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Portfolio Managers' and Novices' Forecasts of Risk and Return: Are There Predictable Forecast Errors?

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ABSTRACT

This study aims to investigate the individual behaviour that underlies the overreaction hypothesis by conducting a controlled experiment. Two areas that were not captured by previous research on the validity of the overreaction hypothesis are investigated. First, actual portfolio managers are employed as forecasters. Second a real-world assessment task is given in the form of predicting the prices of stocks traded on the exchange on a real time basis. The purpose is to explore return expectations and risk perceptions of portfolio managers as well as financially unsophisticated investors by using point and interval forecasts provided for different forecast horizons in bull and bear markets. Contributions stem from three sources. (1) The use of financially sophisticated subjects for the first time in an experimental framework testing the overreaction hypothesis makes possible to control for the effect of expertise. (2) The use of different forecast horizons controls for the effect of forecast period. (3) The use of real-time forecasts of specific stocks traded at the stock exchange, for the first time in an experimental framework testing the overreaction hypothesis enables to control for ecological validity. Discussions will be given as to the portfolio managers' versus naive investors' interpolating asset prices from past trends and hedging behaviour, due to their caution in projections of ranges for future prices.

KEY WORDS stock price forecasts; overreaction; judgement; investor psychology

Recent empirical research on the predictability of asset prices is based on two controversial hypotheses, explaining market behaviour. The efficient markets hypothesis (Fama, 1970, 1991) argues that, in frictionless markets, and with random information flow, prices reflect all available information. Investor forecasts of prices are then rational in the sense that they do not contain a predictable error component and thus can be defined as the expected value of the perfect foresight price, conditional on the randomly flowing information set. In contrast, the overreaction hypothesis (De Bondt and Thaler, 1985, 1989, 1990) argues that price movements are driven not only by the flow of

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new information but also by the overreaction of investors who violate Bayesian rules in updating their beliefs about company prospects. Investor forecasts of prices are then, expected to be adaptive rather than rational; i.e. with the expectation of the continuation of past trends, investors will be optimistic in bull markets and pessimistic in bear markets (De Bondt, 1993). Similar to the observed misperceptions of prices, risk perceptions are also shown to be adaptive, that individual forecasts' probability distributions are left skewed for rising prices and right skewed for falling prices indicating that investors hedge their forecasts (De Bondt, 1993).

Although both the efficient markets hypothesis and the overreaction hypothesis have important implications in terms of investors' forecasts of stock prices, the literature on stock price forecasts is mainly concerned with the accuracy of such forecasts, with conflicting results predominantly stemming from data revisions and biases in aggregating data (Granger, 1992). Actually, one must ensure that '. . .each of the measures that you do use is appropriate for the task' (Fildes, 1992, p. 108). Research concerning the performance of financially sophisticated investors examines mainly expert managed funds (Ippolito, 1989) and their performance is explained relative to market behaviour; i.e. whether the market is efficient or not. Behavioural explanations of the inconclusive results of market efficiency tests are few (Muradoglu and Onkal, 1994) and attempts to 'model the behaviour of representative investors and the nature of their errors' (De Bondt, 1991, p. 90) are limited. 'The earnings literature. . . has recently begun to examine heuristics and biases of judgement, and its compatibility with rational expectations. This research is still in its infancy. Joint efforts by capital market researchers and behaviourists to examine these issues more thoroughly, would considerably enhance our understanding of the role of analysts in the price formation process' (Brown, 1993, p. 315).

The motivation for this study is a series of experiments, with student subjects conducted by De Bondt (1993). He tests two separate but related hypotheses about the return expectations and the risk perceptions of financially unsophisticated subjects in bull and in bear markets: (1) that average expected price change, in bull markets exceeds that in bear markets; and (2) that average skewness in bull markets should be less than that in bear markets. If investors are positive feedback traders (De Long *et al*., 1990), they will expect past trends to continue in the future and forecast accordingly. Also, the anchors used for subjective risks associated with these price predictions will be determined by past price changes (Tversky and Kahneman, 1974) and past price levels (De Bondt, 1993) and confidence interval assessments for time series forecasts are not expected to be symmetric. In fact, De Bondt (1993) indicates that unsophisticated student subjects' confidence intervals are left skewed in bull markets and right skewed in bear markets but results are not statistically significant.

Anchoring and adjustment is used as a heuristic by judgemental forecasters in many forms and settings.[1] In other financial domains, analysis of panel forecasts has shown that expectations are formed by adjusting the previous forecasts as new information arrives (Fildes, 1991). Andreassen (1990) conducting a market simulation experiment of investment forecasting with novice subjects modifies the overreaction hypothesis by showing that departures from Bayes' rule are not necessarily due to the effect that recent news reduces the impact of earlier information. In fact, increases in the relative salience of the information may increase the weight given to that information in a judgemental forecast. Therefore asymmetries in overreaction and mean reversion effects may be due to factors that affect the salience of the information. In this context, price data is the basic foundation of investors' forecasts and price rebound effects are observed

[1] For a detailed discussion on heuristics in judgemental time series forecasting see Goodwin and Wright, (1994).

due to changes in the manner people employ past price levels and past price changes as the anchor.

Lawrence and O'Connor (1992) investigated judgemental forecasts of time series in an experiment with student subjects in order to document the heuristics that apply to time series forecasting. They show that the novice subjects' judgemental forecasts can be described as anchoring and adjusting, with the anchor being the long-term average of the stationary series. Adjustment is made as a proportion of the difference between the mean and the last observation of the series. Bolger and Harvey (1993) conducted an experiment with student subjects and artificially designed daily series in order to study heuristics in different contexts. Although they showed that subjects selected appropriate heuristics, in different contexts, the weight they gave to the adjustment factor was almost three times the optimal weight.

From previous research some characteristics of intuitive assessments of time series data are known. However, few real-world assessment tasks have been studied for stock price forecasting. The first contribution of this study is that it aims to investigate biases in predictions in a financial domain by defining the task as the real-time forecasts of stocks actually traded at the exchange.

The next contribution of the paper lies in the fact that it employs experts, professional fund managers with substantive expertise, as forecasters. Former studies investigating the overreaction hypothesis had employed only student subjects as forecasters. Biases in judgemental forecasting of financial markets have been studied mainly with novice subjects. These studies implicitly assume that any subject given a financial forecasting task (DeBondt, 1993) or an investment task (Andreassen, 1990) represents the typical investor. This may or may not be true. This paper extends our body of knowledge on such biases by investigating experts, who constitute most of stock trading activity via managed portfolios and investment advice. Portfolio managers constitute a better and naturally more realistic definition of the investor than the student subjects. The experimental framework employed in this research also enables us to conduct comparisons as to the differences between novice and expert subjects on various aspects of systematic biases in return expectations and risk perceptions.

Former studies on the comparison of experts with naive forecasters have focused on the accuracy dimension of subjective forecasts. Yates *et al*. (1991) and Onkal and Muradoglu (1994) have reported an inverse relationship between expertise and forecast accuracy. Student subjects in both studies made probabilistic forecasts of stock prices. Employing portfolio managers as experts, Muradoglu and Onkal (1994) investigated the inverse expertise effect at different forecast horizons. The results revealed that for short-term forecast horizons of one week expert forecasts were better. However, for longer horizons, semi-experts achieved better calibration. The authors concluded that the existence of the inverse expertise effect might be contingent on the selected forecast horizon.

The inverse expertise effect can be explained as a by-product of experts' cue utilization (Yates *et al*., 1991). Experts use richer representations (Murphy and Wright, 1984) that make the judgement task more difficult, and distort the accuracy of their forecasts. Naturally, experts are expected to use a larger number of cues compared to novices in their decision-making process. In this process, they can consolidate irrelevant cues as well, and distort the accuracy of their forecasts. Prior research (Muradoglu and Onkal, 1994) also shows that expert subjects are more overconfident in their probabilistic forecasts of stock prices. They tend to give less dispersed probability distributions than novices do. Experts may be giving high credibility to their knowledge (Griffin and Tversky, 1992) and thus become more overconfident than non-experts.

In this research, point and interval forecasts of expert subjects are investigated. Experts are accustomed to reveal their judgement in financial forecasting via point estimates and related intervals in their daily routine. Therefore, possible biases in their forecasts can be interpreted with reliance, knowing that the ecological validity of the task is higher. The experimental framework of this paper enables us to compare another dimension of experts' forecasts with those of novices; namely the differences in anchoring and adjusting. Experts will constitute a better representation of the investor, since they are responsible for an overwhelming part of the trade in the stock market. Hence, it should be expected that the overreaction that is observed with secondary data (DeBondt and Thaler, 1989) will be substantiated with expert behaviour as well.

The third fundamental contribution of the paper stems from the fact that subjective forecasts are made regarding the prices of individual stocks in real time. Including DeBondt (1993) and Andreassen (1990), none of the former studies investigating the issue of overreaction in an experimental framework have studied real-time subjective forecasts of specific stocks actually traded at the stock exchange. Rather, several stock indices or rescaled prices were used to represent stock prices. Real-time price forecasts of individual stocks are in fact more complicated than forecasting the index because factors unique about the firm need to be considered for each and every stock. The information set utilized for forecasting the index is not necessarily the same as that used for forecasting specific stocks.[2] The controlled experiment framework enables us to compare results regarding the real-time forecasts of specific stocks with that of the index and the unknown calendar-time unnamed stocks.

Prior research shows that accuracy and overconfidence of expert subjects forecasting real-time stock prices may change with the forecast horizon (Muradoglu and Onkal, 1994). In fact, experts were more accurate in their probabilistic forecast of one week than in longer horizons. In an emerging market setting, where volatility is inherently high and term structures are low, portfolio managers make predominantly short-term forecasts and are thus more accurate in them. In this research, the forecast horizon is controlled to include short-term as well as long-term forecasts of experts and novices. In designing a controlled experimental framework to include different forecast horizons possible deviations from Bayes' rule will be investigated in order to understand if they are restricted to a specific forecast horizon or not.

This paper investigates whether return expectations and risk perceptions are adaptive rather than rational, and if so, does the anchoring and adjusting behaviour confirm with that of the overreaction hypothesis? The experimental setting of De Bondt (1993) is adapted. DeBondt conducted his experiments using (1) student subjects, (2) various stock indices and exchange rates and (3) short-term forecast horizons. DeBondt himself states two major limitations of his study. The first '. . .limitation of [his] study is the premise that business students majoring in finance are an acceptable proxy for the typical investor. . . .A second concern is the quasi experimental design. . .[He] does not control for all the factors other than past price movements that may affect the subjects' forecasts' (DeBondt, 1993, p. 368).

The experimental framework employed in this study extends DeBondt's work by (1) employing portfolio managers as expert forecasters, (2) using specific stocks' price forecasts as the task to be performed and (3) allowing for short-, medium- and long-term forecasts. As a result, this research enables us to examine the overreaction hypothesis in a controlled decision environment with higher ecological validity.

[2] For a detailed discussion on the different types of information sets and related methods used in forecasting stock prices, see Campbell *et al*. (1997).

Some of the questions that will be answered in this paper are as follows: Are expert investors' forecasts of stock prices also adaptive rather than rational? Are experts' risk perceptions also adaptive or are they rational? Do they also hedge their forecasts? Are there any differences between experts' and novices' expectation-formation processes? Are they similarly optimistic in bull markets and pessimistic in bear markets? Are adaptive forecasts confined to forecasts of the market in general (i.e. stock index), or can they be extended to include the forecasts of specific stocks' prices? Are adaptive forecasts restrained to certain forecast horizons or not?

EXPERIMENTAL SETTING

Financial liberalization in Turkey started at the beginning of 1980s by the introduction of a package encouraged by the World Bank and the IMF. The establishment of the legal framework and regulatory agencies for the stock market were completed in 1982, but it took four more years until the Istanbul Securities Exchange (ISE), the only stock exchange in Turkey, became operational in 1986. During the first two years of its operations individual investors were permitted to enter and place their orders on the trade floor. Trade floor activities were limited to licensed brokers and a manual system was established in November 1987. Also, until 1987, there was no auditing requirement on the financial statements of companies listed at the ISE and employees of the ISE could hold stock portfolios without notification. By the end of 1989 interim financial statements were required, and in 1990 principles for going public were established. It was in 1990 that legislation against insider trading was passed for the first time. Aimed at further liberalization of the system, by the end of 1989, non-residents were allowed to invest in Turkish securities and Turkish investors were allowed to invest in foreign securities through authorized financial intermediaries. By the end of 1993, computer-aided procedures were established and since November 1994 all the stocks listed are traded by the computer-assisted system. Today trading occurs in two sessions—morning and afternoon—on Mondays to Fridays.

The volume of trade has increased from an annual 13 million USD in 1986 to a daily 100 million USD in 1996. The ISE composite index, which represents more than 80% of market capitalization, has increased six times in dollar terms and the number of companies traded at the ISE has increased from 40 to more than 200 since 1986. This increase, however, has continued with annual increases of up to 350% followed by corrections amounting to 70%. The Turkish market is highly volatile compared to developed markets. Standard deviations of weekly returns of the ISE composite index is almost four times larger than that for the USA, eight times larger than that for the UK. Volatility at the ISE is also higher than some other emerging markets, including Brazil, Argentina and Greece (Basci *et al*., 1998).

RESEARCH DESIGN AND PROCEDURE

Subjects of the study were reached at two different locations at the same date. The student subjects were recruited from the graduate and undergraduate classes of the Faculty of Business Administration of Bilkent University. Of the 45 students who participated and completed the study, 19 were MBA students, 26 were undergraduates, who had taken at least one finance course and were exposed to efficient markets hypothesis as well as financial forecasting. There were 7 participants who had previous trading experience or were actively trading in the stock market with the maximum duration of trading being 24 months. The resulting group of novices is comparable in size and structure to DeBondt's (1993) subject groups. The second group was composed of 35 experts working for various bank-affiliated brokerage houses. Professionals in the stock market were reached at a company-paid 20 hour training programme on portfolio management and financial forecasting. All the experts had licences as brokers and their job descriptions included preparing research reports and databases (15 subjects), managing investment funds and giving investment advice to customers with investments above 50 000 USD (20 subjects). The minimum work experience of stock market professionals was 8 months and the maximum was 6 years.

No monetary or non-monetary bonuses were offered to the participants. The study was depicted as one that gives the participants an opportunity to forecast stock prices (return expectations) and describe their uncertainty (risk perceptions) by giving forecast intervals. Participants were given a folder containing five separate forms. The first form contained information about the purpose of the study. Next, the subjects were given two forms containing the price series for the unnamed stocks presented in graphical and tabular forms respectively. The related response sheets accompanied these forms. After the forecasts for unnamed stocks were completed, the subjects were given the form and response sheets for real-time forecasts. Finally, participants received a questionnaire that was designed to provide information about the subjects' year in university (duration of work experience for experts), field of study (and department for experts), previous and current experience in stock market or trading and its duration, and the information sources utilized in making their forecasts.

The first task was defined as the prediction of closing stock prices for six unnamed stocks. The subjects were given folders containing the instructions and the weekly closing prices of the preceding 24 weeks in both tabular and graphical forms for the unnamed stocks. Similar to DeBondt (1993), they also saw the six graphs with 24 weekly prices also presented in tabular form on an overhead projector. The graphs actually plotted the ISE composite index for three bull markets and three bear markets.

The true numbers of the ISE composite index were divided by either 10 or 100 to make all the prices four-digit numbers—a plausible price range where it is difficult to identify individual stocks. None of the participants recognized the series; only three subjects named specific stocks on the answer sheet but none of them named the ISE index. On each graph prices were indicated on the vertical axis and time was given as weeks 1–24 on the horizontal axis. The graphs were presented in random order and unnamed stocks were given numbers according to the order in which they were presented. After reading the instructions, the experimenter used a pen to show the points on all the price series by reading out the prices at every point.

The participants were asked to give point and interval forecasts of the prices of the six unnamed stocks for forecast horizons of one week, two weeks, four weeks and twelve weeks. In particular they were asked to predict, to the best of their ability, Friday closing prices of the unnamed stocks one, two, four and twelve weeks later in Turkish Liras (TL). They were also asked to give interval estimates for each price prediction; i.e. the price levels for which they assign a 10% probability that the price will turn out higher (X_{90}) and a 10% probability that the actual price will turn out lower (X_{10}). Specifically they were asked to complete the following response form for each unnamed stock and for each forecast horizon of one, two, four, and twelve weeks:

I estimate the Friday closing price, one week from now as . . . . TL.
The probability that the Friday closing price one week from now is <u>greater than</u> . . . .
TL is 10%.

The probability that the Friday closing price one week from now is less than . . . . TL is 10%.

The forecast horizons were chosen by considering the maturity structures of alternative investments which rarely go beyond three months (Selcuk, presentation at the EEA meeting, New York, 1995) due to the high uncertainties imposed by structurally high inflation in Turkey and, the volatility of stock prices described in the previous section.

After the completion of the first task, the subjects were given the folder that contained the response form of the real-time forecasting tasks which was the same as those used in the previous task except that the first sheet was headed ISE composite index. There were eight other response forms on which the name of the stock was to be entered by the forecaster. The subjects were told to chose as many specific stocks as they liked to forecast their prices. Unlike the first task, which was completed in the classroom, subjects were allowed to take the folders with them and complete their forecasts at home in order to duplicate real forecasting settings. All the participants, experts and students, were given the real-time response sheet on Friday afternoon and were requested to submit the completed forms by Monday at 9 am before the opening of the morning session at the ISE. Subjects were permitted to use any source of information other than the other participants of the study.

MEASURES

Expected price change

The efficient markets hypothesis (Fama, 1970, 1991) states that stock prices fully reflect all available information. Empirically testable forms of the hypothesis define expected price as the mathematical expectation of the perfect foresight price conditional on a relevant information set. Therefore it is assumed that investors have rational forecasts of stock prices that contain random error which, of course, is not predictable. The overreaction hypothesis (DeBondt and Thaler, 1985), on the other hand, assumes that stock prices are determined not only by the information flow but also by the investors' systematic misperceptions of value. In this study, the behavioural validity of the overreaction hypothesis is investigated as opposed to the efficient markets hypothesis by examining the return expectations of investors in bull and bear markets. For that purpose, the point forecasts given by the subjects are evaluated to determine the possible existence of investors' tendency to discover trends in past prices and to expect their continuation. If investors are trend followers, the average expected price change in bull markets should exceed that in bear markets (DeBondt, 1993), i.e.

$$\overline{EPC_i}\text{, bull} > \overline{EPC_i}\text{, bear} \tag{1}$$

Where $EPC_i(= F_{ijk} - P_0)$ is the expected price change defined as the difference between the subject's (k) point forecast of a stock (j) for a forecast horizon of ($i = 1,2,4,12$) weeks (F_{ijk}) and the last known price level (P_0). The average EPC_i is calculated as

$$\overline{EPC_i} = \Sigma_{jk} EPC_{ijk} \tag{2}$$

For the unnamed stock price forecast task, a bull market is defined as one with a visible upward trend and a bear market as one with a downward trend. (The complete stimulus series are available from the author upon request.) The real-time price forecast are made (1) for four different time horizons and (2) for the index and a number of stocks actually traded at the ISE. So each forecaster reports his or her forecasts on a variety of series with naturally different trends, if different starting points were used as benchmarks. In order to be systematic in defining a trend for each series, the forecast period was taken as the benchmark. For the real-time price forecasts of the ISE and the specific stocks, bull and bear markets are defined by using the past prices for a period symmetric to the forecast period—if $P_{-i} > P_0$, the forecast F_i is said to be given in a bear market and if $P_{-i} < P_0$, the forecast F_i is said to be given in a bull market. For example, take the one-week forecast (F_1) of the ISE (stock j) given by subject k. It is classified as a forecast made in a bull market if the price one week before the Friday closing price of the current week (P_{-1}) is less than the Friday closing price of the current week (P_0).

Risk perceptions

The subjective risks associated with the price predictions are measured when considering the confidence intervals revealed by the interval estimates of the subjects. It is known that the expert forecasters are especially overconfident in unpredictable domains (Griffin and Tversky, 1992; Muradoglu and Onkal, 1994) and are more likely to assess tighter probability distributions. A number of other factors are also examined to investigate the confidence of subjects in extrapolating time series. The findings were different in different domains. Investigating, directional probability forecasts, Bolger and Harvey (1995) report that people are underconfident in their estimates of where the next point will lie in a time series, with the bias being greater for the trended series. Seaver *et al.* (1978) reveal that for knowledge tasks, this is not the case. Lawrence and O'Connor (1993) examine the effect of scale of presentation and the level of variability on subjective forecasts' uncertainty. They report that at large scales and high variability confidence intervals are narrower, displaying higher overconfidence.

However, whether investors hedge in a certain manner when assessing the confidence intervals has not been investigated extensively. De Bondt (1993) provides evidence that student subjects hedge their forecasts via skewed confidence intervals. In this context, it is assumed that investors use two anchors to fit a trend line to past prices and establish confidence intervals: the first anchor is the past price changes and the second is the past price levels. The investor starts estimating the future price by adding the price change per period but then makes an adjustment to drag the upper and lower estimates towards the average price level during the anchor period. The resulting confidence interval series are therefore not symmetric. If the prices are rising, the confidence interval is negatively skewed as both the upper and the lower interval estimates are adjusted towards the average price level, which is lower than the point estimate. Similarly, if prices are falling, the confidence interval will be positively skewed, as the interval estimates will be pulled up. If investors are trend followers, the hedging theory of confidence intervals (De Bondt, 1993) implies that the average skewness in bull markets should be less than that in bear markets:

$$\overline{S}_{i,\text{bull}} < \overline{S}_{i,\text{bear}} \tag{3}$$

where

$$\overline{S}_i = \Sigma_{jk}(UCI_{ijk} - LCI_{ijk}) \tag{4}$$

Consistent with De Bondt (1993), risk perceptions of the investors are represented by the skewness coefficient (S_{ijk}) which is defined as the difference between the upper confidence interval (UPC_{ijk})

and the lower confidence interval (LCI_{ijk}). Upper and lower confidence intervals are defined as, respectively:

$$UCI_{ijk} = H_{ijk} - F_{ijk} \tag{5}$$

$$LCI_{ijk} = L_{ijk} - F_{ijk} \tag{6}$$

Where F_{ijk} is the subject's (k) point forecast of a stock (j) for a forecast horizon of i weeks; H_{ijk} is the high forecast (X_{90}) and L_{ijk} is the low forecast (X_{10}) of subject k for stock j for a forecast horizon of i weeks. In this case, if an investor gives interval estimates H_{ijk} and L_{ijk} as symmetric around the point estimate, F_{ijk}, the skewness coefficient will receive the value zero ($S_{ijk} = 0$). If the subject expects the price to be closer to the high estimate (H_{ijk}) rather than the low estimate (L_{ijk}), the skewness coefficient will receive a negative value ($S_{ijk} < 0$), and if the subject expects the price to be closer to the low estimate (L_{ijk}), $S_{ijk} > 0$.

Tests for differences in return expectations and risk perceptions

Before conducting tests with the pooled data, consistent with De Bondt (1993) expected price changes (EPC_{ijk}) and skewness coefficients (S_{ijk}) are normalized by dividing them by the matching standard deviations (σ_{ij}) of actual one-week price changes for the 24 weeks prior to the subjects' forecasts. Since each time series is at a different level, this standardization is necessary to eliminate the variations due to price level differences and to be able to process the pooled data. The analyses utilizing these measures are conducted at three levels by using t-statistics for differences in means.

First, differences in return expectations and risk perceptions are investigated by comparing the forecasts for unnamed stocks versus real-time forecasts of the index and the specific stocks within each subject group in bull and bear markets. The complexity of the task is different in each case. For the unnamed stocks, subjects are not given any contextual information. They are expected to extrapolate a given time series with the basic knowledge that it represents stock prices. For the real-time forecasts, task complexity increases first due to the fact that subjects are expected to use timely and salient information in addition to past prices in giving their forecasts. Second, task complexity is higher for forecasts of specific stocks than that for the index. The subjects are expected to utilize company-specific information as well as the stocks' relation to market movements and the market itself. Next, possible differences due to the expertise of the investor are analysed by comparing the return expectations and risk perceptions of experts and novices using the same procedure. Finally, the effect of the length of the forecast horizon on investor behaviour is investigated by considering the forecasts given for one, two, four and twelve weeks.

RESULTS

Tables I–III present the results from forecasts of unnamed stocks (Table I), real-time forecasts of the index-ISE (Table II) and real-time forecasts of specific stocks traded in the stock exchange (Table III). Mean expected price changes ($\overline{EPC}$) and skewness ($\overline{S}$) for novices and experts for the four forecast horizons of interest are depicted. For both $\overline{EPC}$ and $\overline{S}$, differences at bull versus bear markets are also illustrated. Further for unnamed stocks and the real-time forecasts of specific

Table I. Expected price changes and perceived skewness: price forecasts of unnamed stocks

Panel 1: Group means

	Bull market	Bear market	*p*-value
WEEK 1			
Novice			
Mean EPC	0.1770	0.1890	0.11
Mean skewness	0.5553	0.5409	0.87
Experts			
Mean EPC	0.2817	−0.0755	0.02*
Mean skewness	0.3430	0.3854	0.64
WEEK 2			
Novice			
Mean EPC	0.2263	−0.0005	0.06
Mean skewness	0.5659	0.5663	0.93
WEEK 4			
Novice			
Mean EPC	0.3471	0.0576	0.04*
Mean skewness	0.6791	0.6422	0.76
Experts			
Mean EPC	0.3860	−0.1767	0.01*
Mean skewness	0.4539	0.4412	0.90
WEEK 12			
Novice			
Mean EPC	1.6738	0.5258	0.08
Mean skewness	1.9763	1.0257	0.11
Experts			
Mean EPC	2.0550	0.6788	0.00**
Mean skewness	1.3402	0.6763	0.05

Panel 2: F-statistics for analysis of variance

	Expertise	Market conditions	Forecast horizon
EPC			
Expertise	0.83		
Market conditions	3.73	26.73**	
Forecast horizon	2.16	10.54**	22.80**
Skewness			
Expertise	3.74		
Market conditions	1.14	14.24**	
Forecast horizon	1.40	15.71**	29.06**

Notes: In Panel 1, p-values represent the significance levels for the t-statistics related to the test of differences in means. F-statistics are reported in Panel 2 for variations within groups on the diagonal and interactions elsewhere. * $p < 0.05$ ** $p < 0.01$.

stocks an analysis of variance (ANOVA) is conducted which permits us to test the significance of each of the causes of variation.[3] The results are evaluated at a 5% significance level in all cases.

Table I reports the results for the forecasts of the ISE index which were presented to the subjects as unnamed stocks; i.e. no contextual information other than the graphs of the price series were given to the subjects. First, consider the signs of $\overline{EPC}$ and $\overline{S}$. For the shorter horizons of one, two and four weeks, experts expect the past trends to continue. The mean *EPC* is positive in bull markets and negative in bear markets. The differences in means are also significant. But for twelve-week forecasts of experts, mean *EPC* is positive in both bull and bear markets, indicating an expectation of price reversals in the long run. For experts, skewness is also marginally significantly larger in bull than that in bear market conditions. As we have seen for twelve-week horizons, in bear markets, experts expect a price reversal, i.e. an increase in prices. They therefore also speculate on their prediction of a rising price by assigning confidence intervals such that the upper confidence interval is larger than the lower confidence interval. A similar picture is depicted for predictions in the bull market. Experts expect the bullish trend to continue, and speculate on their predictions by assigning higher upper confidence intervals. Mean skewness being higher in bull than in bear markets indicates that experts hedge their speculations (not their forecasts!) in bear market conditions. They give smaller upper confidence intervals in bear than in bull markets for their predictions of a price increase.

This clearly contradicts with De Bondt's (1993) finding that for student subjects, negative mean *EPC* scores were attained in bear markets, and negative $\overline{S}$ was achieved in bull markets. The hedging theory of confidence intervals implies that if subjects are trend followers, the average skewness in bull markets should be negative and thus less than that in bear markets. For longer forecast horizons, experts expect the continuation of a bullish trend and speculate on it, but predict mean reversion in bearish markets and speculate on that as well. However, they speculate less in bear than in bull markets.

For the short run, expert behaviour is similar to that represented by De Bondt with student subjects. Experts predict the continuation of past trends for the shorter forecast horizons of one, two and four weeks. As the significantly larger $\overline{EPC}$'s indicate, experts are more optimistic in bull markets than in bear markets. A similar representation is understood for all forecast horizons when student subjects are considered but the differences are not statistically significant. Portfolio managers tend to extrapolate past experience in the short run.

An analysis of variance is conducted for unnamed stocks by using a $2 \times 2 \times 4$ factorial design with one between (novice versus expert) and two within-subject variables (bull versus bear markets and the four forecast horizons). Interaction plots are given in Appendix 1. ANOVA results confirm the above analysis. The mean effect of expertise is not significant. For both *EPC* and *S* significant within-group variation is reported for market conditions and forecast horizon.

This shows that *EPC* and *S* were significantly different for bull versus bear markets and at different forecast horizons. F-tests also indicate significant interactions between market conditions and forecast horizon, highlighting the relationship. In their forecasts of the unnamed stocks significant F values of *EPC* on interaction coefficients indicate that subjects expect past trends to continue for short-term forecast horizons only and price increases in bullish markets and price decreases in bearish markets in the short term and they expect price reversals for the longer term.

[3] I would like to thank Fergus Bolger for his guidance and support with this analysis.

Similarly significant F-values for S on interaction coefficients indicate that in general larger confidence intervals are given for long-term forecasts and smaller confidence intervals are given for shorter horizons. This may naturally be due to the subjects' revealing higher uncertainty about prices to be observed in the long run. In addition, it refers to subjects' speculating on their forecasts in bull markets and hedging them in bear markets. This finding, combined with significant F-values for within-group variations, confirms the t-test results. People speculate on predictions of the continuation of bullish trends by assessing higher upper confidence intervals and they hedge their speculations of price reversals in bear markets by assigning positive but smaller confidence intervals in bear markets.

Table II reports the results of the real-time forecasts of the ISE index. For the 12-week forecast horizon, the level of the ISE index at week 12 (P_{12}) was less than that 12 weeks prior to the experiment (P_{-12}) for the two instances when the experiment was run. According to the definition of the bull and bear markets employed in this study as described in the previous section, bull market results for 12-week forecasts do not exist.

Table II. Expected price changes and perceived skewness: real-time price forecasts of the ISE index

	Bull market	Bear market	p-value
WEEK 1			
Novice			
Mean EPC	2.0967	0.0763	0.00**
Mean skewness	1.2169	0.5966	0.04*
Experts			
Mean EPC	2.3131	−0.5698	0.04*
Mean skewness	0.4625	0.3483	0.56
WEEK 2			
Novice			
Mean EPC	1.3501	0.0921	0.00**
Mean skewness	0.8500	0.2184	0.00**
Experts			
Mean EPC	1.3966	−0.0424	0.00**
Mean skewness	0.3208	0.1999	0.33
WEEK 4			
Novice			
Mean EPC	0.7661	0.0776	0.00**
Mean skewness	0.4266	0.2201	0.13
Experts			
Mean EPC	0.7559	0.0143	0.00**
Mean skewness	0.2110	0.1142	0.16
WEEK 12			
Novice			
Mean EPC	—	0.2821	—
Mean skewness	—	0.1388	—
Experts			
Mean EPC	—		
Mean skewness	—	0.1127	—

Note: P-values represent the significance levels for the t-statistics related to the test of differences in means. They are marked * if $p < 0.05$ and ** if $p < 0.01$.

For the shorter horizons of one, and two weeks, experts expect the past trends to continue. The mean *EPC* is positive in bull markets and negative in bear markets. The differences in means are also significant.

Contrary to the findings of De Bondt, novices in this study expect price reversals in bear markets for all forecast horizons. Real-time forecasts of the ISE given by novices reveal that $\overline{EPC}$'s are positive in bear markets as well as in bull markets. This shows that novices are optimistic in all cases and for all forecast horizons. They expect bullish trends to continue and predict price reversals in bearish markets. $\overline{EPC}$ is larger in bull than in bear markets, indicating optimism in both cases, with the former being enhanced with the tendency to extrapolate the bullish trend. Contrary to the findings of De Bondt once more, the skewness scores of novices are positive and higher in bull markets than in bear markets for one- and two-week forecast horizons indicating that instead of hedging they speculate on their optimistic forecasts. We must note here that none of the subjects use contrarian strategies in bull markets, and this might support the view of speculative behaviour of subjects in bull markets.

Table III presents the results for the real-time forecasts of specific stocks traded on the ISE. Once again, contrary to the findings of De Bondt, both subject groups have positive mean *EPC* scores in bull as well as in bear markets. For specific stocks, not only novices but also experts are optimistic to expect the past bullish trends to continue and bearish trends to be followed by price reversals. For expert subjects, $\overline{EPC}$'s in bull markets are larger than those in bear markets for the medium and long horizons, namely the four- and twelve-week forecasts. For novices, $\overline{EPC}$'s exhibit a similar behaviour for shorter forecasts horizons of one, two and four weeks. Experts have a tendency to exhibit significantly higher degrees of optimism in bull markets for longer horizons. Novices have the same inclination for shorter forecast horizons. This shows that subjects hedge their optimism in bear markets relative to bull markets by predicting smaller price increases.

Conclusions similar to that of ISE forecasts prevail regarding the skewness coefficients. Contrary to the findings of De Bondt, mean skewness is positive and larger in bull than in bear markets. With actual stocks, experts speculate on their forecasts for shorter horizons while novices speculate at all forecast horizons. Portfolio managers' average skewness ($\overline{S}$) in bull markets is greater than that in bear markets for the two- and four-week forecast horizons. Novices' average skewness ($\overline{S}$) is greater in bull markets than in bear markets for all forecast horizons.

Analysis of variance for the real-time forecasts of specific stocks is conducted by using a $2 \times 2 \times 4$ factorial design with three between-subjects variables and treating subjects as random. Interaction plots are given in Appendix 2. ANOVA results confirm the three-way interactions discussed above. For both *EPC* and *S* significant within-group variation is reported for all treatments; namely expertise (novice versus expert), market conditions (bull versus bear) and forecast horizon (week 1, week 2, week 4 and week 12).

Significant within-group variations for expertise gives additional information that experts are more optimistic then novices but they hedge their optimism, whereas novices speculate on their optimism. Experts' mean *EPC* scores are larger than those of novices in both bull and bear market conditions. That means that although both groups are optimistic in expecting prices to increase, experts are more optimistic. However, experts hedge their forecasts in both market conditions by assigning lower confidence intervals than novices. The higher skewness coefficients of novices indicate that they speculate more than experts on their optimism. This shows that, compared to novices, experts speculate more in their belief that a price reversal will follow falling prices in the short run. Compared to novices they predict a higher price increase to follow a fall in stock prices.

Table III. Expected price changes and perceived skewness: real-time price forecasts of specific stocks traded on the ISE

Panel 1: Group means

	Bull market	Bear market	*p*-value
WEEK 1			
Novice			
Mean EPC	0.3417	0.0302	0.00**
Mean skewness	1.1745	0.5634	0.00**
Experts			
Mean EPC	0.2622	0.2541	0.92
Mean skewness	0.6347	0.5845	0.70
WEEK 2			
Novice			
Mean EPC	0.4811	0.1683	0.01*
Mean skewness	1.3128	0.6073	0.00**
Experts			
Mean EPC	0.5334	0.3759	0.22
Mean skewness	0.8452	0.5039	0.01*
WEEK 4			
Novice			
Mean EPC	0.7675	0.3223	0.00**
Mean skewness	1.5172	0.7022	0.00**
Experts			
Mean EPC	1.0117	0.2850	0.00**
Mean skewness	0.9817	0.5147	0.01*
WEEK 12			
Novice			
Mean EPC	1.7704	1.5137	0.43
Mean skewness	2.3132	1.3631	0.00**
Experts			
Mean EPC	3.0334	1.8764	0.00**
Mean skewness	1.8309	1.1870	0.09

Panel 2: *F*-statistics for analysis of variance

	Expertise	Market conditions	Forecast horizon
EPC			
Expertise	15.03**		
Market conditions	0.50	28.13**	
Forecast horizon	5.61**	4.54**	124.43**
Skewness			
Expertise	16.91**		
Market conditions	14.17**	42.17**	
Forecast horizon	0.09	3.40*	30.23**

Notes: In Panel 1, *p*-values represent the significance levels for the *t*-statistics related to the test of differences in means. *F*-statistics are reported in Panel 2 for variations within groups on the diagonal and interactions elsewhere. * $p < 0.05$, ** $p < 0.01$.

Significant within-group variation for market conditions gives the additional information that optimism in bull markets is more pronounced than optimism in bear markets. Both the *EPC* and skewness scores are higher in bull market conditions than in bear markets. This indicates that people expect higher price increases in bull markets and also speculate on their optimism by assessing higher upper confidence intervals while prices are increasing than while the market is bearish.

Significant within-group variation in forecast horizon gives us the additional information that as the forecast horizon extends from short term to long term both the mean *EPC* and mean *S* scores increase, indicating that participants expect higher price increases accompanied by wider upper confidence intervals. All subjects predict higher price changes and higher confidence intervals for the distant future. Similar to the case in unnamed stocks, all subjects reveal higher uncertainty about prices to be observed in the long run. At the same time they speculate on their forecasts in bull markets that the trend will continue but hedge their forecasts of price reversals in bear markets.

F-tests for the analysis of variance also revealed significant interactions for forecast horizon and expertise as well as market conditions for *EPC*. For skewness coefficients significant interactions were reported for market conditions and expertise as well as for forecast horizon. Significant interactions between forecast horizon and expertise for *EPC* indicate that experts are more optimistic than novices and this is more pronounced in the long term than in the short term. Significant interactions between forecast horizon and market conditions for mean *EPC* indicate that mean *EPC* scores are higher in bull markets than in bear and this discrepancy widens in the long term.

Significant interactions between expertise and market conditions for the skewness coefficients indicate that the optimism in bull markets is better hedged by experts who assign smaller upper confidence intervals than novices. Interactions between market conditions and forecast horizon are marginally significant at the 5% level. This indicates that the skewness coefficients in bull markets are higher than those in bear markets and this is more pronounced for longer forecast horizons. This may naturally be due to the subjects' revealing higher uncertainty about prices to be observed in the long run. It also refers to subjects' speculating on their forecasts in bull markets and hedging them in bear markets.

DISCUSSION

This study has investigated two domains that were not captured by previous research on the validity of the overreaction hypothesis. First, actual portfolio managers are used as forecasters. Second, a real-time, real-world assessment task is given in the form of forecasting the prices of specific stocks traded on the stock exchange. The focus is on the biases in the forecasting behaviour in financial markets. Expert and novice behaviour is compared in their stock market forecasts. The main goal of the study was to accumulate evidence as to the expectation-formation process of investors, which is assumed to be rational by the advocates of the efficient markets hypothesis while most behaviourists assume overreaction.

The major contribution of this study is that the general claim that investors predict stock prices, by extrapolating from past trends, with proper hedging, is not substantiated for all subject groups, all forecast horizons, and all forecasting tasks. Differences are observed in return expectations and perceived risks due to (1) the presence of contextual information, (2) the trends in the stock market and (3) participants' level of expertise. The results of this study are different from those of De Bondt (1993) in various respects. These differences are mainly due to the effects of factors that were manipulated in this study while they were not in the De Bondt experiments.

Experts extrapolate past trends—bullish and bearish—for short forecast horizons and for unnamed stocks and the ISE index. Experts are optimistic in bull and pessimistic in bear markets in less complicated decision tasks and for short horizons. This is similar to the findings of De Bondt. However, in the remainder of the findings, there are noticeable differences from the student subjects of De Bondt, who extrapolated past trends for unnamed stocks and hedged their forecasts properly.

First, for experts, consider the less complex tasks of predicting prices of unnamed stocks and the ISE index. Their long-run behaviour is different. For the long run, they predict price reversals in bear markets, while they expect the continuation of bullish trends. An investigation of experts' skewness coefficients also reveals this type of behaviour. Even for short horizons, when experts extrapolated past trends, their bull market skewness coefficients were positive and larger than that in bear markets. This was precisely the case for their optimistic long-run forecasts as well. Contrary to De Bondt, experts did not hedge but speculated on their predictions for increasing prices. In bearish markets they also had positive skewness coefficients as well, indicating that they had higher upper confidence intervals, characterizing their optimism further. They hedged their forecasts when they expected the fall to continue in the short run, and speculated on their predictions of increasing prices in the long run.

Second, consider the forecasts of novices. We cannot trace any significant biases in novices' forecasts of unnamed stocks. However, contrary to De Bondt, the results for ISE forecasts are strikingly optimistic. For all forecast horizons, they expect the bullish trend to continue, while at the same time they predict price reversals, i.e. an increase in the index level, in bear markets. Once again, skewness coefficients were positive in bull as well as bear market forecasts. Novices speculated on their optimistic forecasts, with the speculation being less in bear markets than in bull markets. Subjects admitted the possibility of a downward trend even when they were optimistic in a bearish market.

None of the participants, experts or novices, used contrarian strategies in their long-run forecasts of the ISE index in bull markets. However, contrarian strategies were used in bear market conditions by almost 50% of the subjects for one- and two-week forecast horizons by 63% of the subjects for the four-week forecast horizon and by 82% of the subjects for the twelve-week forecast horizon.

Third, investigation of the forecasts of prices of actual stocks traded on the ISE supports the findings of the previous real-time forecasting task, with marked differences due to the level of expertise and forecast horizon. Contrary to De Bondt, all subjects—experts and novices—have positive mean *EPC* scores in bull as well as in bear markets, indicating that they expect the prices to increase in both cases. All subjects have positive skewness coefficients in bull markets indicating that they speculate on their prediction that the trend will continue. Experts speculate on their optimistic predictions in bull markets for short horizons, while novices speculate in all horizons. However, the optimism in bear markets is hedged to a certain degree by allowing for a possibility of a downward trend.

Finally, investigation of forecasts, at different forecast horizons, reveals that subjects reveal their uncertainty about the distant future by expecting higher price changes and assigning larger confidence intervals. Exceptions are novices' bull market expected price changes and bear market skewness coefficients of ISE index forecasts. For the ISE, novices speculated more on their expectations that the bullish trend will continue in the short run than in the long run. Similarly, confidence intervals were wider for expected price reversals in bear markets for short-run forecasts than for long-run.

Experts extrapolated trends in the short run, with series that did not contain any real-time or contextual information. This is similar to the findings of De Bondt's (1993) experiments with student subjects. Investors are positive feedback traders when they are exposed to a time series without being supplied with real-time information. However, forecasting with contextual information and forecasting in real time is different. Subjects extrapolate bullish trends and expect price reversals in bearish trends. Mean reversion in prices is expected but in bear markets only.

The optimism of experts as well as novices in forecasting stock prices—a complex, real-world assessment task—needs to be elucidated. 'Most people's beliefs are in the direction of optimism. Optimists exaggerate their talents; that is why more than 80% of drivers believe they are, like all children ... above average.' (Kahneman and Riepe, 1998, p. 54). This type of optimism may be due to two mechanisms. First, subjects might have chosen to report the price forecasts of stocks, whose prices they expect to rise, as is the case with experts in their reported investment advice as well. Sell recommendations are rare, whereas buy or hold recommendations are more frequently made. This type of bias has roots in the consequences of investment advice. If you expect a stock's price to fall and advise your customer to sell it off, and prices go up, she may later regret what she did. Otherwise, if you advise your customer to buy a stock whose price you expect to increase, and the price falls, she can always hold the stock until the price increases again! That is why losers ride for too long. Most investors try to minimize regret rather than maximizing expected pay-offs.

Second, this type of pure optimism may indicate that subjects underestimate the likelihood of bad outcomes. Novices were optimistic at all forecast horizons while experts were optimistic mainly for the long-run forecasts. In addition, comparisons of the overall skewness coefficients of experts and novices reveal that expert forecasters are more overconfident in unpredictable domains because they assess tighter probability distributions. Optimism, in many cases, is also accompanied by overconfidence. Subjects, instead of hedging, speculate on their optimistic forecasts, indicating their confidence in them. 'The combination of overconfidence and optimism is a potent brew, which causes people to overestimate their knowledge, underestimate risks and exaggerate their ability to control events, (Kahneman and Riepe, 1998, p. 54).

In this case, such an immaculate optimism can be interpreted as a behavioural explanation of the higher volatilities (Ohlsen, 1998) and observed inefficiencies in emerging markets. As is the case for many emerging markets, higher volatilities on the ISE may be due to the speculative behaviour of investors besides other institutional and structural factors. This does not mean ignoring or underestimating fundamental factors such as interest rates, inflation, economic growth, etc. Rather, one should also acknowledge that market behaviour could also be influenced by investor behaviour. In fact in the Turkish language investments in the stock market are expressed as 'playing the stock market'; the same wording as is used for gambling (e.g. playing blackjack). The observed inefficiencies in the Turkish stock market (Muradoglu and Unal, 1994; Muradoglu and Metin, 1996; Aydogan and Muradoglu, 1998) might also be explained by investor psychology.

A further concern at this point is the description of the expectation-formation process. Expectations may be adaptive rather than rational. But can the expectation formation process be generalized to what De Bondt (1993) has described as one that extrapolates the trends while hedging them at the same time? This study shows that one needs to be cautious in making such generalizations. Different decision processes may be at work on different occasions. It might also be argued here that the actual heuristic used in this case depended on the amount of serial dependence on the series. The subjects might be using, as the anchor, the last observation (Bolger and Harvey, 1993) rather than the past price sequence in making their predictions. Another possibility is the utilization of a long-term mean (Lawrence and O'Connor, 1992) as an anchor. Experts working at the ISE practise under conditions of sticky and high inflation. They may be accustomed to working with price series having a natural upward trend due to inflation in the long run. They might have a long-term mean return expectation in real terms—rather than nominal—in their minds. In that case, for long-term forecasts, they might use that long-run real mean return as the anchor rather than the past sequence.

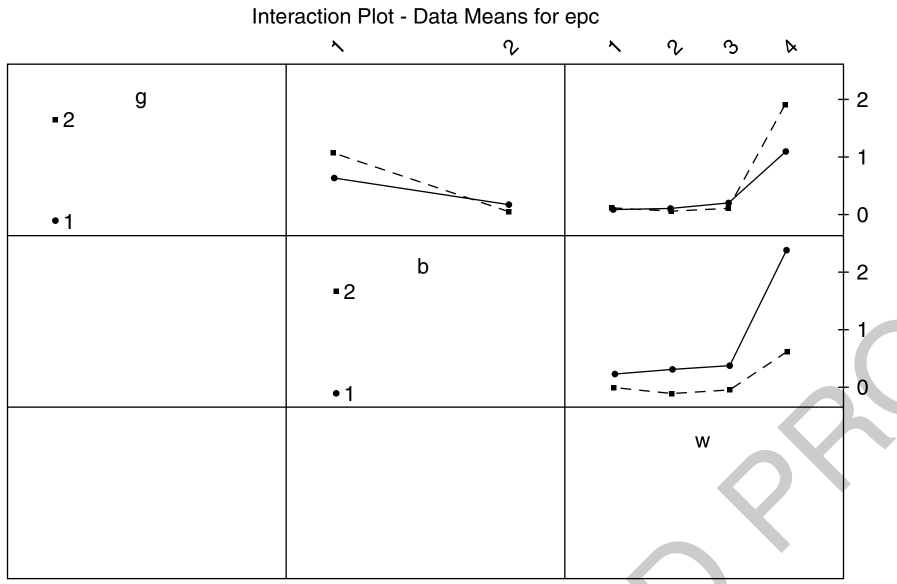
Overall, the results of this study show that potential investors are positive feedback traders as described by De Bondt (1993) when they are exposed to a time series without any contextual information. Forecasting with contextual information and forecasting in real time is different. Optimism is the norm here. Bullish trends are extrapolated and mean reversion is expected in bear markets only. Also expert behaviour is different from novice behaviour. Experts are in general more optimistic than novices. However, they hedge their optimism better.

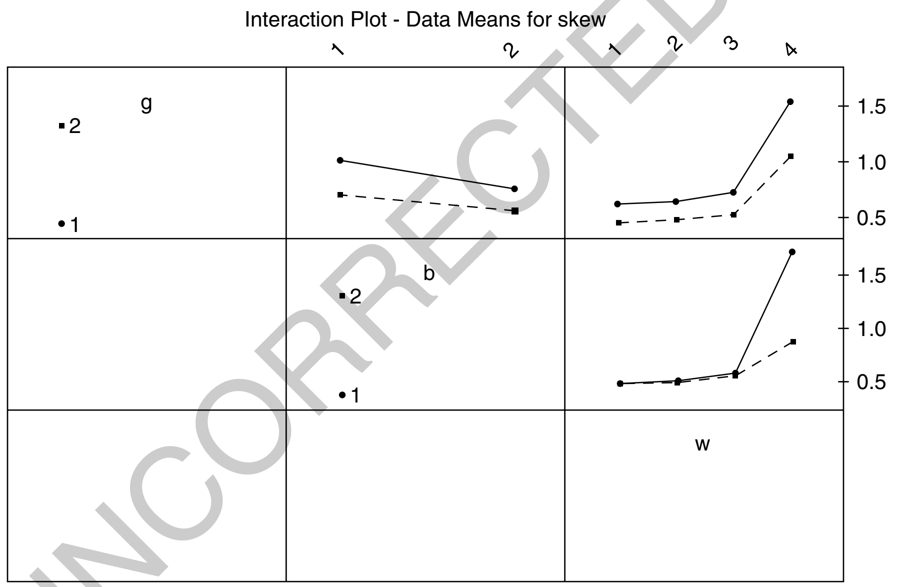
CONCLUSIONS

The major contribution of this study is to investigate the two domains that were not captured by previous research on the overreaction hypothesis: utilization of actual portfolio managers as forecasters and the real-time, real-world assessment in the form of forecasting the prices of specific stocks traded on the stock exchange. The general claim of previous research (De Bondt, 1993) that investors predict stock prices by extrapolating from past trends with proper hedging is not substantiated for all subject groups, all forecast horizons, and all forecasting tasks. Differences are observed in return expectations and perceived risks due to the presence of contextual information, the trends in the stock market and the participants' level of expertise.

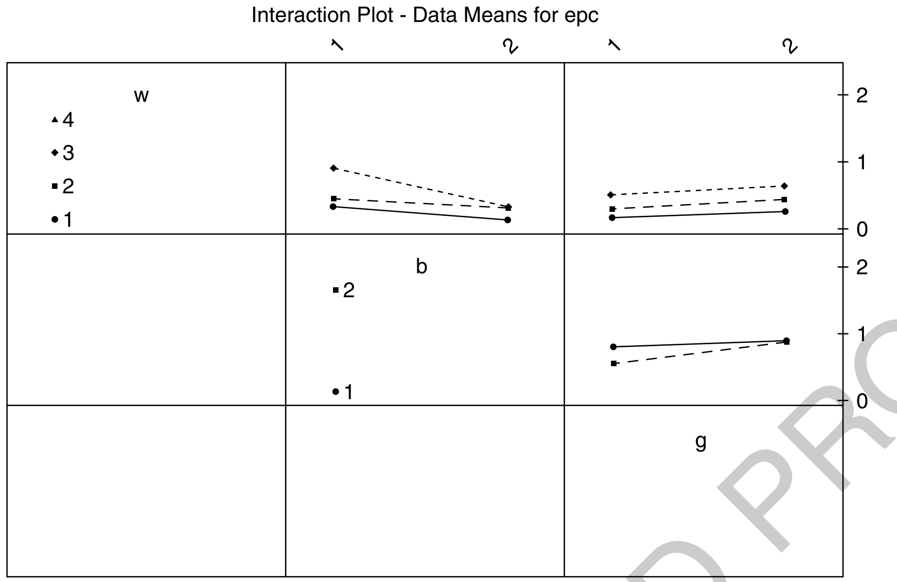
The possible implications of this study for finance are two. First, the behavioural assumption of the efficient markets hypothesis that expectations are rational should be treated with caution. Scepticism about the rational expectations hypothesis is hardly new (Hudson, 1982; Pesaran, 1987; Shefrin, 1983). However, clearly much needs to be done to examine how investors form their beliefs in order to explain empirical findings. That apparent anomalies can be due to methodology (Fama, 1998) is but one explanation. Melding psychological and financial research is necessary for a better understanding of the market mechanism in general and financial markets in particular. Next, risk perceptions might differ across investors with different expertise, across bull versus bear markets, and across real-world versus simulated environments. This should be studied further in developing better asset pricing models. Variations in risk premia should be attributed not only to stocks being more risky in terms of traditional risk measures or changes in risk aversion but also to differences in risk perceptions. This is especially true in evaluating the thinly traded emerging markets where economic aggregates and indicators are different from those in mature markets. Further research in this area is expected to validate the relevance of these findings. Studies combining the knowledge structures and cognitive theories with the actual behaviour of economic agents in financial settings will help financial theory to be based on more realistic assumptions and thus practitioners to work with better models.

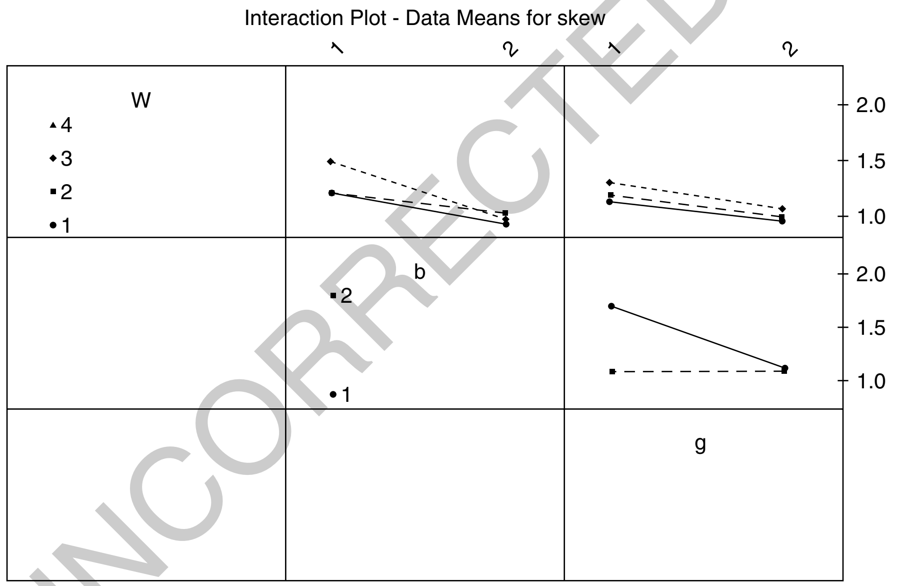
APPENDIX 1: INTERACTION PLOTS FOR ANOVA CONDUCTED FOR UNNAMED STOCKS





APPENDIX 2: INTERACTION PLOTS FOR ANOVA CONDUCTED FOR SPECIFIC STOCKS TRADED ON THE ISE





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Query No.	Query
TS1	Please supply.