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Betting on trends: Intuitive forecasts of financial risk and return

Werner F.M. De Bondt

Graduate School of Business, University of Wisconsin–Madison, 1155 Observatory Drive, Madison, WI 53706, USA

Abstract

Based on nearly 38 000 forecasts of stock prices and exchange rates, it appears that non-experts expect the continuation of apparent past 'trends' in prices. Thus, they are optimistic in bull markets and pessimistic in bear markets. Interestingly, the subjects hedge their forecasts, i.e. their subjective probability distributions are skewed in the opposite direction. As a result, perceived risk also depends on prior performance.

Keywords: Investor psychology; Noise traders; Overreaction; Confidence intervals

1. Introduction

Recent empirical research finds that changes in asset prices are somewhat predictable. Major stock market indices, such as the Dow Jones Industrial Average (DJIA) or the Standard & Poor's Index (S&P), are mean-reverting over 3–5 year horizons. After a long bull market, an index decline is more likely than a continued upward movement. Conversely, after a fall in prices, the chances of a turnaround exceed those of further decline.[1]

The mean-reversion in prices was discovered by testing the efficient market hypothesis against a psychological alternative, the overreaction hypothesis. The tests were motivated by the literature on heuristics and biases as well as by the immediate fact that share prices are extremely volatile. Much price volatility remains unexplained [see Cutler et al., (1989); Schwert (1989); Shiller (1989)]. The efficient markets view is that at any moment stock prices correctly reflect the available information [See Fama (1970, 1991)]. In contrast, the overreaction hypothesis suggests that prices often deviate from intrinsic values because non-expert investors ('noise traders') overreact to news. Prices overshoot. Eventually, however, they get corrected as future events predictably turn out to be less rosy or more pleasant than originally thought. This price behavior may explain the profitability of contrarian strategies: prior stock market losers outperform prior winners by about 8% per year [see De Bondt and Thaler (1985); Chopra et al. (1992)].[2]

While most researchers in finance either wonder whether the data may still be consistent with efficient markets—e.g. because risk premia ra-

[1] See De Bondt and Thaler (1989) for a literature review. It cannot be excluded that the appearance of mean-reversion is a statistical artifact [see, for example, Richardson (1988); Kim et al. (1988)].

[2] Alternatively, the overreaction evidence may also be linked to changing company risk, the size-effect, year-end tax-loss selling, and the January seasonal in stocks [see De Bondt and Thaler (1989) for references].

tionally vary with time [see Fama and French (1988)]—or examine the theoretical circumstances which prevent rational arbitrageurs from correcting market prices [see De Long et al. (1990a, b)], there has been little or no study of the claims about *individual behavior* that underlie the overreaction hypothesis.[3] Indeed, the important question of what is meant by 'overreaction' is still not fully resolved. In this paper, I start to fill this void. I begin by motivating two hypotheses about the return expectations and the risk perceptions of financially unsophisticated subjects in bull and bear markets. Thereafter, four different studies test the theory. The paper ends with a summary of the results and their implications.

2. Investor behavior and asset valuation

Why do stock prices fluctuate? Economists argue that, with rational behavior and frictionless markets, the prices of a share now (P_0) equals the dividend that the investor expects to receive (D_1) *plus* the future price (P_1) at which the share can be sold, both properly discounted at the opportunity cost of capital (ρ). Since, initially, both D_1 and P_1 are uncertain, market prices vary as news arrives and expectations of the future change. In addition, prices move with ρ, the return that investors require to hold assets of equivalent risk.[4]

Stocks are perpetuities and, if the investor is to consume his savings, he may need to sell at some point. Alternatively, he may simply enjoy trading. When should he buy or sell? In efficient markets, the answer does not depend on whether prices seem high or low. Rational forecasts of D_1 and P_1 may contain random error but no predictable error. Consider a discounting model where dividends, now and in the future, are expected to be D_{t+1}. The price P_t should then be D_{t+1}/ρ. Since actual dividends equal expected dividends plus white noise, the true value which the investor receives (P_t^*) equals P_t plus random error. More formally, and conditional on what is known, the market price is the mathematical expectation of the perfect foresight price. This result, which is easily generalized [see Le Roy (1989)], means that in efficient markets investors always receive fair value. The timing of stock trades does not get anyone rich, unless they are lucky.

In contrast, if investor psychology matters, stock price movements are *not solely* driven by news about economic fundamentals. Rather, some 'excess' volatility, relative to discounting models, derives from market fads and from systematic misperceptions of value. What is it that investors do wrong? One view [see De Bondt and Thaler (1985)] is that many people violate Bayes' rule when they update their beliefs about companies' prospects for profit, i.e. the capacity to pay future dividends. In this view, the public puts too much emphasis on the latest, most striking news (say, unexpectedly large company sales) and too little on base-rate information (e.g. whether from historical trends the sales growth can be maintained). This is an application of the representativeness heuristic [see Tversky and Kahneman (1974)].

Consistent with this theory, the earnings forecasts of financial analysts appear to be systematically too extreme and there is an inverse relationship between analysts' predictions of earnings growth and later returns [see De Bondt and Thaler (1990); De Bondt (1992)].[5] The motives behind corporate earnings management may also

[3] An exception is Andreassen (1987, 1988, 1990). Other experimental studies of financial forecasting include Schmalensee (1976) and Stael von Holstein (1972). There is also a literature on 'experimental markets' [see, for example, Camerer (1987)] but its focus is more on market than on individual behavior.

[4] Of course, the cost of capital changes through time. But it seems unlikely that movements in ρ contribute much to stock price variability. Nevertheless, if one insists that market forecasts of D_1 and P_1 are rational, then rapidly and strongly fluctuating discount rates are implied by the surprising day-to-day volatility of stock prices. Therefore, the arguments for time-varying risk premia are the logical complement of the efficient markets view.

[5] It is unclear, however, what causes the errors in analysts' forecasts. Klein (1990) and Abarbanell and Bernard (1992) agree with De Bondt and Thaler (1990) that the forecast errors are not easily viewed as an overreaction *to past reported accounting earnings* or *to past stock prices*. In fact, Abarbanell and Bernard find that analysts underreact to past earnings and Klein concludes that they underreact to security returns. Still, for past winner stocks, the earnings predictions in Klein's sample are typically too high. For loser stocks, the optimism lessens as prices fall. (I thank Joshua Ronen for this interpretation of Klein).

be understood in this context. Executives do not like to report poor earnings because they fear that the news depresses share prices [see Froot et al. (1991)]. As a result, they may want to 'smooth' reported company income [see Schipper (1989)].

2.1. *Betting on trends*

However, this paper examines a second view of overreaction which focuses on misperceptions of future prices (rather than of earnings or dividends). Over short horizons, stock price changes are highly unpredictable. Nevertheless, many people are prone to discover 'trends' in past prices and to expect their continuation. De Long et al. (1990a) call these investors positive feedback traders. The tendency to detect price patterns may explain investor demand for the advice of technical analysts.[6] As it happens, the opinions of investment advisors, captured by an industry-wide sentiment index, also lag market developments [see Solt and Statman (1988)]. That investor enthusiasm moves with the market is further confirmed by the fact that, with every major bull market, millions of Americans buy stock for the first time [see Shiller (1989, p. 18)]. Finally, there is much experimental evidence documenting the compulsive structuring of random walk data. These findings are relevant for prediction, as research on the 'hot hand' in basketball [Gilovich et al. (1985)] illustrates [see Wagenaar (1972); Hogarth (1975); Eggleton (1976, 1982) for reviews of the literature].

Below, I compare subjects' expected price (index) changes in bull and bear markets. Define P_0 as the last known price level, e.g. of the Dow Jones, and F as an individual's point estimate. Then, with the expected price change (EPC) equal to $F - P_0$, the hypothesis that the average subject expects the continuation of past trends implies:

$$H_0: \overline{\mathrm{EPC}}^{\mathrm{bull}} = \overline{\mathrm{EPC}}^{\mathrm{bear}}$$

$$H_A: \overline{\mathrm{EPC}}^{\mathrm{bull}} > \overline{\mathrm{EPC}}^{\mathrm{bear}}$$

Thus, the average EPC in bull markets should exceed the average EPC in bear markets.

2.2. *Past prices and future risk*

The subjective risk associated with price predictions is of interest because establishing a time-series forecast and a confidence interval (or 'credible interval') are probably related activities. However, apart from comparisons of accuracy, 'little is known' about either [see Lawrence and Makridakis (1989, p. 172)]. Tversky and Kahneman (1974) propose that *anchoring-and-adjustment* plays a role in explaining why confidence intervals are often too narrow. They offer the example of selecting values of the Dow Jones (X_{10} and X_{90}) so that there is only a 10% chance that the true number turns out either lower or higher at a future date. According to these authors, 'it is natural to begin by thinking about one's best estimate of the Dow Jones and to adjust this value.. but ..if this adjustment—like most others—..is insufficient, then.. the assessed probability distribution will be too tight' (p. 1129).

This paper suggests instead that, when subjects fit a trend line to past prices and establish confidence intervals, not one but *two* anchors are at work. The first anchor is the one proposed by Tversky and Kahneman. It is determined by the expected continuation of past *price changes*. The second anchor is a price that is representative of past *price levels*, more or less independent of recent movements. For example, if the share price of XYZ, Inc. rose over 6 weeks from $23 to $41, increasing by $3 each week, one's best estimate for the price at the end of the seventh week would probably equal $44 but a typical past price may well be around (or below) $32. I propose that, when the subjects set confidence intervals, they start from $44, but the representative past price of $32 drags both X_{10} and X_{90} down. As a result, the confidence interval for

[6] Books on technical analysis devote much space to simple patterns that allegedly have predictive significance [see Edwards and Magee (1948); Pring (1991)]. Trading practices based on past trends are well-known to experts. In Schwager's (1989, p. 309) book of interviews with top traders, James Rogers quotes his mother who '..calls me up and says, 'Buy me XYZ stock.' I ask her, 'Why?' 'Because the stock has tripled,' she answers.' Rogers calls it the magical stage of the bull market when 'people are hysterical to buy, because they know that the market is going to go up forever.' 'It's always the same cycle,' he says, 'The whole process..repeats itself on the downside'.

series with rising prices is not symmetric but left-skewed. Similarly, with falling prices, the confidence interval should right-skewed as both X_{10} and X_{90} are pulled up.[7] I refer to this hypothesis as 'the hedging theory of confidence intervals'.

Let H be the 'high' forecast (e.g. X_{90}), L the 'low' forecast, and F the point estimate. Also, define upper and lower confidence intervals as, respectively, $\mathrm{UCI} = H - F$ and $\mathrm{LCI} = F - L$. Skewness (Δ) is then measured by the differential between UCI and LCI so that $\Delta = H + L - 2F$. Note that, if an individual perceives the distribution of the future price to be symmetric around his point estimate, $\Delta = 0$. In this case, F equals $(H + L)/2$, the mid-point between the high and low price. But, if the subject expects the price to be closer to H than to L, $\Delta < 0$. Conversely, if the price is expected to be closer to L, $\Delta > 0$. If most subjects extrapolate past trends, the hedging theory implies:

$$H_0 : \bar{\Delta}^{\text{bull}} = \bar{\Delta}^{\text{bear}}$$

$$H_A : \bar{\Delta}^{\text{bull}} < \bar{\Delta}^{\text{bear}}$$

Thus, average skewness should be less in bull markets than in bear markets.

3. Study 1: Forecasts of the S&P-Index

3.1. *Method*

Twenty-seven subjects were together in a classroom and played a 'technical analysis' game. On an overhead projector, they saw six graphs with 48 monthly prices of 'unnamed stocks' on each. The graphs actually plotted the S&P Index for three bull markets (ending in 1967, 1980, and 1986) and three bear markets (1970, 1974 and 1982). In bull markets, the S&P return for the last year was respectively, 19.6, 35.6 and 31.8%. In bear markets, it was −26.0, −27.5, and −16.7%. The graphs were presented in random order. Prices were indicated on the vertical axis and there was a grid running across the graphs. The horizontal axis showed time in months but the actual calendar time was concealed. The true numbers of the S&P were divided either by 3, 5 or 10 to make the prices fall in a plausible range ($10–$95). After reading the instructions and after one test trial, the experimenter showed the six relevant graphs. Each time, he used a pen to run over the complete price series, calling out prices at every turning point in the series.

The subjects were asked to predict '. . to the best of [their] ability, the price *7 and 13 months* later.' They were also asked for interval estimates, i.e. '. . price levels for which you think that there is only a *one-in-ten* chance that the actual price will turn out higher, and only a *one-in-ten* chance that the actual price will turn out lower.' To make sure that the subjects did not try to recognize the series and predict from memory, the instructions stated that 'While I do not tell you what the actual historical series are, I think it is extremely unlikely you recognize them. In fact, it is so unlikely that I offer $5 to every player who correctly guesses what any of the series is and which period it applies to. As a result, the only strategy you can use in this game is, [1], to try to detect a pattern in the series, whatever that pattern may be, and [2], to be very lucky.' On the answer sheets, few subjects named specific stocks. Nobody named the S&P Index. The instructions also warned that, since the game was like 'investing in the stock market, there is no obvious strategy or trick that guarantees success.'

All subjects, 25 male and 2 female, were college juniors, seniors, and MBA students at the University of Wisconsin–Madison. Their average age was 22 years. Each had taken at least two finance courses and knew about the efficient market hypothesis. About half of the subjects subscribed to the *Wall Street Journal*. The subjects served for class credit and for a $20 prize. For each forecast, the prediction errors were squared. Then, all squared errors were summed. The individual with the lowest sum of

[7] The XYZ, Inc. example follows Andreassen (1987) who asks whether the salience of past price changes and price levels affect stock trading. But Andreassen does not study confidence intervals. A second author who comes close to suggesting the hedging theory is Lynch (1990). He emphasizes skewness in risk perceptions. Chapter 18 refers to 'If it's gone this high already, how can it possibly go higher?' and 'If it's gone down this much, it can't go much lower' as two of the 'the twelve silliest (and most dangerous) things people say about stock prices'. The hedging theory is 'silly and dangerous' because, in reality, return distributions do not vary with past price changes in this way.

Table 1
Expected S&P Index changes and perceived skewness (Study 1)

	7-month forecasts			13-month forecasts		
	Bull markets	Bear markets	t-Stat.	Bull markets	Bear markets	t-Stat.
Mean EPC	0.40	−0.06	2.67***	0.72	0.05	2.53***
Mean Δ (All)	−0.26	0.08	−1.52	−0.19	0.11	−0.97
Mean Δ for						
Trend followers	−0.50	0.18	−2.21**	−0.69	0.70	−2.63***
Contrarians	0.14	0.25	−0.17	0.21	−0.15	0.40
t-Statistics	−1.45	−0.18		−1.27	1.27	

Notes: Expected changes (EPC) and skewness parameters (Δ) are normalized by the standard deviations of actual 1-month S&P Index changes for the 48 months prior to the subjects' forecasts. All t-statistics test for differences in means. They are marked ** if $0.01 < p < 0.05$ and *** if $p < 0.01$.

squared errors won the prize. All other participants received nothing. The whole procedure took 40 minutes. There was no time pressure. At the end, the subjects were debriefed. They were provided with correct answers. The winner of the game was announced one week later.

3.2. Results

Table 1 shows forecasted S&P Index changes. The *expected changes* equal the 7- or 13-month forecasts (F_7 or F_{13}) *minus* the last known level of the S&P Index (P_0). To conduct tests with pooled data, the predict changes 'for each stock' are divided by the matching standard deviations of actual 1-month S&P Index movements for the 48 months prior to the forecast (σ). Table 1 confirms that, on average, subjects show more optimism in bull than in bear markets.[8] As in Lawrence and Makridakis (1989), the predicted trends are muted relative to past experience.[9]

Table 2 illustrates the subjects' tendency to extrapolate in a different way. I classify forecasts by the pattern the subjects perceive in the price series. Let a 'weak' upward trend be defined by

Table 2
Percentage of subjects who detect a trend in the S&P index (Study 1)

	Bull markets	Bear markets	χ^2 Test
Weak upward trend	61.7	39.5	8.00***
Weak downward trend	14.8	38.3	11.43***
χ^2-Test statistic	23.29***	0.01	
Strong upward trend	50.6	32.1	5.73**
Strong downward trend	11.1	24.7	5.08**
χ^2-Test statistic	20.48***	0.78	

Notes: t-Statistics are marked ** if $0.01 < p < 0.05$ and *** if $p < 0.01$.

[8] The comparisons of means (and the associated t-statistics) in Table 1 are straightforward. Even so, because subjects serve both in bull and bear market conditions, the (block) design allows me to control for individual differences. In addition, since each subject sees six graphs, there may be a practice effect. Finally, there may be a treatment × trial interaction.
A much better way to analyze the data relies upon analysis of variance (ANOVA). Study 1 is a two-factor within-subjects (repeated-measures) design or, in the notation of Keppel (1982, ch. 19), an $(A \times B \times S)$ design with $A = 2$, $B = 6$, and $S = 27$. The F-statistics for the effect of the bull/bear factor (A) on 7- and 13-month EPC are, respectively, 6.25 ($p < 0.025$) and 5.54 ($p < 0.025$). The F-statistics for the trial factor (B) and the interaction between A and B never approach significance.
The above findings are for standardized expected changes (shown in Table 1) but the ANOVA produces qualitatively identical results if the expected changes are measured as a percentage of the level of the S&P at the time of the forecast, i.e. $\text{EPC} = (F - P)/P$. In bull markets, the 7-month (13-month) expected change is on average 3.9% (6.4%); for bear markets, it is −0.7% (1.5%). I thank a referee for suggesting the ANOVA approach, as well as different ways to present the data.

[9] The average *past* 7-month (13-month) rise in bull markets was 0.58σ (1.08σ). However, the equivalent 7-month (13-month) decline in bear markets was only -0.05σ (-0.10σ). That subjects are less willing to extrapolate in bear markets agrees with Andreassen and Kraus (1990). Not only are the downtrends which I showed less steep, they are more noisy. For bull markets, the average ratio σ/P_0 equals 0.088. For bear markets, it is 0.137. I wanted to use data for which experts' predictions were available. See the discussion below.

$F_7 > P_0$ and $F_{13} > P_0$ and a 'strong' trend by $F_{13} > F_7 > P_0$. Similarly, a weak downward trend has $F_7 < P$ and $F_{13} < P_0$ and a 'strong' trend, $F_{13} < F_7 < P_0$. We may think of subjects who see upward trends in bull markets and downward trends in bear markets as 'trend followers'. Conversely, those who perceive opposite trends are 'contrarians'. In bull markets, 50.6% of the subjects are strong trend followers but only 11.1% are contrarians. As indicated by the χ^2-statistics, this difference is statistically significant ($p < 0.01$). In bear markets, subjects are about as likely to see an uptrend as a downtrend. Another way to look at the data is to compare the percentage of the subjects that find a given price pattern in bull markets with the percentage that find the same pattern in bear markets. For example, 14.8% of the subjects perceive a weak downtrend in bull markets, whereas 38.3% do so in bear markets. The χ^2-statistics are significant in all cases.

Table 1 also shows normalized *measures of skewness*: $\Delta_7 = (\text{UCL}_7 - \text{LCI}_7)/\sigma$ and $\Delta_{13} = (\text{UCI}_{13} - \text{LCI}_{13})/\sigma$. In many instances, the skewness in the confidence intervals is substantial. Consider, for example, 7-month forecasts by trend followers in bull markets. The average confidence interval—defined as $(H_7 - L_7)/\sigma$—amounts to $3.35\,\sigma$, but UCI_7 ($1.42\,\sigma$) is much smaller than LCI_7 ($1.93\,\sigma$) so that $\bar{\Delta}_7 = -0.50$. Thus, the skewness represents 15% of the confidence interval. For *all* 7-month bull market forecasts, the average $\bar{\Delta}_7$ corresponds to about 6% of the confidence interval.

The hedging theory of confidence intervals predicts that, if many subjects extrapolate, the average Δ is negative in bull markets and positive in bear markets. By implication, $\bar{\Delta}^{\text{bull}} < \bar{\Delta}^{\text{bear}}$. The t-statistics in Table 1 have the predicted sign but they are not statistically significant.[10] More direct tests, run for trend followers and contrarians separately, are in weak agreement with the hedging theory. A third approach (not shown in Table 1) is to regress Δ on the corresponding forecasted changes. This method adjusts for the magnitude of the EPC. Are the estimated slope parameters negative, so that confidence intervals grow more right-skewed as larger price declines are predicted, and vice versa? I study 7- and 13-month forecasts separately but, in each regression, I pool the data for bull and bear markets. The slopes equal -0.161 (t-statistic: -1.58) and -0.302 (-3.47). Thus, for every unit of σ that a typical subject expects prices to rise over the next 13 months, he decreases Δ_{13} by $0.30\,\sigma$. For trend followers, the slopes are even more negative: -0.235 (t-statistic: -1.78) and -0.459 (-4.61). But, for contrarians, the slopes are not significantly different from zero. Maybe these subjects realize that their forecasts already contradict consensus opinion.

3.3. Discussion

The finding that subjects expect past trends in stock prices to continue is intuitively plausible and perhaps not surprising. However, it becomes more interesting in view of the opposite behavior shown by experts. In fact, Study 1 was developed with this contrast in mind. It is built upon some of the same price series that earlier confronted professional economists. Since 1952, Joseph Livingston (a journalist with the *Philadelphia Enquirer*) and the *Federal Reserve Bank of Philadelphia* have collected over 5400 S&P-forecasts from well-known academic, business, and government economists. Each June/December, about 40 economists provide point (but not interval) estimates for the following June/December.

Obviously, the experts have much information besides past levels of the S&P. Nevertheless, with efficient markets, the correct forecasting approach is to ignore this extra information and to start from the level of the S&P (P_0). Next, the economists could add x points so that, in percentage terms, the expected return x/P_0 equals the average past 7- or 13-month return on the index. On the other hand, if the economists are intuitive contrarians and believe in mean-reversion, they should predict negative returns after bull markets and unusually large positive returns after bear markets. This is what happens [see

[10] Here again, ANOVA is a superior way to analyze the data. See footnote 8. However, the interpretation of the results remains unchanged. The F-statistics for the bull/bear factor (A) are, respectively, 2.18 ($p < 0.25$) and 0.99 for the 7- and 13-month skewness forecasts. The F-statistics for factor B or the interaction $A \times B$ are also insignificant. These conclusions remain valid if Δ is scaled differently, e.g. as the fraction of the confidence interval above the point forecast, $\Delta = (H - F)/(H - L)$.

Table 3
Expected point changes in the S&P index: experts vs. novices (Study 1)

Bull markets (DJIA)				Bear markets (USDM)			
Date	Experts	Novices	t-Stat.	Date	Experts	Novices	t-Stat.
7-Month forecasts							
11.1967	3.57	0.56	−1.56	05.1970	3.36	−2.14	−2.17**
11.1980	−20.37	8.20	6.23***	11.1974	6.21	−0.41	−2.50**
05.1986	−5.21	16.48	5.03***	05.1982	8.18	1.21	−2.55**
13-Month forecasts							
11.1967	5.90	3.60	−0.69	05.1970	8.21	−1.12	−2.39**
11.1980	−11.14	11.53	3.67***	11.1974	16.01	3.29	−3.42***
05.1986	−0.38	23.86	3.73***	05.1982	15.52	0.31	−4.56***

Notes: t-Statistics are marked ** if $0.01 < p < 0.05$ and *** if $p < 0.01$.

[De Bondt (1991)]. Between 1952 and 1986, there are 70 forecast dates which I rank by the prior three-year performance of the S&P. I study the 10 most extreme bull and bear markets. In bull markets, the experts predict that for the next seven months the S&P will fall at an annual rate of 6.4%. Over half of the survey participants (52.6%) detect a weak downward trend. In bear markets, only 17.8% expected a further decline and fully 65.4% see a strong upward trend.

Table 3 compares the behavior of the experts and the subjects for the six forecast dates of Study 1. I report average predicted point changes for the S&P. Again, the tests are for differences in means. In all cases but 1967 do the economists expect larger price reversals. A comparison of the frequencies of types of perceived trends (not shown in Table 3) leads to the same conclusion. For example, the percentage of experts who predict a strong upward trend after a bear market (73.2%) is much larger than the percentage of novices (32.1%).

Rather than assuming that *expertise* causes the discrepancy in the forecasts, a skeptic may suggest that, if actual market conditions were simulated more closely, the subjects would be intuitive contrarians also. In practice, investors have much more information than past price series only! Also, in Study 1, there is no outcome feedback and no opportunity to learn. A final objection is that the results are based on a mere 320 forecasts. Can they be replicated with more subjects? All these questions motivate the next three studies of stock price and exchange rate forecasts. Study 2 examines mail surveys of individual investors since 1987. Studies 3 and 4 analyze real-time forecasts made by business students for the periods between February and April 1986, September and October 1986, and February and March 1991. In total, about 29 300 point estimates (Studies 2, 3, and 4) and 8300 confidence intervals (Studies 3 and 4) are studied.

4. Study 2: Mail surveys of individual investors

Since July 1987, the *American Association of Individual Investors* (Chicago, IL) (AAII) has conducted a weekly mail survey of 125 investors, asking for the likely direction of the stock market during the next 6 months. The participants are randomly selected from almost 100 000 AAII members and the average response rate is around 75%. The exact survey question is as follows: 'What do you feel the direction of the stock market will be in the next 6 months?' The respondents have a choice of three answers: (1) bullish; (2) bearish; or (3) neutral. Every Friday, the research analysts of AAII tabulate the results based on the survey answers received that week (typically, the returned postcards were sent out during the previous week). The percentage of bullish individual investors is published as an index of 'investor sentiment' in monthly editions of the *AAII Journal*. Since July 1989, the index has also been published in *Barron's* on a weekly basis. Below, I use data for 234 weeks, until January 10, 1992. Thus, since the average number of respondents is about 90, more than 21 000 forecasts are indirectly examined.

In order to test whether investor sentiment varies with past stock market movements, I employ regression analysis. Let BULL, BEAR, and NEUT represent, respectively, the percentage of investors who are bullish, bearish, and neutral (NEUT = 100 − BULL − BEAR). Also, define NBUL as BULL *minus* BEAR, and POLAR as NBUL/NEUT. POLAR scales net bullishness by the proportion of investors who are neutral. Compared with NBUL, this measure of 'polarization' gives extra weight to net bullishness (or bearishness) if few investors are neutral. For example, if the excess of bulls over bears is 20%, that excess may be less meaningful when 50% of investors remain neutral (POLAR = 0.4) than when only 10% are neutral (POLAR = 2.0).

Past price movements are dated relative to the survey week (t). Three explanatory variables are used: (1) the percentage change in the Dow Jones for the last 5 trading days prior to the survey week, i.e. for calendar week $t-1$; (2) the percentage price change between weeks $t-5$ and $t-2$ (20 trading days); and (3) the percentage change between weeks $t-20$ and $t-6$ (75 trading days). The price changes are denoted, respectively, R5, R20, and R75.

Table 4 lists sample statistics for the measures of investor sentiment and market movement. It appears that between July 1987 and January 1992 there were, on average, nearly as many bears as there were bulls. However, the means values of BULL, BEAR, NBUL, and POLAR mask strong variability. And, as it is seen from R5, R20, and R75, the stock market was also quite volatile. The sample period includes the 1987 crash.

Table 4
Mail surveys of individual investors: Descriptive statistics (Study 2)

Variables	Mean	S.D.	Minimum	Maximum
BULL	32.5	10.3	12.0	66.0
BEAR	30.6	10.5	6.0	67.0
NBUL	2.0	18.3	−54.0	60.0
POLAR	0.1	0.7	−2.7	2.1
R5	0.2	2.6	−13.2	5.9
R20	0.4	4.9	−24.5	13.2
R75	2.3	9.5	−34.8	18.1

Notes: There are 234 weekly observations between July 24, 1987 and January 10, 1992. The variables are defined as follows: BULL, the percentage of survey respondents that is bullish on the Dow Jones for the coming 6 months; BEAR, the percentage of respondents that is bearish; NBUL equals BULL *minus* BEAR; POLAR = NBUL/(100 − BULL − BEAR); R5, the percentage price change in the DJIA for the week prior to the survey week; R20, the percentage change between 4 weeks and 1 week prior to the survey; R75, the percentage change between 20 and 5 weeks prior to the survey.

If trader sentiment shows extrapolation bias, increased bullishness is predicted after a market rise and increased bearishness after a market fall. Thus, in a regression of BULL (or NBUL, or POLAR) on R5, R20, and R75, we expect positive slopes. With BEAR as the dependent variable, a negative relationship is predicted. In contrast, it may also be that investors agree with Brealey and Myers (1984, p. 271) that the market 'has no memory' or that they detect a tendency towards mean-reversion. In this case, the link between BULL and past returns is nonexistent or negative. Either result would weaken the view that a majority of small investors are positive feedback traders.

As it happens, the regressions in Table 5 leave little doubt that small investor sentiment moves *with* the market. A rise in the Dow Jones unambiguously pushes up the percentage of bullish investors and pulls down the percentage of bears. The impact of DJIA movements is larger if they are more recent. Indeed, NBUL increases by as much as 1.3% for every percentage point that the Dow rises during the week prior to the survey. The explanatory power of the GLS regressions is substantial, but a large part of it derives from the autoregressive terms. These trends reflect serial correlation in the dependent variables. For instance, for NBUL, the first- and second-order autocorrelations are, respectively, 0.65 and 0.50. (They are comparable for BULL, BEAR, and POLAR.) The results of Table 5 do not change qualitatively if past returns are measured with respect to the S&P Index. Neither do they change for subperiods or when the 1987 crash is left out. A drawback of the regressions with BULL and BEAR as the dependent variables is that nothing ensures that the estimated values fall in the unit interval. But when I try a LOGIT model, as in Judge et al. (1982, p. 521), the conclusions again do not change.

Table 5
Regressions of investor sentiment on past price changes (Study 2)

	Intercept	Independent variables			AR(1)	AR(2)	D–W	R^2
		R5	R20	R75				
Dep. var.								
BULL	31.6	0.54	0.62	0.37	0.44	0.23	1.98	0.48
	(20.4)	(2.9)	(3.8)	(3.1)	(6.8)	(3.6)		
BEAR	31.7	−0.78	−0.47	−0.32	0.53	0.18	2.10	0.48
	(18.0)	(−4.3)	(−2.7)	(−2.5)	(8.1)	(2.7)		
NBUL	−0.0	1.30	1.06	0.66	0.51	0.16	2.04	0.48
	(−0.0)	(4.0)	(3.6)	(3.1)	(7.7)	(2.5)		
POLAR	−0.0	0.05	0.04	0.02	0.47	0.23	2.04	0.51
	(−0.1)	(4.1)	(4.1)	(3.0)	(7.1)	(3.5)		

Notes: The variables are as defined in Table 4. AR(1) and AR(2) are autoregressive terms. t-Statistics are in parentheses. D–W represents the Durbin–Watson coefficient.

5. Study 3: Forecasts of the Dow Jones and the US Dollar/Deutschmark exchange rate

The mail surveys are interesting but, unfortunately, do not ask for interval estimates. These estimates can help to determine whether perceived risk also depends on past prices. Therefore, in Studies 3 and 4, I study the financial forecasts of business students. In both cases, the predictions were made in real time, i.e. as (now) history developed.

For stocks, the year 1985 saw the beginning of the big bull market of the decade, an upsurge that would only end in September of 1987. The Dow Jones rose from about 1200 to near 1600. 1985 also marked the dramatic decline of the US dollar relative to other currencies. In March, one dollar was worth about 3.4 Deutschmarks; by year-end, the exchange rate was close to 2.4 Marks. Obviously, both developments received much attention in the news media. They were a useful setting in which to contrast the expectations of naive subjects in a bullish (the Dow Jones) and a bearish (the dollar) environment.

5.1. Method

For nine Wednesdays between February 19 and April 23, 1986, 154 college juniors, seniors, and MBA students at the University of Wisconsin–Madison (109 male, 45 female, with an average age of 23.2 years) predicted the closing levels of DJIA and the US dollar/Deutschmark exchange rate (USDM) for the Wednesdays of the following *2 weeks*. The subjects also provided interval estimates '. . so that there is only a *one-in-four* chance that the DJIA and USDM eventually turn out higher and a *one-in-four* chance that the DJIA and USDM eventually turn out lower.'

The subjects participated for class credit. All had completed at least two finance courses (the average was 3.5), all were familiar with the efficient markets hypothesis, and a majority subscribed to the *Wall Street Journal*. Fifty subjects personally owned some stock at the time the experiment began. Performance was measured by the sum of squared prediction errors for the point estimates. The quality of the interval estimates did not affect the score. By common agreement before the start of the 'investment game', a small part of the course grade (10%) depended on the student's ranking relative to everyone else in the class.

One week before the experiment started, instructions and answer sheets were handed out and the rules of the game were explained. The subjects received plots of the DJIA and the USDM for the last 100 weeks before the first forecast date (the observations were at the close on Wednesday of each week). The subjects were also given photocopies of relevant financial columns in the *Wall Street Journal*. They used specially prepared answer sheets to hand in their forecasts in person at 4 p.m. All were aware that concepts taught in class would not necessarily be useful in this 'difficult if not impossible task'.

Table 6
Expected changes for DJIA and USDM (Study 3)

	1-Week forecasts			2-Week forecasts		
	Bull market (DJIA)	Bear market (USDM)	t-Stat.	Bull market (DJIA)	Bear market (USDM)	t-Stat.
Mean EPC	0.520	−0.175	17.85***	0.625	−0.237	21.83***
Mean EPC						
After up weeks	0.449	−0.171	10.90***	0.638	−0.245	15.91***
After down weeks	0.606	−0.177	14.46***	0.609	−0.233	15.18***
t-Statistics	−2.77***	0.12		0.50	−0.23	

Notes: Expected changes are normalized by the standard deviation of actual 1- or 2-week price changes for the 100 weeks prior to the time when the subjects make their first prediction. t-Statistics are marked *** if $p<0.01$.

Table 7
Percentage of subjects who detect a trend in DJIA and USDM (Study 3)

Forecast no.	Bull market (DJIA)		Bear market (USDM)	
	Uptrend	Downtrend	Uptrend	Downtrend
1	84.4	7.1	14.9	72.1
2	77.9	5.8	13.0	66.2
3	68.8	9.1	21.4	46.8
4	27.3	41.6	18.2	56.5
5	59.7	14.3	25.3	47.4
6	69.5	11.0	25.3	45.5
7	69.5	13.6	31.2	42.9
8	60.4	16.9	23.4	27.9
9	51.3	25.3	33.1	40.9
Means (i)	68.7	17.5	24.9	54.0
(ii)	55.6	7.8	13.8	42.2

Notes: The percentages are computed under the assumption that the last known price is the closing price on Tuesday. A set of 1- and 2-week forecasts is considered 'up' ('down') if both forecasts exceed (are below) the last known price. The mean percentages for all nine forecast dates appear in row (i). The means in row (ii) are computed similarly but assume that a forecast is 'up' ('down') if (1) the 1-week forecast exceeds (is below) the last known price and, (2) the 2-week forecast exceeds (is below) the 1-week forecast.

Table 8
Perceived skewness for DJIA and USDM (Study 3)

	1-Week Δ			2-Week Δ		
	Bull market (DJIA)	Bear market (USDM)	t-Stat.	Bull market (DJIA)	Bear market (USDM)	t-Stat.
Mean Δ	−0.41	0.04	−9.20***	−0.46	0.11	−11.49***
Mean Δ for						
Trend followers	−0.54	0.09	−8.58***	−0.77	0.33	−16.57***
Contrarians	0.18	−0.15	−0.26	0.27	−0.30	5.35***
t-Statistics	3.41***	−2.48**		12.62***	−6.63***	

Notes: Skewness parameters (Δ) are normalized by the standard deviation of actual 1- or 2-week price changes for the 100 weeks prior to the time when the subjects make their first prediction. t-Statistics are marked ** if $0.01<p<0.05$, and *** if $p<0.01$.

The investment game created much talk, investigation, and some mild anxiety among subjects.

5.2. Results and discussion

As in Study 1, the hypotheses are tested with expected price changes and measures of skewness. However, to make the bull and bear market numbers comparable, the *expected price changes* are now divided by the standard deviation of the actual 1- and 2-week price changes for the 100 weeks prior to the first forecast (σ_1 and σ_2). Table 6 reports the mean forecasted changes. They are computed with the closing price on Tuesday as the base. (The results are qualitatively similar if it is assumed instead that the last known price is the closing level on Wednesday.)

Once again, the typical subject expects past trends to continue. The mean EPC is positive in bull markets (t-statistics are 18.6 for 1-week EPC and 20.8 for 2-week EPC) and negative in bear markets (t-statistics: -6.5 and -9.0). The differences in means are also significant (see Table 6).[11] It can be supposed that the subjects' response may differ depending on what happened during the most recent week. For example, after an 'up' week in a bear market, the subjects may be more willing to see a turnaround than after a 'down' week. However, from Table 6, it does not seem that short-term developments weaken or strengthen the basic underlying trends. Table 7 shows the percentage of the subjects who see uptrends or downtrends. In bull markets, many more expect a price rise than a decline. In bear markets, the reverse is true. Both observations hold irrespective of whether weak or strong trends are considered. Note that there is no obvious pattern in the way in which the proportion of subjects which see a particular trend varies from one forecast to the next.

Tables 8 and 9 focus on perceived *skewness*. I normalize the 1-week skewness measures by σ_1 and the 2-week measures by σ_2. On average, $\Delta < 0$ in bull markets (t-statistics are -13.2 for 1-week Δ and -12.4 for 2-week Δ) and $\Delta > 0$ in bear markets (t-statistics: 0.9 and 3.2). The differences in means are significant (see Table 8).[12] The subjects recognize that the direction of their point estimates is tentative. For predicted increases, they acknowledge substantial downward potential; for predicted decreases, upward potential. As in Study 1, the signs of the skewness parameters differ for trend followers and contrarians. In bull markets, $\bar{\Delta}$ is larger for contrarians. In bear markets, $\bar{\Delta}$ is smaller, admitting the possibility of 'catastrophe'.

There is a strong negative relationship between perceived skewness and expected price changes. This is easily demonstrated with regression analysis. Δ is the dependent variable. To save space, Table 9 only reports the estimated slopes, t-statistics, and R-squares. I also pool the

Table 9
Regressions of skewness on expected price changes (Study 3)

Sample	Slope	t-Stat.	R-square
Dependent variable: 1-week Δ			
All subjects	−0.247	−12.3***	0.06
Trend followers	−0.242	−8.8***	0.06
Contrarians	−0.133	−2.8***	0.03
Dependent variable: 2-week Δ			
All subjects	−0.370	−17.9***	0.12
Trend followers	−0.404	−17.5***	0.20
Contrarians	−0.332	−7.2***	0.17

Notes: All regressions are OLS. To save space, the intercepts are not reported. t-Statistics are marked *** if $p < 0.01$.

[11] As in Study 1, a better way to analyze the data is as an $(A \times B \times S)$ design. See footnote 8. Here, $A = 2$ and $B = 9$. At times, there is a limited loss of subjects ($S < 154$). I drop these subjects from all treatment conditions to keep the ANOVA balanced.
The ANOVA is run multiple times: (1) with EPC and Δ standardized by past price changes, and (2) with $\mathrm{EPC} = (F - P)/P$ and $\Delta = (H - F)/(H - L)$. The results are similar. Based on the second set of definitions, the F-statistics for the effect of the bull/bear factor (A) on the 1- and 2-week expected changes are, respectively, 20.0 ($p < 0.001$) and 178.0 ($p < 0.001$). The average 1-week EPC is 0.5% in bull and −0.8% in bear markets. The equivalent 2-week EPC is 0.9% and −0.9%. For the forecasts of Δ discussed later, the F's for factor A are, respectively, 20.7 ($p < 0.001$) and 63.4 ($p < 0.001$). The F-statistics for factor B and the interaction $A \times B$ are usually not statistically significant. However, for the 1-week EPC, the F-statistic for factor B is 12.3 ($p < 0.001$). In this case, the interaction $A \times B$ is also significant.

[12] The ANOVA agrees with the simple comparison of means. See footnote 11. For DJIA forecasts, the average 1-week (2-week) LCI is about 7% (11%) larger than the UCI. For USDM forecasts, the average 1-week (2-week) LCI is 1.5% (5%) smaller than the UCI.

observations for bull and bear markets. Overall, for every unit of σ_1 that the average subject expects prices to rise, Δ_1 falls by 0.25 σ_1. Per unit of σ_2, Δ_2 decreases by 0.37 σ_2. Separate regressions for trend followers and contrarians indicated that the slopes are more negative for trend followers but, as Chow tests (not reported in Table 9) show, not in a significant way.[13]

Logically, the skewness must affect the subjects' calibration and this is indeed the case. Each individual predicts X_{25} and X_{75}, a task which is probably easier than in Study 1, where X_{10} and X_{90} are wanted. (In Study 1, fully 55% of the realized values fall outside the confidence limits. Thus, the data show gross overconfidence.) At first, the 1-week forecasts appear well-calibrated. For example, in the bear market condition (USDM), 51.1% of the 1-week realizations ($p = 0.69$) fall outside the confidence interval. However, upon inspection, it turns out that the proportion of actual values larger than X_{75} is 20.4% ($p < 0.001$), while the proportion smaller than X_{25} is 30.7% ($p < 0.001$). Thus, the skewness in perceived risk leaves the average subject with too little confidence on the upside and too much on the downside. Exactly the opposite pattern occurs in bull markets (DJIA).[14] The results are very similar for 2-week forecasts. However, the percentage of realizations outside the intervals now rises to 58.1% in bear markets ($p < 0.001$) and to 55.4% in bull markets ($p < 0.001$).[15]

6. Study 4: More forecasts of the Dow Jones

Studies 1, 2, and 3 offer a nearly uniform picture. The data suggest that: (1) expected prices changes follow past 'trends'; and (2) confidence intervals are skewed in the opposite direction from the trend. Most readers would agree that the second result is the more surprising and new. Study 4 therefore examines its robustness with new forecasts of the Dow Jones, collected in 1986 and 1991. The basic research design was not altered but two small variations were tried. In 1986, the subjects were asked for 1-, 2-, and 3-week forecasts; in 1991, for 1-, 2-, 3-, and 4-week forecasts.

6.1. Method

For seven Thursdays between September 18 and October 30, 1986, 87 students, (66 male, 21 female) predicted the closing levels of the DJIA for the Wednesdays of the following *3 weeks*. Similarly, for six Mondays between February 11 and March 18, 1991, forty students (34 male, 6 female) predicted the Dow for the Mondays of the following *four* weeks. In both cases the subjects also provided interval estimates so that 'there is only a *10%* chance that DJIA will turn out higher and a *10%* chance that DJIA will eventually turn out lower.'

The age and background of the subjects was similar to Study 3. The procedures were identi-

[13] The regression analysis has two limitations: (1) it gives great weight to outliers, and (2) it assumes that the relationship between Δ and EPC is linear. Fortunately, non-parametric tests yield similar conclusions. For example, for the two-week DJIA forecasts, the Spearman rank correlation between Δ and EPC is −0.36 ($p < 0.001$); for USDM forecasts, it is −0.21 ($p < 0.001$). A related concern is whether the regression findings depend on the scaling of Δ. However, if $\Delta = (H - F)/(H - L)$, the results never change. The R-squares are nearly identical to those in Table 9.

[14] By comparing actual frequencies with those expected subjectively, one runs the danger of confounding accuracy of judgment with calibration. Conclusions about 'too little' or 'too much' confidence may be artifacts of inaccurate forecasts. However, there was no obvious *ex post* trend in the US dollar/Deutschmark exchange rate during the 9-week forecast period. The rate first rose from 2.23 Marks per dollar to 2.37 Marks and then fell back to about 2.17 marks. On the other hand, for the Dow Jones, the effect of skewness on calibration may be inflated because the index rose approximately 100 points during the forecast period.

[15] These findings are in agreement with O'Connor (1989): calibration is a function of task characteristics. Interestingly, though, the confidence intervals in Study 3 do not change much with time. Why? Maybe two effects offset each other. On the one hand, the subjects' awareness of 'hard' facts and the focus of the media on news items that justify market trends may build an illusion of understanding that tightens confidence intervals [see Koriat et al. (1980)]. On the other hand, news exposure may make it easier to learn from past mistakes. Feedback reduces overconfidence in some contexts [see Arkes et al. (1987); Sharp et al., (1988)]. In Study 3, Pearson and Spearman rank correlations between subjects' confidence intervals for the predictions of this week and the absolute forecast errors of last week are always positive. The correlations are small — typically about 0.10 — but, given the sample size, still strongly significant ($p < 0.001$ in most cases).

cal. Thus, performance was again measured by the sum of squared errors for the point estimates. However, subjects received no other compensation but the satisfaction of obtaining the lowest score 'to win the investment game'. Total error scores were announced in late November 1986 and late April 1991.

6.2. Results and discussion

Table 10 shows expected index changes and skewness measures. Since the tests below do not require normalized data, all are expressed in index-points. In 1986, EPC is calculated with the closing level on Wednesday as the base. (The results are similar with the Thursday close as the base.) In 1991, EPC is based on the closing DJIA level for the previous Friday. I classify forecasts as 'bullish' if the 3- (in 1986) or the 4-week EPCs (in 1991) are positive. Other forecasts are considered 'bearish'. (The results are similar if bullishness and bearishness are defined as in Studies 1 and 3.) In 1986, a clear majority of the forecasts (67.6%, $p<0.001$) were bullish. In 1991, the number of bullish and bearish forecasts was about equal. Consistent with the hedging theory, there are substantial differences in perceived skewness. At all forecast horizons, $\bar{\Delta}^{\text{bull}} < \bar{\Delta}^{\text{bear}}$.

Table 11 presents by now familar regressions of Δ on EPC. I only report the estimated slopes, t-statistics, and R-squares. The slopes are reliably negative. This remains true if Δ is redefined as $(H-F)/(H-L)$ (not shown in Table 11). Also, Spearman rank correlations between Δ and EPC are negative. For example, for the 1-, 2- and 3-week forecasts made in 1986, they are

Table 11
Regressions of skewness on expected price changes (Study 4)

Dependent	Slope	t-Stat.	R-square
September 1986–November 1986			
1-Week Δ	−0.381	−6.4***	0.07
2-Week Δ	−0.272	−5.3***	0.06
3-Week Δ	−0.285	−6.3***	0.07
February 1991–April 1991			
1-Week Δ	−0.606	−7.5***	0.21
2-Week Δ	−0.415	−5.9***	0.14
3-Week Δ	−0.500	−7.1***	0.20
4-Week Δ	−0.580	−9.7***	0.27

Notes: All regressions are OLS. To save space, the intercepts are not reported. t-Statistics are marked *** if $p<0.01$.

Table 10
Expected DJIA-index changes and perceived skewness (Study 4)

	Mean All subjects	Mean 'Bulls'	Mean 'Bears'	t-Stat.
September 1986–November 1986				
Expected price changes				
1 Week	4.4	11.2	−9.8	13.7***
2 Weeks	8.5	19.5	−14.4	19.2***
3 Weeks	11.3	26.4	−19.9	23.1***
Skewness				
1 Week	−10.1	−12.3	−5.7	−2.7***
2 Weeks	−12.1	−15.1	−5.9	−3.3***
3 Weeks	−12.6	−18.2	−1.1	−5.8***
February 1991–April 1991				
Expected price changes				
1 Week	2.6	19.9	−14.7	4.5***
2 Weeks	−5.0	36.6	−46.5	9.7***
3 Weeks	−8.8	51.9	−69.4	13.3***
4 Weeks	−8.7	72.1	−89.4	15.8***
Skewness				
1 Week	−19.2	−22.9	−15.5	−0.7
2 Weeks	−15.2	−27.8	−2.6	−2.3**
3 Weeks	−15.7	−42.4	11.0	−4.1***
4 Weeks	−13.8	−54.9	27.3	−5.4***

Notes: Expected changes and skewness parameters are in DJIA-points. 'Bulls' are subjects for which the 3-week (4-week) expected price change is positive. 'Bears' are all other subjects.

−0.29, −0.27, and −0.29 ($p<0.001$ in each case). As in Study 3, the skewness in the forecasts affects the subjects' calibration. For instance, the Dow did not follow any apparent trend during the 1986 forecast period. Yet, the prediction errors are one-sided: the proportion of realizations above X_{90} never exceeds 4.5%.[16]

7. Summary and general discussion

At this time, little is known about the intuitive assessment of time-series data. From previous research by Lawrence and Makridakis (1989), it appears that the characteristics of the time-series (trend, variability) and the presentation mode (numerical, graphical) influence how forecasts are made. But few real world assessment tasks have been studied. This paper studies the prediction of speculative price series which differ in their apparent past trends. Directly or indirectly, 38 000 forecasts are examined.

The analysis supports two major results. First, many individuals predict asset prices by extrapolating from past trends. Second, the subjects exhibit caution in their projections of the range of future prices. They hedge their forecasts. If a large price increase is predicted, the subjective probability distribution of future prices is left-skewed, recognizing a possible decline (and, vice versa, if a price decrease is expected).

How robust are these findings and how relevant are they to the actual behavior of investors? Only more research can tell. A limitation of Studies 1, 3, and 4 is the premise that business students majoring in finance are an acceptable proxy for the typical investor. Fortunately, the results of mail surveys suggest that this assumption is not wholly unreasonable—at least when it comes to the prediction of future prices. However, more studies of small investor behavior—perhaps based on regular telephone surveys or the study of investment clubs—could add value. A second concern is the quasi-experimental design of Studies 3 and 4. My goal is to simulate actual information flows ('the financial news'). But this injection of realism has its price. I do not control for all the factors *other* than past price movements that may affect the subjects' forecasts.

The results are of considerable interest from the perspective of intuitive judgment. The subjects' price predictions conflict with the gambler's fallacy or a more universal belief that 'what goes up, must come down'. Yet the interval estimates do recognize the chances of reversal. Why does this perception not express itself in a more regressive forecast? The answer to this basic and puzzling question will require more research.

Perhaps the subjects predict the near future with an eye towards recent price changes, but past price levels anchor their long-term forecasts of the range of possible prices and explain the asymmetry in confidence intervals. This interpretation of the data is suggested by Andreassen (1988), who finds that the regressiveness of prediction depends on whether price levels or recent price changes are more salient. Thus, people intuitively distinguish between temporary and permanent price movements. The theory is consistent with the exchange rate surveys of Frankel and Froot (1987) and Ito (1990). Investors who think long-term tend to subscribe to regressive expectations and those who think short-term tend to have static expectations. Traders' concern with long-run price levels may also explain the popularity of moving average statistics in the financial press.

A second hypothesis is that, at the time of the forecast, people anticipate disappointment and/or self-doubt if their predictions turn out to be 'seriously' in error. Maybe, to avoid discomfort, people intentionally hedge their bets. The data support this view in at least three ways: (1) perceived skewness always shows the *opposite sign* of expected price changes; (2) Δ varies inversely with the *magnitude* of EPC; and (3) the negative link even applies to *contrarian* fore-

[16] But overall calibration was poor: 38.2% of the outcomes fall outside the 1-week 10% confidence limits, 38.9% outside the 2-week limits, and 43.7% outside the 3-week limits. Stock prices moved as follows. One week after the first forecast date (September 24, 1986), the Dow stood at 1803. Three weeks after the last forecast date (November 19), it was 1827. Between these dates, the DJIA varied between 1783 and 1899.

casters. On the other hand, this theory fails to explain why subjects typically choose confidence intervals that are too narrow rather than too wide.[17]

The findings in this paper also have implications for finance. First, for portfolio theory, they warn us that the assumption of rational expectations cannot be taken for granted. In their experimental tests of the mean-variance model, Kroll et al. (1988, p. 401) report like I do that subjects 'attempted to discover patterns or trends in the rates of return' even though the sampling was random and independent. As a consequence, investors' portfolios were often inefficient.[18] Here, I suggest, in addition, that people's intuitive perceptions of risk and return are intertwined. For instance, the mere fact that a stock goes up in price increases its 'downward potential'. Thus, investors may become reluctant to buy more shares (slowing the advance in prices), no matter how optimistic they are about the firm's fundamentals. Perhaps then, as the proponents of efficient markets believe, risk premia vary through time. However, in this case, the premia change because risk perceptions change, not because of changes in the public's willingness to bear risk, or because objectively the stock became more risky.[19]

Second, the results underscore the possible relevance for market valuation of noise trader models [as in De Long et al. (1990a,b)]. Most individual investors seem to extrapolate past trends, but the forecasts of economic experts—a proxy for well-informed rational traders?—are strikingly different. What is the nature of this difference and why is not every investor 'rational'? The explanation probably rests with people's conflicting implicit theories or knowledge structures. It is unusual for people not to have prior expectations about meaningful data but, as suggested by Kelly's (1963) personal construct theory, layman's thinking is typically much less sophisticated than scientific thinking. In most realms of life, there is a continuum of mental theories. People's beliefs evolve with experience [Murphy and Wright (1984)] and these beliefs are generally useful [Wright and Murphy (1984)]. However, in the stock market, it is difficult to know which theory is objectively more correct. Perhaps for this reason cognitive bias sometimes distorts investor perceptions of America's 'growth industries' or 'best-managed companies'. [Hunter and Coggin (1988) suggest that even financial analysts' earnings forecasts vary with the dominant financial theories of the time.] The bias also implies that, with costly arbitrage, it becomes important to characterize the quasi-equilibria that prevail when noise traders affect prices.

[17] Yet, in Studies 1 and 3, the confidence intervals grow signficantly as subjects predict—in absolute terms—larger changes from the price level at the time of the forecast. Controlling for EPC, however, subjects do not set wider confidence intervals if they perceive more skewness, i.e. if the absolute value of (UCI-LCI)/(H-L) rises. In this context, another interesting aspect of the data is that the magnitudes of the lower and upper confidence intervals usually move together, i.e. Spearman rank correlations between UCI and LCI are always above 0.40. I thank a referee for suggesting the 'error-aversion hypothesis'.

[18] The experiments of Lipe and Maine (1992, p. 34) also lead these authors to conclude that unsophisticated investors 'do not naturally use variance and covariance of returns' and that their behavior 'may not be well-described by portfolio theory'.

[19] Also, risk changes in the *opposite* direction to that predicted by standard theories. Winner stocks appear more risky as they rise in price and loser stocks appear less so. Note that the hedging theory may explain why traders hang on to prior losers but are eager to sell winners – a phenomenon that Shefrin and Statman (1985) explain with prospect theory, loss aversion, and mental accounting.

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Biography: Werner F.M. DE BONDT is Frank Graner Professor of Finance at the University of Wisconsin-Madison. He received his PhD from Cornell University in 1985. His research interests include investment decision-making, the psychology of financial markets, and business cycles.