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When it is Adaptive to Follow Streaks: Variability and Stocks

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Abstract

Streaks of events are ubiquitous yet understanding the behavioral effects of them has been restricted by the lack of testable hypotheses concerning the most basic question: When do we tend to follow streaks (positive recency), and when do we tend to go against streaks (negative recency)? From an analysis of positive recency in terms of adaptivity, I develop two elements of people's representation of the process generating a sequence which should be predictive of people's use of positive recency. The first factor is *randomness*, which has already been tested empirically, and the second is *variability* which is tested here. The context used is stocks because not only do people seem to give weight to streaks in the stockmarket, but recent evidence suggests that it may be beneficial to do so. Participants were told that a small company (more variable price) and a large company (less variable price) had experienced a streak of six months of increased/decreased stock prices. As predicted, participants were more likely to predict that the small company would continue the streak next month. However, regardless of the initial streak, participants tended to switch which company would do better between six months and ten years. The results show that there are interesting behavioral phenomena associated with streaks, and that Burns' (2001, under review) analysis generates testable predictions.

Streaks and Basketball

A streak is simply a sequence of repeated outcomes in an event stream experienced by a person. In response to a streak, two expectations are possible for the next outcome: The person may expect the streak will end (negative recency), or that the streak will continue (positive recency). Both behaviors have been observed empirically. Negative recency is often known as the *gambler's fallacy* (Laplace, 1951) and an example of positive recency is belief in the *hot hand* (Gilovich, Vallone & Tversky, 1985). As far back as Fernberger (1913) negative recency effects in perceptual experiments have been noted. Recently, Huettel, Mack and McCarthy (2002) have shown with fMRI studies that particular areas of the frontal lobe are activated by streaks of events and that the magnitude of the response depends on streak length. This suggests that streaks may have a pervasive, even automatic, effect on behavior. However, that the brain is sensitive to streaks does not answer a fundamental question about the behavioral reaction to them: why do people sometime tend to display positive recency, and sometimes negative recency?

Possibly the best known empirical study of positive recency is Gilovich et al.'s (1985) analysis of basketball. They found that basketball fans overwhelmingly agreed with a set of statements about the hot hand including the following two: (Statement 1) “Does a player have a better chance of making a shot after having just made his last two or three shots than he does after having missed his last two or three shots?”; (Statement 2) “Is it important to pass the ball to someone who has just made several (two, three, or four) shots in a row?” However Gilovich et al.'s analysis of 3200 shots attempted by a professional basketball team over a season's worth of home games, found no evidence of shot dependencies. (Perhaps more surprisingly, Gilden [2001] pointed out that their analysis also implied stationarity of shot success probabilities, suggesting that a player's shooting percentage is a constant over the whole season.)

Tversky and Kahneman (1971) explained belief in the gambler's fallacy as due to the representativness heuristic leading to a belief in a *law of small numbers*. In order for a sequence of events to be considered representative, people think that every segment of a random sequence should reflect the true proportion. Thus a streak of one type of event must quickly end and be “evened out” by the other events. Gilovich et al. (1985) argued that belief in the hot hand is also due to belief in the law of small numbers. A belief that things should "even out" will be challenged by a long streak, therefore basketball players may reconcile the apparently unusual streak and their belief in the law of small numbers by assuming that the events are dependent. However it is problematic to explain the opposite behavior with the same principle (Gigerenzer, 2000, p. 290-291), yet this is what has been done with the gambler’s fallacy and the hot hand. The law of small numbers makes no prediction regarding when people will display negative or positive recency. However, analysis of streaks in terms of adaptiveness predicts two aspects of people's representation of the process generating events that should influence their use of positive recency: randomness and variability.

Adaptiveness and Streaks

Various investigators in recent years have developed models of cognitive processes based on the principle of adaptivity (e.g., Anderson, 1990; Gigerenzer, 2000). The adaptivity approach starts with the question of what helps the system attain its goals, and then attempts to play out the implications for the aspect of cognition under study. Thus, for example, Gigerenzer and Todd (1999) focus on how reasoning relates to the goals of the organism. Burns (2001, under review) argues that the wrong conclusion has been drawn regarding the hot hand phenomenon in basketball, and that by applying the criterion of adaptiveness a different conclusion can be drawn.

Thinking in terms of adaptiveness puts an emphasis on the behavior associated with the hot hand, which reveals that there are two different aspects of the hot hand that Gilovich et al. (1985) did not distinguish. Statement 1 (i.e., better chance of hitting after a streak) concerns a belief in the dependency of shots; whereas Statement 2 (give the next shot to a player experiencing a streak) concerns the behavior of allocating shots between players. Thus there is a hot hand belief and a hot hand behavior.

The distinction between the hot hand behavior and belief is critical to evaluating the adaptivity of positive recency in basketball as a heuristic. Gilovich et al.'s (1985) empirical results have held up over time and led many to cite belief in the hot hand as an example of a strong human reasoning fallacy. However, this conclusion is based on the implicit assumption that showing a belief (dependence) to be a fallacy is equivalent to showing a behavior (use streaks as an allocation cue) is also invalid, but this connection cannot be assumed. In basketball the goal is to maximize team scoring, so if belief in the hot hand increases scoring, then the behavior that appears to be based on it is adaptive. Burns (2001) demonstrated by simulation that the hot hand behavior meets the adaptive criterion of helping basketball players achieve their goal of maximizing their team's scoring, even if shots are in fact independent events.

A formal model

A closed-form analysis of the adaptivity of the hot hand behavior has been developed by Burns (under review). Briefly, the analysis treats the first two shots of a basketball game as a Markov model, and specifies two players on the same team, X and Y. (There is no loss of generality in simplifying the situation to only two players, or treating a single hit as a "streak"). There are four model parameters. The first two are x and y, the shooting percentages of Players X and Y, respectively. The third parameter is a bias b to give the ball to Player X. This parameter can represent any bias that is not based on streaks, for example the fact that Player X has a high shooting percentage. The fourth parameter is h, which temporarily elevates the probability of a player receiving the next shot after a hit. Thus, the probability of Player X receiving the shot after a hit is $b + h(1 - b)$, instead of b. The values of these parameters can range from 0.0 to 1.0. (Tversky & Gilovich [1989] report that players are in fact more likely to receive the next shot after they score, implying $h > 0$.) The model assumes that the probability of hitting a given shot is independent of hitting any other shot. After two shots, there are 16 possible states, because for each shot there are two choice points: who gets the shot and whether that player hits. The expected number of hits after two shots is calculated by summing the 16 states' expected number of hits, which yields Equation 1 (a full derivation appears in Burns, under review):

$$\text{E(hits after two shots)} = 2(b(x - y) + y) + h(b - b^2)(x - y)^2$$

There are two critical aspects of Equation 1. First, the term $h(b - b^2)(x - y)^2$ is *never* negative, which means that application of the hot hand as a heuristic for allocating shots can never lower the expected number of hits. The second critical aspect is that any positive value of h will raise the expected number of hits. However, there are two precise conditions under which h has zero effect. When $x = y$, there is no difference between the players so h is irrelevant, as is any allocation cue. Also, h is irrelevant when $b = 0$ or $b = 1$, but for good reasons allocating all shots to the same player is never observed in real basketball (and rarely in any form of sequential choice). Although the model simplifies basketball shooting, doing so is justified by Gilovich et al.'s (1985) data. Given that they showed that shooting is equivalent to a stationary Bernoulli process, my analysis shows that following streaks must increase scoring. Any other conclusion must refute Gilovich et al.'s data.

This analysis can be applied to any sequence of decisions that must be made between two options. Burns (under review) expands on this and discusses the condition under which following streaks should be beneficial.

Randomness

One implication of the model is that positive recency should be beneficial when the possible options have unequal probabilities of success. Thus positive recency should be observed when this is true (as it is in basketball), however Nickerson (2002) pointed out that observation is insufficient to determine the actual probabilities of events (except in the limit), thus the *representation* people have of the process generating a sequence should have a significant effect on their utilization of positive recency. If they have a representation that implies unequal probabilities then they should be more likely to display positive recency. Assuming that people's representations generally correlate with reality, it is adaptive for people to do so. In effect, positive recency may be a heuristic that people have learnt to apply to events generated by a mechanism they think offers options with unequal probabilities. Therefore if people's representations of the process generating a sequence was manipulated, that should affect their tendency to use positive recency, even when the sequence and the probabilities of events are kept constant. This could be tested by manipulating people sense that a process is *random*.

Nickerson (2002) suggested that the most common assumption people make about a process they think is random is that it selects events with equal probabilities. Wagenaar (1991) proposes two other conditions: there is a fixed set of candidate events, and the process that selects an event ignores previous events (i.e., events are independent). Thus if someone represents a fixed set of candidate events as generated nonrandomly, that implies either they think that independence or equal probability is violated. Without knowledge of its nature, violation of independence alone does not predict negative or positive recency. In contrast, *any* representation in which the assumption of equal probability is violated should lead a person to use positive recency (in the absence of clear information about the direction of dependencies). Thus if nonrandomness implies unequal probabilities, a representation of the process generating a sequence as nonrandom should result in people displaying positive recency.

The implication that positive recency should be observed more often if people represent the process as nonrandom, was affirmed by Burns and Corpus (in press). They showed that people were more likely to predict a streak to continue when they were presented with a situation in which they thought the generating process was nonrandom. Burns (2002) presented another demonstration of this effect.

Variability

This paper will test another predictor that should influence people's choice between negative and positive recency: variability in success probabilities. This result is not directly derived from the model presented, but from an analysis of its limitations. In particular, the model does not allow any variability in the probabilities of events. This was justified on the basis of Gilovich et al.'s (1985) data, but as a result the expected outcome is at a maximum when $b=1$ (i.e., the best shooter takes 100% of the shots). If a professional basketball team was to ever attempt to implement the strategy of giving 100% of their shots to their one best shooter, then that player would quickly find himself surrounded by five opponents and would be likely to experience a lowered shooting percentage (and a losing team). Thus there would arise a negative sequential dependency for that player's success in hitting shots. Perhaps this is why no player in Gilovich et al.'s (1985) data took more than 24% of the team's shots. At the levels of b professional teams seem to use, the negative dependencies a pure strategy would create do not appear to arise. In probability learning experiments (e.g., Estes, 1964) with constant probabilities, a pure strategy would be optimal but it is rarely observed. Perhaps this is because it is only optimal under narrow conditions, given that variability (or at least its possibility) is the more usual state of the world.

Variability in success probabilities could be added into the analysis generating Equation 1 but would require further assumptions about the nature of that variability. However, it is possible to reason through what implications variability should tend to have for positive and negative recency. In general, when the environment is unstable streaks should increase in importance as allocation cues. This is because the probability of a streak changes immediately when there is a change in the underlying likelihoods of events, whereas success rates are based on history and thus there is a lag in their reaction to change. To take an extreme example, a player injured such that he or she is incapable of shooting a basketball will miss every shot they attempt. Thus a streak of misses will immediate form but that players' career shooting percentage will only change slowly. The impact of variability underlies models such as McNamara and Houston (1985) that argue that a forager should give greater weight to recent information than older information. In any multi-cue decision making process when the validity of one cue is decreased, that suggests giving greater relative weight to the other cues. If variability in success probabilities increases, then in most cases the validity of base-rate (e.g., shooting percentages) as an allocation cue should decrease relative to the validity of streaks as an allocation cue.

Thus a second predictor for positive recency can be derived. If streaks are a stronger allocation cue the more variable is the probability of success of an event, then the decision maker's representation of this variability as characteristic of the generating process should influence their use of recency. People should be more likely to display positive recency for a process they represent as having more variability in its probability of success, than for a process they represent as having less such variability.

Streaks in stocks

Gilovich et al.'s (1985) findings have long attracted interest from economists partly because of the implications they seem to have for behavior. Camerer (1989) framed the question of interest to economists in terms of “whether mistaken beliefs like the hot hand fallacy make allocation of resources sub-optimal" (p. 1257). Empirical findings regarding streaks interest economists because many aspects of the economy form streaks. Furthermore, people tend to act on streaks, in particular with regard to stocks.

Following streaks in stock markets has a history almost as long as stock markets themselves. Under various names, (*Momentum trading*, *technical analysis*, *charting*) some investors have believed in buying stocks which have recently been increasing in value, independent of other factors. Just like basketball fans' belief in the hot hand, many portfolio managers and stock analysts have this belief to some degree (Jegadeesh & Titman, 2001). Yet Lo, Mamaysky and Wang (2000) note that academics labeled this "voodoo finance" and advocated *fundamental analysis*, which sees stock price as purely a function of the underlying qualities of the company.

However starting with Jegadeesh (1990) and Lehman (1990), analyses of US stockmarket data going back to the 1920's have shown that momentum strategies could yield abnormal profits. Jegadeesh and Titman (1993, 2001) documented that momentum profits continued into the 1990's. Rouwenhorst (1998) extended these findings to 12 European countries, and Rouwenhorst (1999) did so for a sample of 20 emerging markets. Thus the results have been consistent enough that they cannot be dismissed.

How to explain momentum profits is a topic of current dispute. Some explanations have focused on faulty reasoning by investors. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) speculate that momentum effects are due to overconfidence (e.g., Fischhoff, Slovic, & Lichenstein, 1977) or the self-attribution bias (e.g., Langer & Roth, 1975). Others explanations suggest that they may be due to properties of markets. For example, Johnson (2002) proposes that momentum effects can be rational in that they may arise due to persistent growth rate shocks.

Conrad and Kaul (1998) propose that momentum effects are due to the dispersal of mean rates of return across the universe of all stocks, similar to the argument presented here for the adaptiveness of the hot hand as taking advantage of the dispersal of players' shooting percentages. Jegadeesh and Titman (2001) argue against Conrad and Kaul (1998) on the grounds that momentum effects do not last forever, they are most effective up to a period of nine months. However, stock streaks may provoke a reaction once people notice then, thus putting a limit on how long following a streak will be effective. Consistent with this is that Moskowitz and Grinblatt (1999) found that momentum effects are strongest for small (in terms of capital), less analyzed stocks. They suggest that this was because information about them is diffused more slowly. However, people also seem to expect more price variability for small than for large stocks. My analysis suggests an alternative explanation of Moskowitz and Grinblatt's findings, as it predicts that following streaks may be more effective for more variable stocks because streaks are inherently more informative for such stocks.

If people expect stock to differ in degrees of variability, stocks may provide an interesting domain for testing the hypothesis that people are more likely to display positive recency for generating processes they see as more variable.

An Experiment

To test the hypothesis that people will be more likely to display positive recency for processes they see as more variable in their probabilities of success, participants were presented with two stocks: one from a large, well established company; and one from a small recently established company. The assumption that participants would think the small company had a more variable stock price than the big company was tested.

Participants were told either that the stock of both companies had increased in each of the last six months, or that the stock of both companies had decreased in each of the last six months. Thus there were two conditions: *positive streak* and *negative streak*. Participants chose between the two companies for three different time periods: which stock would be more likely to increase next month, which would yield greater profits over the next six months, and which over the next ten years.

Participants were predicted to be more likely to indicate that the small (more variable stock price) company would be the one more likely to continue the streak next month, regardless of the direction of the streak. Thus they should favor the small company to increase in price next month in the positive streak condition, but favor the big company to increase in price next month in the negative streak condition. What will happen for the six-month and ten-year periods was an issue to be explored. However on the basis that momentum traders do not predict a stock experiencing a streak to go up for ever, it was expected that most participants would not answer all three questions the same.

Method

Participants. A total of 216 members of the Michigan State University subject pool participated in the experiment.

Materials and Procedure. Participants in the positive streak condition read the following text:

"Imagine that you are examining the history of the stock prices of two different retail companies. One is big and well established, the other is small and recently established. In examining each, you notice that the stock price of both has increased in each of the last six months. Please try to answer the following questions by circling your response."

Participants in the negative streak condition read the same text, but "increased" was changed to "decreased." They were then asked to make a choice between the two companies for three different time periods:

1. The stock of which company do you think is most likely to increase in the next one month period?
2. If you were a short term investor looking to make a profit in a six month period, which company would you be more likely to invest in?
3. If you were a long term investor looking to make a profit in a ten year period, which company would you be more likely to invest in?

Participants were also asked, "Which company do you think is likely to have the more stable stock price?" Then, "Have you ever bought or sold any stocks yourself?"

Results

The variability manipulation was effective in that 94% of participants indicated that they thought the big company would have the more stable stock price (positive streak condition 101 out of 107, negative streak condition 102 out of 109). Twenty percent of participants indicated that they had traded stocks, but this variable had no effect on the other variables, so no separate analysis will be reported for participants with or without experience with stocks.

Table 1: Number of participants answering *big* company or *small* company for each time period.

	Answer		
	Big	Small	Total
Next month			
Positive streak condition	43	64	107
Negative streak condition	74	35	109
Next six months			
Positive streak condition	55	52	107
Negative streak condition	64	45	109
Next ten years			
Positive streak condition	70	37	107
Negative streak condition	70	39	109

Table 1 shows participants' responses to the three questions about which company they expected to do better in each of the three time periods. As predicted, there was a significant relationship between which company participants expected to experience an increase in stock price in the next month, and the direction of the streak, $X^2(1) = 16.7$, $p < .001$. Participants were more likely to display positive recency for the small company that they considered to have the less stable price, in that more expected the price of the small company to increase if the streak was positive (64/107) but fewer expected it would increase if the streak was negative (35/109).

The effect of streak direction seemed to wear off for the six month, $X^2(1) = 1.17$, $p = .28$, and ten years, $X^2(1) = 0.34$, $p = .85$, periods. However, an interesting effect emerges if we look at how participants varied their answers for the three different time periods. Table 2 presents how many participants gave each of the eight combinations of answers.

Only 15% of participants answered all three questions identically, indicating that most participants did not expect one company or the other to do best over all three time periods. The most critical transition appears to be between the six-month and the ten-year periods. Table 3 presents the frequencies of participants' combinations of answers to these two questions, over both streak conditions.

Table 2: Number of participants giving each combination of answers to the question of which company would do better over one month, six months, or ten years.

Next month	Six months	Ten years	*n*
big	big	big	30
big	small	big	49
big	big	small	37
big	small	small	1
small	big	big	16
small	small	big	24
small	big	small	57
small	small	small	2

Table 3: Relationship between answers to the six month and the 10 year time period questions, for each streak condition.

		Answer next six months	
		Big	*Small*
Positive streak			
Answer next ten years	*Big*	19	51
	Small	36	1
Negative streak			
Answer next ten years	*Big*	27	43
	Small	37	2

There was a significant relationship between participants' answers to these two questions in both the positive streak condition, $X^2(1) = 47.7$, $p < .001$, and the negative, $X^2(1) = 32.8$, $p < .001$. Overall, only 23% of participants thought the same company would do best over both time periods.

Table 4 shows that there were also significant relationships between participants answers for the one month and six month periods in both the positive streak condition, $X^2(1) = 5.41$, $p = .020$, and the negative, $X^2(1) = 9.89$, $p = .002$. However for these periods, participants tended (64%) to give the same answer to these questions.

Overall the results show that streaks had an effect on the immediate period, but their effect seemed to diminish as the time horizon increased. However most participants did not settle down to a consistent bias towards one stock or the other.

Table 4: Relationship between answers to the one month and six month questions, for each streak condition.

		Answer next six months	
		Big	*Small*
Positive streak			
Answer next month	*Big*	28	15
	Small	27	37
Negative streak			
Answer next month	*Big*	51	23
	Small	13	22

Discussion

The results supported the hypothesis that participants would be more likely to predict the generating process with the more variable probability of success (i.e., the small company) to display positive recency in the next time period. This is consistent with the analysis suggesting that following streaks is more advantageous for more variable than for less variable processes, assuming that people are sensitive to such an advantage. Thus another factor that has predictive value for when people apply negative and positive recency can be added to the randomness effect that Burns and Corpus (in press) found.

The results highlight another important aspect of streaks: people do not expect them to continue forever. Thus people do not necessarily interpret streaks as evidence that the option experiencing the streak must be better than other options. Instead a streak is just a temporary indicator that is allocated a temporary increase in weight.

The model described earlier does not incorporate any concept of time horizon, thus this is a limitation of the model given that it would predict people should extrapolate streaks infinitely into the future. However there are no other existing theoretical tools for dealing with this phenomenon either. Although decision making research often looks at what people will do now in response to recent history, how that information is extrapolated over different time periods has not been explored. That people discount current information as a predictor of events extended further into the future makes sense from an adaptive viewpoint. In a variable environment, assuming the current streak will be predictive far into the future would be a poor strategy.

To advocates of momentum trading strategies it may not be surprising that 85% of the participants altered their choice over different time periods. A feature of these strategies is not just following streaks, but trying to pick when streaks will stop. However, it is not clear why the six month to ten years transition was critical, although it is consistent with Jegadeesh and Titman's (2001) finding that momentum advantages are strongest over a medium term (nine months). This finding needs more research before it can be concluded that this is a general effect.

A possible limitation of this study is that participants were presented with a description of a streak, rather than experiencing it. Although this may mirror the way people often use streaks in the stock market, to generalize this effect it should be tested with streaks that participants experience one event at a time.

Further research should try to generalize the variability effect, and to investigate whether the reversal of choices is something specific to stocks or a more general phenomenon. More generally though, this study illustrates that the analysis of streaks developed by Burns (2001, under review) generates testable predictions, unlike descriptions of streaks such as the law of small numbers.

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