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# Predicting the next step of a random walk: experimental evidence of regime-shifting beliefs <sup>☆</sup>

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## Abstract

Barberis et al. (J. Financial Econ. 49 (1998) 307), construct a model in which investors use the prevalence of past trend reversals as an indicator of the likelihood of future reversals. While such “regime-shifting” beliefs are consistent with a variety of psychological theories, other contrary predictions are consistent with the same theories. We report two experiments with MBA-student participants that strongly support the existence of regime-shifting beliefs. We conclude that regime-shifting models can provide a useful framework for understanding market anomalies, including underreactions to earnings changes and overreactions to long-term earnings trends. © 2002 Published by Elsevier Science B.V.

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## 1. Introduction

Barberis et al. (1998, hereafter “BSV”) propose a model in which investors underreact to individual earnings surprises on average, while still overreacting to long-term trends in earnings. This paper reports experimental results that support a

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key assumption in BSV's model, which is that investors use the prevalence of past trend reversals as an indicator of the likelihood of future reversals. The participants in our experiments did so, even though they were told quite clearly that the sequences they were predicting were random walks, and that past outcomes provided no information about future outcomes.

In BSV's model, a firm's earnings follow a simple Markov process (random walk) in which each period's earnings are either \$1 more or \$1 less than the prior period's earnings. Both events take place with equal probability. Because the firm pays all earnings out as dividends, the true value of the firm follows a random walk. BSV assume that investors believe that the earnings process shifts between two regimes: one in which earnings changes tend to reverse themselves (a "mean-reverting" regime) and one in which earnings changes are followed by similar changes (a "trending" regime). As a result, investors erroneously use the frequency of recent earnings reversals to predict the likelihood that the current earnings change will be reversed. This error leads investors to underreact to changes following a sequence with many recent reversals, while overreacting to changes following a sequence with few recent reversals.

Prior experimental evidence on representativeness heuristics (Kahneman and Tversky, 1973) and overreliance on unreliable data (Griffin and Tversky, 1992) suggests that investors will not view random-walk series as random. However, little light has been shed on whether deviations from randomness will follow the form of regime-shifting that BSV propose. The same theories that can be used to predict regime shifting behavior can also be used to predict a wide variety of prediction errors incompatible with BSV's model. For example, Rabin (2002), who draws on much of the same psychology literature, constructs a formal model of inference based on the law of small numbers and "local representativeness". His model can also explain short-term underreaction and long-term overreaction, but makes predictions based on outcomes of sample proportions, not the rate of past reversals.

This paper reports the results of two experiments that test whether investors' over- and underreactions to changes in a random walk are influenced by the prevalence of recent reversals. In both experiments, we told MBA students that they would see portions of sequences generated by a process that is indistinguishable from a random walk (a symmetric Markov process that always changes by +1 or -1). In Experiment 1, participants saw 16 different eight-period sequences. In Experiment 2, participants saw 30-period rolling windows of a single sequence. In both experiments, participants selected a price for a security whose value was determined by the next change: the value is equal to one hundred (zero) if the next change is upward (downward). Because beliefs about regime shifting might depend on investors' perceptions of the causal process generating the sequence, we told half of our participants in each experiment that the sequence was derived from a model of coin flipping, and told the other half that the sequence was derived from models of "surprises" in firm performance. We measured investors beliefs about future changes using a variant of a Becker et al. (1964) mechanism that allows participants to maximize expected cash payments by setting prices equal to their estimated probability of an upward change.

Because the likelihood of an upward change is always 50%, participants maximize their expected winnings by setting a price of 50 for each security. Investors might deviate from this strategy not only because they believe they can predict a random walk (as postulated by BSV), but also because they might make random errors or because they simply enjoy trading (Black, 1986). Therefore, we test not for the *existence* of deviations from 50 (which could arise for many reasons), but for the *directional relationship* of those deviations with the rate of past reversals. In other words, we are not testing why investors might deviate from random-walk predictions, but whether their predictions will deviate in a manner consistent with regime shifting.

Our analyses show that investors overreacted more (or underreacted less) to changes preceded by fewer reversals. In debriefing questions, the majority of participants stated that they used past patterns to predict future changes. Results were the same whether participants were told that the sequences were derived from a model of coin flipping or a model of firm performance, although participants told the latter were more likely to report focusing on patterns in Experiment 2, and tended to view the rolling sequence as less stable. These results are consistent with BSV's regime-shifting model, although they would also be consistent with a broad class of models in which investors act as if the rate of reversals in random-walk sequences varies predictably over time.

BSV's model can account for both underreactions and overreactions only if investors do not assess too high an unconditional prior probability that they will observe trending (unconditional on the rate of recent reversals). In our experiments, however, it takes a relatively high rate of recent reversals to lead investors to underreact to the most recent change. As a result, we see very few underreactions and a great many overreactions. Future research might examine how this aspect of our results might vary with changes in experimental settings.

The remainder of the paper is organized as follows. Section 2 presents the design of Experiment 1 and its results. Section 3 presents the design of Experiment 2 and its results. Section 4 presents some analyses of participants' responses to debriefing questions. Section 5 discusses the implications and limitations of the study and suggests directions for future research.

## 2. Experiment 1

### 2.1. The regime-shifting model

BSV's model is motivated by two empirical anomalies: market prices underreact to recent earnings surprises (Bernard and Thomas, 1990), but overreact to sustained extreme performance (De Bondt and Thaler, 1985, 1987).<sup>1</sup> To reconcile these apparently contradictory results, BSV develop a model in which the value of a

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<sup>1</sup>For a review of the literature on over- and underreactions, see Daniel et al. (1998) and Fama (1998).

security is determined by the present value of the sum of future earnings, which are paid out immediately as dividends. In each period, the earnings series either moves up by \$1 or down by \$1. Each outcome is equally likely, regardless of past outcomes. Assuming a constant discount rate of  $\delta$ , the value of the firm at any point is  $N_t/\delta$ , where  $N_t$  represents the most recent earnings number.

BSV assume that the representative investor in the market is a Bayesian, but holds a prior belief that is faulty in an important respect. That is, even though performance follows a random walk, investors are certain that this is not the case. Instead, investors believe that performance alternates between two regimes. In a “mean-reverting” regime, investors believe that changes are more likely to be followed by changes in the opposite direction than by changes in the same direction. In a “trending” regime, investors believe that changes are more likely to be followed by changes in the same direction than by changes in the opposite direction.

Regime shifting leads investors to use the proportion of recent changes that are reversals as an indicator of the likelihood of further reversals. Because more reversals make it more likely that the firm is in the mean-reverting regime, investors underreact more and overreact less following a sequence with many reversals. This regime-shifting assumption thus generates overreactions and underreactions similar to the empirical anomalies described above.

BSV’s model also includes parameters specifying the investor’s belief over how likely each regime is (unconditional on the history of reversals) and how predictable each regime is of the next outcome, given that regime. Their model can account for both underreactions and overreactions only if investors do not place too high an unconditional prior probability on observing trending changes.

## 2.2. Experimental method

BSV motivate their model with psychological evidence that “people think they see patterns in truly random sequences.... While a consistent pattern of high growth may be nothing more than a random draw for a few lucky firms, investors see ‘order among chaos’ and infer from the in-sample growth path that the firm belongs to a small and distinct population of firms whose earnings just keep growing” (p. 316).

A large body of literature indeed suggests that investors will attend to patterns that arise by chance, even if they have little or no predictive validity.<sup>2</sup> However, there is as yet no evidence that people will attend to the *particular* patterns that play the central role in BSV’s model (the rates of reversals), nor is there evidence that they will expect rates of reversal to persist over time. Instead, they might focus on recent trends and expect them to continue (as in De Bondt, 1993) or believe that periods of reversal are followed by periods of trending. Both of these errors would be consistent

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<sup>2</sup>See, for example, Slovic et al. (1974, p. 192), Tversky and Kahneman (1971, 1974), Kahneman and Tversky (1973), Langer (1975), Davis et al. (2000), Ross et al. (1977), Andreassen (1987, 1990), Koehler (1991), and Bloomfield et al. (2000). Papers focusing specifically on time-series predictions include Andreassen (1987, 1990), Bloomfield et al. (2001), Lim and O’Connor (1996), and O’Connor et al. (1993).

with the psychological results motivating BSV's model, but would lead to a pattern of price errors very different from what BSV's model predicts. The goal of our experiment is, therefore, to test the specific form of errors that arise from BSV's model: investors are more likely to expect reversals after a high rate of recent reversals.

To conduct our experiment, we recruited 38 MBA students from the Johnson Graduate School of Management at Cornell University. We presented these participants with 16 graphs depicting the last eight changes in a sequence. After seeing each graph, participants set a price at which robot traders could buy or sell shares of a security. The security paid a dividend of \$100 (denominated in "laboratory dollars") if the next change in the sequence was upward and paid a dividend of \$0 if the next change in the sequence was downward. We measured investors' beliefs about future changes using a variant of a Becker et al. (1964) mechanism that allows participants to maximize expected cash payments by setting prices equal to their estimated probability of an upward change. Because participants were told that the sequences were generated by a computer model that followed the rules of a random walk, the profit-maximizing price is \$50. At the end of the experiment, laboratory dollars were converted into US dollars, giving participants a financial incentive to set prices that accurately reflected their predictions of future outcomes.

We constructed the 16 graphs by first selecting, from a long random walk, eight eight-period sequences with varying numbers of reversals (0, 1, 3, 4, 6, and 7 reversals), as shown in Fig. 1.<sup>3</sup> We then created another eight sequences by creating mirror images of the first eight (every upward change becoming a downward change, and vice versa).<sup>4</sup> Our primary tests compare how prices differ across sequences with few reversals (0 or 1), a moderate number of reversals (3 or 4), or many reversals (6 or 7). We used one sequence for each number of reversals, except that we used three different sequences containing only one reversal.

Each participant saw all 16 sequences, so both the number of reversals and the orientation of the sequence are manipulated as within-subject variables. We also manipulated two other factors as between-subject variables: the order in which they saw the sequences and the description of the sequence. Half of the participants saw the sequences in one predetermined random order while the other half saw the sequences in the reverse order. Also, the participants were randomly assigned to one of two sequence descriptions, as discussed below.

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<sup>3</sup>Using graphical representations of the sequences, rather than tables of numbers, might highlight patterns, pattern changes, and changes in overall levels, thereby increasing the magnitude of our effects. However, we see no reason that graphical representation of the sequences (or the details of those graphs) would influence the *direction* of participants' predictions, which are the focus of our tests. For further discussion of presentation effects in prediction tasks, see Andreassen (1988) and Andreassen and Kraus (1990).

<sup>4</sup>Hand-selecting short sequences means that the histories observed by our participants are not truly random. However, the outcomes they are attempting to predict are random. As a result, we are not deceiving participants when we tell them that future outcomes are unpredictable given past outcomes.

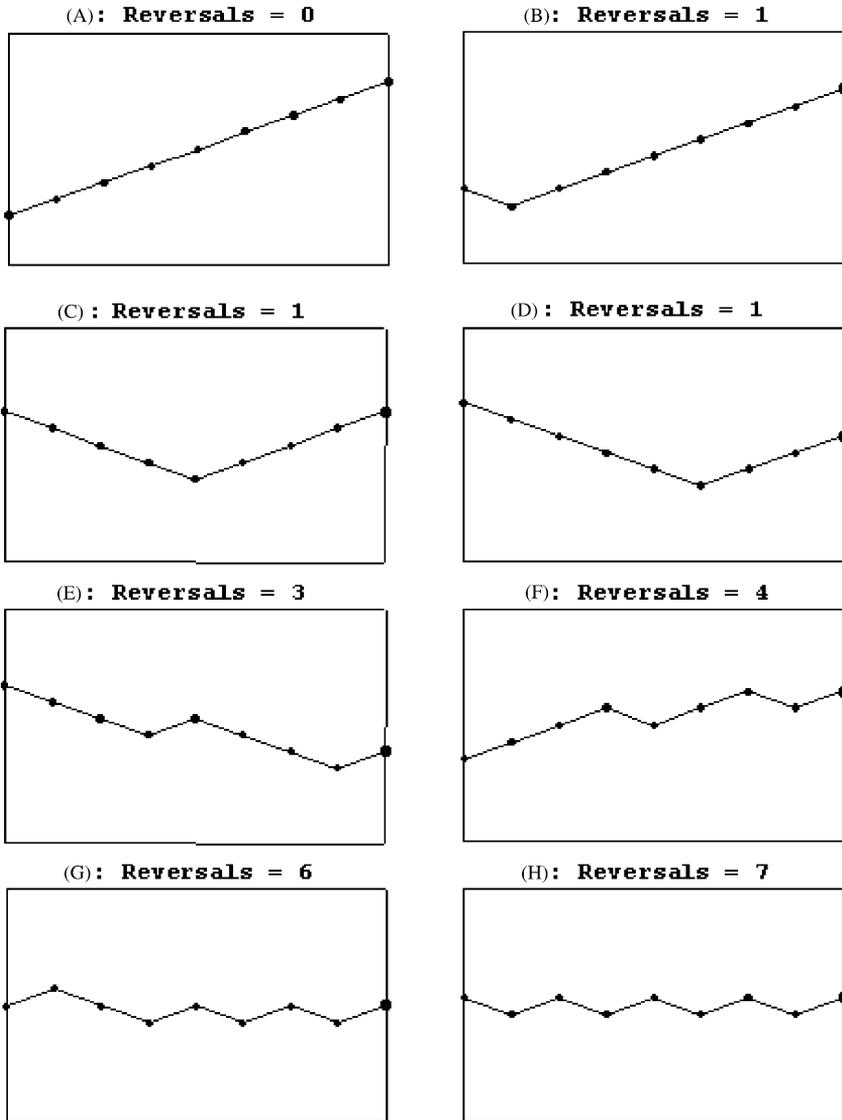


Fig. 1. Sequences from Experiment 1. This figure shows the eight different eight-period histories (lettered A–H), and indicates the number of reversals in each. In addition, participants also saw inverted versions of the same eight histories (each upward change replaced with a downward change, and vice versa), making 16 histories in total used for the analyses.

### 2.2.1. Information provided to participants

BSV's model assumes that investors will not believe that the earnings series follows a random walk, even though it does. To allow a strong test of the model, we clearly informed participants that changes follow a random walk and, therefore, cannot be

predicted on the basis of past changes. Evidence supporting BSV's prediction, despite this instruction, is a strong indication that participants might not believe that a sequence follows a random walk even though it does. Alternative approaches would provide weaker evidence. For example, we could have provided only vague information about the true time-series properties and allowed participants enough observations of the series that they should be able to assess those properties. However, support for BSV's predictions in such a setting might just indicate that people did not observe enough periods. We discuss this aspect of our experiment in more detail in Section 5.

Psychological forces that lead participants to believe they can predict future changes in a random walk might be related to participants' beliefs about the underlying nature of the process. Participants might be more likely to see patterns in earnings surprises than in coin flips, and, if they see patterns in both, the way in which they deviate from a random walk might differ depending upon their beliefs about the underlying processes generating the series. We therefore manipulated those beliefs by telling half of the participants that the process reflected the outcome of a series of coin flips (the coin context), while telling the other half of the participants that the process reflected the performance surprises for a publicly traded firm (the firm context). Specifically, we told participants in the coin context the following:

We have constructed a model of a random process that works much like flipping a fair coin. Using this model, we have created sequences of outcomes. An upward movement indicates a "heads" outcome, and a downward movement indicates a "tails" outcome.

Since outcomes of coin flips are unpredictable, they result in a sequence known as a "random walk." That is, statistical models are unable to predict future outcomes from past ones and, on average, there is no upward or downward trend. Random walk sequences almost always contain intervals of recognizable patterns. However, since these patterns can change greatly at any time, statistical models are still unable to predict future outcomes.

We told participants in the firm context the following:

We have studied large numbers of publicly traded firms, and constructed models of their performance patterns. Using these models, we created sequences to represent patterns of "surprises" (actual performance minus predicted performance). An upward movement indicates a "positive surprise," which results when the firm performs better than predicted, and a downward movement indicates a "negative surprise" when the firm performs worse than predicted.

Since performance surprises are unpredictable, they result in a sequence known as a "random walk." That is, statistical models are unable to predict future surprises from past ones and, on average, there is no upward or downward trend. Random walk sequences almost always contain intervals of recognizable patterns. However, since these patterns can change greatly at any time, statistical models are still unable to predict future outcomes.

### 2.2.2. Incentives

Participants were given financial incentives to reveal as accurately as possible their prediction of the next period's change. Specifically, participants were told that each history they saw was associated with a security that would have a value of zero if the subsequent change was downward, and a value of one hundred if the subsequent change was upward. They were then asked to do the following:

Before each number is revealed, you will be asked to state a price at which you are willing to buy or sell shares. If you state a price **above** \$50, you will **buy** one share at \$51 and at each price up to (and including) the price you state. For example, if you state a price of \$54, you will buy a total of four shares: one share at \$51, one share at \$52, one share at \$53, and one share at \$54. If you state a price **below** \$50, you will **sell** one share at \$49 and at each price down to (and including) the price you state. For example, if you state a price of \$46, you will sell a total of four shares: one share at \$49, one share at \$48, one share at \$47, and one share at \$46.

This device, which is similar to a Becker et al. (1964) mechanism, gives risk-neutral agents an incentive to set a price equal to their probability estimate of an upward movement. We explained this to the participants as follows:

The first thing to consider when setting a price is your expectation of the value of the security. You will make the most money on average if you **set a price equal to the expected value of the security**. To see why, assume that you believe a security is worth \$72. If you set a price of exactly \$72, you will buy one share at every price from \$51 to \$72. This is good, because all of these prices are below expected value, and you expect to make money on each of these trades. Setting a price of \$72 also guarantees that you won't buy any shares at prices higher than \$72. This is good, because buying at prices above expected value would cause you to expect to lose money.

More extreme prices expose participants to more risk, as they will buy or sell more shares. Assuming that participants are risk averse, this biases against deviations from the normative price of 50 because participants would need to be quite confident in their predictions to deviate far from 50. Some participants might have been confused by the pricing mechanism. However, because all of our comparisons are between different prices provided by the same person given different histories, such misunderstandings cannot account for differences across treatments.

Participants were told that their winnings from trading would be converted into US dollars and that the more laboratory dollars they earned, or the fewer they lost, the more money they would take home. Participants were also told that average winnings would be about \$20, but that the amount that they personally won would depend on their own performance in laboratory dollars.

Finally, participants answered (on a computer) a series of questions to make sure they understood the instructions they were given. They were required to answer all questions correctly before being allowed to begin the experimental task.

### 2.3. Results

Experiment 1 tests BSV's prediction that participants will underreact more (or overreact less) to changes that are preceded by many reversals. To create a measure (reaction) of under- and overreaction, we first subtract the normative price of 50 from each participant's price for each security. We then sign this difference by the most recent change so that overreactions are positive and underreactions are negative. Specifically, the sign is positive if the price is above 50 when the most recent change was upward or below 50 when the most recent change was downward. The sign is negative if the price is above 50 when the most recent change was downward or below 50 when the most recent change was upward.

Table 1 reports participants' mean reactions for each of the eight sequences, averaged across their two mirror images. For our primary tests, we average these numbers across securities with few reversals (0 or 1), moderate reversals (3 or 4), and many reversals (6 or 7). These averages show a clear negative relation between reversals and reactions. Participants overreact to the most recent change by an average of 11.2 when given sequences with few reversals, while underreacting to the most recent change by an average of 6.9 given sequences with high reversals. Investors overreact by about 0.9 when given sequences with moderate reversals. To assess whether this pattern is statistically significant, we compute the average reaction for each participant within each of these three classes of reversals. We then conduct a *t*-test on each of the three means and on the differences between the means. Each test uses 38 independent observations (one for each participant). We find that the overreactions for low-reversal sequences and the underreactions for high-reversal sequences are both statistically significant ( $p < 0.01$ ), while there is no significant reaction for the moderate-reversal sequences ( $p > 0.8$ ). The reactions to the low- and high-reversal sequences are also statistically different from the reactions to the moderate-reversal sequences and from one another ( $p < 0.01$  for all comparisons).

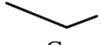
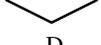
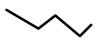
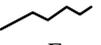
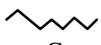
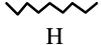
To determine whether the effect of reversals varies with other factors, we conduct a repeated-measures ANOVA, which accounts for the dependence in data that arises when each participant makes multiple decisions. Our tests effectively treat each participant as providing only a single observation, avoiding an overstatement of sample size. The model includes context (coin or firm) and order (forward or reverse) as between-subject factors, and includes reversals (low, medium, or high) and orientation (natural or mirror image) as within-subject factors. After controlling for all other variables, the level of reversals is strongly statistically significant ( $p < 0.0001$ ). The variables for context and order are not statistically significant. We also created variables to capture participants' experience, coursework, and career plans. We find no evidence that the association between reactions and reversals is affected by past experience in security analysis or other Wall Street work, plans to start such a career after graduation, or more extensive coursework in finance or accounting.

We do observe a statistically significant effect of orientation ( $p = 0.0426$ ) and an orientation-by-reversal interaction ( $p = 0.0046$ ). However, these effects of orienta-

Table 1

Results from Experiment 1

This table shows the mean reaction and the absolute deviation of price from 50 for each sequence shape, with summaries for each category of reversal level. A reversal is defined as a change in the opposite direction of the immediately preceding change. Reaction is the signed price deviation from 50, where the sign is positive if the participant expected a continuation (i.e., a positive deviation after an upward change and a negative deviation after a downward change) and is negative if the participant expected a reversal (i.e., a negative deviation after an upward change and a positive deviation after a downward change). Positive (negative) reactions therefore indicate over- (under-) reactions.

Sequence shape	Reversal category	Reversals	Reaction	Mean reaction for category
 A	Low	0	17.5	
 B	Low	1	10.4	
 C	Low	1	12.8	
 D	Low	1	4.0	<b>Low</b> <b>11.2**</b>
 E	Moderate	3	-8.2	
 F	Moderate	4	9.9	<b>Moderate</b> <b>0.9</b>
 G	High	6	-5.5	
 H	High	7	-8.2	<b>High</b> <b>-6.9**</b>

\*\*Statistically different from zero at a  $p$ -level less than 0.01, using 38 observations (one for each participant).

tion do not affect the interpretation of our results. For both orientations, we observe overreactions for sequences with few reversals and underreactions for sequences with many reversals. The interaction between reversals and orientation is driven primarily by sequences E and F, which have moderate numbers of reversals.<sup>5</sup> While we are not

<sup>5</sup>For sequence E (with three reversals), investors overreact by 1.58 when the last change is upward, but underreact by 17.89 when the last change is downward. For sequence F (with four reversals), investors overreact by 15.45 when the last change is upward, but overreact by 4.32 when the last change is downward.

sure why we observe this interaction, the orientation-by-reversals effect does not appear to drive or eliminate the main effect of reversals.

### 3. Experiment 2

#### 3.1. Motivation

Experiment 1 supported BSV's prediction that investors underreact to changes that are preceded by many reversals, and overreact to changes preceded by very few reversals. However, that experiment presented investors with a number of unrelated sequences and observed a cross-sectional association of reactions and reversals. Our second experiment tests for a longitudinal association, which would provide more direct evidence that, as BSV predict, investors expect a single sequence to switch between trending and mean-reverting regimes.

#### 3.2. Experimental method

Our second experiment uses the same participants as in Experiment 1. Each participant remains in the same context as in Experiment 1 (firm context or coin context). We constructed a single 80-period sequence that is statistically indistinguishable from a random walk. Half of the participants saw the sequence shown in Panel A of Fig. 2; the other half saw a mirror image of that sequence (with each upward change converted to a downward change, and vice versa). In each period of the experiment, participants saw the past 30 outcomes. Some sample periods are shown in Panels B and C of Fig. 2.

We told participants in the firm [coin] context the following:

In Part II, your task will be largely the same as in Part I—to predict the direction of future **performance surprises [coin flips]**. The main difference is that, instead of looking at many different sequences, you will be looking at **ONLY ONE** sequence over time. You will start in period one by seeing a history of the prior 30 **performance surprises [coin flips]**. After you make your trading decision, you will learn the next period's surprise, and be asked to make your next trading decision. All other aspects of the task will remain the same as in Part I. You will make a total of 50 predictions.

Incentives for accurate prediction are similar to those in Experiment 1: each change to be predicted was associated with a security that had a value of zero if the next change was down, and a value of one hundred if the next change was up. Participants used the same price-setting mechanism and cash incentives as in Experiment 1. To keep participants from being confused by repeated trading decisions for a single time series, we told them the following:

Although you will see the **SAME** sequence in every period of Part II, in each period you will trade a *different* security whose value depends **ONLY** on the

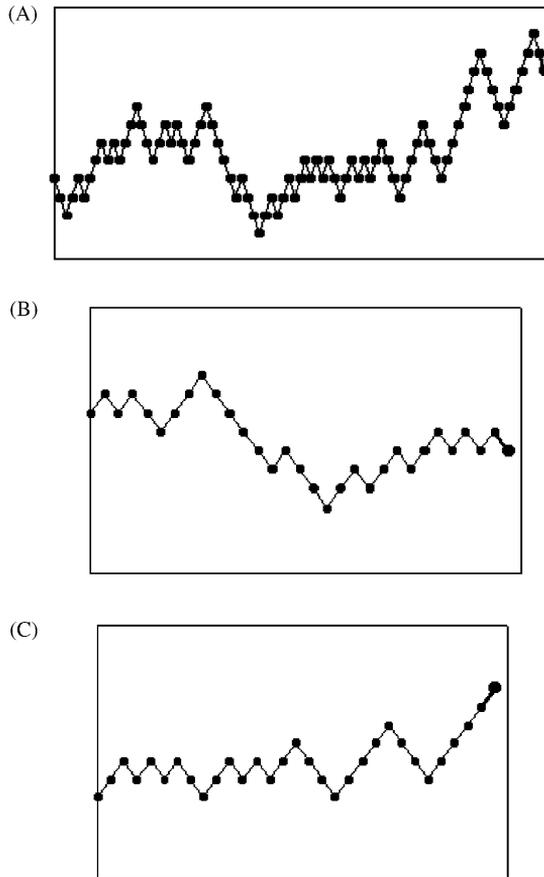


Fig. 2. Sequences from Experiment 2. Participants saw a 30-period history at any given time. Half of the participants saw an inverted version this sequence. (A) Entire sequence. (B) High-reversal segment. This segment has six reversals in the last eight changes, ten reversals in the last 16 changes, and 17 reversals in the last 30 changes. (C) Low-reversal segment. This segment has one reversal in the last eight changes, four reversals in the last 16 changes, and 14 reversals in the last 30 changes.

change in the NEXT PERIOD. For example, the *only* thing that affects your gain or loss in period 8 is how many shares you bought or sold in period 8, and whether the sequence moves UP or DOWN in period 9.

### 3.3. Results

Experiment 2 tests whether, across time, participants underreact more (or overreact less) to changes in a single series that have been preceded by many reversals. To test this hypothesis, we compute the reaction variable for each price in a manner identical to that in Experiment 1, so that positive reactions indicate overreactions and negative reactions indicate underreactions.

Table 2

Results from Experiment 2

This table shows the means for reaction by history length over all periods. Participants saw 50 overlapping 30-period histories of a single rolling sequence. A reversal is defined as a change in the opposite direction of the immediately preceding change. Low-reversal histories are defined as those with fewer than three, seven, and 14 reversals in histories of eight, 16, and 30 periods, respectively. Reaction is the signed price deviation from 50, where the sign is positive if the participant expected a continuation (i.e., a positive deviation after an upward change and a negative deviation after a downward change) and is negative if the participant expected a reversal (i.e., a negative deviation after an upward change and a positive deviation after a downward change). Positive (negative) reactions therefore indicate over- (under-) reactions.

	Low reversals (number of periods)	High reversals (number of periods)	Difference
Eight-period histories	7.2 ( <i>n</i> = 28)	1.9 ( <i>n</i> = 22)	5.3**
16-period histories	7.3 ( <i>n</i> = 30)	1.2 ( <i>n</i> = 20)	6.1**
30-period histories	8.9 ( <i>n</i> = 23)	1.4 ( <i>n</i> = 27)	7.5**

\*\*Statistically different from zero at a *p*-level less than 0.01, using 38 observations (one for each participant).

Table 2 reports reactions to the most recent change, segregated by whether there was a high or low rate of reversal in the preceding periods. The limited number of observations kept us from creating a “medium reversals” category that would have been analogous to that level in Experiment 1. The first line reports the results looking at an eight-period history, to maintain comparability with Experiment 1. Across the entire sequence, the number of reversals in the preceding eight periods ranged from zero to seven. We compute separate means for periods in the lower half of this range (0–3 reversals) and for periods in the upper half of this range (4–7 reversals). As the first line in the panel shows, investors overreacted to the most recent change by 7.2 when it was preceded by few reversals, but overreacted to that change by only 1.9 when it was preceded by many reversals. To conduct statistical tests, we compute the average difference between high and low reversal periods for each of the 38 investors, and then conduct a *t*-test on those differences with the null that this difference is not positive. Using this analysis, the difference of 5.3 is strongly significant ( $p < 0.002$ , one-tailed). A repeated-measures ANOVA shows that the difference is not influenced by the context in which the decision was made (coin or firm), the orientation of the sequence (upward trend or downward trend), or the work experience, training, or career plans of the investors.

The second and third lines of the table report the results of similar analyses based on longer histories. Across the entire sequence, the number of reversals in the preceding 16 periods ranged from three to 12. We compute separate means for periods in the lower half of this range (3–7 reversals) and for periods in the upper half of this range (8–12 reversals). As the first line in the table shows, investors overreacted to the most recent change by 7.3 when it was preceded by relatively few

reversals, but overreacted to that change by only 1.2 when it was preceded by many reversals. The difference of 6.1 is statistically significant ( $p < 0.001$ , one-tailed). The number of reversals over the previous 30 periods (all of the periods the investors could see at any given time) ranged from ten to 19, which we split into a low range of 10–14 reversals and a high range of 15–19 reversals. We observe overreactions of 8.9 following relatively few reversals and overreactions of 1.4 following many reversals. The difference of 7.5 is statistically significant ( $p < 0.001$ , one-tailed). Our results do not appear to be driven by any association of reversals with trend because the results are similar even after controlling for the trend over each of the three history lengths.

An alternative “two-stage” analysis further confirms these results. First, we estimated the regression model  $REACT = a + b REVERSALS$  for every participant in each of the three history lengths. Next, we used the  $t$ -statistic from the  $b$  in each regression as the dependent variable. Of the 38  $t$ -statistics for the eight-period histories, we find that 33 are negative (consistent with regime-shifting behavior), while only three are positive. (The remaining two participants provided no meaningful  $t$ -statistic, as they chose exactly the same price in every period.) We find similar results with 16-period and 30-period histories.

## 4. Supplementary analyses

### 4.1. Debriefing questions

We examined answers to debriefing questions from Experiment 2 for any effects of context that were not apparent in our price analyses. We found several such effects. Compared to participants in the coin-flip context, participants who were told that the sequence reflected the time-series properties of surprises in firm performance reported that the pricing task was more difficult ( $p < 0.05$ , one-tailed), that the sequence was less stable ( $p < 0.10$ , one-tailed), and that they paid more attention to older elements of the sequence in making their predictions ( $p < 0.10$ , one-tailed). Answers to an open-ended question confirmed these results. We asked all participants the following question:

What advice would you give someone on this task? Specifically, when do you recommend setting high and low prices? When do you recommend being cautious, and setting prices near \$50? (We will have a panel of experts evaluate all of the advice given by participants. The participants giving the best advice will win \$100 each.)

We then coded the responses (blind to each participant’s context condition) as recommending either a strategy of pattern recognition, a strategy of ignoring patterns, or making no recommendation regarding patterns. Overall, 22 participants recommended a strategy of pattern recognition, while only seven recommended avoiding strategies based on patterns. (Five subjects provided no response, while another four recommend neither pattern recognition nor avoidance of pattern recognition.) Significantly more participants focused on pattern recognition in the

firm context (15 of 17) than in the coin context (7 of 12), a significant difference ( $p < 0.05$ , one-tailed). Analysis of the specific responses indicate that while context might increase attention to patterns, participants pay attention to different patterns and recommend responding to them in different ways. As a result, context does not influence regime-shifting behavior, which is one particular response to one particular pattern.

#### 4.2. *The reversion prediction*

BSV's model can account for both underreactions and overreactions only if investors do not assess too high an unconditional prior probability of observing trending (unconditional on the rate of recent reversals). Overall, however, we detect a strong tendency of participants to predict trending. Table 1 shows that, in Experiment 1, overreactions to sequences with few reversals are approximately twice the size of underreactions to sequences with many reversals. All of the averages in Table 2 indicate overreactions. Of the 50 rounds of Experiment 2, we observe an average overreaction in 32 rounds and an underreaction in 18.

One interpretation of our evidence is that the psychological forces leading participants to expect trending outweigh the forces leading them to expect reversal. Examples of the former would be "hot hand" biases (e.g., Gilovich et al., 1985). Examples of the latter would be "gambler's fallacy" biases (e.g., Tversky and Kahneman, 1971).<sup>6</sup> However, our experiment is not designed to examine this issue; doing so would require an experiment that manipulates factors hypothesized to alter the balance of the relevant psychological forces. In general, one must be cautious in interpreting the average levels of dependent variables in experiments because those levels can be influenced by any number of features held constant across the experiment. For example, the preponderance of overreactions might be driven by our use of graphical representation for the time series or by our subject pool. In contrast, our evidence on regime shifting is easy to interpret because we show that a change in the rate of past reversals causes a change in the level of overreaction, holding constant all other characteristics of the setting (such as the graphical interface and the subject pool). Libby et al. (2002) provide a more detailed discussion of these experimental design issues.

### 5. Discussion

We conducted two experiments in which we presented participants with time series closely resembling the model in Barberis et al. (1998). As BSV predicted, MBA student investors used the recent rate of reversals in a sequence to predict the

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<sup>6</sup>Overreactions could predominate because participants who expect trending are more confident than participants who expect mean-reversion (Lawrence and Makridakis, 1989; O'Connor and Lawrence, 1992). However, we find no evidence supporting this conjecture because underreactions and overreactions are not different in size in either experiment.

likelihood of future reversals, even though they are told very clearly that the sequence was a random walk and that future outcomes could not be reliably predicted from past outcomes. Investors in our experiment showed a strong tendency to predict reversion after seeing many reversals and to predict trending after seeing few recent reversals. This regime-shifting behavior was not affected by the process from which the random-walk sequence was said to have been derived (from a model of coin flips or from a model of firm performance) or by investors' work experience, training, or career plans. We conclude that BSV's regime-shifting model seems to be a reasonable framework in which to interpret some market anomalies.

BSV's model assumes that investors are certain that a random walk time series does not follow a random walk. We provide a strong test of this assumption by telling our participants explicitly that the series follow a random walk. An alternative would be to provide no such information, but to allow participants to learn the nature of the time series by observing patterns of outcomes for a long time. We doubt, however, that this alternative approach would yield substantially different results. Regardless of the experimental method, one could argue that deviations from random-walk beliefs would have been smaller, and possibly eliminated, under conditions with more feedback, clearer instructions, better training, higher incentives, or smarter participants. For this reason, we focus our analysis not on the existence or magnitude of such deviations, but rather on the direction of those deviations and on how they vary with the rate of recent reversals. We see no reason to believe that clearer instructions or other changes would alter evidence supporting the cross-sectional predictions of BSV's model (unless it eliminated *all* deviations from random-walk predictions, which we believe is highly unlikely).

BSV's model can account for both underreactions and overreactions only if investors do not assess too high an unconditional prior probability that they will observe like changes (unconditional on the rate of recent reversals). Overall, however, we detect a strong tendency of participants to predict trending. Future research might examine factors that alter the nature of such overall beliefs in trending. Future research might distinguish between the sign and magnitude of earnings changes. As in BSV's model, our experiment presents investors with sequences in which all earnings changes are of identical magnitude (\$1). It might be that investors believe that large changes are more likely to reverse than smaller changes. Future research might also examine whether other market forces might lead prices to underreact to changes, even when investors' expectations do not. Such "sluggishness" in prices is often observed in laboratory market studies, such as Bloomfield (1996a, b) and Gillette et al. (1999).

Future research might also examine how variations in regime-shifting beliefs affect trading volume and liquidity in market settings. BSV's model assumes a single representative investor, as if all investors behave identically. To the extent that investors vary in their responses to histories, however, histories with different levels of reversals might lead to greater trading volume and more liquid markets.

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