Behavioral Biases and Investor Behavior: Predicting the Next Step of a Random Walk (Revisited and Extended)[†]

Elena Asparouhova[‡], Michael Hertzel [§], and Michael Lemmon[¶]

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ABSTRACT

Bloomfield and Hales (2002) (BH) reports results from experiments that support the existence of regime-shifting beliefs of the type theorized by Barberis, Shleifer, and Vishny (1998) (BSV). We revisit and extend the BH experiments to provide new evidence on BSV and on a competing model by Rabin (2002). We first argue that the BH experiments cannot provide a definitive test of BSV because the set of sequences shown to subjects are not from a random walk process, but instead are more consistent with what would be expected if the true underlying process was of a regime-shifting type. That is, the BH experiments cannot distinguish whether subjects rationally conclude that the underlying process is of a regime-shifting type or whether belief in regime-shifting arises from behavioral biases as suggested by BSV. We modify the experimental setting to be consistent with the BSV model by showing subjects patterns from a random process, while refraining from telling them what the underlying process is. We also expand the testing methodology to consider the impact of streaks on investor expectations. The results of our experiment are consistent with investor belief in the law of small numbers as modeled in Rabin and are not supportive of investor belief in regime-shifting as modeled in BSV.

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[‡]University of Utah, e.asparouhova@utah.edu

[§]Arizona State University

[¶]University of Utah

I. Introduction

A recent paper by Bloomfield and Hales (2002) reports results of laboratory experiments with MBA-student participants that strongly support the existence of regime-shifting beliefs of the type theorized by Barberis, Shleifer, and Vishny (1998) (hereafter BSV).[1] The model in BSV is motivated by evidence documented by cognitive psychologists on two systematic biases that arise when people form beliefs: conservatism and representativeness.[2] These biases are captured in a regime-shifting framework where the earnings process follows a random walk, but investors instead hold the flawed belief that the process switches between a "reversal" regime (in which earnings changes tend to reverse themselves in sign) and a "continuation" regime (in which earnings changes are more likely to be followed by changes of the same sign).

The Bloomfield and Hales tests focus on a key feature of the BSV model: investors look at the frequency of past performance reversals in forming expectations about future reversals. In the laboratory experiments, subjects observe eight separate graphical representations of historical sequences (and their mirror images) of eight outcomes (up or down). Participants are told that the sequences are generated from a random walk, and a pricing mechanism is used to elicit their expectations about the direction of the ninth outcome in the sequence. Consistent with BSV, Bloomfield and Hales finds that the subjects consistently rely on the prevalence of past performance reversals when assessing the likelihood of future reversals. More specifically, the subjects showed "a strong tendency to predict reversion after seeing many reversals and to predict trending after seeing few recent reversals." (p. 412.)

We revisit and extend the Bloomfield and Hales experiment to provide new evidence on BSV and on a competing model by Rabin (2002) that similarly focuses on quasi-rational investors who look at patterns in past performance in forming expectations. In Rabin, earnings changes are also assumed to be independent but the flaw in reasoning built into the model is that

[1] The model in Barberis, Shleifer, and Vishny (1998) provides an explanation for two pervasive empirical regularities documented by finance researchers: short-term momentum and long-term reversal in stock returns.

[2] Conservatism refers to the tendency to underweight new evidence relative to prior beliefs and is suggestive of investor under-reaction. Representativeness bias comes in many forms. Relevant here is the belief that even small samples will reflect the properties of the parent population. This can lead to overinference from small samples and is suggestive of investor over-reaction.

investors falsely believe they are drawn from an urn without replacement. Rabin shows that this behavior causes prices to exhibit similar under- and over-reaction as in the BSV model.

We begin by revisiting the Bloomfield and Hales experiment. We argue that their experiment cannot provide a definitive test of BSV because the set of sequences shown to subjects are not consistent with what would be observed under a random walk process, but instead are more consistent with what would be expected if the true underlying process was of a regime-shifting type. A simple chi-square goodness of fit test based on the frequency of reversals strongly rejects that the set of sequences used in the experiment were drawn from a random walk process. Furthermore, consistent with an underlying regime-shifting process, the sequences have far too many observations in the tails of the distribution of reversal rates. More specifically, an eight-outcome sequence generated by a random walk process will yield zero or one reversal only 6.25% of the time. However, of the 16 patterns that Bloomfield and Hales employ, 50% have zero or one reversal.[3] Similarly, 25% of the sequences employed are in the high-reversal end of the distribution, where a random process would generate six or seven reversals only 6.25% of the time. Although there may be sound methodological reasons for employing extreme sequences, one unintended consequence is that it results in an experiment that is unable to distinguish whether subjects *rationally* conclude that the underlying process is of a regime-shifting type or whether the subjects' belief in regime-shifting arises from behavioral biases as suggested by BSV.[4]

As a way of illustrating our critique, we modify the Bloomfield and Hales laboratory setting to be consistent with the crucial assumption in BSV that the underlying data-generating process is random by having our subjects observe historical sequences with rates of reversals that are consistent with a random walk process. In particular, rather than using the sixteen hand-selected Bloomfield and Hales sequences, participants in our experiment observe sequences of historical outcomes produced by a random number generator, which results in a distribution of reversal rates that is nearly identical to the expected distribution under a random walk. The effect of this simple modification on the experimental outcome is dramatic: we find that

[3]The odds of this occurring if the true data-generating process is a random walk is equal to 1.8992×10^{-6}.

[4]For the BSV model to work, it is crucial that the regime-shifting belief is *wrong*. If instead the true process is a regime-switching one, then the behavior of the BSV investor will be indistinguishable from that of a rational investor, and consequently the desired over- and under-reaction results will not obtain.

subjects are more likely to believe that the next move will be a reversal the fewer the number of past reversals. This finding is directly opposite of that documented by Bloomfield and Hales and is inconsistent with the BSV prediction that subjects should be more likely to expect continuations after observing sequences with fewer reversals.

That the results from our simple modification of Bloomfield and Hales do not support BSV is not surprising. There is considerable experimental evidence suggesting that if subjects are told a process follows a random walk and they are in fact shown patterns that are drawn from a random process, a gambler's fallacy effect (as we observe here) will result (e.g., Barberis and Thaler (2002, p. 1070)).[5] Gambler's fallacy is sometimes referred to as a manifestation of the "law of small numbers" where individuals believe that even small samples should be representative of the population as a whole; a classic example of this bias is when, after a string of reds at the roulette wheel, bettors expect that a "black is due" in order to balance out the string of reds. Given the experimenter instructions on the underlying random process, the results from our first experiment highlight that the Bloomfield and Hales findings in support of BSV likely reflect the set of "non-random" patterns shown to subjects.

Our illustrative experiment, however, does not allow for a useful test of BSV, since in that model investors do not know the underlying data-generating process. Thus, in our second experiment, we further modify the Bloomfield and Hales laboratory setting by not telling the subjects what the underlying data-generating process is. To provide discriminating evidence on BSV and Rabin, we also expand the testing methodology to examine how streak length (number of consecutive like outcomes) affects subjects' expectations of future outcomes.

In BSV, the affect of streaks on expectations is straightforward: investors become more confident that they are in the continuation regime, as the time since the most recent reversal increases. As BSV (1998, p. 310) put it, "when a positive surprise is followed by another positive surprise, the investor raises the likelihood he is in the trending regime, whereas when a positive surprise is followed by a negative surprise, the investor raises the probability he is in the mean-reverting regime."

[5]Studies that present evidence on gambler's fallacy include Tversky and Kahneman (1971), Burns and Corpus (2004), Bar-Hillel and Wagenaar (1991), Rapoport and Budescu (1992), Clotfelter and Cook (1993), and Terrell (1994). See also Rabin (2002) for a review of the evidence.

In Rabin, short streaks are expected to be reversed whereas long streaks are expected to continue. The following simple example illustrates the formation of expectations in Rabin's model. Consider an investor with a prior that puts considerable weight on firms being "average", in the sense that they generate equal numbers of good and bad outcomes, who also allows for the possibility of "good" and "bad" firms as well. When this investor observes short streaks of like outcomes, due to the strong average prior, he believes that a reversal is due. When the observed streak is long enough, this investor's posterior departs from his prior, and he starts believing that he is facing a "good" or a "bad" firm. As a result, after observing a long streak, the investor would find it more likely that the next change in earnings will be of the same sign as the previous one.

The results of our second experiment are not consistent with the model in BSV. Although we find that subjects are more likely to believe the next move will be a reversal the greater the number of past reversals, we do not find that subjects believe more strongly in continuation the longer the current streak.[6] Instead, when streak length is relatively short (less than five), we find that subjects are more likely to bet on a reversal the longer the streak. For longer streaks the above effect reverses and subjects are more likely to bet on continuation the longer the streak. While inconsistent with investor belief in regime-shifting of the type modeled in BSV, this behavior is what one can expect from investor belief in the law of small numbers, as modeled in Rabin (2002).

The remainder of the paper proceeds as follows. Section II provides additional evidence and discussion concerning expectations on reversal rates under a random walk process and the actual rates employed in the Bloomfield and Hales experiment. It also presents the results from our first modification of the Bloomfield-Hales laboratory setting where subjects are shown patterns from a random process. Section III presents the results of our second experiment where again subjects are shown patterns from a random process, but are not told that the underlying

[6] Another recent study investigates whether the Bloomfield and Hales laboratory results carryover to the marketplace. Using data from the college football point-spread betting market, (Durham, Hertzel and Martin (2005)) examine whether the rate of past reversals in outcomes against the spread affect changes in the spread during the week. They show that the distribution of reversal rates of outcomes is not significantly different than would be expected under a random walk, but that investors tend to bet *against* teams on long winning streaks.

data-generating process is random. Section IV concludes with a brief discussion and some thoughts regarding future research.

II. Experiment I: Bloomfield and Hales Revisited

The Bloomfield and Hales (2002) experiment uses the eight graphs shown in Figure 1, and their mirror images, to test for investor belief in regime-shifting. Although participants were instructed about the random nature of the underlying data-generating process, we conjecture that they may have *rationally* concluded that the observed sequences were from a regime-shifting process. To illustrate graphically, Figure 2 presents a comparison of histograms showing the frequency distribution of the number of reversals (in an eight-outcome sequence) that would be expected under a random walk process and the actual frequency distribution of reversals shown to subjects in the Bloomfield and Hales treatment. The figure makes clear that sequences with both low (0 or 1) and high (6 or 7) numbers of reversals are over-represented, leading to the possibility that subjects logically concluded that the data was from a regime-shifting process, rather than from a random walk.

We recognize that participants did not see all patterns in advance and thus could not make the type of assessment suggested by a simple chi-square test. Thus, much depends on the order in which subjects were shown the sequences. Still, the patterns were sufficiently extreme that subjects may have come to the regime-shifting conclusion reasonably quickly. For example, of the eight patterns employed, both the quintessential trending regime pattern (8 like outcomes in a row) and the quintessential reversal regime pattern (each outcome a reversal) are used. While it is obviously possible that these two patterns can result from a random walk process, the presence of both of these extreme patterns may reasonably be expected to lead subjects to conclude that the underlying data-generating process is not random. The fact that the mirror images are also used (the subjects see 16 patterns in total) compounds the problem. That is, while eight heads in a row may raise suspicion regarding the fairness of a coin (chance of this in 8 outcomes is 3.9%), seeing eight tails in a row from the same coin (in close proximity; i.e., within 16 trials) may very well confirm that suspicion. More generally, we also note that eight of the 16 sequences shown to subjects contain zero or one reversal. The odds of this occurring if the true data-generating process is a random walk is less than 0.001%. At the other extreme, 4 of the 16 patterns have 6 or 7 reversals; the likelihood of this outcome being generated from a random walk is equal to 1.51%.

In addition to potentially inducing belief in regime-shifting, the set of patterns used in the Bloomfield and Hales study may lie behind the finding of a strong tendency for subjects to predict trending. This result is troubling for BSV since the model can only account for both under-reaction and over-reaction if investors do not place too high an unconditional probability on the trending regime. We suggest that the tendency of the subjects to predict trending in the Bloomfield and Hales experiment may be due to the fact that 50% of the patterns were strongly suggestive of trending (0 or 1 reversal) whereas only 25% were suggestive of reversion (6 or 7 reversals). Thus, a trending pattern was twice as likely. Bloomfield and Hales suggest "Future research might examine factors that alter the nature of such overall beliefs in trending." (p. 412.). Thus, in addition to testing our conjecture that the particular patterns employed induced investor belief in regime-shifting, our first modification of the Bloomfield and Hales experiment will also shed light on the specific tendency to predict trending that was observed in their study.[7]

The aim of the experiment here is to investigate whether evidence consistent with Barberis, Shleifer and Vishny (1998) still obtains when subjects are indeed shown sequences that are drawn from a random process. For comparison purposes, and as a control, we also replicate the basic design of experiment 1 in Bloomfield and Hales.[8] We refer to this as the BH treatment and to our simple modification as the Bloomfield and Hales Revisited (BHR) treatment. The BH treatment consisted of five sessions (BH1, BH2, BH3, BH4, and BH5) with 62 participants in total. The BHR treatment consisted of three sessions (BHR1, BHR2, BHR3) with a total of 43 subjects. The experiments were conducted at the University of Utah Laboratory for

[7]Bloomfield and Hales also perform a second experiment in which subjects observe a 30-period rolling window of outcomes rather than the 16 pre-selected sequences used in experiment 1. The subjects still exhibit a tendency to predict a continuation following sequences with few recent reversals, however the degree of over-reaction is mitigated relative to their experiment 1. Although the sequences used in experiment 2 appear to be more random, the *same* subjects participated in the second experiment after participating in the first, potentially leading to carryover effects across the two experiments.

[8]We refer the interested reader to p.399 of Bloomfield and Hales (2002) for a description of this experiment.

Experimental Economics and Finance (UULEEF) between April and June 2004. All subjects were students from the University of Utah who had not previously participated in experiments. The BH sessions lasted 40-50 minutes, and the per subject payoff averaged \$10.20. The BHR sessions lasted a little longer–50 to 70 minutes, and the average payoff was \$11.10. In all sessions a notional currency called "francs" was used. At the end of each session the franc earnings were converted to dollar earnings at a rate that made the average earnings equal to a pre-announced dollar amount.[9] The software eTradeLab was used in all sessions.[10]

A. BH Treatment: Replication using the Bloomfield and Hales Sequences

As in Bloomfield and Hales (2002), subjects in this treatment were told that the underlying data-generating process followed a random walk; we duplicated the exact language used by Bloomfield and Hales in the description of the sequence-generating process.[11] In each session the participants were presented with the 16 sequences used by Bloomfield and Hales. Figure 1 shows eight of those sequences, the other eight were mirror images of the ones shown. The sequences were shown to the subjects in the same order used by Bloomfield and Hales.[12]

We elicited the subjects' assessment of the next outcome being UP using the variant of the Becker, DeGroot, and Marschak (1964) (BDM) mechanism described in Bloomfield and Hales.[13] More specifically, after observing each of the sequences, participants had the opportunity to buy or sell (depending on what price they state) units of an asset whose payoff was 100 francs if the next outcome in the sequence was UP and 0 francs if the next outcome

[9]For sessions BH1 and BHR1 the average dollar payoff was equal to \$5, for sessions BH2, BH3, BH4, and BH5 it was \$13, while for sessions BHR2 and BHR3 it was \$15. The first sessions within each setting were with students taking an introductory investments class and all participants received (flat) extra credit for participation in addition to the (variable) dollar amount.

[10]A snapshot of the eTradeLab screen is given in the instructions in the Appendix. Also, the interested reader can visit (uID=2, email address=p2) http://uuleef.business.utah.edu/eTradeLab8 for the BH experiments and http://uuleef.business.utah.edu/eTradeLab7 for the BHR experiments.

[11]A copy of the instructions provided to the subjects is included in the Appendix.

[12]We thank Robert Bloomfield for providing us with the ordering in which the sequences were shown to subjects. This is not the ordering shown in Figure 1 of their paper. Note that Bloomfield and Hales also show the sequences in reverse order to some of the subjects but find no evidence that the order matters. We therefore use only one of their orderings.

[13]The BDM mechanism is a (incentive-compatible)quadratic scoring rule. Reporting the perceived probability of an UP move provides maximal expected payoff. We follow the presentation of Bloomfield and Hales, see the attached instructions for more details.

was DOWN. If a price above 50 was stated, subjects would be required to buy one share at 51 and at each price up to and including the stated price. If a price below 50 is stated, subjects would be required to sell one share at 49 and at each price down to and including the stated price. A subject would maximize expected earnings by setting the price of the asset at his/her subjective probability (in percentages) of an UP movement (which is also equal to the expected value of the asset, using the subjective probability measure).[14]

Once a subject had set the price, she was prompted to press a button and reveal the ninth step of the current sequence. The realization of the ninth outcome was not the same across subjects. A random number generator determined the direction of the last step of each sequence. The payoff from the round was computed and displayed in a payoff table available for viewing at any time. Each subject went through the sixteen repetitions of the above procedure at her own pace.[15]

B. BHR Treatment: Revisit of Bloomfield and Hales using Random Sequences

In this treatment, instead of being shown the same set of pre-selected historical sequences, each participant observed a different set of random sequences.[16] Because of the random sequence generation, the observed sequences differed across subjects. The specific details of the experiment are reported in the Appendix. In order to obtain sequences that have low probability of occurring (those with low and high reversal frequencies) we increased the number of sequences observed by each subject from 16 to 50. The same instructions (with minor modifications to conform to this treatment) were provided to subjects and the same pricing mechanism was used to elicit subjects' subjective probabilities about the direction of the ninth move in the sequence.

[14]Of course, because the actual probability of an UP move is 50%, all subjects maximize their expected payoffs by setting the price equal to 50, the objective expected value of the asset.

[15]Before starting the actual 16 rounds, subjects complete two practice rounds, and fill in a questionnaire. The experimenters checked the answers of each of the participants individually after each of the practice rounds.

[16]We control for subject specific effects in all of our analysis.

C. Results

The Bloomfield and Hales (2002) experiments focus on the BSV prediction that investors believe the probability of a reversal is higher, the higher the rate of past reversals in the sequence. To test this prediction they calculate a signed reaction measure, computed as the price bid by the subject less the normative price of 50, all multiplied by +1 if the last move observed was UP, and by -1 if the last move observed was DOWN. The signed reaction measure ranges between -50 and 50, with positive numbers indicating that the subject places a higher likelihood on continuation, and lower numbers indicating that the subject places a higher likelihood on reversal.

Table I presents the mean values of the signed reaction measures for the two treatments across subsamples grouped according to the number of past reversals. The first column of the table also reproduces the summary statistics reported by Bloomfield and Hales for their Experiment 1. As in Bloomfield and Hales, we average results for sequences with low reversals (0 or 1), moderate reversals (3 or 4) and high reversals (6 or 7).[17]

Turning first to the BH treatment (our replication of Bloomfield and Hales), the second column in the table shows that for the low reversal sequences the mean reaction is 0.093, indicating that subjects believe a continuation to be more likely when the number of past reversals is low. The mean reaction is, however, not statistically different from zero. In contrast, for high reversal sequences, the mean reaction measure is -2.45, although again not significantly different from zero. The mean reaction for medium reversal sequences is between those of the low and high reversal groups. A chi-square test cannot reject the hypothesis that the mean reaction measures across the three reversal groups are equal. As evident from Table I, Bloomfield and Hales find a similar ordering of reaction measures across reversal groups, but find much stronger statistical evidence that the size of the reactions differ across reversal categories.[18]

[17]As described earlier, sequences with either two or five reversals do not appear in the Bloomfield and Hales data.

[18]Although we follow the Bloomfield and Hales (2002) design, there are differences in the experiments that may explain the difference in the strength of results. One difference is that Bloomfield and Hales use MBA students, whereas we use general population undergraduates as subjects. These groups may differ in important ways on dimensions like mistrust of the experimenter and understanding/sophistication with markets. We were

The third column reports the results of the BHR treatment where subjects are shown sequences generated by a random process. In sharp contrast to the results in Bloomfield and Hales, and our replication of their design, the mean reaction for the subsample of low reversal sequences is negative and highly significant; the point estimate is -5.84 with a p-value < 0.01. The mean reactions for the moderate and high reversal subsamples are -0.821 and -1.245 respectively, and neither is statistically different from zero. The chi-square test for equality of means is nearly significant at the 0.10 level (p-value = 0.11). These findings imply that subjects expect that a reversal is more likely after seeing historical sequences with *fewer* reversals. This finding is exactly opposite the BSV prediction that subjects should be more likely to expect continuations after observing sequences with fewer reversals.

To provide a more direct comparison of the two treatments, we conduct a cross-sectional regression analysis of the data. The dependent variable in the regression is the reaction measure. The independent variables include an indicator equal to 1 if the observation is from the BHR treatment (BHRDUM), the reversal variable (REVERSAL), which takes a value of 1 if the number of past reversals is 0 or 1, a value of 2 if the number of past reversals is 3 or 4, and a value of 3 if the number of past reversals is 6 or 7. The regression also includes an interaction term between the BHR treatment indicator and the reversal variable. The regression controls for subject specific random effects.

Table II presents the results. The coefficient estimate on the BHR treatment indicator is negative and statistically significant at the 0.05 level, indicating that, on average, subjects in the BHR treatment place higher probabilities on reversals compared to subjects in the BH treatment. This finding is more consistent with the BSV assumption that, overall, investors tend to expect reversals in outcomes. Differences in the distributions of reversal rates shown to subjects may explain this finding. In the BH treatment, trending patterns (0 or 1 reversal) were twice as likely as reversal patterns (6 or 7 reversals) whereas in our modification, there is a balance between trending and reversal patterns.

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also unable to control for the outcome of the bet as revealed in the ninth move. This, in addition to the rate of reversals, is likely to have an important impact on belief formation in subsequent rounds.

The coefficient estimate on the reversal variable is negative, indicating that the reaction measure under the BH treatment is decreasing in magnitude as the number of past reversals increases. This finding is consistent with the Bloomfield and Hales findings and with the BSV prediction that investors are more likely to expect a reversal in performance as the rate of past reversals increases. The coefficient estimate is not statistically significant, however. The interaction term, which measures the incremental effect of past reversals on the reaction measure under the BHR treatment, is positive and statistically significant at the 0.10 level. The positive estimate on the interaction term indicates that when shown patterns from a random walk process, subjects place higher probabilities on reversal when the number of past reversals is low; a finding opposite that for the BH treatment. Moreover we reject the hypothesis that the effect of the number of past reversals on the reaction measure is equal across the two treatments. Overall, our results suggest that the evidence in Bloomfield and Hales is driven by the set of non-random sequences shown to subjects.

III. Experiment II: Testing for BSV Regime Shifting and Rabin Law of Small Numbers Beliefs

As the results from the prior section indicate, when subjects are told that the underlying data-generating process is random *and* they are shown patterns that are drawn from a random process, a gambler's fallacy effect is observed. This result is inconsistent with regime-shifting beliefs as hypothesized by BSV. However, in the BSV model investors do *not* know that the underlying data-generating process is random. Thus, in our second experiment, we further modify the Bloomfield and Hales laboratory setting by continuing to show subjects data that is drawn from a random walk, while refraining from informing them up front what the underlying data-generating process is. This modification also allows for a test of Rabin's model where investors similarly do not know that the underlying process is random. We refer to this treatment as the AHL treatment.

Specifically, in the AHL treatment we use the following language to describe the data-generating process:

> You will observe sequences of performance surprises that are representative of a typical firm. In each of the 50 periods of this experiment you will observe one such sequence of firm performance surprises. Each sequence will contain eight UP and/or DOWN movements (outcomes). An UP outcome indicates that the firm performed better than expected (i.e., a positive surprise). A DOWN outcome indicates that the firm performed worse than expected (i.e., a negative surprise). All of the 50 performance sequences that you will observe are generated by the same firm (that is you are observing the same firm in all periods).

The experiment was conducted in three sessions with a total of 47 subjects. One session was conducted at the University of Utah Laboratory for Experimental Economics and Finance (UULEEF) and the other two were conducted at the Arizona Laboratory for Experimental Finance (ALEF) between February and March 2005. All subjects were students from the University of Utah and Arizona State University who had not previously participated in any versions of this experiment.

In addition to altering the laboratory setting we also expand the testing methodology to include (in addition to the rate of past reversals) an analysis of the impact of the most recent streak (number of consecutive like outcomes) on subjects' expectations of future outcomes. Including streaks in the analysis allows us potentially to differentiate between the two competing explanations of under- and over- reaction provided by BSV and Rabin. An important implication of BSV is that all else equal, investors become more confident that they are in the continuation regime, as the time since the most recent reversal increases. In contrast, as the streak length increases, the investor in Rabin does not necessarily become more confident that the next outcome will be the same as the most recently observed one. More specifically, the investor expects reversals after short streaks and continuations after long streaks.

Table III presents regression estimates of the reaction measure on the number of reversals and streak length (included separately and together.)[19] The model in BSV predicts that the coefficient on the number of reversals should be negative and the coefficient on the streak

[19] All of the regression models presented in the table include subject specific random effects to account for unobserved heterogeneity across subjects.

length should be positive.[20] The first regression includes the number of reversals alone and yields a negative value for the reversal coefficient, which is significant at the 0.01 level. The second regression includes only the current streak length and yields a negative value on the streak coefficient, which is significant at the 0.10 level. The final regression includes both the reversal and streak length variables. In this regression, the coefficient on the reversal variable is negative and statistically significant at the 0.01 level as predicted by the BSV model. However, the coefficient on the streak length variable is also negative and is statistically significant at the 0.01 level. This latter result is inconsistent with the model in BSV. Rather than becoming more confident that they are in the continuation regime following a string of like outcomes, subjects in our experiment are more likely to predict a reversal the longer the streak length. Thus, our results suggest that even when subjects are not told the properties of the underlying data-generating process they continue to exhibit a gambler's fallacy bias.

To provide evidence on the model in Rabin, Table IV presents the results of a piecewise linear regression that allows us to examine the impact of short and long streaks on expectations. In the estimation model, we define a short streak to be one with up to K consecutive like-outcomes (the table presents results for $K = 4$ and $K = 5$). The dependent variable is the reaction measure. In addition to a constant, the independent variables are the number of reversals ($REVERSALS$), a variable capturing the streak length effect for short streaks ($STREAK1$), and a variable for the streak length effect for long streaks ($STREAK2$). More specifically,

$$STREAK1 = \begin{cases} STREAK & \text{if } STREAK \leq K \\ K & \text{if } STREAK > K, \end{cases}$$

[20] We carried out a simulation exercise to establish the signs in the coefficients in the joint regression. The BSV model contains four exogenous parameters: The probability of continuation in the reversal regime, π_L; the probability of continuation in the continuation regime π_H; the probability of switching from the reversal regime to the continuation regime, λ_1; and the probability of switching from the continuation regime to the reversal regime, λ_2. As illustrated in BSV, only a subset of the possible parameter values can produce both under-reaction and over-reaction in the model. In our simulations, however, we examine all possible parameter combinations. For each set of parameter values we compute the posterior probability that the next outcome will be UP for each of the 256 possible eight-outcome sequences. These posterior probabilities coincide with the optimal prices in the BDM mechanism and are consequently used to form the reaction measure used in our simulations. The 256 reaction measurements are then regressed on the number of reversals and the current streak length of the corresponding sequences. The estimated model is $Y_i = \mu + \beta_1 R_i + \beta_2 S_i + \epsilon_i$, $i = 1, ..., 256$. Here Y is the reaction variable, R measures the number of reversals, and S is the number of moves after the last reversal in each 8-move sequence. For all parameter values the coefficient β_1 is negative, while β_2 is positive.

and

$$STREAK2 = \begin{cases} STREAK - K & \text{if } STREAK > K \\ 0 & \text{if } STREAK \leq K. \end{cases}$$

Rabin's model predicts that the slope coefficient on $STREAK1$ should be negative, while the coefficient on $STREAK2$ should be positive.[21] As indicated by the estimated coefficients on the streak variables, conditional on the streak being short, the longer the streak, the more likely the subjects are to bet on reversal (the corresponding coefficient is negative and statistically significant at the 1% significance level). When long streaks are considered, the longer the streak, the more likely the subjects are to bet on continuation (although the coefficients in both of our specifications are positive, neither is significant at conventional levels). Thus, as predicted by Rabin's model, we find a differential effect of streak length on the reaction measure. A gambler's fallacy effect shows up in short streaks, and a continuation effect is evident after long streaks.

IV. Discussion and Conclusions

In this paper we reexamine whether investors exhibit behavior that is consistent with regime-shifting beliefs as hypothesized by Barberis, Shleifer, and Vishny (1998) and as documented in laboratory experiments by Bloomfield and Hales (2002). We also extend Bloomfield and Hales to provide evidence on a competing model by Rabin (2002). We contend that the evidence supportive of BSV documented in Bloomfield and Hales may instead reflect a rational response by subjects to hand-selected historical patterns that reasonably could have been determined to be from a regime-switching process. A simple goodness of fit test rejects that the Bloomfield and Hales patterns are from a random process and, further, the concentration of patterns with too few and too many reversals is suggestive of a regime-shifting process.

[21] We carried out a simulation exercise on Rabin's model similar to the one with the BSV model to establish the signs on the coefficients in the regression presented in Table IV. When the actual outcomes are from a random walk (or from an "average" firm) but the investor has a prior that allows for "good" and "bad" firms, the coefficient on the reversal variable is negative. The coefficient on STREAK1 is negative, while that on STREAK2 is positive.

To illustrate our critique, we modify the Bloomfield and Hales experiment to be consistent with the crucial assumption in BSV that the underlying data-generating process is random by showing subjects patterns that have reversal rates that are consistent with a random process. With this simple modification, we find no evidence supportive of investor belief in regime-shifting. Instead, consistent with the well-documented gambler's fallacy effect, subjects in our experiment are more likely to expect a reversal in performance, rather than trending, after observing sequences with fewer reversals.

The results of our first experiment suggest that investor behavior is crucially dependent on whether the properties of the underlying data-generating process are known. Thus, in our second experiment, to be consistent the model in BSV, we continue to show subjects patterns from a random process but refrain from telling them what the underlying process is. We also expand the testing methodology to examine another essential implication of the BSV model, namely that, all else equal, investors become more confident that they are in the continuation regime, as the time since the most recent reversal increases. Although we find that subjects are more likely to believe the next move will be a reversal the greater the number of past reversals, we do not find that subjects believe more strongly in continuation the longer the current streak. The evidence that subjects are more likely to expect a reversal following a streak of like outcomes is not consistent with the regime-shifting model in BSV.

Finally, we use a piecewise linear regression analysis to determine the importance of streak length on investor expectations. Consistent with Rabin, we find that subjects expect short streaks to reverse and long streaks to continue. Thus, our findings are more consistent with investor belief in the law of small numbers as modeled in Rabin than in investor belief in regime-shifting as modeled in BSV.

Independent evidence on the validity of behavioral models designed to explain over- and under-reaction in stock markets is sparse. We believe that the experimental approach, first used in this line of inquiry by Bloomfield and Hales, is a sensible way to provide such evidence. To that end, we hope our critique and extension of their paper encourages other laboratory experiments. While our results are consistent with the underlying behavioral assumptions in Rabin, more research is certainly needed to differentiate between that model, the model in

BSV and other competing models that address under- and over-reaction in market settings. Such research could also lead to development of better models.

Table I
Reaction Means[a]

#Reversals	Mean Reaction for category[b]		
	Bloomfield and Hales[c]	BH	BHR
Low[d]	**11.2***	**0.0930**	**-5.8370**
	($p < 0.01$)	(0.0793)	(-2.4821)
Moderate[e]	**0.9**	**-0.2090**	**-0.8210**
	($p > 0.8$)	(-0.1299)	(-0.8401)
High[f]	**-6.9***	**-2.4510**	**-1.2450**
	($p < 0.01$)	(-1.5236)	(-0.5233)

[a]The estimated model for BH and BHR is $Y_{ij} = \mu + \beta_1 D_{1ij} + \beta_2 D_{2ij} + u_i + \epsilon_{ij}$, $i = 1, ..., N$; $j = 1, ..., J_i$, where Y_{ij} is the reaction measure of the i-th subject at the j-th trial, and $D_{1(2)}$ is a dummy variable taking value of 1 if the number of reversals is low(high) and 0 otherwise. $\epsilon_{ij} \sim N(0, \sigma^2)$ is independent of $u_i \sim N(0, \tau^2)$. The results reported in the table are the maximum-likelihood estimates of the dummy slopes in the above equation. The equation is estimated separately on the BH and BHR data sets.

[b]Reaction is the measure used by Bloomfield and Hales (2002). T-statistics for BH and BHR are reported in parenthesis.

[c]This column reports the results from Bloomfield and Hales (2002).

[d]A sequence is categorized as having a low number of reversals if it has 0 or 1 reversals.

[e]Sequences with 3 and 4 reversals are included in the Moderate Reversals category.

[f]The number of reversals is 6 or 7 for the High Reversals category.

Table II
Treatment Effect for Reaction on Reversals[a]

Coefficient Estimates[b]			
Intercept	BHRDUM[c]	REVERSALS[d]	BHRREV[e]
1.453	-7.461	-1.184	3.509
(0.738)	(-1.961)	(-1.194)	(1.888)

[a]Reaction is the measure used by Bloomfield and Hales (2002). The estimated model is $Y_{ij} = \mu + \beta_1 D_{ij} + \beta_2 R_{ij} + \beta_3 I_{ij} + u_i + \epsilon_{ij}$, $i = 1, ..., N$, $j = 1, ..., J_i$. Here R (reported as REVERSALS in the table) is a categorical variable taking the value of 1 if the number of reversals is low, 2 if it is medium and 3 if it is high. D (reported as BHRDUM) is a treatment dummy, while I (reported as BHRREV) is the interaction term, i.e. $I = R * D$. The table reports the maximum likelihood estimates of the coefficients.

[b]T-statistics reported in parenthesis. The value of the Chi-Square (3 degrees of freedom) Test of Model Fit is 3.955, for a p-value of 0.2663

[c]BHRDUM is a dummy variable taking a value of 1 if the observation is from the BHR treatment.

[d]REVERSALS takes the value of 1 if the number of reversals in a sequence is 0 or 1, 2 if this number is 3 or 4, and 3 if it is 6 or 7.

[e]BHRREV=BHRDUM*REVERSALS.

Table III
AHL: Effect of Reversals and Streaks on the Reaction Measure[a]

Coefficient Estimates[b]		
Intercept	REVERSALS[c]	STREAK[d]
3.090	-0.714	
(2.348)	(-2.173)	
1.700		-0.538
(1.864)		(-1.708)
0.6	-1.413	-1.258
(0.921)	(-3.648)	(-3.391)

[a]Reaction is the measure used by Bloomfield and Hales (2002). The estimated model is $Y_{ij} = \mu + \beta_1 R_{ij} + \beta_2 S_{ij} + u_i + \epsilon_{ij}$, $i = 1, ..., N$, $j = 1, ..., J_i$. Here R (reported as REVERSALS in the table) measures the number of reversals. S (reported as STREAK) the number of moves after the last reversal in each 8-move sequence. The table reports the maximum likelihood estimates of the coefficients.

[b]T-statistics reported in parenthesis.

[c]REVERSALS is the demeaned raw number of reversals

[d]The demeaned number of moves in the sequence since the last reversal.

Table IV
AHL: Piecewise linear Regression[a]

	Coefficient Estimates			
	Intercept	REVERSALS	STREAK1	STREAK2
K=4	9.143	-1.401	-1.949	0.607
	(4.483)	(-3.619)	(-3.895)	(0.620)
K=5	8.934	-1.400	-1.797	2.194
	(4.452)	(-3.619)	(-4.107)	(1.430)

[a]Reaction is the measure used by Bloomfield and Hales. The estimated model is $Y_{ij} = \mu + \beta_1 R_{ij} + \beta_2 S1_{ij} + \beta_3 S2_{ij} + u_i + \epsilon_{ij}$, $i = 1, ..., N$, $j = 1, ..., J_i$. Here R measures the number of reversals. $S1$ (is equal to STREAK if STREAK $\leq$ K, where K=4,5 and equal to knot otherwise. $S2$ (reported as STREAK2) is equal to STREAK-K if STREAK $>$ K, K=4,5 and equal to 0 otherwise.

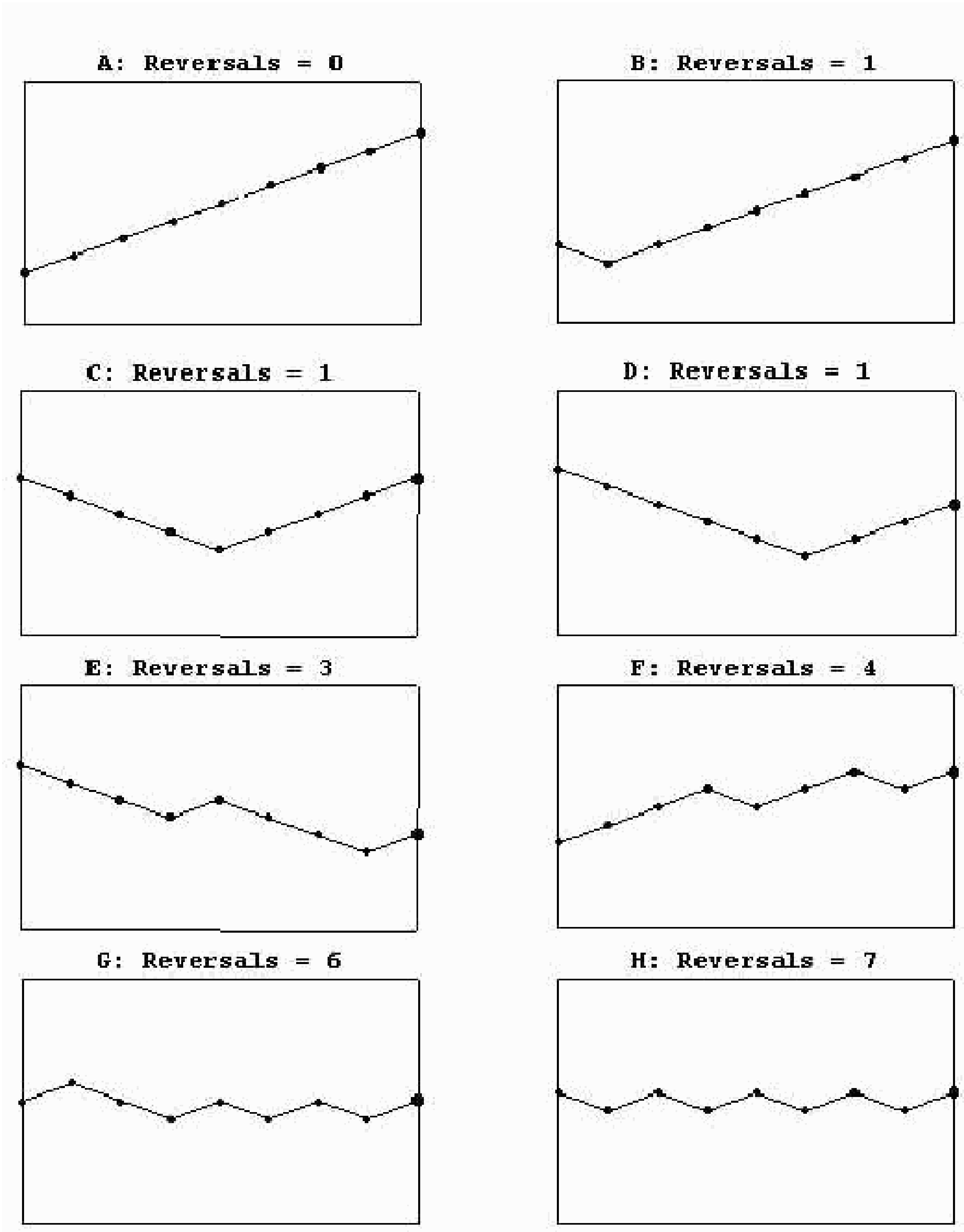

Figure 1. The sequences used by BH. The above is a copy of Figure 1 in Bloomfield and Hales (2002).

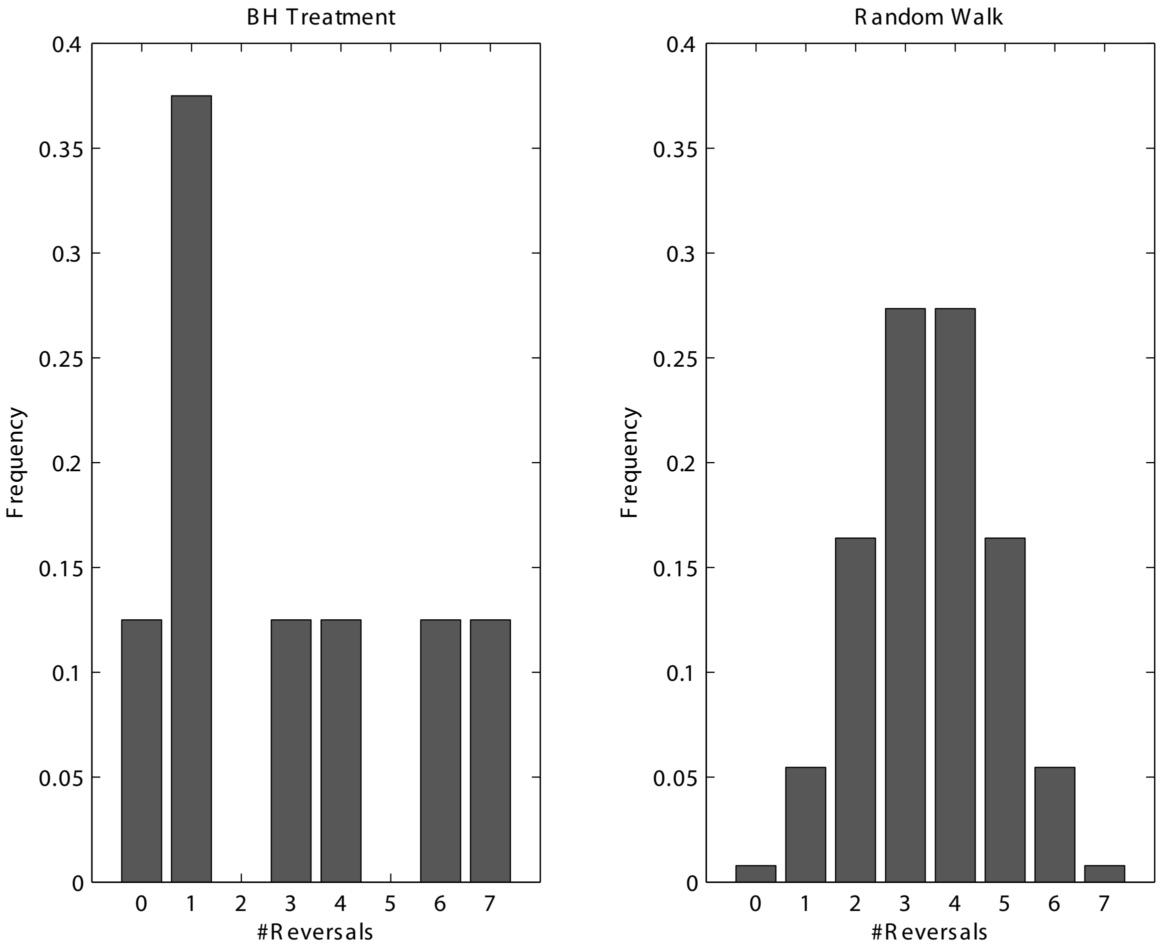

Figure 2. Histograms for the BH and BHR treatments.

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Appendix A. Instructions

This is an experiment about decision making. You will be paid for participating, and the amount of money you earn will depend on the decisions that you make. At the end of this experimental session you will be paid privately and in cash for your decisions.
Your name will never be associated with any of your decisions. In order to keep your decisions private, please do not reveal your choices to any other participant. You have been assigned an ID number. All information regarding your choices will be stored under this ID number and not under your name.

The currency used in this experiment is called "francs." Each franc that you accumulate during the experiment will be converted to dollars at a rate announced at the end of the session today. The conversion rate will be chosen in such a way that the average payoff per person from this experiment is equal to \$10. For example, if there are 10 participants in this experiment, \$100 will be paid out. Of course, this amount will not be evenly distributed among you; the participants with the highest franc earnings (or lowest franc losses) will receive the highest dollar earnings. You, however, will not be playing against the other participants in the experiment. Your payoff will depend on your decisions only. You will start this experiment with 0 francs in your account. In addition to that you will all be given \$3 for coming here on time and listening to the instructions. You are entitled to this show-up fee even if you decide not to participate in the experiment after listening to the instructions.

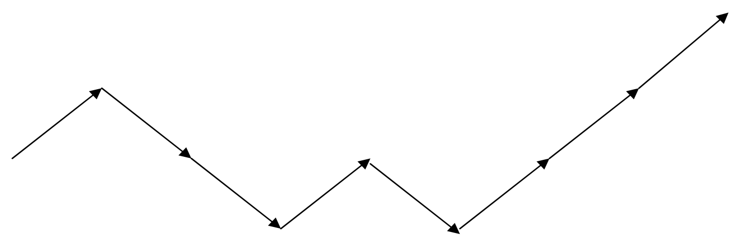
The funds for this experiment are provided by the David Eccles School of Business.

If you have any questions during the instruction period or during the experiment, please raise your hand and one of us will come and answer your question privately. We ask you not to communicate with each other during this experiment.

This Experiment

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. You will be presented with sequences using the coin-flipping model. Each such sequence will contain eight UP and/or DOWN movements. Below is an example of one such sequence (UP, DOWN, DOWN, UP, DOWN, UP, UP, UP):



Before the next (ninth) move is revealed, you will be asked to state a price at which you are willing to buy or sell shares of this asset. If you state a price above 50, you will buy one share of the asset at price of 51 and one share 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 at 51, one at 52, one at 53, and one at 54 francs. If you state a price below 50, you will sell one share at 49 and one share 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 at 49, one at 48, one at 47, and one at 46 francs.

This experiment consists of sixteen rounds. In each of the sixteen rounds you will be presented with one eight-move sequence. Your payoff for each round depends on the realization on the ninth move of this sequence and on the price that you stated. If you bought shares of the asset, your profit (which may be negative) from each share will be equal to the final payoff of the asset (0 if DOWN and 100 if UP) minus the price that you paid for this share.

$$profit_{from\ buying} = payoff - price$$

Your total payoff will be equal to the sum of the profits from the individual shares that you bought. If you sold shares, the profit from each share sold will be equal to the proceeds from the sale of this share minus the payoff of this asset at the end of the round (0 if DOWN and 100 if UP).

$$profit_{from\ selling} = price - payoff$$

Your total payoff will be equal to the sum of the profits from the shares that you sold.

Examples

Example 1:

You state a price of 55. Therefore you buy shares at prices 51, 52, 53, 54, and 55 francs. The payoffs and profits are presented in a table below:

Price Per Share	Payoff if UP	Payoff if DOWN	Profit Per Share if UP	Profit Per Share if DOWN
51	100	0	100-51=49 francs	0-51=-51 francs
52	100	0	100-52=48 francs	0-52=-52 francs
53	100	0	100-53=47 francs	0-53=-53 francs
54	100	0	100-54=46 francs	0-54=-54 francs
55	100	0	100-55=45 francs	0-55=-55 francs

Your total payoff if the outcome is UP will be 49+48+47+46+45=235 francs. If the outcome is DOWN, your total payoff will be -51-52-53-54-55= -265 francs. In other words you will realize a loss of 265 francs if the outcome is DOWN.

Example 2:

You state a price of 45. Therefore you sell shares at prices 49, 48, 47, 46, and 45 francs. The payoff is presented in a table below:

Price Per Share	Payoff if UP	Payoff if DOWN	Profit Per Share if UP	Profit Per Share if DOWN
49 100		0	49-100=-51 francs	49-0=49 francs
48 100		0	48-100=-52 francs	48-0=48 francs
47 100		0	47-100=-53 francs	47-0=47 francs
46 100		0	46-100=-54 francs	46-0=46 francs
45 100		0	45-100=-55 francs	45-0=45 francs

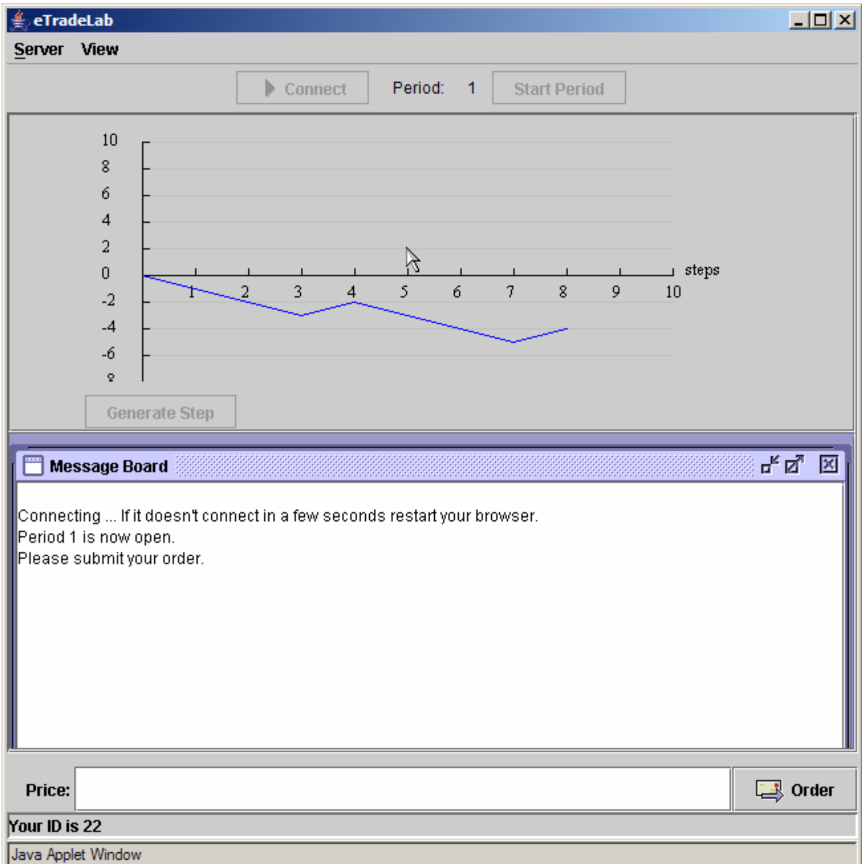
Setting the Price

The first thing to consider when setting a price is to determine what you think the probability is of the next move being UP. This probability turns out to be your expectation of the value of shares of the asset. For example, if you believe that the probability of UP is 72%, the expected value of the asset is 72 francs (=72% of 100 francs). You will make the most money on average if you set a price equal to the expected value of the shares, or equivalently to the probability (in percentages) you assign to the next move being UP. To see why, assume that you believe the asset is worth 72 (i.e. you believe that the probability of UP is 72%). If you set a price of exactly 72, you will buy one unit of the asset at every price from 51 to 72. This is good, because all of these prices are below the expected value, and you expect to make money on each of these shares. Setting the price at 72 also guarantees that you won't buy shares of the asset at prices higher that 72. This is good because buying at prices above expected value would cause you to expect to lose money. By setting the price below 72, you forgo the opportunity to buy shares at favorable prices. Similarly, suppose you believe that the asset is worth, say, 45 francs (i.e. you believe that the probability of an UP move is only 45%) your best strategy is to announce a price of 45. If you set a price of exactly 45, you will sell one share of the asset at every price from 45 to 49. This is good, because all of these prices are above expected value, and since you are selling at those prices, you expect to make money on each of these trades. Setting the price of 45 also guarantees that you won't sell shares at prices lower than 45. This is good because selling at prices below expected value would cause you to expect to lose money. By setting the price above 45, you forgo the opportunity to sell shares at favorable prices.

In short, if you believe that the next move is more likely to be UP, your best strategy will be buying shares of the asset. The more confident you are that the next move is UP the higher your price should be (but not higher than the probability you assign to the next move being UP). Conversely, if you think that it is more probable that the next move will be DOWN you should sell shares of the asset. The more confident you are that the next move is DOWN the lower price you should set (but not lower than the probability you assign on the next move being UP).

Trading Screen

The experimental software used for this experiment is called eTradeLab. A snap shot of the interactive screen is presented on the next page.



Practice Periods

We will now conduct two practice rounds. Please, do not click on any of the buttons unless you are instructed to do so.

Practice Period 1:

1. Click on the "Start Period" button. By clicking on this button you initiate a new period.

2. During this period you will be presented with one sequence.

3. Enter a price of 60. Since the price is above 50, you will be buying shares of the asset. Hit the "Order" button.

4. Please fill in the following questionnaire:

   a. How many shares of the asset will you buy?

   b. Fill in the prices of the shares you will buy and enter for one of those prices (whichever one you choose) the payoff of the share if the next move happens to be UP, and also the profit from this share (equal to the payoff minus the price of the share). Then enter the payoff if the next move is DOWN along with the profits (losses) per share.

Price per share	Payoff if UP	Payoff if DOWN	Profit Per Share if UP	Profit per share if DOWN

5. Click on the "Generate Step" button in order to see the ninth move in the sequence.

6. From the "View" menu choose "Earnings" to see your payoff from this round. Note that your "Earnings" are the sum of the profits (or losses) for each share that you bought.

This was a practice round and the payoff from it will not count towards your final payoff.

Practice Period 2:

1. Click on the "Start Period" button. You have now initiated a second period.
2. During this period you will be presented with one sequence.
3. Enter a price of 48. Since the price is below 50, you will be selling shares of the asset. Hit the "Order" button.
4. Please fill in the following questionnaire:

a. How many shares of the asset will you buy?

b. Fill in the prices of the shares you will buy and enter for one of those prices (whichever one you choose) the payoff of the share if the next move happens to be UP, and also the profit from this share (equal to the payoff minus the price of the share). Then enter the payoff if the next move is DOWN along with the profits (losses) per share.

5. Click on the "Generate Step" button in order to see the ninth move in the sequence.

6. From the “View” menu choose “Earnings” to see your payoff from this round. Note that your “Earnings” are the sum of the profits (or losses) for each share that you bought.

This was a practice round and the payoff from it will not count towards your final payoff.

Below are tables with all possible total profits from a single period depending on the price entered and the move realized. Are there any questions?

Earnings for all prices if the next move is UP

Price	Profit	Price	Profit	Price	Profit	Price	Profit
0	-3775						
1	-3675	26	-1500	51	49	76	949
2	-3576	27	-1426	52	97	77	972
3	-3478	28	-1353	53	144	78	994
4	-3381	29	-1281	54	190	79	1015
5	-3285	30	-1210	55	235	80	1035
6	-3190	31	-1140	56	279	81	1054
7	-3096	32	-1071	57	322	82	1072
8	-3003	33	-1003	58	364	83	1089
9	-2911	34	-936	59	405	84	1105
10	-2820	35	-870	60	445	85	1120
11	-2730	36	-805	61	484	86	1134
12	-2641	37	-741	62	522	87	1147
13	-2553	38	-678	63	559	88	1159
14	-2466	39	-616	64	595	89	1170
15	-2380	40	-555	65	630	90	1180
16	-2295	41	-495	66	664	91	1189
17	-2211	42	-436	67	697	92	1197
18	-2128	43	-378	68	729	93	1204
19	-2046	44	-321	69	760	94	1210
20	-1965	45	-265	70	790	95	1215
21	-1885	46	-210	71	819	96	1219
22	-1806	47	-156	72	847	97	1222
23	-1728	48	-103	73	874	98	1224
24	-1651	49	-51	74	900	99	1225
25	-1575	50	0	75	925	100	1225

Earnings for all prices if the next move is DOWN

Price	Profit	Price	Profit	Price	Profit	Price	Profit
0	1225						
1	1225	26	900	51	-51	76	-1651
2	1224	27	874	52	-103	77	-1728
3	1222	28	847	53	-156	78	-1806
4	1219	29	819	54	-210	79	-1885
5	1215	30	790	55	-265	80	-1965
6	1210	31	760	56	-321	81	-2046
7	1204	32	729	57	-378	82	-2128
8	1197	33	697	58	-436	83	-2211
9	1189	34	664	59	-495	84	-2295
10	1180	35	630	60	-555	85	-2380
11	1170	36	595	61	-616	86	-2466
12	1159	37	559	62	-678	87	-2553
13	1147	38	522	63	-741	88	-2641
14	1134	39	484	64	-805	89	-2730
15	1120	40	445	65	-870	90	-2820
16	1105	41	405	66	-936	91	-2911
17	1089	42	364	67	-1003	92	-3003
18	1072	43	322	68	-1071	93	-3096
19	1054	44	279	69	-1140	94	-3190
20	1035	45	235	70	-1210	95	-3285
21	1015	46	190	71	-1281	96	-3381
22	994	47	144	72	-1353	97	-3478
23	972	48	97	73	-1426	98	-3576
24	949	49	49	74	-1500	99	-3675
25	925	50	0	75	-1575	100	-3775