The Long and Short of It: Why Are Stocks with Shorter Runs Preferred?

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This article examines how consumers process graphical financial information to estimate risk. We propose that consumers sample the local maxima and minima of a graph to infer the variation around a trend line, which is used to estimate risk. The local maxima and minima are more extreme, the higher the run length of the stocks (the consecutive number of upward or downward movements of a price series with identical mean, variance, skewness, and kurtosis). Three experiments show that this leads to stocks with higher run lengths being perceived as riskier: the run-length effect. Importantly, the run-length effect is greater for investors who are more educated, are employed full time, trade more frequently, have had longer experience trading, and trade a wider range of financial instruments. Implications for the communication of financial products, public policy, and consumer welfare are discussed, as are theoretical implications for the processing of visual and financial information and behavioral finance.

q1 Individuals' decisions for the purchase or sale of financial instruments are among the most important ones they make. Consumer investment decisions involve more stock market allocation of wealth than exists in major integrated oil and gas ($1.238 trillion), application software ($445 billion), and auto manufacture ($324 billion; Yahoo Finance 2009). These investments are in both mutual funds and stocks. According to the Investment Company Institute (ICI 2009), individual investment in the stock market through mutual funds reached $10.35 trillion at the end of 2008. ICI also estimated that 45% of all U.S. households (92 million individuals, 58% of whom have incomes between $25,000 and $100,000) invest in mutual funds with a median portfolio of $100,000, including tax-deferred accounts. Attesting to the growth of individual investing, e-trade reported 4.5 million customers with $174 billion in assets at the beginning of 2009, claiming that they add an average of 1,000 new accounts each day (e-trade 2009).

In the stock market as well, over the last decade, there is a large and growing individual investor base, with this group contributing to a substantial level of activity. In 1999, nearly half (48%) of all U.S. households collectively held over 40% of all corporate equities: an increase of 71% over a decade (Vogelheim et al. 2001). As many as 51 million of these individuals own corporate stocks directly (vs. mutual funds). The Federal Reserve estimates that U.S. households have increased their stock holdings from 14% to 34% of all financial assets (15%–24% of all assets) from 1982 to 1998. Individual investors are also a large and growing segment in non-U.S. markets. The Nomura Research Institute reported that individual investors accounted for 40% of all trading on the Tokyo Stock Exchange in 2006 (up from 20% in 2002; Tanaka 2006). This percentage is higher than that of institutional or foreign investors (both $\simeq$ 35%).

Financial decisions are primarily made on the basis of trade-offs between risk and return. These individuals' decisions are likely to be based on recommendations or information about the risk and return of individual stocks that

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John Deighton served as editor and Baba Shiv served as associate editor for this article.

Electronically published September XX, 2009

 0093-5301/2010/3606-0008$10.00. DOI: 10.1086/644762

consumers get from companies, brokers, or third parties. We propose and show that perceptions of risk are based on the manner in which information is graphically presented. Examining the effect of graphical presentation formats on estimates of risk is important as financial services providers, agents, and consumer finance Web sites frequently present financial information graphically. This facilitates investors who make their investment decisions on the basis of a financial instrument's historical performance. The visual display of stock information has increased, and the number of commercial purveyors of stock analysis information has mushroomed. Companies such as Bloomberg, Reuters, Yahoo!, and Google provide information on debt, commodities, and foreign exchange markets graphically. Many online sites (e.g., Yahoo!) allow investors to customize graphs, enabling richer visual analysis. Consumer newsletters of mutual funds companies (e.g., Vanguard) also display their fund returns versus those of market indexes in graphical form. Reflecting the wide use of graphics, the study of visual displays of quantitative information has become an area of investigation in and of itself (Tufte 2001).

This article examines how people make risk judgments based on graphical information about stocks. The increasing use of graphical data to make financial decisions suggests that it is likely that visual biases in data interpretation may proliferate into price effects. That the use of graphical data may result in systematic effects on perceptions of risk begs the question as to which form of graphical interface might inject the greatest bias. This article adds to the literature on biases in consumers' judgments due to visual information in a novel domain (Krishna 2008).

We argue that certain data points on a graph are more likely to be sampled due to their perceptual salience in estimating noise around a trend line and therefore affect perceptions of risk. Research on spatial judgments based on visual cues has shown that the elongation of a perceptually salient aspect of a three-dimensional container leads to longer containers being perceived as larger (Piaget 1967; Raghubir and Krishna 1999; Wansink and Ittersum 2003). The literature on visual information processing suggests that attention is drawn to perceptually salient points to simplify the information-processing task (Raghubir and Krishna 1996, 1999).

An understanding of the antecedents of biases in financial decision making should help in controlling the biases or in marketing financial products. It should assist data providers (e.g., Reuters) in presenting financial information, let regulators visualize how market data should be presented during panics and crashes, and help consumer welfare groups understand how the manner of presentation of financial information can bias choices. This could foster public policy governing how financial information is presented, analogous to rules governing product packaging.

This article complements the literature in behavioral finance that is replete with empirical studies contradicting the assumption that investors are unbiased, risk-averse utility optimizers (Barber and Odean 2000, 2001; DeBondt et al. 2008; DeBondt and Thaler 1985, 1987; Lo and MacKinlay 1988; Raghubir and Das 1999; Shefrin 1999, 2005; Shefrin and Statman 1985; Statman 2002; Thaler 2000). The anomalies in this literature have invoked behavioral explanations, including investors' loss aversion (Benartzi and Thaler 1995), inaccurate inference (Shefrin and Statman 1993, 2000), and the use of simple heuristic rules of thumb to make decisions (Bikhchandani, Hirshleifer, and Welch 1992). Research has also shown that perceptions of professional traders using technical analysis and charting methods can be biased (Lo, Mamaysky, and Wang 2000).

However, the behavioral finance literature has not examined perceptual and visual biases associated with information presentation formats, which have been shown to affect a range of consumer judgments (Krishna 2008). It has primarily been conducted at the aggregate market level and has yet to translate into a systematic experimental examination of how individuals process financial information to make associated judgments.

This article examines whether the literature on spatial judgments based on visual cues has implications for financial judgments based on graphical stimuli. Given the large amount of data presented on a graph, we hypothesize that people simplify their task by sampling points from a financial instrument's price history to estimate trend and noise. This sampling strategy leads to perceptual biases when the sample points are chosen as a function of their salience and are not representative of the price series.

There are two main summary aspects of a string of financial data: one, the trend (e.g., increasing or decreasing, linear or exponential) or pattern (e.g., cyclical) and, two, the noise around this trend or pattern (captured through its variance and higher-order moments). A string of data may be thought of as a loosely constructed band of points, with the angle of the band capturing start-end information and the width (or amplitude) of the band capturing the path deviations around this general direction. The amplitude would be constructed from the extreme points of the distribution—the local maxima and minima across the path. The local maxima is the largest value and the local minima is the smallest value that a price sequence takes within a given neighborhood. On a graph, the local maximum looks like the peak, and the local minimum looks like a valley. Said differently, a local maximum (minimum) is a member of the set of peak (trough) points in a series that has many up and down movements.

Three studies examine how run length, a feature of graphs that highlights the noise (width of the band surrounding the trend line), by affecting the local maxima and minima of the series, affects judgments of the risk and return of stocks. Study 1, conducted with a group of affluent investors, shows that stocks with a run length of 10 and, correspondingly, higher maxima and lower minima are perceived to be riskier than stocks with a run length of 3. Study 2 reports results that attest to the robustness of the run-length effect at lower run lengths: 2, 3, 4, and 8.

Study 3 demonstrates these effects with a random sample of individual investors and identifies sociodemographic moderators of the run-length effect. These include education level, employment status, and length, frequency, and range of investing experience. Results show that these factors, which are typically associated with individual differences in ability to make unbiased judgments, moderate the run-length effect in a counterintuitive manner. The run-length effect is greater for investors who are more educated, are employed full time, trade more frequently, have had longer experience trading, and trade a wider range of financial instruments. After a brief literature review, the studies are described.

PROCESSING LONGITUDINAL GRAPHICAL INFORMATION

A graphical representation of data can present a near infinite quantity of information. Given that people have limited information-processing ability, they are likely to use a variety of heuristics when faced with large amounts of information. Sometimes these are adaptive, sometimes not. Researchers have documented systematic biases in the manner in which people view graphical information (Cleveland and McGill 1984; Kosslyn 1989; Pinker 1981, 1983; Simkin and Hastie 1987; Tufte 2001). Aspects of graphs that have been shown to affect judgments include the type of graph (line/bar), colors, grids, aspect ratio of width to height, scales (Cleveland 1985, 1993), and the manner in which these are interpreted contingent on the observers' judgment task (Simkin and Hastie 1987). We examine the effect of local maxima and minima via the effect of run length on judgments of risk and return.

How Are Points Sampled?

We propose that people use simplifying strategies that lead to systematic biases in estimating risk from graphs of financial performance. Specifically, information processors aiming to reduce the cognitive complexity of their task may choose to sample points from a population of data rather than use all the points contained in the population. However, this sample may not be drawn at random, resulting in systematic biases. The greater the salience of a data point, the greater is its likelihood of inclusion in the sample. We define such a perceptual bias as a systematic deviation in the perception of a string of numerical financial data as compared to an objective description of that data.

Specifically, as the price path represents a possibly infinite amount of information, specific sample points of the path that are perceptually salient are likely to be used to simplify the information-processing task. This sample could be biased if the prices surrounding a point change its likelihood of being sampled. If a price is more extreme than other prices surrounding it, it will be more likely to be sampled. If the local maxima and minima are more likely to be sampled than other points in the distribution, then the larger the difference between the local maxima and minima, the greater the estimate of noise, and the riskier the stock will be perceived to be.

How Are Risk Judgments Made?

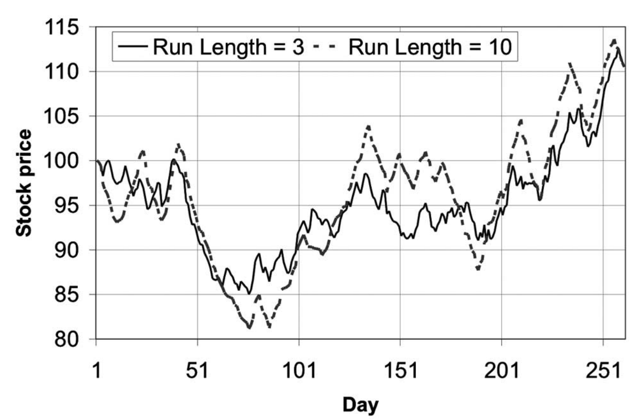
We propose that investors estimate the risk of an instrument by identifying the extent of noise around the trend line. This is based on the difference between maxima and minima. Run length of a stock is one way to manipulate the difference between local maxima and minima without affecting the moments of the distribution (see fig. 1). Increases in run length imply increases in graph extrema, holding fixed the statistical moments of returns (see app. A).

The run length of a stock is defined as the number of consecutive periods over which a stock continues its upward or downward movement. A run is a sequence of positive or negative returns. In the sequence + + − − − 0 + + − + + 0 0 0 − −, the run lengths are 2, 3, 1, 2, 1, 2, 1, 2. A sequence of zeros is treated as a single run of length 1 (not 3). That is, a negative or positive stock movement, rather than the absence of stock movements, is defined as a run. (Alternate treatments of zero returns are also analyzed in the literature; Das and Hanouna 2009.) Stocks with longer run lengths have higher maxima and lower minima controlling for all statistical moments of the price series (including mean, variance, skewness, and kurtosis).

While the relationship between run lengths and extrema is probabilistic rather than deterministic, the analyses presented in appendix A show that, on average, sequences with higher run lengths are associated with higher extremal differences. While it is possible to manipulate local extrema using other methods (e.g., by changing the average size of

FIGURE 1

STIMULI USED IN STUDY 1



Note.—Graphs were embedded among others. Study participants were shown the graphs separately, not together on one plot. Each graph consists of a sequence of 260 returns with mean annual return equal to 10% and standard deviation of 15% (the skewness and kurtosis are 0). The returns are simulated using Excel, and the optimizer is used to constrain the series so that two graphs have different run lengths of 3 and 10. Color version available as an online enhancement.

a return and shortening its run length), these methods affect the other moments of the series as well, leading to any resulting change in risk perceptions being attributable to actual changes in risk level. Run length, to our knowledge, is the only feature of a series that allows for extrema to be affected without affecting the actual statistical moments of a return series.

Historically, run lengths are not positively correlated with the variance of returns (app. A). This is important because if such an empirical relationship exists, then any difference in risk perceptions may be explainable in terms of respondents' prior experience (rather than extrema). Specifically, an analysis of three financial portfolios from July 1963 to December 2002 (n = 9,944 trading days) first establishes that, in the United States, all three portfolios have higher mean run lengths than would be expected if there were an equal likelihood of up or down movements in returns (i.e., stock prices follow a symmetric random walk). These portfolios are the excess return of the market portfolio over the risk-free return, the Fama-French portfolio of returns on small minus big (SMB) stocks, and the Fama-French portfolio of high minus low (HML) book-to-market stocks. A follow-up analysis of all stocks with nonzero trading volume on the NYSE, AMEX, and NASDAQ from January 1962 to December 2005 (n = 109,601 stock years) using Das and Hanouna's (2009) data shows that mean run lengths were not correlated with the standard deviation of stock returns ($r = -.09$, NS). To summarize, increases in run length imply increases in graph extrema, on average, holding fixed the statistical moments of security returns, and there is no evidence of a positive relationship between run lengths and the variance of equity returns from 1962 to 2005 (app. A). Thus, run lengths are an experimentally rigorous way to manipulate the local extrema of a set of identical returns without affecting the four moments of the series. We test the operational hypothesis that the longer the average run length, the higher the perception of risk.

STUDY 1: THE RUN-LENGTH EFFECT

Method

q2 *Participants.* Study participants were 71 adults (male = 41) recruited through an elementary school. The Parent Teacher Association received $20 for each completed questionnaire. The sample was well educated (95.8% college graduates) and affluent (74.3% reported annual household income > $100,000), with the majority in the 36–50-year age group (85.9%). Around four-fifths (78.9%) reported having worked for 15 years or more, with 75% reporting that they currently worked full time. One-third (32.4%) reported having worked in a finance-related job, and over a fifth of the sample (22.5%) reported having worked in the financial sector. The sample reported having a sizable amount of their assets in financial instruments: 83% reported investing >25% of their assets in financial securities. As many as 36% reported investing >75% of their assets in financial securities, and 78.8% reported owning five or more stocks. More than half the sample reported trading multiple times a year (57.8%). Up to 93% of the participants reported holding a stock (or fund) for at least a year before selling it. Thus, the sample was highly educated and relatively affluent.

Procedure. Participants were asked to assume that they were investing in stocks for the purposes of long-term growth, such as a college fund. They were given a booklet of graphs of eight stocks, embedded within which were the two target stocks that differed in run length in positions five and six. They were asked to keep them open while answering questions. Participants responded to risk and return perceptions and then completed demographic details. The procedure took around 25 minutes.

Stimuli Generation. We manipulated the level of the local maxima and minima of a set of identical returns by changing run lengths. This allowed us to test whether statistically identical returns in which the average number of consecutive upward or downward movements was longer in one sequence versus the other were perceived to be riskier. We used a within-subjects design manipulating average run length at 3 versus 10. The stock graphs were prepared using Excel, subject to all four moments of the stock return paths being controlled to be the same ($M = .10$; SD = .15; skewness = 0; excess kurtosis = 0; see fig. 1). The procedure is described in further detail in appendix B.

Measures. Participants chose which of the two stocks they believed was riskier. They then estimated the annualized rate of return for the following year as well as their best guess for the range of returns, including the minimum as well as the maximum return that they thought the stock would achieve. The estimates of maximum and minimum return served the function of a manipulation check to assess whether the stock with the longer run length was perceived to have greater extrema, with no difference in the average return. According to the representativeness heuristic (Grether 1980; Tversky and Kahneman 1974), if people encode local extrema differently in the two graphs, then they would expect a greater range for the graph with the longer run length.

Subsequently, using 7-point scales, participants rated how confident they were of their estimates (1 = not at all; 7 = very confident) and their subjective perceptions of risk for the two stocks (1 = not at all; 7 = very risky). They were then asked to allocate $100 between the two target stocks, cash, and four other stocks from the booklet they had been given. The percentage allocated to the short (vs. long) run-length stock was used to estimate preference.

Results and Discussion

Due to partial nonresponse, the total sample size is different across measures.

Manipulation Checks. Stocks with a longer run length were perceived to have a higher maximum (26.13%) and a lower minimum (−14.45%) than stocks with a shorter run length (max = 23.40%; min = −6.82%; $F(1, 61) = 5.76$ and 6.79 for maximum and minimum returns, respectively, both with $p < .05$). This check confirms that investors noted that the stock with a higher run length was perceived to have greater extrema.

Checks for Confounders. There was no difference in the estimates of the average return of the two stocks. These were estimated accurately at approximately 10% ($F < 1$). There was also no difference in the confidence with which returns were estimated for the two stocks ($M = 2.86$ vs. 2.74 for run length 3 vs. 10, respectively; $F < 1$).

Risk Estimates. As hypothesized, the stock with a longer run length was perceived to be riskier. In the paired comparison task, 57/63 (90%) believed that the stock with an average run length of 10 was the riskier one ($p < .001$). In the interval-scaled subjective risk estimate, a repeated-measures ANOVA showed a main effect of run length ($F(1, 66) = 60.91$, $p < .01$), such that the stock with the longer run length was estimated as riskier ($M = 5.25$ vs. 3.97 for longer vs. shorter run lengths, respectively; higher numbers indicate perceptions of greater risk).

Preference. A repeated-measures ANOVA on the percentage of money allocated to the two stocks showed a main effect of run length ($F(1, 67) = 8.23$, $p < .01$) reflecting a higher percentage allocation to the stock with a shorter run length ($M = 15.72\%$ vs. 8.59% for stocks with run lengths of 3 vs. 10 respectively). The three return measures were used to compute a perceived risk-adjusted return (mean/[max − min]). The stock with the shorter run length had a higher estimated risk-adjusted return ($M = .664$ vs. .489 for run length 3 vs. 10; $F(1, 60) = 5.20$, $p < .05$). Overall, results suggest that stocks of shorter run lengths are perceived to be less risky and are preferred.

Discussion. To summarize, we found that a sample of adult investors believe that between two stocks with identical mean, variance, skewness, and kurtosis, the stock with a longer average run length (with greater extrema) is perceived to be riskier and is less preferred. In this study, the effect of runs of two disparate lengths (3 and 10) were examined. Given that stocks with average run lengths greater than 4 are relatively uncommon (Das and Hanouna 2009, app. A), it is unclear whether the run-length effect would only hold for stocks with an unusually high run length (i.e., 10) or whether it would generalize to run lengths that reflect historical reality. To test this, study 2 examines the generalizability of the run-length effect using runs of length 2, 3, 4, and 8; the first three of which are a better reflection of the average run length of stocks in the U.S. market. Stocks with run lengths between 2 and 4 account for over 88% of all stocks in the NYSE, AMEX, and NASDAQ from January 1962 to December 2005 (see app. A).

Another limitation of using a stock with run a length of 10 is that it is relatively rare in reality and may have been perceived to be more unusual than the stock of run length 3. To rule out this explanation, study 2 examines judgment of how unusual the stocks are perceived to be. Finally, the manipulation of run length in study 1 used a within-subjects design that could have led to people comparing the two graphs in a manner that they would not have done if they had been presented just one of the graphs at a time. Study 2 aims to rule out that the run-length effect is an artifact of a within-subjects design.

STUDY 2: EXAMINING THE GENERALIZABILITY OF THE RUN-LENGTH EFFECT

The goal of study 2 is to replicate the results of study 1, using a between-subjects design, a richer set of dependent measures, and shorter run lengths: 2, 3, 4, and 8.

Method

Participants. Study participants were undergraduates ($n = 150$; male = 59) recruited from the X-lab subject pool at the University of California, Berkeley, who completed the experiment for a payment of $20. Their average age was 20.27 years (range = 18–27 years), and they came from a range of majors (business/economics = 41; science and engineering = 53; humanities = 36; others = 20). Two-thirds of them reported Asian ethnicity ($n = 100$), with another 36 reporting a Caucasian ethnicity (others = 14).

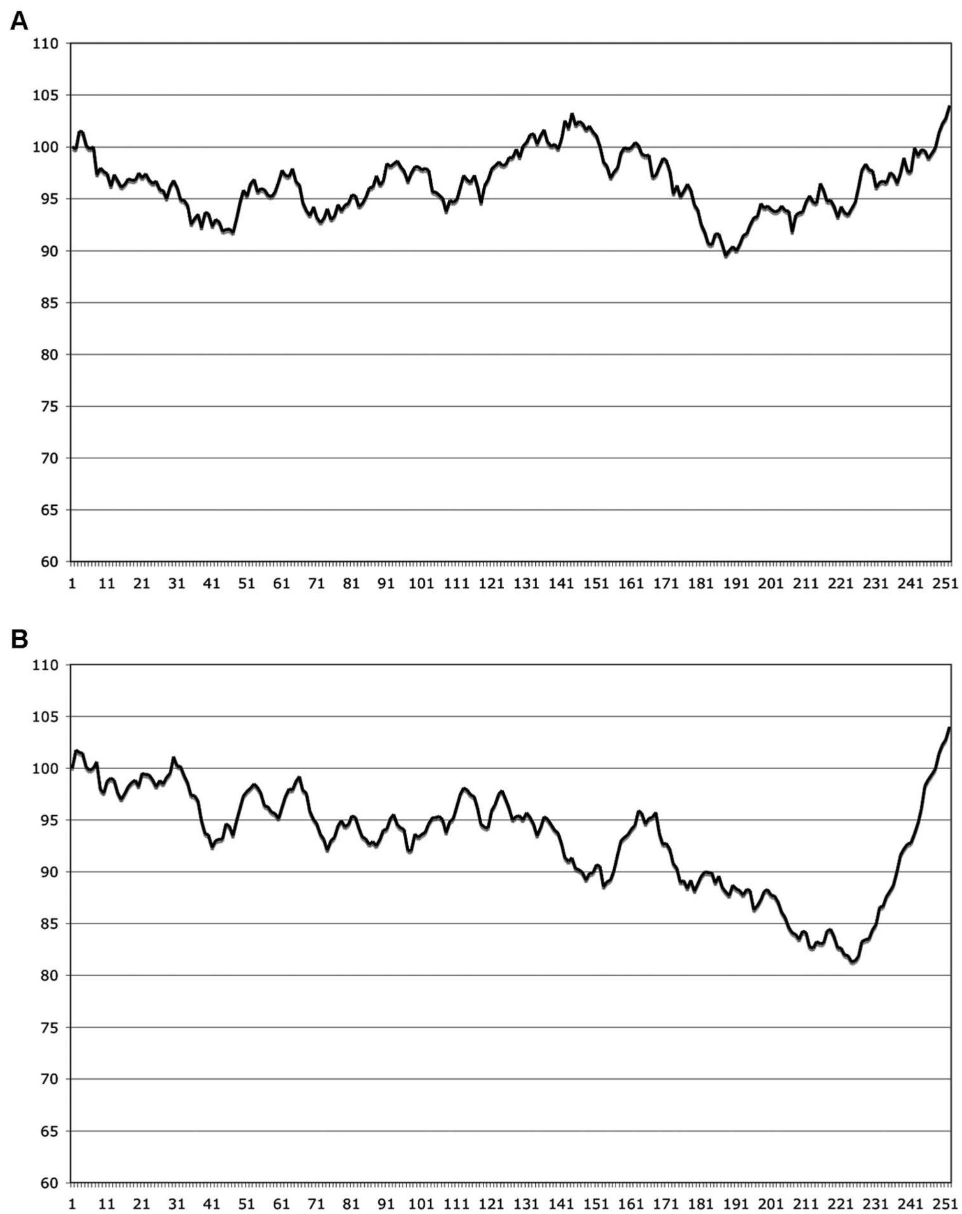
Procedure and Design. Participants were provided a graph documenting the price of a stock over 1 year. We used a between-subjects design manipulating average run length at four levels: 2, 3, 4, and 8 (see app. A for details regarding the manner in which the stimuli were generated). The stimuli are shown in figure 2.

Participants had to rate the stock using seven scales: not at all/very good, not at all/very exciting, a poor buy/a good buy, low potential/high potential, not at all/very risky, unusual/common, and unsafe/safe. An exploratory factor analysis across these seven scales with a varimax rotation yielded two orthogonal factors (61.25% variation explained). The first factor included ratings of good (loading = .76), a good buy (loading = .80), and high potential (loading = .69), with an eigenvalue of 2.41. This factor was named "value," with the three items averaged to form a value index ($\alpha = .70$). The second factor included ratings of exciting (loading = .74), risky (loading = .87), and safe (loading = −.76), with an eigenvalue of 1.88. This factor was named "risk," with the last item reverse coded and then averaged with the first two items to form a risk index ($\alpha = .72$). The rating of "unusual" did not load on either factor.

Subsequently, participants were asked to estimate the percent return over 1 year, using an open-ended measure. The value and risk indexes were used to examine the effect of run length. In a later task, all participants were asked to estimate how risky (1 = not at all; 7 = very risky) a range of financial instruments were. Included in the list was "stocks." These ratings were used to ensure that the four

FIGURE 2

STIMULI USED IN STUDY 2 (*A*, *B*)



run-length conditions were matched in terms of participants' beliefs regarding the overall riskiness of stocks (M = 5.50; run-length effect p = .82).

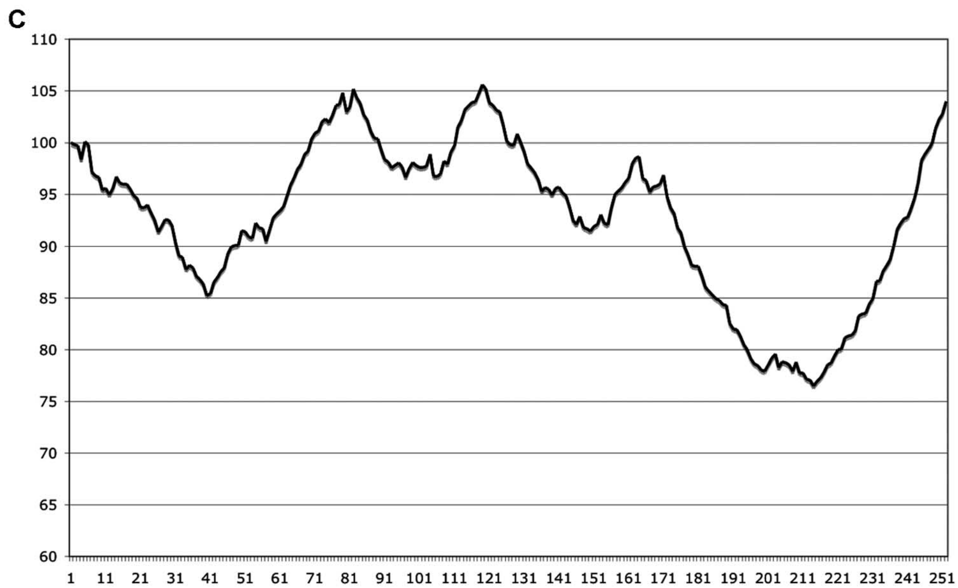
Results and Discussion

A one-way ANOVA on perceptions of risk revealed significant main effects of run length ($F(3, 145) = 26.64$, $p < .001$; $\eta^2 = .355$). The stock with run length 2 was rated the least risky (M = 3.44), followed by the stock with run length 3 (M = 4.54), run length 4 (M = 4.92), and run length 8 (M = 5.24). Tests of mean differences showed that the stock with run length 2 was rated significantly less risky than each of the others ($p < .05$), and the stock with the run length of 8 was rated as more risky than the stocks with run lengths of 2 and 3. There was no effect of run length on perceptions of value (M = 4.37), open-ended estimates of return (M = 17.90%), or ratings of unusualness (M = 4.95).

To summarize, this study showed that stocks with longer run lengths are perceived to be riskier, using run lengths that are commonly seen in the marketplace. These results

FIGURE 2

STIMULI USED IN STUDY 2 (*C*, *D*)



NOTE.—Generated from an identical time series of 252 returns. The mean return for all four graphs is 3.93% per annum with an annualized return standard deviation of 14.13%. The returns are reshuffled so that the run lengths are set to 2 (*A*), 3 (*B*), 4 (*C*), and 8 (*D*), respectively. Study participants were shown the graphs separately.

attest to the robustness of the run-length effect using smaller run lengths: the biggest difference in risk perceptions occurs between stocks of run lengths 2 and 3 and then increases at a lower rate at higher run lengths. This is important because as many as 74% of all stocks in the NYSE, AMEX, and NASDAQ stocks markets from 1962 to 2005 have run lengths between 2 and 3 (see app. A). It also showed that the run-length effect is robust to experimental method and measures. One limitation may be the external validity of study 2, given that it was conducted with an undergraduate sample. Further, it is important to understand the factors that would moderate the run-length effect so as to better understand its antecedents. Finally, it is necessary to examine the extent to which run length can affect actual investors' investment decisions by assessing how important this construct is in reality. Study 3 addresses these issues.

STUDY 3: EXTERNAL VALIDITY, DEMOGRAPHICS, AND PUBLIC POLICY

Method

Despite the presented evidence that people's estimates of risk are higher, the higher the length of a run, questions that remain are as follows: Do investors actually use graphs to make their financial decisions? If so, will actual investors be prone to the run-length effect, given their experience investing? If they are prone to the run-length effect, then will greater experience and ability attenuate the run-length effect, or might they exacerbate it? If the run-length effect is a perceptual bias as has been argued, then factors, such as experience and ability, that are typically associated with attenuating a bias in information processing have the reverse counterintuitive moderating effect—the greater an individual's ability and experience, the greater is the bias (Raghubir 2008). The response to this question has implications for public policy and consumer welfare. If biases are greater among those who invest more frequently and across a wide range of instruments, they are more likely to aggregate to market effects. If they are stronger among those with longer experience, then investors are clearly unable to learn from their past behavior. Study 3 aimed to answer these questions.

Participants. Study participants were a random sample of individual investors ($n = 217$, 213 of whom completed the demographic questions) recruited through Zoomerang Market Tools. The sample consisted of 152 males (females = 61), predominantly white (81%), with a mean age of 35 (over two-thirds were between 25 and 54 years). Over half the respondents reported being married, and over half had completed an associate, bachelor's, or graduate degree (15% had not completed high school). Two-thirds were employed full time (including self-employed, with <6% unemployed and looking for work). The sample was predominantly middle class (almost two-thirds reported an annual household income between $50,000 and $200,000, 4% earned >$200,000, 21% reported earning <$50,000, and 12% preferred to not respond to the income question).

Overall, the sample was active in investing (46% reported investing for >5 years). Whereas half the sample reported trading less often than annually, approximately a third reported trading more often than once a quarter. Over two-fifths of the sample reported financial assets (excluding movable and immovable property) of more than $50,000, with as many as 8% reporting a portfolio size of $500,000 or more (22% preferred to not respond).

Procedure and Design. Participants were asked which financial instruments they invested in (mutual funds, stocks, bonds, etc.). They were then asked to what extent they used five different sources of information to evaluate a stock or mutual fund (1 = not at all; 7 = very often). These were historical performance in graphs, overall percentage return over a period, balance sheet and accounting information, advice from others, and information about the market. Subsequently, they rated the usefulness of four methods of getting historical information about the markets (1 = not at all; 7 = very useful). These were line graphs showing prices over time, bar graphs showing volume of trading, digital numbers displaying summary statistics of returns, and information about the details of a company/stocks.

The next set of questions asked them to rate six stocks (two run lengths: 2 and 3 × 3 replications) using three semantic differential scales: not at all/very good, risky, and unusual. There were three replicates used for each of the run-length manipulations using the same method of stimuli generation as in study 2 (app. B). The first replicate was the one used in study 2. Within a given replicate manipulation of run length, the length of the *x*-axis and the maximum value of the *y*-axis were the same. At the end of the survey, participants responded to questions regarding their gender and other sociodemographic information, as well as their experience in investing in financial instruments. All variables were measured using response categories rather than open-ended responses.

Results

As in study 1, due to partial nonresponse, the total sample size is different across measures. q3

Use of Graphical Information. Overall, respondents stated that they found line graphs showing prices over time the most useful ($M = 5.65$ on a 1–7, not at all/very useful scale) of the four sources of information rated (bar graphs showing volume of trading = 4.86, digital numbers displaying summary statistics of returns = 5.10, and verbal information giving details of a company/stocks = 5.05; all paired *t*'s vs. line graphs $p < .001$). Further, historical information itself ($M = 4.20$) is perceived to be more useful than balance sheet and accounting information ($M = 3.70$; $p < .05$) or information from others ($M = 3.93$) and at par with market reports ($M = 4.19$). It was only rated as less useful than overall percentage return over a period ($M = 4.33$). This presents direct evidence that investors use graphs to evaluate stocks.

Run-Length Effect. A 2 (run length) × 3 (replicate) ANOVA on perceptions of risk revealed significant main effects of replicate ($F(2, 432) = 42.92$, $p < .001$; $\eta^2 = .166$), run length ($F(1, 216) = 91.48$, $p < .001$; $\eta^2 = .298$), and their interaction ($F(2, 432) = 5.46$, $p < .005$; $\eta^2 = .025$). The run-length effect replicates and is large, with runs of length 2 estimated to be less risky ($M = 3.89$) than runs of length 3 ($M = 4.48$; $F(1, 216) = 91.48$, $p < .001$; q4 $\eta^2 = .30$). This is true for each of the price series ($M = 3.91$ vs. 4.28, 4.34 vs. 4.96, and 3.42 vs. 4.20; $p < .001$ for each pair).

Moderators of the Run-Length Effect. We examined whether the run-length effect was moderated by sociodemographic characteristics by incorporating these, one at a time, using two- or three-way categorization splits as a measured between-subjects factor in the 2 × 3 (runs × replicate) ANOVA. The results of each of these ANOVAs are presented below, with results of significant moderators presented in figure 3.

Education level (recoded as those who had not completed
q5 a college degree = 79; those with a bachelor's degree or higher = 133) moderated the run-length effect ($F(1, 210) = 9.93$, $p < .005$; $\eta^2 = .045$). The pattern of the means shows that higher-educated respondents show a
q6 greater run-length effect (fig. 3*A*). This suggests that the effect is not due to the inability of respondents to estimate risk, for if it were, level of education would have been more likely to attenuate the effect.

Employment status also moderated the run-length effect ($F(1, 215) = 4.54$, $p < .05$; $\eta^2 = .021$), with respondents who reported being employed full time ($n = 122$) showing a greater run-length effect than those who reported being
q7 employed part time, self-employed, or not employed ($n = 95$; fig. 3*B*).

Frequency of trading moderated the run-length effect in the same counterintuitive manner ($F(2, 209) = 3.70$, $p < .05$; $\eta^2 = .022$). Those who reported trading quarterly or more often ($n = 69$) or semiannually or annually ($n =$
q8 31) showed a greater run-length effect than those who reported trading less than once a year ($n = 112$). They also estimated the risks as higher than the less frequent traders (main effect of trading frequency; $F(2, 209) = 3.51$, $p < .05$; $\eta^2 = .032$; fig. 3*C*). This result is consistent with the findings of Barber and Odean (2000), who reported that those who traded more often were more likely to make suboptimal investment choices.

The above findings imply that experience may exacerbate rather than attenuate the run-length effect. A median split of investors in terms of the number of years they had been actively trading in the stock market (5+ years = 98; <5 years = 115) revealed a significant interaction between the number of years that investors have traded and the run-length effect ($F(1, 211) = 4.15$, $p < .05$; $\eta^2 = .015$; fig. 3*D*). The same analysis done with a three-way split of experience (10+ years = 60; 1–10 years = 82; inactive = 71) revealed that the interaction effect was robust ($F(2, 210) = 6.72$, $p < .001$; $\eta^2 = .06$), with a main effect of investing experience also significant ($F(2, 210) = 3.53$, $p < .05$; $\eta^2 = .033$). Thus, investors with longer experience are as much or more biased than those with lesser experience, with inactive investors the least biased.

A similar conclusion is suggested by an analysis of the number of different investment vehicles that the respondents said they invested in (mutual funds, stocks, bonds, commodities, foreign exchange, and other). Respondents were categorized as reporting that they invested in none of these
q9 ($n = 66$), one of these ($n = 64$), and two or more of these ($n = 87$). This three-way split of investment type was included as a between-subjects variable in the 2 (runs) × 3 (replicate) ANOVA on risk perceptions and showed that the number of investment vehicles an investor reported investing in interacted with the run-length effect ($F(2, 214) = 2.89$, $p < .058$; $\eta^2 = .026$; fig. 3*E*). The means show that those who invest in more vehicles are more prone to the run-length effect and also perceive greater risk overall ($F(2, 214) = 3.67$, $p < .05$; $\eta^2 = .033$).

These five sociodemographic variables are correlated. For example, those who have completed a college degree are more likely to be employed full time ($\chi^2 = 7.39$, $p < .01$), trade at least annually ($\chi^2 = 21.00$, $p < .01$), own two or more investment vehicles ($\chi^2 = 33.47$, $p < .01$), and have over 5 years of experience trading ($\chi^2 = 22.15$, $p < .01$), as compared to those who have not completed a college degree. Thus, the moderating effect of each of these variables may be due to the same underlying reason: higher levels of education. The fact that the variables are not orthogonal also precludes running a multivariate ANOVA on these factors.

Gender had no significant main effect or interaction effect with the runs factor, and neither did age. The marital status q10
of the investor, income (<\$75,000 = 97; >\$75,000 = 86), total value of financial investments (<\$100,000 = 95; >\$100,000 = 68; prefer not to respond = 47), and self-reported expertise all had no moderating effect on the run-length effect. Responses to the extent to which people looked at historic performance in line graphs and used line graphs to make decisions also did not interact with the run-length effect.

Discussion

To summarize, this study demonstrated that individual adult investors (i) use graphical information to make financial investment decisions, (ii) rate line graphs showing historical performance as among the most useful sources of financial information, (iii) demonstrate the run-length effect, and (iv) show a greater bias, the more educated they are, the more frequently they trade, and the longer and wider their experience of trading. These sociodemographic moderators of the run-length effect suggest that education and experience that are typically associated with attenuating biases in information processing and judgments are instead associated with an exacerbation of the effect. It implies that the biases may not be controllable through greater ability and motivation, suggesting that they may be partially automatic in nature (Raghubir 2008).

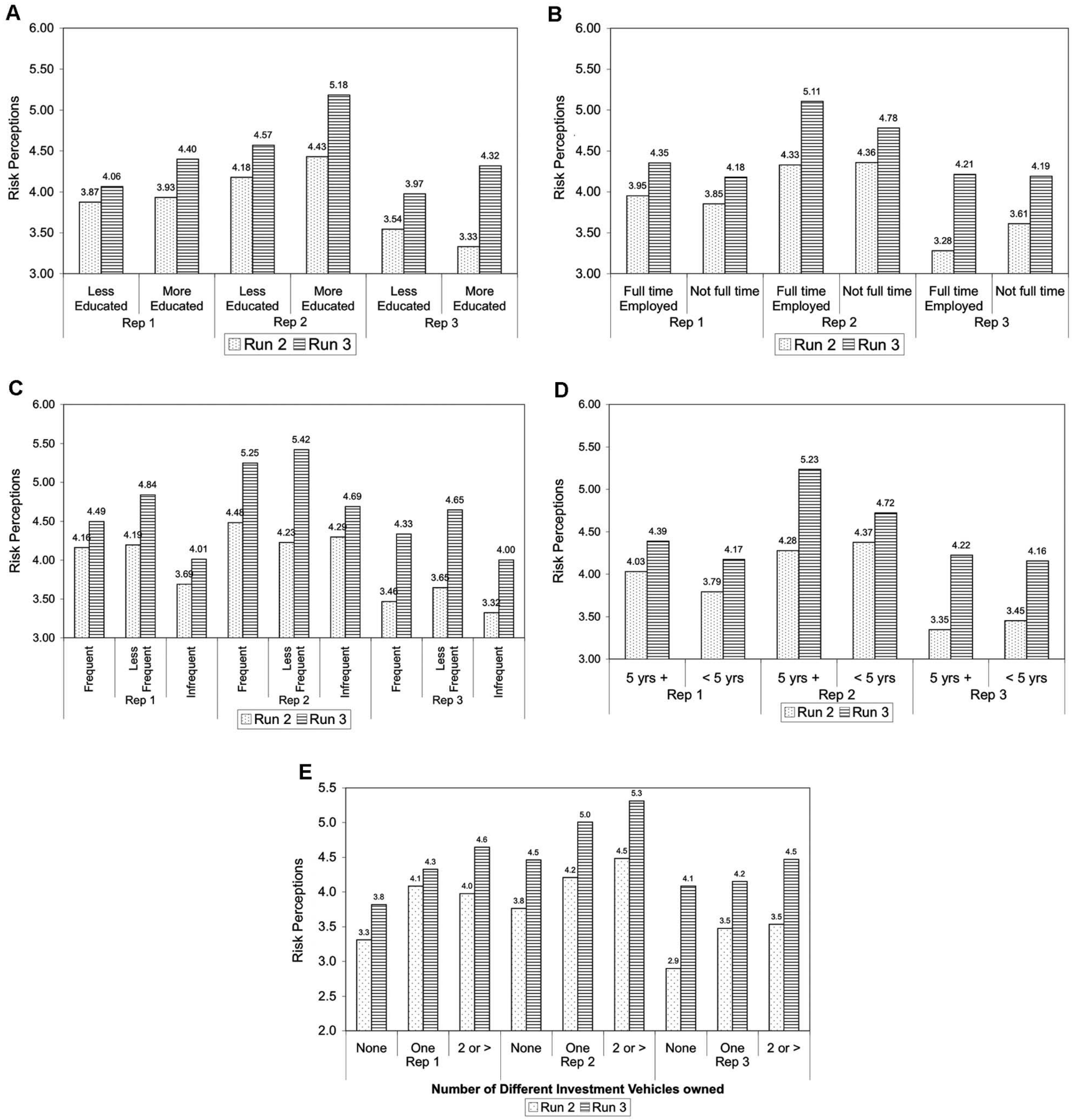
The pattern of moderation emphasizes the importance of examining these biases from the point of view of consumer welfare and public policy. If people who trade more are prone to the run-length effect, then these effects could aggregate and affect entire markets.

GENERAL DISCUSSION

This article offers an information-processing account of how people process visual information to make judgments of risk and return. We suggest that when faced with a large amount of information, people sample perceptually salient points of information to estimate risk. In a time series of stock prices, these are the local maxima and minima. The persistence of positive and negative return episodes in the

FIGURE 3

RESULTS OF STUDY 3



NOTE.—Differences in risk perception elicited on a 7-point scale (1 = not at all risky; 7 = very risky) for three replications of graphs that have identical mean and standard deviation but have a mean run length of either 2 or 3 due to the reshuffling of the returns are plotted as a function of individual demographic differences. *A*, Level of education: perception of risk of the stocks with run length 3 versus 2 is plotted separately for participants who reported not having completed a bachelor's degree and were categorized as less educated ($n = 79$) and those with a bachelor's degree or higher who were categorized as more educated ($n = 133$). *B*, Employment status: perception of risk of the stocks with run length 3 versus 2 is plotted separately for participants who reported being employed full time ($n = 122$) and those who reported being employed part time, self-employed, or not employed ($n = 95$). *C*, Frequency of trading: perception of risk of the stocks with run length 3 versus 2 is plotted separately for participants who reported trading quarterly or more often ($n = 69$) and were categorized as frequent traders, those who trade semiannually or annually ($n = 31$) and were categorized as less frequent traders, and those who reported trading less than once a year and were categorized as infrequent traders ($n = 112$). *D*, Number of years of experience trading. A median split was conducted on investors who reported the number of years that they had actively traded in the stock market. Perception of risk of the stocks with run length 3 versus 2 is plotted separately for traders with longer experience (5+ years; $n = 98$) and traders with fewer years of experience (<5 years; $n = 115$). *E*, Width of trading: number of investment vehicles invested in. Participants were asked to indicate whether they invested in mutual funds, stocks, bonds, commodities, foreign exchange, and other. Perception of risk of the stocks with run length 3 versus 2 is plotted separately for investors who reported investing in two or more of these investment vehicles ($n = 87$), traders who reported they invested in only one of these investment vehicles ($n = 64$), and those who reported that they invested in none of these vehicles ($n = 66$).

data determines their run length. As stock series with longer run lengths are associated with higher local maxima and minima, even though their return moments are controlled, they are perceived as riskier and are less preferred.

Study 1 showed that a stock with a shorter run length is preferred to one with a longer run length, holding constant the mean, variance, skewness, and kurtosis of returns. This preference appears to be because stocks with shorter run lengths are perceived to be less risky when, in fact, their statistical moments are controlled. The results are robust to financial expertise, experience, gender, other demographics (study 1), run-length manipulations, and measures (study 2) and are exacerbated, the greater the individual's ability and experience (study 3).

Implications for Visual Information Processing

The results of this article are consistent with the idea that the effects of run length are via their effects on local maxima and minima, which, in turn, are more perceptually salient and likely to be sampled to estimate trend and noise in a graph. In fact, trading volumes for stocks are found to spike when the price crosses a prior 52-week high or low, suggesting that investors pay attention to extrema (Huddart, Lang, and Yetman 2009). However, future research using eye-tracking methods could garner more direct evidence for this process.

Prior literature has shown that visual perceptual bias effects operate at a nonconscious level, are difficult to control, and increase with ability and motivation (Raghubir 2008). It would be interesting to examine whether increasing the stakes in decision making, which attenuates a controllable effect but exacerbates a hardwired one (cf. Raghubir 2008), would be a necessary or sufficient condition to eliminate these biases.

Implications for Biases in Judgment and Decision Making in Financial Markets

This article adds to the financial literature on run-length effects and antecedents of risk. Previous work in finance has examined run lengths as a predictor variable for market behavior such as efficient markets and stock market bubbles. Fama (1965) used run lengths and the number of runs to assess the efficiency of stocks based on the serial dependency of returns. He concluded in favor of weak-form market efficiency; that is, returns were not serially dependent. Easley, Kiefer, and O'Hara (1997) used a runs test to detect the presence of information in the stream of trading data in their study of market-maker behavior. The information extracted enables an understanding of how the market maker decides on the amount of informed trading there is in a stock. McQueen and Thorley (1994) found that longer runs evidenced greater probability of market bubbles, that is, stock prices increasing at a higher rate than they had historically. Recently, Das and Hanouna (2009) demonstrated the implications of run length for stock liquidity. They showed that stocks with longer run lengths have lower liquidity with lower trading volume than those with shorter run lengths. This article contributes to the literature on run lengths in finance by demonstrating the effect of run length on a stock's local maxima and local minima and how this translates into perceptions of higher risk.

The research presented here has implications for the literature on behavioral finance (Kahneman 2003; Shefrin 1999, 2005). An examination of biases at the individual level can help inform whether biases in individual consumer judgments have aggregate implications for financial markets (Raghubir and Das 1999). Given that traders make split-second decisions using common data that is presented graphically or as strings of numerical data, systematic biases in risk perceptions may permeate the market uniformly, resulting in persistent biases in prices.

For example, prior research has found that in financial markets people expect past patterns to continue into the future (DeBondt 1993; Hendricks, Patel, and Zeckhauser 1993). This is based on research conducted by Gilovich, Vallone, and Tversky (1985), who showed that people expect runs when, in fact, they do not exist—the "hot hands" effect. If this expectation is true, then even random, noninformative sequences may be prone to run-length effects as discussed here. Trend expectations have been exploited in momentum trading strategies (Jegadeesh and Titman 1993). These effects motivate contrarian investors who do not invest as per the rest of the market's expectancies but do the reverse (e.g., buying stocks that are losing and selling those that are winning), thereby enjoying higher returns than the market average (Lakonishok, Shleifer, and Vishny 1994).

When trend expectancies are disconfirmed (the run reverses), then financial markets overreact, resulting in prices overshooting fundamentals at the time of information releases (DeBondt and Thaler 1985, 1990; Stein 1989). It is plausible that viewing prices graphically could exacerbate these overreaction effects; a conjecture that requires further research. Johnson, Tellis, and MacInnis (2005) found that people tend to chase winners (positive runs) and dump losers (negative runs) under specific conditions. In other cases they found support for the disposition effect that has been widely studied in the behavioral finance literature, first documented in Shefrin and Statman (1985) and later shown to be robust in other settings (Jegadeesh and Titman 1993; Odean 1998; Shefrin 1999; Weber and Camerer 1998).

DeBondt et al. (2008) provide a detailed review of how cognitive errors and biases affect decision making by managers and investors, as well as the impact of these errors on market prices. They show that portfolios are distorted by false beliefs and irrational choices that at an aggregate level result in excess volatility in stock and bond values seen in situations such as the 1987 market crash, the Japanese bubble of the 1980s, the 1987 Asian financial crisis, the long-term capital management problem in 1998, and the financial crisis of 2008. The aggregation of systematic and automatic cognitive errors such as those studied in this article forms the basis for trading strategies such as contrarianism and technical trading models (Pring 2005). q11

Public Policy and Consumer Welfare Implications

Whereas many investors rely on experts' opinions and press coverage when they make their investment choices, to the extent that investors also interpret stock graphs to assess risk, the results of this article have public policy and consumer welfare implications. Day traders are a case in point. Investor Home estimates that at least a quarter-million people trade daily from home, using computer systems (2004). To the extent these traders use the easily accessible past performance of a financial instrument as a source of information to make their judgments, it is possible that these judgments could lead to biased portfolio allocation.

Study Limitations and Areas for Future Research

From an internal validity point of view, our evidence is consistent with the account that increased attention to a stimulus increases the size of an effect as that attention is directed to the biasing aspects of the stimuli rather than to alternate diagnostic information that could be used to make the judgment. However, we do not have direct physiological attention measures. Future research, using different measures, could examine whether this is, in fact, the case.

This article argued that people sample the maxima and the minima, and, therefore, run length affects perceptions of risk. Run length is one of many different factors that could affect the salience of extrema in a visual display. To increase the nomological validity of the findings, further research could manipulate extrema using other methods, such as the visual salience (colors/boldness) of points in the graph, subliminal priming, and goals, to better understand what factors drive the manner in which investors sample graphical information. We examined how people judge risk using visual cues. Similar effects may also exist when information is presented digitally and if there are systematic differences in the perception of risk and return as a function of graphical or digital presentation.

Future research could also examine the definitions of risk across pedagogies and people. What is risk? Does it mean different things to different people? While consumer psychology research has defined perceived risk as the subjective likelihood that an aversive event will occur in the future, statisticians define risk in terms of the moments of a series of returns, traders define risk in terms of volatility, actuaries define it in terms of defaulting on a future obligation, and economists describe it as the probability of occurrence of a rare event (for a review of risk definitions, see Menon, Raghubir, and Agrawal 2007). In the context of financial investing, risk may be defined as the likelihood that a stock will lose money or make less money than expected or than an alternate investment (Behavioral Portfolio Theory; Shefrin and Statman 2000). While risk has specific definitions in the different domains in which it is studied, an overarching understanding of what risk means to the average investor would be of interest to public policy makers, consumer welfare advocates, and others. The run-length effect may not be a "bias" or a cognitive error, given that stocks with longer run lengths have higher liquidity risk (Das and Hanouna 2009). Clearly, the statistical moments of a return distribution do not completely capture investor's perceptions of risk. Identifying other antecedents of perceived risk would be an interesting endeavor.

APPENDIX A

RUN LENGTHS AND GRAPH EXTREMA: THEORETICAL AND EMPIRICAL RELATIONSHIPS

This appendix examines the relationship between run lengths, statistical moments, and extremal points of a graph. It shows that, holding fixed the statistical moments of security returns, increases in run length imply increases in graph extrema. We first develop the intuition for this result using a series of graphs. Second, we extend this intuition with a formal simulation result. Third, we consider the relationship of run length and mean reversion, via simulation and empirical data. Finally, we present historical evidence of the relationship between run lengths and the standard deviation of equity returns from 1962 to 2005.

A SIMPLE EXAMPLE

A run is a continuous series of movements in a random variable in the same direction. The length of a run can vary from 1 to the maximum length of the series of the random variable. This appendix explains why, on average, increases in run length correspond to increases in the difference between the maxima and minima (called the extremal difference) of a time series, within the context of a sequence of stock returns.

Run length is a mathematical property of a signed sequence of random variables. Run length does not depend on the magnitude of the movements but, rather, the sequence of signs of the moves in the random variable. Hence, to develop the intuition for the connection of extrema to run lengths, it is easiest to consider a pure random walk. This is a series that increments by +1 or decrements by -1 with equal probability. Such a sequence has a mean value of 0 and a standard deviation of 1.

We manipulate the average run length of a series of 20 data points—10 of value +1, and 10 of value -1—while keeping the statistical moments of the data the same. We do this by reshuffling the data in order to increase run length and then progressively examining how this affects the extremal difference (difference between the maximum and minimum) of the data series.

We begin with the shortest possible mean run length for this series: a sequence of alternating values of +1 and -1. Each run is exactly of length 1, and there are 20 runs. The mean run length is 1, that is, the total length of the series (20) divided by the number of runs (20). This is graphed in figure A1. q12

The maximum value of the series is +1, and the minimum value is 0. Hence, the extremal difference is 1. The same

FIGURE A1

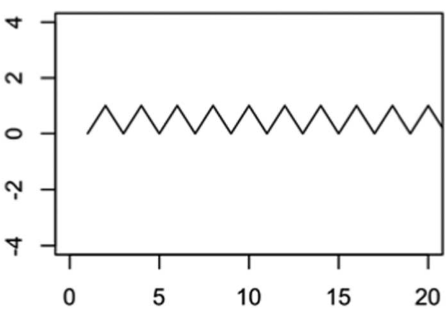
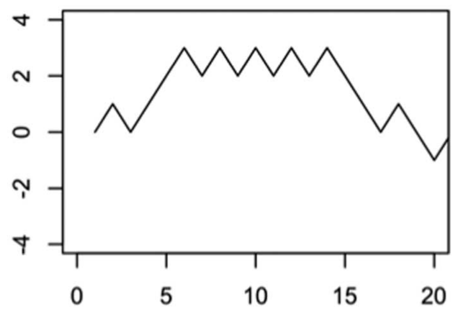


FIGURE A3



result follows if the first element in the sequence is −1 instead of +1. The maximum value would be 0, and the minimum value would be −1, for an extremal difference of 1.

As the mean run length is the length of the series divided by the number of runs, any reordering will reduce the number of runs and result in an increase in mean run length. A minimal perturbation of the previous series is graphed in figure A2.

The number of runs declines from 20 to 19, and the mean run length is 1.05 (20/19); the maximum value of the series is +1 and the minimum is −1. The extremal difference is 2. Here, an increase in mean run length corresponds to an increase in extrema.

We further perturb the preceding graph by randomly choosing some points of value +1 and the other of value −1 and flipping their signs to reorder the sequence minimally yet keep the number of ups and downs the same. In figure A3, the number of runs is 15, and the mean run length is 1.3 (20/15); the extremal difference is 4 (3 minus −1). Again, an increase in run length results in raising the extremal difference.

We undertake yet another perturbation, where the mean run length remains 1.3 and the extremal difference remains 4, resulting in the figure A4. Figure A5 shows two more iterations of 13 runs with an average run length of 1.5 (20/13). The extremal difference in the figure A5*A* is 4, and in figure A5*B* it is 5. This illustrates that (1) run length can increase but the extremal difference may not (compare fig. A5*A* with figs. A3 and A4) and (2) run length can remain the same but the extremal difference can increase (compare fig. A5*A* and *B*). This is on account of the integer granularity of the extremal difference. Figure A6 shows two more examples in which we further raise mean run length to 1.8. Figure A6*A* has an extremal difference of 5, and figure A6*B* has an extremal difference of 6.

Thus, whereas there is a positive relationship between run length and extremal difference, this is not a deterministic difference. On average, sequences with higher run lengths are associated with higher extremal differences. What is important to note is that each and every graph begins and ends at zero since we have only reshuffled returns. Further, the size and number of changes are held constant (10 each of +1 and −1), ensuring that the graphs have identical moments (mean, variance, skewness, and kurtosis). Other manipulations that can change the extremal values (e.g., through a combination of long run lengths and relatively small daily price movements or short run lengths and relatively large daily price movements) would affect the moments of the distribution. Changing the sequence of run lengths does not. However, as the relationship between run lengths and extrema is probabilistic, it is imperative to demonstrate how strong and robust it is. This is done next.

FORMAL SIMULATION EXPERIMENT FOR 10 MOVES EACH OF +1 AND −1

To rigorously examine the relationship between run lengths and extremal values, we conducted a formal simulation using the same random walk as in the examples above (i.e., a set of 10 each of +1 and −1 moves). The values were randomly shuffled, and the mean run length and the

FIGURE A2

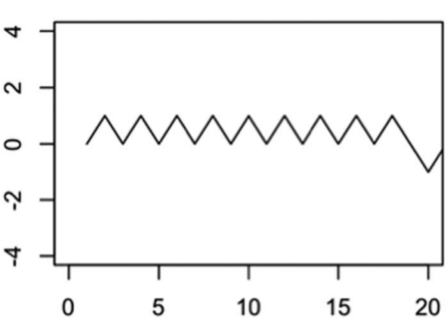


FIGURE A4

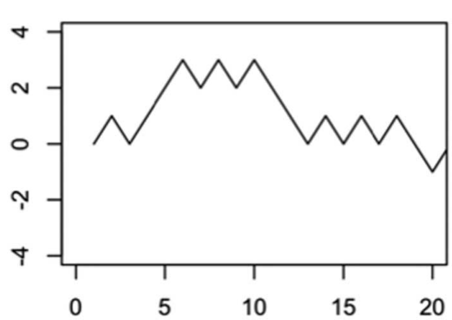
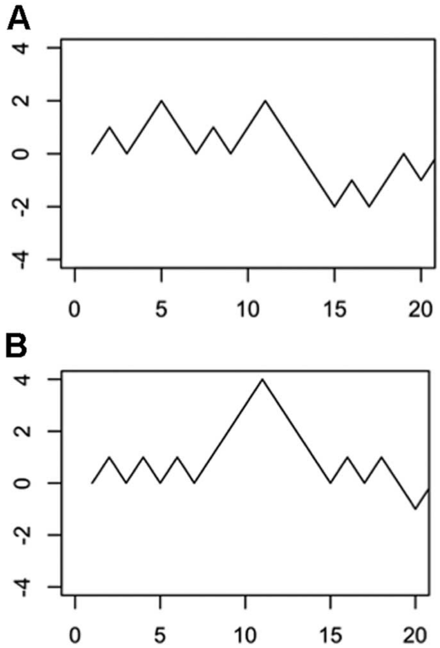


FIGURE A5



extremal difference were computed. Of the maximum possible 184,756 distinct sequences ($^{20}C_{10}$), 10,000 simulations
q13 were run. Figure A7 plots extremal differences (ranging from the minimum of 1 to the maximum of 10) against the mean run length (the numbers on the graph are the mean run length).

As figure A7 shows, in this case, the relationship between mean run length and extremal difference is positive and monotonic but not linear. The graph shows that small differences in average run length are associated with big differences in extremal value. The next analyses examine whether this relationship is true for longer sequences that vary in the average size of their daily price movements.

SIMULATION ANALYSIS OF RUN LENGTHS, MEAN REVERSION, AND EXTREMA

The goal of this analysis is to show that graphs with longer run lengths (consecutive upward or downward movements) have lower rates of mean reversion and greater extrema, holding the variance of returns constant. Mean reversion is the tendency of a variable to revert to its long run mean at a rate proportional to its distance from the mean. The higher the run length of a stock, the lower its mean reversion, that is, the lower the probability that it will revert to its long run mean. This lower mean reversion leads to graphs with longer run lengths having higher maxima and lower minima.

Stock Price Simulation

We simulated the evolution of a year's stock price using the following model (Uhlenbeck and Ornstein 1930): the first equation presents the evolution of stock returns in continuous time with mean reversion at rate k; the second equation translates it into discrete time; the third equation translates returns back into their stock prices.

$$dr(t) = k[\theta - r(t)]\,dt + \sigma\,dZ(t), \qquad \textbf{(A1)}$$

$$r(t+h) = r(t)e^{-kh} + \theta(1 - e^{-kh}) + \sigma\int_{t}^{t+h} e^{-k(t+h-s)}\,dZ(s), \qquad \textbf{(A2)}$$

$$S(t+h) = s(t)e^{r(t+h)}, \qquad \textbf{(A3)}$$

where $r(t)$ = continuously compounded return on the stock at time t, k = rate at which a stock return reverts to its long run mean (θ), θ = long-run mean of the stock, $S(t)$ = stock price at time t, and h = length of the time interval.

The Relationship between Mean Reversion and Run Length

We calculated the variance (V) of the stock return over a time interval of length h as

$$Vh = \frac{\sigma^2}{2k}(1 - e^{-2kh}). \qquad \textbf{(A4)}$$

The variance declines as k increases. The process equation (dr) shows that as the rate of mean reversion, k, increases

FIGURE A6

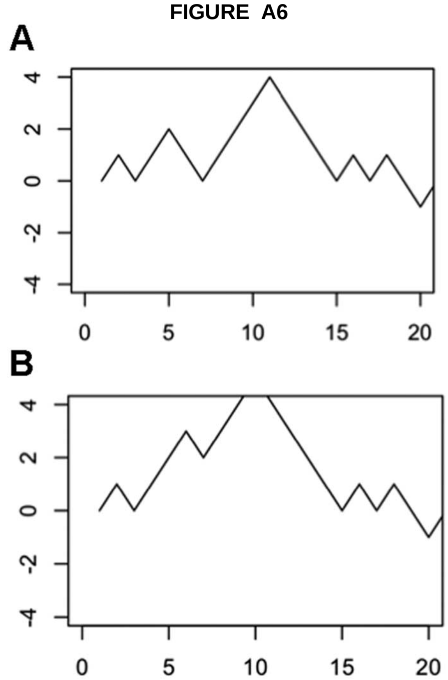
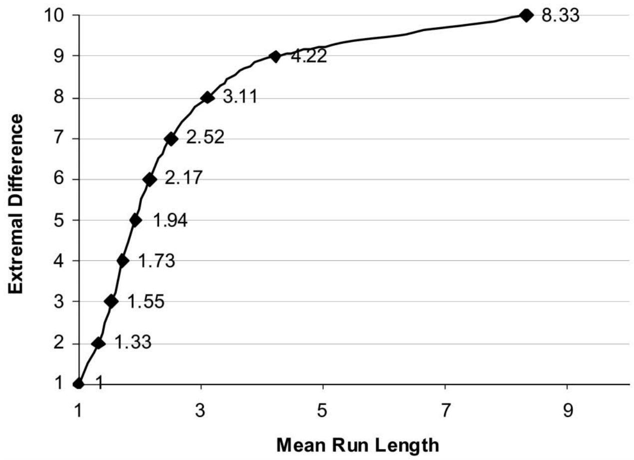


FIGURE A7



(i.e., stocks return to their long run mean θ), the run length (consecutive upward or downward movements in the price of the stock) reduces. This is because movements away from the long run mean, θ, are more likely to be followed by movements back toward it, the higher the rate of mean reversion, k.

Monte Carlo Simulation at Different Mean-Reversion Parameters

We simulated the evolution of a year's stock price at two different parameters for mean reversion: low ($k = .1$) and high ($k = .9$), holding other parameters constant. These are start price ($S_t = 100$), variance (V), and length of time interval (h). Holding V constant while manipulating k and σ ensures that the variance of stock prices for low and high mean reversion is identical: an essential control to eliminate the alternative explanation that stocks with higher run lengths may have higher variance in their stock prices. In this simulation, (*a*) we computed the maximum and minimum stock price for each simulation, (*b*) the simulations were repeated 100 times each, and (*c*) we computed the mean maximum and minimum prices for the 100 simulations separately under the low ($k = .1$) and high ($k = .9$) mean reversion assumptions.

Simulation Results Showing the Relationship between Mean Reversion and Maxima and Minima

Results across the 100 simulations each for the low and high mean-reverting stock series show that when $k = .1$ (i.e., longer run lengths and lower mean reversion), stock prices have a lower minimum and a higher maximum stock price than when $k = .9$ (short run lengths and higher mean reversion). Specifically, the average minimum stock price is lower for the lower mean-reverting (higher run-length) stock ($M = 92.10$; SD $= 12.51$) than for the higher mean-reverting (lower run-length) stock ($M = 94.34$; SD $=$ 9.46), and the average maximum stock price is higher for the lower mean-reverting (higher run-length) stock ($M = 122.22$; SD $= 27.10$) than for the higher mean-reverting (lower run-length) stock ($M = 118.30$; SD $= 20.04$).

Thus, this simulation generalizes the results of the previous simulation to longer sequences, while at the same time relaxing the conditions of an equal number of positive and negative movements of the same size. We next examine the relationship between run lengths and the mean and variance of stock returns in the U.S. market to see whether the simulation results reflect historical reality.

EMPIRICAL ANALYSIS OF HISTORICAL RUN LENGTHS AND THEIR RELATIONSHIP TO STOCK RETURNS

The question is, Do historical price trends show that stocks with longer run lengths have higher variance (V) in their returns? It is important to answer this question because if such an empirical relationship exists, then any difference in risk perceptions may be explainable in terms of respondents' prior experience. We have proposed that run lengths lead to higher risk perceptions due to their effect on extrema, after controlling for the moments of returns. If there is a historical relationship between variance and run length, then this could imply that respondents expect the two to be correlated. This is an alternative explanation for why stocks with higher run lengths that are perceived as riskier do not invoke extrema but, instead, their historical relationship with variance. To examine this question, we conducted the following analysis.

Data

We examined the descriptive statistics of three well-known financial portfolios from July 1963 to December 2002 ($n = 9{,}944$ trading days). These are (*a*) excess return of the market portfolio over the risk-free return, (*b*) the Fama-French portfolio of returns on SMB stocks, and (*c*) the Fama-French portfolio of HML book-to-market stocks.

Results

If there is an equal likelihood of an up or down movement in returns, then stock prices should follow a random walk, or the returns from one period to the next should be independent of each other and symmetric. This translates into an average run length of 2, which serves as our point null hypothesis. The results show that all three portfolios had average run lengths > 2. The SMB portfolio had a lower average run length as compared to the HML portfolio ($t = 4.82$, $p < .01$) and the excess market return portfolio q14 ($t = 3.82$, $p < .01$). Results are provided in table A1 and show that for all three portfolios the average run length is higher than would be predicted by a random walk (French 2008).

Having established that average run lengths in the United States are historically higher than would be predicted using

TABLE A1

PORTFOLIO RESULTS

	Excess return (market less risk-free return)	Small less big stocks index return	High less low book-to-market portfolio return	Standard normal (i.e., random walk; $N(0, 1)$)
Return	4.69	1.19	5.14	
	(14.18)	(7.79)	(7.37)	
Run length	2.27[a]	2.15[b]	2.33[a]	2.00[c]
	(1.65)	(1.74)	(1.87)	(1.41)
t versus $N(0, 1)$	8.71	4.89	9.65	

NOTE.—Numbers in parentheses denote standard deviations. Mean run lengths that do not share the same superscript are different at $p < .01$.

a normal random walk, we next examine whether mean run lengths are related to the variance in stock returns, using the data set used by Das and Hanouna (2009). Their sample covers all stocks with nonzero trading volume on the NYSE, AMEX, and NASDAQ from January 1962 to December 2005. We first computed the distribution of run lengths for each year for each stock ($n = 109{,}601$). Stocks with prices below $5 and above $1,000 were eliminated to ensure robustness of the sample. The distribution of run lengths is given in table A2 and shows that an overwhelming majority of stocks have run lengths between 2 and 3 (74%), with as many as 14% with run lengths greater than 3.

We next calculated the correlation between the mean run length and the standard deviation of stock returns. A positive correlation would imply that stocks with higher run lengths historically had a greater variance in their stock returns and would be an alternative explanation for why stocks with higher run lengths could be perceived to be riskier. Das and Hanouna (2009, table 2) calculated the mean and the standard deviation of run lengths and stock returns for all stocks listed on the NYSE, AMEX, and NASDAQ exchanges across 9 quinquennial periods from 1962 to 2005. Using their summary descriptive data, we examined whether mean run lengths were correlated with the standard deviation of stock returns for all 9 periods ($r = -.09$, NS) and for each subset of 20 years (4 quinquennial periods). Six of the seven computed correlations were negative (except 1971–90). The data are reproduced in table A3 and provide convergent evidence that the perception of higher risk for stocks with longer run lengths does not reflect historic reality. q15

To summarize, using a simple example and two simulations, we showed that, holding fixed the statistical moments of security returns, increases in run length imply increases in graph extrema on average. Further, we showed that historically in the United States, run lengths are >2 and that there is no evidence of a positive relationship between run lengths and the variance of equity returns from 1962 to 2005. Thus, the manipulation of run length affects extremal value but not actual variance of returns. The higher risk perception associated with higher run lengths cannot be explained in terms of a historical empirical relationship, suggesting it may represent a bias.

TABLE A2

RUN-LENGTH DISTRIBUTION

Run-length range	Number of firm years	% of total	Reverse cumulative
[1, 2]	13,091	11.94	100.00
(2, 3]	81,068	73.97	88.06
(3, 4]	7,873	7.18	14.09
(4, 5]	2,428	2.22	6.91
(5, 6]	1,182	1.08	4.69
(6, 7]	828	.76	3.61
(7, 8]	575	.52	2.86
(8, 9]	371	.34	2.33
(9, 10]	300	.27	1.99
(10, 15]	776	.71	1.72
(15, 20]	296	.27	1.01
>20	813	.74	.74
Total	109,601	100.00	

TABLE A3

RUN-LENGTH SUMMARY DATA AND CORRELATION

	Mean run length	SD return	Correlation
Quinquennial:			
1962–65	2.55	1.65	. . .
1966–70	2.48	2.23	. . .
1971–75	2.59	2.28	. . .
1976–80	2.53	2.12	. . .
1981–85	4.43	2.19	. . .
1986–90	3.95	2.52	. . .
1991–95	3.08	2.77	. . .
1996–2000	2.51	3.32	. . .
2001–5	2.19	2.76	. . .
1962–2005	. . .	. . .	−.09
1962–80	. . .	. . .	−.15
1966–85	. . .	. . .	−.11
1971–90	. . .	. . .	.36
1976–95	. . .	. . .	−.03
1981–2000	. . .	. . .	−.97
1986–2005	. . .	. . .	−.61

APPENDIX B

TECHNICAL NOTE ON STIMULI GENERATION METHODOLOGY

PROCEDURE

1. We started a series with the price at time period 1
q16 ($S_1 = 100$).
2. We generated a year's daily stock returns (T observations) by sampling from a normal-distribution random-number generator, subject to an overall mean return of μ and a standard deviation of σ (10% and 15% per annum, respectively, for study 1, and 3.93% and 14.13% for study 2). These stock returns were simulated using a Geometric Brownian motion that is based on independent continuously compounded returns that are normally distributed (theoretically 0 skewness and excess kurtosis). The returns series are $\{R_1, R_2, \ldots, R_T\}$.
3. As prices (S_t) are related through continuously com-
q17 pounded returns ($S_t = S_{t-1} \exp(R_t)$), the returns' series was used to get a time series of prices.
4. To obtain series with different run lengths holding constant the mean, variance, skewness, and kurtosis of the returns in study 1, we use an optimizer to generate and perturb returns such that the two series have identical moments and the desired run lengths of 3 and 10. (In studies 2 and 3, we reshuffled the return observations, a method that also allows for identical moments with differing run lengths.)

ADVANTAGES OF THE USE OF THE PROCEDURE

The procedure used to achieve different run lengths has the following advantages: the start and end points of the stock series remain the same irrespective of the order of R_t values: start point = 100; end point =

$$S(T) = S(0) \exp\left[\sum_{t-1}^{T} R(t)\right]. \quad \textbf{(B1)}$$

The risk-adjusted return of the two series is the same. Historical volatility, or the extent to which prices deviate from the overall mean, is not affected and is computed as follows:

q18

$$\sigma = \sqrt{T[V(R(t))]}, \quad \textbf{(B2)}$$

$$R(t) = \ln\left[\frac{S(t)}{S(t-1)}\right]. \quad \textbf{(B3)}$$

ILLUSTRATION OF PROCEDURE USING AN EXAMPLE

To illustrate with an example, assume there are two stock price series that both start at the price of $100.00 and end at a price of $99.18. They have the same set of returns. The first series has returns of 2%, 6%, 7%, −5%, −6%, and −4%: average run length = 3. The prices that these returns reflect are 100.00, 102.00, 108.12, 115.69, 109.90, 103.31, and 99.18, with a local maximum of 115.69. The second series has the same set of returns, but in the following sequence: 6%, −4%, 7%, −6%, 2%, and −5%: average run length = 1. The prices in this series are 100.00, 106.00, 101.76, 108.88, 102.35, 104.40, and 99.18, with multiple local maxima: 106.00, 108.88, and 104.40.

EXAMINING GRAPH CHARACTERISTICS AND ROBUSTNESS TO SUBPERIODS WITHIN THE HORIZON

The average autocorrelation (i.e., correlation between two consecutive price movements, across t periods) of the graph with a longer run length was higher ($r = .4668$) than that of the graphs with a shorter run length ($r = .1998$). Given this, we examined the stimuli for robustness to the time horizon: that is, if the stock was not held for the entire period, we examined whether the subperiod of time for which the stock was held within the period differed across the two run lengths. We transacted all possible buy-and-sell "holding period" strategies for the period possible over any two dates in the trading year and calculated the annualized percentage return (APR = ln (closeout price/buying price) × t/(number of days of round-trip return period) for each round-trip trade.

The mean, standard deviation, skewness, and kurtosis of the APRs based on this simulation for the graph with run length 3 = 0.0940, 0.5264, −0.0649, and 19.0583, and for the graph with run length 10 = 0.1427, 0.6922, −0.1857, and 9.7144, respectively. Thus, the results of this holding period simulation show that the graph with run length 3 does not have a higher risk-adjusted return (M/SD = .1786) than the graph with run length 10 (M/SD = .2061). In fact, the risk-adjusted APR of the stock with run length 10 is higher than that of the stock with run length 3. We do note, however, that the skewness is more negative for the run length 10 stock, but it has lower kurtosis than the run length 3 stock. Neither stock stochastically dominates the other.

This implies that a preference for a stock with a shorter run length cannot be explained in terms of actual differences in risk. The holding period simulation results can also rule out any explanations for the preference of the shorter run-length stock based on people's assumptions that they were buying or selling for shorter periods of time (than the total time frame spanned by the graph).

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