\text{Positive imbalance}}\underbrace{-}_{\text{Most recent}} \longrightarrow \text{negative reversal.}$$

This general definition of trends defined by consistency encompass streaks as a special case. For example, a streak of four consecutive positive surprises requires the most recent surprise to be positive while also requiring the positive imbalance in a firm's prior three surprises to equal its maximum of 100%. In contrast, according to the gambler's fallacy, if 9 of the last 10 draws at a roulette wheel are red, then black is perceived to be more likely for the next draw than red regardless of when the black draw occurred. Unlike streaks, the imbalances that define trends do not depend on the exact sequencing of prior earnings surprises. Indeed, trends based on consistency can be defined over a firm's entire history of prior earnings surprises, although streaks longer than 10 quarters occur infrequently in our sample. Furthermore, all earnings surprises can be classified into either trends or reversals using the consistency definition. In contrast, the streak definition that requires at least two consecutive surprises of the same sign is not able to classify alternating sequences (such as when a positive SURP is followed by a negative SURP and then another positive SURP).

The exact number of prior earnings surprises that investors condition on when forming their expectations is unknown. Using a large number of prior earnings surprises may obscure the distinction between trends and reversals. For example, suppose 20 positive earnings surprises follow 30 negative earnings surprises. Although the majority of the past 50 earnings surprises are negative, investors may focus on the most recent 20 earnings surprises that are positive. Therefore, we examine imbalances over prior horizons ranging from one to five years.[10] To be included in the long or short portfolio of our trading strategies, stocks are required to have earnings announcements in the specified prior horizon. According to Table 6, the number of stocks included in these portfolios increases as the prior horizon becomes shorter.

As with streaks, the results in Table 6 indicate that trends defined by consistency predict returns, whereas reversals are usually associated with insignificant return predictability. The return predictability of trends is relatively stable and significant across each horizon, with our trading strategy generating a return between 0.608% (five years) and 0.873% (two years). In contrast, reversals only induce significant return predictability, albeit a mere 0.217%, at the one-year horizon, and all five reversal quintiles have insignificant returns when consistency is defined over a three-year horizon. Overall, the stronger return predictability of trends compared to reversals is robust to different horizons over which imbalances in past SURPs are computed.[11]

[10] We also examine consistency defined using prior earnings surprises over the firm's entire history and reach similar conclusions.

[11] A purged consistency factor that parallels our earlier purged streak factor achieves a similar level of success in reducing PEAD's four-factor alpha. In particular, 49% (52%) of PEAD's four-factor alpha is removed when consistency is defined using SURPs over the prior three years (two years).

4.5. Fama–MacBeth Regressions

Fama and MacBeth (1973) regressions confirm our earlier portfolio-level results with additional control variables. Several specifications of the following cross-sectional regressions are estimated whose dependent variable, $R_{t+1,\,t+6}$, denotes six-month buy-and-hold returns of individual stocks:

$$\begin{aligned} R_{t+1,\,t+6} &= \gamma_0 + \gamma_1 Beta_t + \gamma_2 \log BM_t + \gamma_3 \log Size_t + \gamma_4 PRET_t \\ &\quad + \gamma_5 SURP_t + \gamma_6 SURP_t^P + \gamma_7 SURP_t^N + \gamma_8 Streak_t \\ &\quad + \gamma_9 Streak_t^P + \gamma_{10} Streak_t^N + \gamma_{11} Consistency_t \\ &\quad + \gamma_{12} LagSURP_t + \gamma_{13} Lag2SURP_t + \gamma_{14} \sum LagSURP_t \\ &\quad + \boldsymbol{\alpha}'\mathbf{X} + \varepsilon. \end{aligned} \tag{2}$$

A firm's market beta is estimated using monthly returns over the prior three calendar years, whereas BM ratios and size, which represents a firm's market capitalization, are measured according to Fama and French (2006). PRET denotes past buy-and-hold returns over the prior 12 months after omitting the most recent month. The most recent earnings surprise is also divided into positive and negative surprises, where the $SURP^P$ and $SURP^N$ variables equal SURP when it is positive and negative, respectively, and zero otherwise. Thus, these continuous variables differentiate between positive and negative earnings surprises. The *Streak* variable is defined as

$$\begin{cases} +1 & \text{for positive streaks,} \\ 0 & \text{otherwise,} \\ -1 & \text{for negative streaks} \end{cases}$$

for streaks of at least two consecutive quarters. The positive and negative components of the *Streak* variable, denoted by $Streak^P$ and $Streak^N$, are dummy variables (not continuous variables) that equal one when the *Streak* variable is positive or negative, and zero otherwise. The *Consistency* variable is defined as

$$\begin{cases} +1 & \text{if the majority of prior earnings surprises and} \\ & \text{the most recent SURP are positive,} \\ 0 & \text{otherwise,} \\ -1 & \text{if the majority of prior earnings surprises and} \\ & \text{the most recent SURP are negative.} \end{cases}$$

The majority is determined using earnings surprises over the prior three years. We also control for the magnitude of prior earnings surprises because returns may capture the cumulative return continuation following earnings surprises before the most recent quarter. Lagged earnings surprises, denoted *LagSURP*

Table 6 Using Consistency to Define Trends

	SURP quintiles					
	Smallest	2	3	4	Largest	Spread
			5 years of past SURPs used to define consistency			
Trends	−0.250**	−0.041	0.217**	0.305***	0.358***	0.608***
	(−2.44)	(−0.40)	(2.21)	(3.25)	(3.58)	(5.21)
Reversals	0.174*	0.211**	0.228**	0.212**	0.036	−0.138
	(1.66)	(2.26)	(2.35)	(2.08)	(0.27)	(−1.01)
Difference	−0.424***	−0.252***	−0.011	0.093	0.322**	0.746***
	(−4.29)	(−3.20)	(−0.20)	(1.30)	(2.58)	(4.22)
			Average number of stocks per month			
Trends	181	247	360	306	287	
Reversals	306	311	474	354	267	
			4 years of past SURPs used to define consistency			
Trends	−0.418***	−0.125	0.018	0.271***	0.419***	0.837***
	(−4.69)	(−1.36)	(1.26)	(3.03)	(4.67)	(7.91)
Reversals	0.055	0.091	0.140	0.176*	0.205**	0.151*
	(0.61)	(1.06)	(1.63)	(1.94)	(2.54)	(1.68)
Difference	−0.473***	−0.215***	−0.032	0.095	0.214***	0.686***
	(−5.71)	(−3.20)	(−0.64)	(1.40)	(2.64)	(5.15)
			3 years of past SURPs used to define consistency			
Trends	−0.474***	−0.046	0.115	0.271***	0.355***	0.828***
	(−4.98)	(−0.41)	(1.36)	(3.00)	(3.96)	(7.56)
Reversals	0.067	0.126	0.139	0.170	0.133	0.066
	(0.68)	(1.48)	(1.43)	(1.54)	(1.34)	(0.66)
Difference	−0.541***	−0.172*	−0.024	0.101	0.221**	0.762***
	(−5.79)	(−1.86)	(−0.36)	(1.08)	(2.31)	(5.42)
			2 years of past SURPs used to define consistency			
Trends	−0.418***	−0.154*	0.089	0.280***	0.455***	0.873***
	(−4.89)	(−1.70)	(1.06)	(3.07)	(5.09)	(8.25)
Reversals	0.164*	0.130	0.131	0.165*	0.238***	0.074
	(1.95)	(1.50)	(1.49)	(1.95)	(3.06)	(0.86)
Difference	−0.582***	−0.284***	−0.042	0.115*	0.217***	0.798***
	(−7.08)	(−3.84)	(−0.83)	(1.86)	(2.68)	(5.91)
			1 year of past SURPs used to define consistency			
Trends	−0.350***	−0.111	0.088	0.290***	0.414***	0.764***
	(−4.18)	(−1.24)	(1.06)	(2.95)	(4.49)	(7.11)
Reversals	0.088	0.068	0.130	0.168**	0.305***	0.217***
	(1.09)	(0.80)	(1.48)	(2.12)	(4.08)	(2.73)
Difference	−0.438***	−0.179**	−0.043	0.122*	0.109	0.547***
	(−5.41)	(−2.50)	(−0.95)	(1.80)	(1.34)	(4.10)
			Average number of stocks per month			
Trends	199	261	451	481	481	
Reversals	555	501	633	417	334	

Notes. This table reports the returns from calendar-time strategies from 1987 to 2009. A trend is defined by the consistency between the sign of prior SURPs and the most recent SURP. A trend (reversal) occurs when the most recent SURP has the same (opposite) sign as the majority of a firm's prior SURPs. Each panel shows consistency based on prior horizons ranging from one to five years. At a minimum, stocks are required to have past SURPs over the relevant horizon. Because the analyst forecasts start in 1984, portfolio formation for the five-year window starts in 1989. SURP is a firm's quarterly earnings surprise (I/B/E/S actual earnings minus the most recent mean consensus forecast) scaled by its stock price. Each month, firms are sorted into quintiles based on their most recent SURP. Stock are held for six months and stocks with lagged prices below five dollars are excluded. Equally weighted returns are computed each month and the time series of these monthly returns less the risk-free rate are regressed on the four-factor model to obtain alpha estimates that are reported as percentages. For brevity, the average number of stocks per month is omitted over the two-, three-, and four-year horizons.

*10%, **5%, and ***1% statistical significance, with the associated t-statistics in parentheses.

and *Lag2SURP* for previous horizons of three to six months and six to nine months, respectively, are included to address this possibility. We also include the sum of all a firm's prior earnings surprises, denoted, by $\sum$ *LagSURP*, excluding the most recent quarterly earnings surprise.[12] All SURP variables are winsorized at the 0.1 percentiles to mitigate the effects

[12] Excluding *LagSURP* and *Lag2SURP* from this sum does not alter our results.

of outliers. The **X** vector contains an array of control variables that account for cross-sectional differences in firm characteristics pertaining to liquidity, information transmission, and uncertainty. These variables include square of SURP, Amihud's (2002) illiquidity measure, idiosyncratic volatility, log of turnover, analyst forecast dispersion, log of one plus analyst coverage, and institutional ownership.[13]

Table 7 reports the time-series averages of the monthly Fama–MacBeth coefficients (multiplied by 100). The standard errors associated with the *t*-statistics are Newey–West adjusted with six lags because the returns are generated from overlapping six-month horizons. The premium for exposure to market-level return fluctuations, the value premium, and the size premium are captured by the γ_1, γ_2, and γ_3 coefficients, respectively, whereas the γ_4 coefficient for PRET is consistent with price momentum. The positive γ_5 coefficients for SURP are consistent with the existing PEAD literature. Furthermore, the positive γ_6 and γ_7 coefficients indicate that the magnitude of SURP influences returns for both positive and negative earnings surprises.

The positive γ_8 coefficients show that streaks predict returns. This is the most important finding in Table 7. In particular, consistent with the returns from our first trading strategy, the positive γ_8 coefficient implies that positive streaks and negative streaks result in higher returns and lower returns, respectively. The positive γ_9 and γ_{10} coefficients confirm that positive and negative streaks predict returns. Nonetheless, the *Consistency* variable also predicts returns because its γ_{11} coefficients are positive, even after controlling for streaks. Thus, investors do not appear to focus exclusively on the most recent sequence of consecutively positive or negative earnings surprises. Moreover, the magnitudes of earnings surprises during the prior six to nine months (*LagSURP* and *Lag2SURP*) have insignificant γ_{12} and γ_{13} coefficients. The insignificant γ_{14} coefficient that pertains to the sum of all lagged earnings surprises is also insignificant. This shows that the return predictability of streaks is not driven by the same-signed earnings surprises prior to the most recent earnings surprise.

5. Robustness Tests

This section demonstrates the robustness of our results to various alternative specifications and competing hypotheses. It also discusses and tests additional predictions of the gambler's fallacy.

5.1. Prior Literature

Barth et al. (1999) as well as Myers et al. (2007) document that firms with increasing earnings have higher valuations but large price decreases following the termination of earnings increases. However, these studies examine contemporaneous returns in the quarter in which earnings are announced. In contrast, we examine returns after earnings are reported using calendar-time trading strategies to evaluate the return predictability of trends.

We replicate the estimation in Barth et al. (1999). These authors examine annual changes in accounting net income using a panel regression. Despite our use of quarterly SURPs and a different time period, we are able to replicate the essence of their findings using a Fama–MacBeth regression. Beginning with Table 7, we define the next quarter's future return as the three-month buy-and-hold return starting one month after the most recent SURP, whereas the contemporaneous quarter's return is defined using the three-month return *ending* in the month of the most recent SURP announcement. Following the Barth et al. (1999) specification (their Table 5, Panel B), we interact SURP with a dummy variable that equals one when there is a positive streak whose length is at least two. We also interact SURP with a dummy variable for negative reversals that equals one when a positive streak is ended by the most recent SURP being negative.

Using contemporaneous returns as the dependent variable, Barth et al. (1999) report that coefficients for the streak and reversal interactions are positive and negative, respectively. In unreported results, we obtain similar evidence. However, when we investigate future returns, the reversal interaction is no longer economically nor statistically significant. This finding implies that the market does not underreact to reversals. In contrast to reversals, the coefficient for the streak interaction remains significantly positive when future returns are examined. Overall, the market appears to underreact less to reversals than streaks because reversals exert a larger (smaller) impact on contemporaneous (future) returns than streaks. Therefore, consistent with the results in Table 7, this evidence suggests that investors underreact to streaks.

Our paper is further distinguished from the existing accounting literature given its focus on analyst-based earnings surprises that account for earnings predictability. Our more recent sample period and the use of quarterly earnings surprises rather than annual earnings announcements also differ from the existing literature.

[13] In unreported tests, we include analysts' consensus long-term growth forecast as a control and find that these forecasts exert no influence on the return predictability of streaks. This test addresses the concern that streaks are associated with higher growth prospects and hence higher expected returns as a consequence of greater risk.

Table 7 Fama–MacBeth Regressions

	Regression specifications						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Beta	0.292	0.259	0.255	0.225	0.235	0.240	0.202
	(0.35)	(0.31)	(0.31)	(0.27)	(0.28)	(0.29)	(0.32)
Log(*BM*)	1.115**	1.065**	1.045**	1.128**	1.091**	1.093**	0.802*
	(2.18)	(2.09)	(2.05)	(2.21)	(2.14)	(2.15)	(1.74)
Log(*Size*)	−0.066	−0.124	−0.125	−0.150	−0.147	−0.150	−0.628**
	(−0.28)	(−0.54)	(−0.56)	(−0.66)	(−0.64)	(−0.66)	(−2.43)
PRET	2.203**	1.506	1.499	1.702	1.497	1.467	1.727
	(2.04)	(1.43)	(1.41)	(1.60)	(1.42)	(1.38)	(1.47)
SURP	25.581***	18.693***		19.407***	17.956***	21.298***	10.430
	(4.57)	(4.05)		(3.78)	(3.75)	(4.84)	(1.40)
$SURP^P$			23.866***				
			(2.95)				
$SURP^N$			31.468*				
			(1.84)				
Streak		1.454***			0.887***	0.848***	0.760***
		(9.23)			(5.26)	(5.08)	(4.62)
$Streak^P$ dummy			1.062***				
			(4.64)				
$Streak^N$ dummy			−1.795***				
			(−11.02)				
Consistency				1.398***	0.785***	0.782***	0.639***
				(8.60)	(4.41)	(4.47)	(3.76)
LagSURP						5.062	4.411
						(0.98)	(0.67)
Lag2SURP						4.456	6.189
						(0.76)	(0.99)
Sum of all lagged SURPs						0.127	−0.353
						(0.77)	(−1.22)
Squared SURP							−87.844**
							(−2.08)
Amihud's (2002) *measure*							−0.195
							(−1.05)
Idiosyncratic volatility							−62.259***
							(−3.29)
Log(*turnover*)							−0.173
							(−0.50)
Dispersion							−0.084
							(−0.43)
Log(1 + *analyst coverage*)							1.195***
							(2.86)
Institutional ownership							−0.695
							(−0.60)
Number of months	276	276	276	276	276	276	276
Number of firm-months	2,277	2,277	2,277	2,277	2,277	2,277	1,944

Notes. Each month, six-month buy-and-hold returns are regressed on the independent variables in Equation (2). Time-series averages of the monthly coefficients (multiplied by 100) from 1987 to 2009 are then reported. An intercept is estimated but unreported. A firm's market beta is estimated using monthly returns over the prior three years, size is last June's market cap, BM is book divided by market equity, and PRET is buy-and-hold returns over the prior 12 months, skipping the most recent month. *Streak* is +1 for positive streaks (at least two consecutive positive SURPs), −1 for negative streaks, and 0 otherwise. *Consistency* is +1 (−1) whenever the sign of the majority of a firm's prior earnings surprises over a three-year horizon is positive (negative) and the most recent SURP is also positive (negative), and 0 otherwise. SURP is a firm's most recent quarterly earnings surprise (I/B/E/S actual earnings less the mean consensus forecast) scaled by its stock price. $SURP^P$ equals SURP for positive values and zero otherwise. $Streak^P$ is a dummy variable for positive streaks. Other control variables include *lagged SURPs*, *sum of all lagged SURPs*, *squared SURPs*, *Amihud's* (2002) *illiquidity measure*, *idiosyncratic volatility*, log of *turnover*, *analyst forecast dispersion*, log of one plus *analyst coverage*, and *institutional ownership*. All SURP variables are winsorized at the extreme 0.1 percentiles. Stocks with lagged prices below five dollars are excluded.

*10%, **5%, and ***1% statistical significance levels, with Newey–West t-statistics with six lags in parentheses.

5.2. Earnings Surprise Autocorrelation

Analyst-based earnings surprises are not highly autocorrelated because analysts are able to adjust their forecasts to account for earnings predictability.[14] However, Chan et al. (2007) document that in recent years, analyst incentives caused analysts to systematically underestimate earnings, thereby allowing management to beat the consensus forecast. The implication of this bias is that firms reporting earnings that marginally exceed consensus forecasts should not be classified as having positive earnings surprises. To address this issue, we repeat our tests by classifying SURPs as positive if they exceed the cross-sectional median of all SURPs in the past 90 days, and negative otherwise. Under this classification, we find nearly identical results (unreported) as those in Table 3. This similarity provides assurance that our results are insensitive to the potential misclassification of small positive surprises.

The second test we conduct directly relates to the autocorrelation in SURPs. Positive autocorrelation within earnings surprises would increase the likelihood of streaks. Although Rabin and Vayanos (2010) demonstrate that the underreaction to streaks predicted by the gambler's fallacy applies to autocorrelated sequences, Bernard and Thomas (1990) hypothesize that PEAD is caused by investors underestimating the positive autocorrelation in earnings surprises. Thus, Bernard and Thomas (1990) hypothesize that streaks are informative, but investors ignore their informativeness. To test this hypothesis, we examine a subset of firms whose earnings surprises are independent according to the runs test (Campbell et al. 1996) as well as a four-lag autoregressive model.

The first subset of independent quarterly SURPs is obtained by applying the runs test at the 10% significance level to firm-level earnings surprises. The runs test begins in January 1987 for firms with at least 12 quarterly earnings surprises. According to the runs test at the 10% significance level, the subset of observations whose earnings surprises defined by analyst forecasts are autocorrelated comprises only 22.28% of our sample. Thus, the majority of firms have analyst-based earnings surprises that are not autocorrelated.

The second subset of stocks with independent earnings surprises is defined by the following autoregressive model:

$$SURP_t = \alpha_0 + \alpha_1 SURP_{t-1} + \alpha_2 SURP_{t-2} + \alpha_3 SURP_{t-3} + \alpha_4 SURP_{t-4} + \epsilon_t. \quad (3)$$

[14] Earning surprises defined relative to realized earnings (SUEs), as in Chordia and Shivakumar (2006), produce similar results as analyst-based earnings surprises. However, besides being more autocorrelated, SUEs are skewed toward positive earnings surprises.

This regression accounts for regularities in consecutive firm-level earnings surprises that may arise from earnings management or analyst forecast biases. Firms having an R^2 from Equation (3) below 0.25 are placed in the independent subset. A low R^2 indicates that the magnitude (hence, sign) of a firm's earnings surprise next quarter is difficult to predict. We replicate our earlier trading strategies using the independent and autocorrelated subsets.

In unreported results, streaks continue to induce significantly stronger return predictability than reversals in the independent subset as well as the autocorrelated subset. This finding applies to independent SURPs defined by the runs test and the autoregressive model. Indeed, reversals are not associated with significant return predictability, whereas streaks yield significant risk-adjusted returns in all but the middle quintile. Return predictability from streaks also exceeds that from reversals. Thus, the results for independent and autocorrelated SURPs parallel our earlier results in Panel B of Table 3.

We conclude that the return implications of streaks is not driven by the positive autocorrelation in earnings surprises. Instead, our results suggest that investors condition on uninformative streaks in earnings surprises.

5.3. Short-Sale Constraints and Limited Attention

To determine if short-sale constraints explain our results, we proxy for short-sale constraints using low institutional ownership because investors cannot easily borrow shares in these firms. Unreported results confirm that short-sale constraints cannot explain the return predictability of streaks because the stronger return predictability of streaks relative to reversals is equally apparent for firms with high or low institutional ownership. Therefore, short-sale constraints do not appear to drive the return predictability of streaks.

Instead of short-sale constraints, limited attention provides an alternative characterization of our results. Hirshleifer et al. (2009) and DellaVigna and Pollet (2009) find that investors are less attentive on days with more earnings announcements and on Fridays, respectively. To test this alternative explanation, we check whether streaks tend to occur more on low attention days compared to reversals. We find that the percentage of Friday announcements for streaks and reversals is almost identical, at 11.43% and 11.45%, respectively. The average number of firms making announcements is also nearly identical for earnings announcements classified as streaks (133.7) or reversals (133.0). Hence, limited attention is unlikely to be an explanation for the stronger return predictability of streaks.

5.4. Earnings Uncertainty and Diffuse Priors

Our next analysis tests whether long streaks induce less return predictability than short streaks when investors priors are more diffuse. According to Rabin (2002) the gambler's fallacy is predicted to be weaker for longer streaks when investors have more diffuse priors regarding the underlying long-term distribution of signals. Specifically, diffuse investor beliefs allow the hot-hands phenomenon to undermine the gambler's fallacy following long streaks.

We proxy for a diffuse prior regarding future earnings with high realized volatility and high analyst forecast dispersion. We then test whether the return predictability of long streaks is weaker for firms with high realized earnings uncertainty and high analyst forecast dispersion. This exercise replicates Table 4 for both these subsets of firms.

Unreported results confirm that the return predictability following streaks of at least 10 is weaker for firms with high earnings variability or high forecast dispersion. Thus, as predicted by Rabin (2002), the gambler's fallacy appears to be weaker when investors have more diffuse prior beliefs.

5.5. Abnormal Turnover

Provided investors condition on different information sets, Rabin and Vayanos (2010) predict that trading volume would be higher in portfolios containing streaks than reversals. We test this hypothesis using the average abnormal turnover during the six-month holding period. Abnormal turnover is defined as turnover in a particular month divided by the portfolio's average turnover in the prior six months, minus one. Unreported results reveal that the average abnormal holding-period turnover is higher for firms in the streak portfolio than for firms in the reversal portfolio. This evidence is consistent with an initial underreaction to streaks that leads to greater trading volume in the subsequent holding period. Consequently, abnormal turnover is consistent with the gambler's fallacy.

6. Conclusions

We find that streaks consisting of consecutive quarterly earnings surprises with the same sign have important return implications. A trading strategy that conditions on streaks defined by at least two prior earnings surprises yields a significant four-factor adjusted return of 0.603% per month. This strategy buys stocks with positive streaks and sells stocks with negative streaks while ignoring the magnitude of earnings surprises. Conversely, the four-factor adjusted return from conditioning on reversals, which correspond to the termination of streaks, is insignificant. The difference between the return on the streaks strategy and the reversals strategy is also economically and statistically significant.

We also assess the return predictability of streaks after accounting for the magnitude of the most recent earnings surprises. After sorting firms into quintiles according to the magnitude of their most recent earnings surprise, we divide these quintiles into portfolios of streaks and reversals. We then buy stocks with positive streaks in the highest quintile and sell stocks with negative streaks in the lowest quintile. A four-factor alpha of 0.882% per month is obtained from this trading strategy. Again, this strategy's return is significantly higher than that of a similar strategy that conditions on reversals.

Our results show that PEAD is limited to streaks. Indeed, a streak factor from the returns of our first trading strategy explains 54% of PEAD's four-factor alpha. Therefore, despite being a cross-sectional anomaly, PEAD has a significant time series component. Fama–MacBeth regressions confirm the return predictability of streaks after controlling for a variety of firm characteristics that include earnings surprises before the most recent quarter. We also confirm that the autocorrelation in quarterly earnings surprises is not driving our results.

In summary, our results indicate that investor expectations are influenced by trends in prior quarterly earnings surprises. Our evidence supports the gambler's fallacy in Rabin (2002) because investors appear to underreact to trends in earnings surprises. One interesting avenue for future research is to examine the link between the gambler's fallacy and price momentum. Preliminary evidence from our Fama–MacBeth regressions indicates that price momentum is insignificant after controlling for trends in earnings surprises.

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