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September 11 and Stock Return Expectations of Individual Investors ⋆

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Abstract. This study uses data that offers the unique opportunity to analyze how an unprecedented crisis such as the September 11 tragedy influences expected returns and volatility forecasts of individual investors. Via e-mail, we asked a randomly selected group of individual investors with accounts at a German online broker to answer an internet questionnaire at the beginning of August 2001. A second e-mail to the investors who had not yet answered, scheduled five weeks later, was postponed due to the terror attacks until September 20, which was exactly the day with the lowest share prices in Germany in the year 2001. Based on the answers to questions concerning stock market predictions, we find that return forecasts of the investors in our sample are significantly higher after September 11, suggesting a belief in mean reversion. Our results show that investors interpret the large drop in share prices during the ten day period after September 11 mainly as temporary rather than permanent. After the terror attacks, volatility forecasts are higher than before September 11. In two out of four cases, historical volatilities are overestimated. Therefore, investors are not generally overconfident in the way that they underestimate the variance of stock returns. Differences of opinion with regard to return forecasts are lower after the terror attacks whereas differences of opinion concerning volatility forecasts are mainly unaffected.

1. Introduction

Numerous studies analyze the determinants of investor expectations but little is known about how market participants react in a crisis situation with a high degree of uncertainty in connection with a large drop in share prices. Our study uses data that offers the unique opportunity to analyze how an unprecedented crisis such as the September 11 tragedy influences expected returns and volatility forecasts of individual investors. We asked a randomly selected group of individual investors with accounts at a German online broker to answer a questionnaire that we put on the internet. Investors were asked to state a median estimate and upper and lower bounds of a symmetric 90% confidence interval for the value of two German in-

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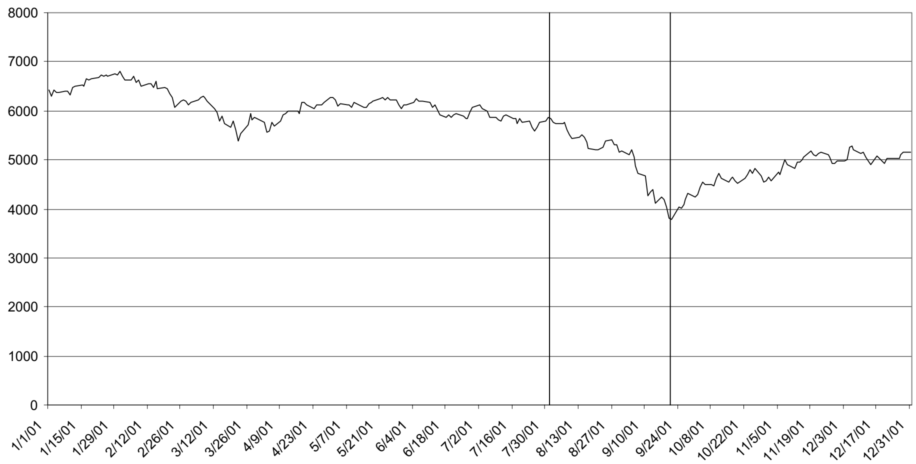

Figure 1. Chart of the DAX in the year 2001. This figure presents the chart of the DAX in the year 2001. The first vertical line in the chart indicates the date of response of the first group (August 2nd, 2001), the second vertical line shows the date of response of the second group (September 20, 2001).

dexes and of the price of two German stocks at the end of the year 2001 (Deutscher Aktienindex DAX, Nemax50 Performance Index, BASF, Deutsche Telekom). Investors received an e-mail with the link to the questionnaire on Thursday, August 2nd, 2001. A second e-mail to the remaining investors who had not yet answered, scheduled five weeks later, was postponed due to the terror attacks of September 11 until Thursday, September 20, 2001. We refer to the group of investors who answered directly after the first e-mail as “first group” and to the group of investors who answered after the second e-mail as the “second group”. The second group of investors answered exactly on the day with the lowest value of the German blue chip index DAX in the year 2001. Figures 1, 2, 3, and 4 present the charts of the four time series in the year 2001. The first vertical line in the respective chart indicates the date of response of the first group, the second vertical line shows the date of response of the second group.[1] With the help of these questions we can analyze how a sharp drop in stock returns due to an event such as September 11 affects point forecasts and volatility estimates of individual investors. Furthermore, we are able to assess whether the level of heterogeneity or disagreement with respect to the forecasts increases or decreases after such an event.

Clearly, we did not design the study to test a specific theory or hypothesis. Sending a second e-mail was planned before the attacks (but postponed due to the attacks). However, a review of the literature might provide hypotheses of what we should have expected ex ante. We present such a comprehensive survey of

[1] The respondents to the first questionnaire had a forecast horizon of 21 weeks, respondents to the second questionnaire had a 14 week horizon.

Figure 2. Chart of the Nemax50 in the year 2001. This figure presents the chart of the Nemax50 in the year 2001. The first vertical line in the chart indicates the date of response of the first group (August 2nd, 2001), the second vertical line shows the date of response of the second group (September 20, 2001).

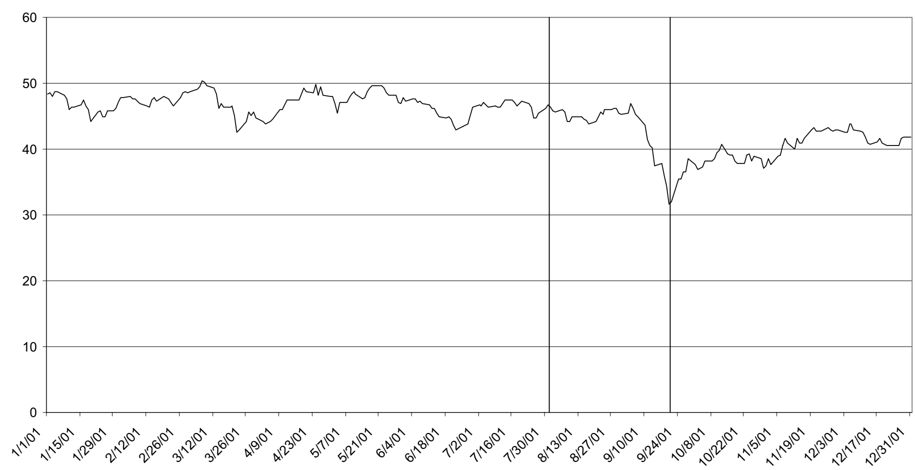

Figure 3. Chart of BASF in the year 2001. This figure presents the chart of BASF in the year 2001. The first vertical line in the chart indicates the date of response of the first group (August 2nd, 2001), the second vertical line shows the date of response of the second group (September 20, 2001).

Figure 4. Chart of Deutsche Telekom in the year 2001. This figure presents the chart of Deutsche Telekom in the year 2001. The first vertical line in the chart indicates the date of response of the first group (August 2nd, 2001), the second vertical line shows the date of response of the second group (September 20, 2001).

related literature in Section 2. The main message of this review is that there is no general tendency of, for example, extrapolative or mean-reverting expectations of investors. Thus, there is no general prediction of what we should have expected. Another reason for the difficulty to come up with a hypothesis is that there is no similar study available. The terror attacks have been unprecedented. One event that is related in the dimension of the drop in stock prices is the stock market crash in October 1987. But even this event is different. There are several studies showing that the 1987 stock market crash was not driven by news or a singular event (see, for example, Shiller (1987) and Shiller et al. (1991)). In contrast, the drop in share prices after September 11 was driven by public news after a singular event.

However, one caveat is in order. It is difficult to disentangle the impact of the large drop in share prices on our investors' forecasts from the apparent reason for the drop, a terrorist attack. Thus, there is some ambiguity in interpretation regarding whether we can draw inference about investor expectations after a terror attack or investor expectations after major price drops. We address this issue in the discussion of our results where we point out what the terror attacks might add to an (hypothetical) investor survey taken after major drops in share prices without an apparent reason for the drop.

Our study is part of and extends the literature that documents how investors actually behave and how they form expectations. This literature, for example, identifies influences on mean forecasts, forecast intervals, and on the heterogeneity of the answers to these questions between investors. Furthermore, in connection with other findings in the literature, it is possible to interpret our results in light of prior results and to suggest directions for future research.

Our study is part of the huge survey literature in finance. Meanwhile, surveys are widely accepted in the financial markets literature.[2] Several arguments are usually put forth in the literature stressing the usefulness of survey or investor expectations data. Black (1993) and Shefrin and Statman (2003) argue that some competing theories involving expected returns cannot be tested using realized returns only as these are only noisy measures of expected returns. Other studies explicitly use expectations of financial markets participants to test asset pricing models (see, for example, Brav et al. (2003)). Shiller et al. (1996) also emphasize that it is impossible to find out what investors think in a crisis situation unless one asks them. MacDonald (2000) especially stresses the usefulness of disaggregate survey data to test heterogeneous behavior or beliefs of investors.

Our paper offers the opportunity to study how a crisis situation that is accompanied by a large drop in share prices over a short time period of only several days affects estimates of expected returns and volatility forecasts of individual investors. In addition to forecasts of expected returns and volatilities we are able to analyze the level of disagreement or heterogeneity among investors ("differences of opinion"[3]).

The main results of this paper can be summarized as follows. Return forecasts of the investors in our sample are significantly *higher* after September 11, suggesting a belief in mean reversion. Our results show that investors interpret the large drop in share prices during the ten day period after September 11 mainly as temporary rather than permanent. After the terror attacks, volatility forecasts are higher than before September 11. In two out of four cases, historical volatilities are *over*estimated. Therefore, investors are not generally overconfident in the way that they underestimate the variance of stock returns. Differences of opinion with regard to return forecasts are *lower* after the terror attacks whereas differences of opinion concerning volatility forecasts are mainly unaffected.

The remainder of this paper is organized as follows. Section 2 discusses related literature. Section 3 describes our data sets and the methodology of the study and shows some descriptive statistics. Section 4 and Section 5 present the results on mean return (point) forecasts and the volatility forecasts, respectively. In Section 6, the heterogeneity of the answers of our investor sample is analyzed and the last section concludes.

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[2] One example is the paper of Graham and Harvey (2001) which was awarded the first prize in the annual Jensen Prizes for Corporate Finance and Organizations competition. The award was given for the best corporate financial paper published during 2001 in the Journal of Financial Economics. Graham and Harvey (2001) survey 392 CFOs about the cost of capital, capital budgeting, and capital structure.

[3] See Varian (1985, 1989), Harris and Raviv (1993), Kandel and Pearson (1995), Hong and Stein (2003), and Diether et al. (2002) for details on the "differences of opinion" literature.

2. Related Literature

In this section, we provide an in-depth discussion of related literature. We classify the literature into the following categories:

- Investor surveys and experimental studies that explicitly measure investor expectations,
- studies analyzing trading behavior of investors which present indirect evidence of investor expectations, and
- literature analyzing the effects of September 11 on financial markets.

The last subsection of this literature review section extracts the main messages of the studies presented and the main lessons we can learn for our study.

2.1. RELATED INVESTOR SURVEYS AND EXPERIMENTAL STUDIES

In this subsection, we present other investor survey studies that are designed to analyze various aspects of investor expectation formation. These studies are most closely related to our study.

Studies analyzing forecasts can broadly be categorized in studies on point or mean return forecasts, interval forecasts, and probabilistic forecasts of stock prices.[4] Furthermore, existing research differs in various other dimensions. Some studies analyze forecasts of real time series, others use artificially created time series. Webby and O'Connor (1996) survey the large literature on judgmental time series forecasting. The time series studied are not necessarily financial time series. Another example is a product sales time series. This strand of literature tries to answer the question whether subjective judgments are preferred over statistical models and how human judgment and statistical methods should be combined in practice to improve forecast accuracy. In their comprehensive survey, Webby and O'Connor (1996) classify empirical and experimental studies according to the series or task characteristics (such as trend, seasonality, noise, or instability of the time series, the number of historical data points presented, the length of the forecast horizon, whether feedback was given or whether a graphical or tabular presentation of the data was used) and according to the characteristics of the judges and the

[4] We do not discuss studies analyzing probabilistic forecasts of investors as we did not ask for probabilities. Önkal and Muradoğlu (1994), Yates et al. (1991), and Staël and von Holstein (1972) are examples of this strand of literature. Furthermore, we do not discuss the huge literature on exchange rate expectations as currency time series usually exhibit other time series characteristics when compared to time series of stock prices (see, for example, Oberlechner and Osler (2004)). MacDonald (2000) presents an extensive survey of this literature. Furthermore, we do not cover the huge literature on analysts' expectations or forecasts. These expectations and forecasts are typically biased and influenced by agency problems such as to benefit the corporate finance side of an investment bank, to enhance stocks held in-house, to support the price of firms in which they own shares or to stimulate investors to trade (see Daniel et al. (2002, p. 148, for details and pp. 147–149 for a survey of this strand of literature)).

environment in which the forecasts were made (such as the level of experience of the judges, the context, and the motivation). However, there are often problems to properly classify real world time series with regard to the time series characteristics mentioned above. Reasons are, among other things, discontinuities of changing trends or noise levels.

De Bondt (1991) analyze data from the Livingston survey. This data set consists of a biannual panel of about 40 economists who state mean forecasts of the Standard and Poor Index at horizons of seven and thirteen months. He finds that the predictions are strongly mean reverting. De Bondt (1993) analyzes around 38,000 forecasts of stock prices and exchange rates and finds that individual investors or non-experts expect trend continuation. Shiller et al. (1996) create a biannual time series of expectations from institutional investors in both Japan and the United States from 1989 to 1994 to analyze why the Japanese stock market lost more than 60% of its value from December 1989 to August 1992 whereas, for example, stock prices in the U.S. rose during this time period. In each questionnaire, they ask for the change in percentage terms of the Nikkei 225 and the Dow Jones Industrial Average for horizons of 3, 6, and 12 months as well as 10 years. They find that expectations do change through time both for the U.S. and Japan. Furthermore, they find that Japanese investors were more optimistic about the Japanese market than were American investors. Bange (2000) analyzes the stock market forecasts and portfolio allocation decisions of individual investors based on survey data. When investors are bullish, they increase their equity holdings, and when they are bearish, they decrease their holdings. Welch (2000) presents survey evidence on equity premium estimates of 226 academic financial economists. He finds that respondents claim to revise their forecast of the equity premium down when the stock market rises. Fraser (2004) analyzes survey data on the expectations of U.S. and Japanese investors on the Dow Jones Industrial Average and the Nikkei and finds that investors appear as biased and inefficient processors of information with the nature of the bias related to the index and its underlying fundamentals rather than the investor base. Investor expectations appear to be formed adaptively as a time-varying, weighted function of past forecast errors. Siebenmorgen and Weber (2004) examine the effects of different investment horizons on investors' risk behavior and find results that are consistent with a belief in mean reversion.

There are other studies that elicit the volatility estimate of investors by asking for confidence intervals for the return or value of an index or the return or price of a stock in the future. These studies usually find that the intervals provided are too tight. Thus, historical volatilities are underestimated (see, for example, Hilton (2001)). The finding that confidence intervals for uncertain quantities are too tight is usually called "miscalibration" or "overconfidence" (see Lichtenstein et al. (1982), Klayman et al. (1999), Soll and Klayman (2004), and Griffin and Brenner (2004)). One example is the study of Graham and Harvey (2003) which analyzes expectations of risk premia, as well as their volatility and asymmetry in a panel survey. On a quarterly basis, Chief Financial Officers (CFOs) of U.S. corporations are asked to provide their estimates of the market risk premium. They find that historical volatilities are underestimated. Furthermore, high past (absolute) returns affect the level of disagreement: the higher the (absolute) returns the higher the level of disagreement of investors over the one-year risk premium. De Bondt (1998) presents results from a study of 46 individual investors. These investors agreed to make repeated weekly forecasts of the Dow Jones Industrial Average and of the share price of one of their main equity holdings. For 20 weeks, subjects were asked to provide point forecasts as well as interval estimates for the value or price two or four weeks later. One important finding is that the confidence intervals are too narrow compared to the actual variability of prices.

2.2. INDIRECT EVIDENCE OF INVESTOR EXPECTATIONS BY TRADING BEHAVIOR

In this subsection, we discuss studies that analyze trading behavior of various investor groups that is influenced by past returns. We first discuss empirical studies analyzing the actual trades of investors. Then, we present some results of experimental studies of trading behavior of experimental subjects.

Dhar and Kumar (2001) analyze the impact of price trends on trading decisions of households with accounts at a discount brokerage house in the U.S. and find that buying and selling decisions of investors in their sample are influenced by short-term (less than 3 months) price trends. They document heterogeneity of investors and classify investors as either momentum (positive feedback) or contrarian investors. Momentum traders expect price continuations and contrarians expect price reversals and, as a consequence, investors trade accordingly. Their results provide some support to the commonly held belief that relatively more sophisticated investors exhibit contrarian trading behavior. Odean (1999) finds that discount broker investors buy and sell securities that have, on average, appreciated prior to purchase or sale. Barber et al. (2003) analyze trading records for households at a large discount broker and investors at a large retail broker. They find that investors buy stocks with strong past returns but they also sell stocks with strong past returns, though this relation is stronger than that for buys at short horizons (one to two quarters). Grinblatt and Keloharju (2000) analyze the extent to which past returns determine the propensity to buy and sell. They find that foreign investors in Finland tend to be momentum investors whereas domestic individual investors tend to be contrarians. Choe et al. (1999) find evidence of positive feedback trading by foreign investors before the period of Korea's economic crisis. However, during the crisis period, positive feedback trading by foreign investors mostly disappears. Grinblatt et al. (1995) find that institutional investors are momentum investors. Griffin et al. (2003) analyze cross-sectional relation between stock returns and the trading of institutional and individual investors using daily and intradaily data from Nasdaq 100 firms. They find that based on the previous day's stock return, the topperforming decile of securities is more likely to be bought in net by institutions and sold by individuals than those in the bottom performance deciles.

Weber and Camerer (1998) find trading behavior consistent with mean reverting expectations in an experimental asset market. Kroll et al. (1988) find in their computer-controlled portfolio selection experiment that subjects attempted to discover trends in the rates of returns of securities. Andreassen and Kraus (1990) find that experimental subjects follow a trend chasing strategy.

2.3. LITERATURE ON THE EFFECTS OF SEPTEMBER 11

This paper belongs to the strand of literature that examines the effects of the terror attacks of September 11 on financial markets and the economy as a whole. Graham and Harvey (2003) analyze, in a study close to ours, expectations of risk premia, as well as their volatility and asymmetry in a panel survey. On a quarterly basis, Chief Financial Officers (CFOs) of U.S. corporations are asked to provide their estimates of the market risk premium. One of these quarterly surveys was distributed on September 10, 2001. Some of the responses were received on September 10, 2001 via fax, others after the September 11 crisis. Graham and Harvey (2003) find that the estimate of the one year risk premium decreases sharply after September 11 whereas volatility forecasts increase. Poteshman (2005) analyzes whether there was unusual option market activity prior to the terrorist attacks of September 11, 2001. He finds that an indicator of long put volume appears to be unusually high which is consistent with informed investors having traded in the option market in advance of the attacks. Andersen and Wagener (2002) analyze the impact of the September 11 crisis on expectations of future Euribor interest rates. Carter and Simkins (2002) investigate the reaction of airline stock prices to the terrorist attacks. Straetman et al. (2003) answer the questions whether U.S. common stocks exhibit a higher propensity towards sharp declines and whether sharp drops in stock prices tend to co-move more frequently since September 11. They do not find much support for a structural change in downside risk as measured, for example, by the Value-at-Risk. Chen and Siems (2004) analyze the effects of terror attacks such as September 11 on global capital markets. They find that U.S. capital markets are more resilient than in the past and recover sooner from terrorist attacks than other global capital markets.[5]

[5] There is further research on the effects of September 11. A special issue of the Economic Policy Review of the Federal Reserve Bank of New York (Volume 8, Number 2) analyzes economic consequences of September 11. Several authors discuss issues like economic costs (costs as direct consequences of the attacks as well as costs arising from efforts to prevent future attacks), the attacks' disruptive effects on the payments and securities settlement systems, and New York City's prospects after September 11. A special issue of the Journal of Risk and Uncertainty (Volume 26, Numbers 2/3) deals with the risks of terrorism with a special focus on September 11. A special issue of the European Journal of Political Economy (Volume 20, Issue 2) deals with the economic consequences of terror.

2.4. SUMMARY

The main findings of the literature review can be summarized as follows:

- There is no "clear picture" and no general tendency that investors expect price continuations or price reversals. A "clear picture" is even a logical impossibility. Grinblatt and Keloharju (2000) highlight this point in the related context of trading behavior as a function of past stock returns: "The ability to analyze the universe of trades in a stock market highlights the oft-ignored fact that if some groups of investors pursue trading strategies in which buys and sells are generated by past return differences across stocks, other investor groups must follow the opposite strategy."[6] In other words, other investors have the opposite expectations. The contribution of the literature discussed and the contribution of our study is to document how a specific group of investors behaves in a specific task and in the respective situation or context.
- Confidence intervals for the future value of risky assets are usually too tight. As a consequence, historical volatilities are underestimated.

Our study contributes to the literature mentioned above in the way that it provides a further not yet analyzed context in which mean return and volatility forecasts are made: the situation with an unprecedented terror attack accompanied by a high degree of uncertainty in connection with a large drop in share prices.

3. Data Sets, Methodology, and Descriptive Statistics

Approximately 3,000 randomly selected individual investors of a German online broker received an e-mail on Thursday, August 2nd, 2001 with a link to the online questionnaire. 129 investors answered around the following week-end. We call this group the "first group". The remaining group of investors received a second e-mail on Thursday, September 20, 2001. 86 investors answered around the following weekend. The group is called the "second group".[7] Thus, we have a response rate of about 7%, which is comparable to the response rates of similar questionnaire studies.[8] In what follows, we compare return and volatility forecasts of two separate groups of investors. The differences of findings in the two groups could, of course, be due to another reason besides September 11: The two groups of individual investors might be different not only in their estimate of, say, expected returns but also in various other dimensions which would make it difficult to argue that we have estimates of a homogenous group of investors. However, we are able to compare the two groups along various dimensions such as trading activity, portfolio positions, portfolio performance, investment strategy, or demographic information.

6 Grinblatt and Keloharju (2000, p. 66).
7 Therefore, our study is comparable to a between subject design in the experimental literature.
8 See, for example, Graham and Harvey (2003).

Table I presents descriptive statistics of various characteristics (age, stock market investment experience in years, information in hours per week, number of transactions in all security categories, number of stock transactions, mean monthly stock portfolio turnover, stock portfolio value in EUR, income in EUR, and mean monthly stock portfolio performance) of the two groups of respondents as well as the p-value of a Mann-Whitney test (Null hypothesis is that the two populations are from the same distribution). Furthermore, Table I presents the percentage of men and women, the percentage of investors who assess their investment strategy as high risk, and the percentage of warrant traders in both groups.[9] Table I shows that differences of the above mentioned characteristics in both groups are small and in most cases insignificant.[10] Only the mean monthly stock portfolio turnover, the stock portfolio value, and income are significantly different in both groups. The difference in the income variable is only marginally significant. Moreover, the income variable is only available for one third of all investors. Thus, the different turnover values of both groups seem to be the only important difference. Turnover is negatively related to the stock portfolio value in our data set.[11] Perhaps, online traders with higher turnover values who trade more often via internet also check their e-mails more often and thus answered directly after they received the first e-mail. The above mentioned results suggest that the two groups can be regarded as two random subsamples of the whole group of investors who received e-mails. In the next sections, we analyze, by using cross-sectional regressions, whether these investor characteristics drive our results.

The investors were asked to state upper and lower bounds of 90% confidence intervals to questions concerning stock market forecasts (Deutscher Aktienindex DAX, Nemax50 Performance Index, BASF, Deutsche Telekom) for the end of the year 2001.[12]

The questions concerning return expectations were as follows:

> *For the following questions, please give three estimates each. The true answer to the questions (e.g., in the first question the value of the DAX at the end of this year) should …*

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9 See Glaser (2003) and Table II for further details on these characteristics.

10 In addition, the whole group of the 215 investors who have answered either in August or September is not significantly different from the whole group of investors or the group of investors that have not responded to the questionnaire. See Glaser and Weber (2004a) for details.

11 See Glaser (2003).

12 There was a fifth question which was a prediction concerning the future price of a stock which was a member of the Nemax50 index in the year 2001. This question was necessary for calculating the overconfidence score based on stock market forecasts in Glaser and Weber (2004a). All results are similar to the predictions of the Nemax50. However, the time series of past prices is very short for this stock which makes it, for example, impossible to compare volatility estimates with historical volatilities. We therefore exclude the answers concerning price and volatility forecasts of this stock in this paper.

Table I. Characteristics of the two groups of respondents

This table presents descriptive statistics of various characteristics (age, stock market investment experience in years, information in hours per week, number of transactions in all security categories, number of stock transactions, mean monthly stock portfolio turnover, stock portfolio value in EUR, income in EUR, mean monthly stock portfolio performance) of the two groups of respondents as well as the p-value of a Mann-Whitney test (Null hypothesis is that the two populations are from the same distribution). Furthermore, the table shows the percentage of men and women, the percentage of investors who assess their investment strategy as high risk, and the percentage of warrant traders in both groups. See Table II for further information on these variables.

		First group	Second group	p-value (Mann-Whitney)
Respondents		129	86	
Age	Median	38	38	0.5603
	Mean	39.65	40.65	
	Standard deviation	9.34	10.60	
	Observations	115	68	
Investment experience (in years)	Median	7.5	7.5	0.6086
	Mean	5.39	5.55	
	Standard deviation	3.14	2.90	
	Observations	95	64	
Information (in hours per week)	Median	4	5	0.8573
	Mean	5.64	6.62	
	Standard deviation	4.81	8.38	
	Observations	129	85	
Number of transactions (all security categories) (Jan 1997–mid Apr 2001)	Median	105	107.5	0.8535
	Mean	166.22	141.09	
	Standard deviation	225.52	135.59	
	Observations	129	86	
Number of stock transactions (Jan 1997–mid Apr 2001)	Median	55	49.5	0.9856
	Mean	89.38	98.34	
	Standard deviation	109.53	124.09	
	Observations	125	80	
Mean monthly stock portfolio turnover	Median	0.36	0.28	0.0397**
	Mean	1.30	1.07	
	Standard deviation	4.21	3.97	
	Observations	122	77	
Mean monthly stock portfolio value (in EUR)	Median	13,139.87	20,897.84	0.0082***
	Mean	34,601.65	41,053.47	
	Standard deviation	123,173.30	67,075.18	
	Observations	125	77	
Income (in EUR)	Median	38,346.89	38,346.89	0.0946*
	Mean	48,012.14	59,559.38	
	Standard deviation	25,805.54	30,779.31	
	Observations	42	30	
Mean monthly stock portfolio performance	Median	0.0042	0.0062	0.1653
	Mean	0.0028	0.0032	
	Standard deviation	0.0207	0.0239	
	Observations	120	75	
Gender	Men	94.57%	94.19%	
	Women	5.43%	5.81%	
High risk investment strategy	Yes	12.40%	8.14%	
	No	87.60%	91.86%	
Warrant trader	Yes	44.19%	44.19%	
	No	55.81%	55.81%	

Table II. Definition of variables

This table summarizes and defines the independent variables of the regression analysis in this paper and presents their respective data source.

Variables	Data source	Description
Age	Self-reported data collected by the online broker at the time each investor opened the account.	Age of investor.
Experience	Self-reported data collected by the online broker at the time each investor opened the account.	Stock market investment experience in years.
Information	Questionnaire	Information in hours per week.
Turnover	Transaction and portfolio data	Average of the monthly stock turnover from January 1997 to March 2001.
Stock portfolio value	Transaction and portfolio data	Average of the monthly stock portfolio value of stocks that were bought in DEM or EUR and that are covered in Datastream.
Gender (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable that takes the value 1 if the investor is male.
High risk strategy (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable that takes the value 1 if the investment strategy is characterized as high risk.
Warrant trader (dummy)	Transaction and portfolio data	Dummy variable which takes the value 1 when the investor trades warrants at least once in the period from January 1997 to mid April 2001.
Stock portfolio performance	Transaction and portfolio data	Average of the monthly stock portfolio performance from January 1997 to March 2001 (with at least 12 observations available).
September 11 (dummy)	Questionnaire	Dummy variable that takes the value 1 if the investor answered the questionnaire after September 11.
Stock in portfolio (dummy)	Questionnaire	Dummy variable that takes the value 1 if the respective stock was in the portfolio at the time the questionnaire was answered.
Return [month –6 to day –1]	Datastream	Past return of the respective index or stock over the last 6 months.
Return [day –10 to day –1]	Datastream	Past return of the respective index or stock over the last 10 days.
Return [month –6 to day –11]	Datastream	Past return of the respective index or stock over the last 6 months until day –11.

Lower Bound:	*... with a high probability (95%) not fall short of the lower bound.*
Estimate:	*... should equally likely be above respectively below your estimate.*
Upper Bound:	*... with a high probability (95%) not exceed the upper bound.*

These types of questions are often used to measure the degree of miscalibration of subjects (see, for example, Lichtenstein et al. (1982), Russo and Schoemaker (1992), Klayman et al. (1999), Soll and Klayman (2004), and Griffin and Brenner (2004)) or to measure the volatility forecast of investors (see, for example, De Bondt (1998), Graham and Harvey (2003), Hilton (2001), and Siebenmorgen and Weber (2004)).

Table III presents descriptive statistics of the answers provided by the individuals in our investor sample. This table presents means of the price and index level forecasts of the two groups of respondents. In addition, the table shows the price and index level of the respective time series at the beginning of the year 2001 and at the time the forecast was made. The last column contains p-values of a two-sided Mann-Whitney test (Wilcoxon ranksum test). Null hypothesis is that the two populations are from the same distribution (return forecasts are equal in both groups). The main finding is that the forecasted levels are *lower* after September 11. However, only the lower bound is significantly (at least at the 10% level) lower after September 11. The upper bound is never significantly lower in the second group.[13] These results results can be interpreted in the following way. Stock prices have a temporary and a permanent component (see Fama and French (1988)). Table III shows that the second set of forecasts reflect a permanent "bad news" component but most of the large drop is regarded as temporary. These results suggest that the forecasts of our investor group can be characterized by a mean reverting model and that investors seem to have a "true" price level in mind towards which current price levels will trend. This "true" price level seems to be only slightly affected by the terror attacks. We come back to this issue in the next sections where we analyze the points discussed above more formally.

4. Results on Mean Return Estimates

4.1. MEAN RETURN ESTIMATES: BASIC RESULTS

In this subsection, we analyze the return point forecasts until the end of the year 2001 (i.e., over a horizon of 21 and 14 weeks, respectively) of our investor group. The investors were asked to state their median forecast of the value of two indexes

[13] Graham and Harvey (2003) also find that differences in forecasts before and after September 11 are not significantly different and attribute this finding to the low number of observations in their study.

Table III. Price and index level forecasts

This table presents means of the price and index level forecasts of the two groups of respondents. In addition, the table shows the price and index level of the respective time series at the beginning of the year 2001 and at the time the forecast was made. The last column contains p-values of a two-sided Mann-Whitney test (Wilcoxon ranksum test). Null hypothesis is that the two populations are from the same distribution (price or index level forecasts are equal in both groups). * indicates significance at 10%; ** indicates significance at 5%.

		First group August 2nd, 2001	Second group September 20, 2001	p-value (Mann-Whitney)
DAX	Index level at the beginning of the year 2001	6433.61		
	Index level when forecast was made	5777.28	3809.67	
	Lower bound	4970.26	4600.67	0.0240**
	Median	5726.79	5520.40	0.3121
	Upper bound	6340.49	6171.33	0.4695
Nemax50	Index level at the beginning of the year 2001	2869.01		
	Index level when forecast was made	1261.30	749.11	
	Lower bound	1150.54	1003.03	0.0527*
	Median	1624.29	1442.50	0.0487**
	Upper bound	2194.69	2125.68	0.5327
BASF	Price level at the beginning of the year 2001	48.45		
	Price level when forecast was made	45.80	31.65	
	Lower bound	39.88	37.20	0.0807*
	Median	47.36	45.26	0.2378
	Upper bound	53.52	51.82	0.6007
Deutsche	Price level at the beginning of the year 2001	32.10		
Telekom	Price level when forecast was made	24.11	16.01	
	Lower bound	20.34	18.34	0.100*
	Median	26.35	24.23	0.0560*
	Upper bound	31.39	30.03	0.3909

(Deutscher Aktienindex DAX, Nemax50 Performance Index) and the prices of two German stocks (BASF, Deutsche Telekom) for the end of the year 2001. In the remainder of this paper, these four time series are indicated by the subscript i, $i \in \{1, 2, 3, 4\}$. We first transform these price or index value forecasts of individual k into returns[14]:

$$r(p)_i^k = \frac{x(p)_i^k}{\text{value}_i^{t_j}} - 1,\ \ p \in \{0.05, 0.5, 0.95\},\ \ i \in \{1, 2, 3, 4\},$$

$$j \in \{1, 2\},\ \ k \in \{1, \ldots, 215\}. \tag{1}$$

[14] Some studies ask directly for returns, others ask for prices. Our method of elicitation was, among others, used by De Bondt (1998), Kilka and Weber (2000) and Loeffler and Weber (1997).

t_1 indicates August, 2nd, t_2 September, 20th.[15] $x(p)$ denotes the p fractile of the stock price or index value forecast, $r(p)$ denotes the p fractile of the respective return forecast with $p \in \{0.05, 0.5, 0.95\}$.

In line with the literature (see, for example, De Bondt (1998), Graham and Harvey (2003), and Kilka and Weber (2000)), we analyze two measures of return forecasts. Our first return forecast measure is the median divided by the value of the respective index or the price of the respective stock. We call this forecast the median return forecast.

According to Keefer and Bodily (1983), our next measure (henceforth mean return forecast) of time series i, $i \in \{1, 2, 3, 4\}$, for individual k, $k \in \{1, \ldots, 215\}$ is:

$$\text{mean}_i^k = 0.185 \cdot r(0.05)_i^k + 0.63 \cdot r(0.50)_i^k + 0.185 \cdot r(0.95)_i^k, \tag{2}$$

where $r(p)_i^k$ denotes the p fractile of the return distribution with $p \in \{0.05, 0.5, 0.95\}$. Keefer and Bodily (1983) show numerically that Equation (2) serves as a good three-point approximation of the mean of a continuous random variable.

Table IV presents the results of return point forecasts. The first observation is that the investors in both groups did not answer all questions concerning stock market predictions. For example, 115 of 129 investors, who answered the questions after the first e-mail, provided median as well as upper and lower bound of a confidence interval to forecast DAX returns. Focusing on the DAX forecast, the median of the mean DAX return forecast is ten times higher after September 11 than before. In the first group (time of response was August 2nd, 2001), the median across subjects is 5.14% over the 21 week horizon until the end of the year 2001. In the second group the median of the return forecast is 56.52%, showing that investors expect stock prices to return to previous levels. A two-sided Mann-Whitney test (Null hypothesis: the two populations are from the same distribution) shows that the difference is highly significant ($p < 0.0001$). Similar results are obtained when we focus on the median return forecast.

Table I shows that there are significant differences in turnover and stock portfolio value between the two investor groups. To assure that the differences in return forecasts shown in Table IV are not driven by investor characteristics, we run cross-sectional regressions on the determinants of the mean return (point) forecasts of the investors. The results are presented in Table V. The independent variables used in the regressions are defined in Table II.[16] Table V shows that the results are almost

[15] The exact time of response is not available. Furthermore, we do not know whether investors answered Thursday night, or on Friday, Saturday, or Sunday. Thus, we use the Thursday closing price in both groups to calculate expected returns. All results are similar when we use the average of the Thursday closing price and the Friday closing price instead of the Thursday closing price in our calculations. Note, that our study shares this shortcoming of not knowing the exact date of response with several other studies. See the survey of MacDonald (2000, p. 92), for details.

[16] We use the natural logarithm of the stock portfolio turnover and the stock portfolio value as these variables are positively skewed. Tests show, that we thus avoid problems like non-normality,

Table IV. Return forecasts

This table presents medians of the mean and the median return forecast as well as the difference between the return forecasts of the two groups of respondents. Median and mean return forecast are defined in Subsection 4.1. In addition, the table shows the past six month and 10 day return of the respective index or stock until the date of response as well as the respective actually realized returns from the date of response until the end of the year 2001. The last column contains p-values of a two-sided Mann-Whitney test (Wilcoxon ranksum test). Null hypothesis is that the two populations are from the same distribution (return forecasts are equal in both groups).

			First group August 2nd, 2001 (1)	Second group September 20, 2001 (2)	Difference of returns (2)–(1)	p-value (Mann-Whitney)
DAX	Past six month return		−12.97%	−34.11%		
	Past 10 day return		−0.90%	−18.42%		
	Mean forecast	Median across subjects	5.14%	56.52%	51.38%	<0.0001
		No. Observations	115	75		
	Median forecast	Median across subjects	3.86%	57.49%	53.63%	<0.0001
		No. Observations	117	75		
	Actual return until the end of 2001		−10.68%	35.45%	46.13%	
Nemax50	Past six month return		−51.73%	−55.31%		
	Past 10 day return		7.91%	−17.88%		
	Mean forecast	Median across subjects	23.19%	95.30%	72.11%	<0.0001
		No. Observations	111	74		
	Median forecast	Median across subjects	18.92%	100.24%	81.32%	<0.0001
		No. Observations	113	74		
	Actual return until the end of 2001		−8.82%	53.53%	62.35%	
BASF	Past six month return		−4.38%	−32.08%		
	Past 10 day return		−2.55%	−27.49%		
	Mean forecast	Median across subjects	7.39%	51.07%	43.68%	<0.0001
		No. Observations	99	66		
	Median forecast	Median across subjects	9.17%	51.66%	42.49%	<0.0001
		No. Observations	103	66		
	Actual return until the end of 2001		−8.62%	32.23%	40.85%	
Deutsche Telekom	Past six month return		−29.30%	−39.81%		
	Past 10 day return		−4.74%	5.26%		
	Mean forecast	Median across subjects	10.07%	58.46%	48.39%	<0.0001
		No. Observations	108	73		
	Median forecast	Median across subjects	11.99%	56.15%	44.16%	<0.0001
		No. Observations	112	73		
	Actual return until the end of 2001		−19.54%	21.17%	40.71%	

completely explained by the September 11 dummy variable. Other explanatory variables (investor characteristics) are not significantly related to the return forecasts. The only variable that is significantly related to the forecasted returns for all four time series is the past realized stock portfolio performance of an investor. This result is intuitive: The higher the past realized stock portfolio performance the more positive is the future outlook for the stock market of the respective investor. Furthermore, we asked the group of investors whether they own the stocks of BASF and Deutsche Telekom at the date of response. Note, that portfolio positions or transaction data are unavailable at the date of response of the investors. Table V shows that the results concerning return forecasts presented in this paper are similar for investors who own or do not own the respective stock at the time of response.[17]

To summarize, investors in our sample expect mean reversion of stock prices after the terror attacks. This result is driven by September 11 and the large drops in share prices after this event.[18] We come back to this issue in the next subsection. We explicitly analyze whether the main result, the belief in mean reversion, is completely driven by past returns or whether September 11 "adds" something in explaining the results.

4.2. MEAN RETURN ESTIMATES: DISCUSSION

The results presented in the previous subsection, i.e., the high return expectations after the terror attacks, do not coincide with the findings of Graham and Harvey (2003) who analyze forecasts of the one year equity premium of CFOs. On September 10, the mean one year equity premium forecast was 0.05% whereas the post crisis estimate was -0.70%. The difference might be explained by the fact that the CFOs in their study possibly answered on different days and perhaps only very few days after the terror attacks in the situation with the highest uncertainty.[19] Our subjects made their forecasts after large drops in stock prices until September 20, which was exactly the day with the lowest blue chip share prices in Germany in the year 2001 (see the German blue chip index DAX in Figure 1). In addition, the results of Graham and Harvey (2003) are not significant due to the low number of observations.

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non-linearity, and heteroscedasticity in the cross-sectional regression analysis. See Spanos (1986, chapter 21, especially, pp. 455–456), Davidson and MacKinnon (1993, chapter 14), and Atkinson (1985, pp. 80–81).

[17] The low adjusted R-squared value in the Nemax50 regression might be explained by the time series chart of the Nemax50. After years of, compared to historical German stock returns, unusually high returns until March 2000, the index dramatically dropped afterwards.

[18] Note, that the different forecast horizons of the two investor groups do not explain the findings. Anything else equal, investors in the second group (i.e., the investors with a shorter forecast horizon), should have lower return expectations, given that the expected stock return over, say, a month, is a positive constant.

[19] The exact dates do not appear in the Graham and Harvey (2003) study. Furthermore, the U.S. stock exchanges closed until September 17 whereas the German stock exchanges remained open.

Table V. Determinants of return forecasts: Cross-sectional segressions

This table presents cross-sectional regression results on the determinants of the mean return (point) forecasts of the investors. Mean return (point) forecasts are defined in Section 4. The independent variables used in the regressions are defined in Table II. Absolute values of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

	DAX	Nemax50	BASF	Deutsche Telekom
Age	0.002	−0.001	0.002	−0.001
	(0.86)	(0.09)	(0.76)	(0.40)
Experience	0.002	0.011	0.007	0.011
	(0.23)	(0.41)	(0.77)	(0.97)
Information	0.0001	−0.005	−0.002	0.003
	(0.04)	(0.45)	(0.58)	(0.67)
ln(Turnover)	0.012	−0.053	0.002	0.045
	(0.62)	(0.88)	(0.12)	(1.77)*
ln(Stock portfolio value)	0.008	0.063	0.009	0.031
	(0.49)	(1.20)	(0.50)	(1.45)
Gender (dummy; men=1)	0.098	0.243	0.177	0.031
	(0.71)	(0.57)	(1.30)	(0.18)
High risk strategy (dummy)	−0.089	−0.422	−0.098	−0.166
	(1.29)	(1.97)*	(1.38)	(1.84)*
Warrant trader (dummy)	−0.038	−0.013	−0.069	−0.097
	(0.80)	(0.09)	(1.38)	(1.60)
Stock portfolio performance	2.596	6.308	1.724	2.303
	(2.64)***	(2.04)**	(1.68)*	(1.83)*
September 11 (dummy)	0.477	0.808	0.412	0.485
	(10.54)***	(5.70)***	(8.54)***	(8.39)***
Stock in portfolio (dummy)			0.003	0.013
			(0.04)	(0.23)
Constant	−0.717	−1.327	−0.665	−0.638
	(3.57)***	(2.10)**	(3.19)***	(2.45)**
Observations	109	107	93	104
Adjusted R-squared	0.54	0.27	0.48	0.45

There are other explanations for the different findings in the Graham and Harvey (2003) study compared to our results. Usually, investors expect higher returns for the stocks in their home country (see, for example, Shiller et al. (1996, p. 159), and Kilka and Weber (2000)). It is possible that return estimates of our investor sample for U.S. stocks would have been lower.

Furthermore, we observe extremely high return estimates after the terror attacks. This result is not unusual. Other studies document one year return estimates between 20% and 30%. For example, Shiller et al. (1996) find that Japanese investors were more optimistic about the Japanese market than were American investors. For example, at a one year horizon, there was often a spread of about 20 percentage points between the Japanese and the U.S. forecasts for the Japanese market even in years without events such as the 1987 stock market crash or the attacks of September 11.

Shiller (1987) finds results comparable to ours after the stock market crash of 1987. He sent out questionnaires to individual and institutional investors at the evening of the day of the crash (October 19, 1987) and the following four days to better understand the causes of the crash and investor behavior in a situation of suddenly dropping share prices. One question asked investors whether they knew when a rebound was to occur. A surprisingly high 29.2% of the individual investors answered "yes" in this unprecedented situation. Investors were thus pretty sure to know when the rebound was likely to occur. Furthermore, many individual investors stated "intuition" or "gut feeling" or just that they "knew there would be a rebound" as reasons for their conjectures.[20] Although we did not ask similar (qualitative) questions, the above mentioned findings by Shiller (1987) might present explanations for our findings of very high return forecasts after the terror attacks in our sample. The investors in our sample, like the investors in the Shiller (1987) sample, also seem to know when the rebound will occur. Their predictions suggest that they think the rebound will occur until the end of the year 2001.[21]

Furthermore, the documented optimism with regard to stock market outlooks shortly after September 11 is not a peculiarity of our investor sample. A few weeks after the terror attacks (to be more precise, on November 7, 2001), Schnusenberg (2002) argued that the observed optimism in the U.S. is unwarranted. We do not argue that the optimism is unwarranted. We note, however, that the optimism concerning stock market forecasts after September 11 is not unique to our investor sample.

Our results are also consistent with the results in the paper of O'Connor et al. (1997). In their laboratory-based study they find that people generally have problems forecasting downward sloping series. They document a behavior that is consistent with a general tendency to anticipate that downward series will reverse

[20] Shiller (1987, pp. 12–13).

[21] Unfortunately, we are not able to analyze whether the respondents of the second group actually bought stocks at the time of response. Due to an organizational restructuring it was impossible to obtain transaction data apart from the data set mentioned above.

themselves. A similar mechanism might be at work for our second group of investors who are confronted with a big downturn in stock prices over a short period of time.

Moreover, the investors in our sample are not completely wrong in their forecasts. When we compare the return forecasts with the actually realized returns until the end of the year 2001, we first observe that investors are optimistic about the future performance of stock prices in both groups. The actual return is overestimated by approximately 15 percentage points in the first group and by approximately 20 percentage points in the second group. However, the return forecast of the second group of about 56% over the 14 week horizon is only 1.6 times the value of the actual return until the end of the year which was 35.45%.

The remaining results of Table IV show that the results concerning DAX return forecasts are robust. Similar results are obtained for the other three time series. The mean and median return forecasts of the investors in our sample are significantly higher in the second group. The actual returns are overestimated in both groups. The second group of investors states return forecasts that are approximately twice as high as the true returns.

Furthermore, column six of Table IV shows that even the difference between the return forecasts of investors in both groups are about the same as the differences in the actually realized returns until the end of the year 2001 across the four time series. For example, the difference of the actual returns of the BASF stock from the respective time of response until the end of the year 2001 is 40.85%. The difference of the return forecasts in both groups is about 43%. This inspection of the data shows that our investor sample states forecasts that seem to be quite plausible.

Why is the expected return for the Nemax50 in the second group about twice as high as the expected return for the DAX? The return of both indexes from September 10 until September 20 is similar (about −18%, see Table IV). Accordingly, the drop in the values of the two indexes from September 10 until September 20 does not help to explain the high expected Nemax50 returns. Perhaps the returns of both indexes over the whole year 2001 until September 20 or over the six month period prior to the questionnaires may serve as an explanation. Whereas the DAX "only" dropped by 40% in this period, the Nemax50 almost crashed with a return of about −75% (see Figure 1 and Figure 2 or the past six month returns presented in Table IV). As our investors expect mean reversion of stock prices, these return differences might be an explanation for the higher expected return for the Nemax50: The lower the returns in the previous months, the higher individuals' return forecasts.

We analyze this issue more formally in a cross-sectional regression analysis including past returns. The results are presented in Table VI. To create this table, we stack data of all four assets in one regression. We thus have eight different past return histories on which to condition the forecasts. Consider, for example, Regression (1). We include the same set of control variables used in the previous

Table VI. Determinants of return forecasts: Cross-sectional regressions including past returns

This table presents cross-sectional regression results on the determinants of the mean return (point) forecasts of the investors. Mean return (point) forecasts are defined in Section 4. The independent variables used in the regressions are defined in Table II. Absolute values of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

	All investors (1)	First group (2)	Second group (3)	All investors (4)	First group (5)	Second group (6)	All investors (7)
Age	−0.001	−0.001	0.001	−0.000	−0.001	0.001	0.0003
	(0.25)	(0.40)	(0.35)	(0.07)	(0.42)	(0.34)	(0.13)
Experience	0.014	0.023	−0.009	0.011	0.023	−0.010	0.009
	(1.56)	(2.56)**	(0.56)	(1.30)	(2.59)**	(0.56)	(1.09)
Information	0.002	−0.003	−0.001	0.001	−0.003	−0.001	−0.001
	(0.67)	(0.54)	(0.22)	(0.20)	(0.56)	(0.21)	(0.21)
ln(Turnover)	0.001	0.004	−0.013	0.001	0.004	−0.013	0.001
	(0.04)	(0.21)	(0.36)	(0.05)	(0.19)	(0.35)	(0.05)
ln(Stock portfolio value)	0.047	0.047	0.011	0.038	0.047	0.011	0.031
	(2.70)***	(2.78)***	(0.33)	(2.32)**	(2.79)***	(0.33)	(1.92)*
High risk strategy (dummy)	−0.222	−0.156	−0.271	−0.208	−0.157	−0.271	−0.196
	(3.07)***	(2.26)**	(2.01)**	(3.05)***	(2.27)**	(2.00)**	(2.98)***
Warrant trader (dummy)	−0.032	−0.055	−0.062	−0.051	−0.055	−0.063	−0.063
	(0.66)	(1.16)	(0.70)	(1.09)	(1.16)	(0.71)	(1.40)
Stock portfolio performance	2.803	4.426	2.502	3.027	4.430	2.488	3.222
	(2.71)***	(3.70)***	(1.67)*	(3.11)***	(3.71)***	(1.66)*	(3.41)***
Return [month –6 to day –1]	−1.440	−0.601	−3.046				
	(10.69)***	(4.95)***	(7.29)***				
Return [day –10 to day –1]				−2.356	0.736	−2.214	−1.119
				(10.90)***	(0.99)	(5.11)***	(3.53)***
Return [month –6 to day –11]				−1.465	−0.406	−2.355	−1.069
				(11.70)***	(2.24)**	(7.30)***	(7.46)***
September 11 dummy							0.344
							(5.20)***
Constant	−0.592	−0.489	−0.613	−0.556	−0.437	−0.375	−0.441
	(3.30)***	(2.76)***	(1.70)*	(3.30)***	(2.44)**	(1.08)	(2.67)***
Observations	413	252	161	413	252	161	413
Adjusted R-squared	0.27	0.20	0.30	0.36	0.21	0.30	0.40

subsection.[22] We also include a past return variable which is the past return of the asset in the six month window prior to the respective questionnaire date.[23] Regres-

[22] We checked the robustness of the results by analyzing various sets of explanatory variables. All results presented in this paper are robust. We do not include the gender variable due to the low number of female investors in the second group as we also run regressions for the second group of respondents only.

[23] The choice of this time window is motivated by studies showing that past monthly returns beyond lag 6 have little or no power in explaining security turnover or investor transaction behavior. See, for example, Glaser and Weber (2004b), Grinblatt and Keloharju (2000) or Statman et al. (2004). Our regression results are similar, but less strong, when we include past 12 month returns. However, when we include a past return variable over the time horizon from seven to 12 months before the respective questionnaire (in addition to the past six month return variable), this variable has almost no explanatory power. Note, that these results are not inconsistent with the Fama and French (1988) study which documents negative serial correlation in multi-year returns. Our forecast horizons are

sion (1) in Table VI once again shows that investors expect mean reversion. The coefficient of the past return variable is significantly negative. This result is also true for the first investor group alone (see Regression (2)). The coefficient (-0.6) is similar in magnitude to the results presented in the Fama and French (1988) study. Fama and French (1988) regress current returns on past returns over several years and they also find a significantly negative relation between current and past returns suggesting mean reversion in long horizon stock returns. A coefficient of -0.6 indicates that, for example, a 10 percent negative return, on average, is followed by a 6 percent positive return forecast for the first group of investors. These regression results are broadly consistent with the results shown in Table IV when we focus on the medians of the return forecasts in connection with the past six month returns. For the second group of investors (Regression (3)), the results are similar in the way that the past return variable is significantly negatively related to the return forecast. However, the coefficient is higher than the one in Regression (2). Unreported regression results show that the coefficient of the past return variable is always between -2 and -3. Thus, investors, on average, expect that the negative past returns are compensated or even overcompensated over the next weeks.[24] One explanation for this finding might be the long period of past negative returns over a longer horizon for the second group of investors, in addition to the sharp drop after September 11. Regressions (4) to (6) show the results when we decompose the past six month returns into two returns measured over two non-overlapping intervals to explicitly capture the drop in share prices over the 10 day window from the terror attacks until the date of the second questionnaire. The past 10 day return variable is not significant for the first group of investors. Although forecasts of both investor groups can be characterized by a mean reverting model, past 10 day returns seem to be important only in the case of large drops over this time period. Furthermore, past returns do not completely explain the positive return forecasts of the second group of respondents. Regression (7) shows that the September 11 dummy variable remains significant with a positive sign even when we control for the past 10 day return, i.e., the drop in share prices that can be ascribed to the terror attacks. This is in line with Schnusenberg (2002). Around 10 days after the attacks, i.e., after the period of high uncertainty and the fear of further attacks, the outlook was positive again.

shorter and the investors studied in the two papers mentioned in this footnote usually have a shorter investment horizon than several years.

[24] Note, that these findings are not inconsistent with the findings presented in Tables III and IV.

5. Results on Volatility Forecasts

5.1. VOLATILITY FORECASTS: BASIC RESULTS

Table VII presents estimations of the standard deviation or volatility of returns. The return volatility estimate of individual k, $k \in \{1, \ldots, 215\}$, for time series i, $i \in \{1, 2, 3, 4\}$, is calculated as follows (see Keefer and Bodily (1983)):[25]

$$\text{stddev}_i^k = \sqrt{0.185 \cdot (r(0.05)_i^k)^2 + 0.63 \cdot (r(0.50)_i^k)^2 + 0.185 \cdot (r(0.95)_i^k)^2 - (\text{mean}_i^k)^2}, \quad (3)$$

with mean_i^k as given in Equation (2). $r(p)_i^k$ denotes the p fractile of the return distribution with $p \in \{0.05, 0.5, 0.95\}$. Keefer and Bodily (1983) show numerically that Equation (3) serves as a good three-point approximation of the standard deviation of a continuous random variable.

The main (and perhaps unsurprising) result of Table VII is summarized as follows. After September 11, the volatility forecasts are higher. A Mann-Whitney test rejects equality of volatility estimates for all four time series (all p-values are below 0.0001).

In the case of the DAX, we are able to calculate the implied volatility over the respective forecast horizon using the German VDAX. The VDAX expresses the fluctuation range or implied volatility of the DAX index, as expected by the forward market.[26] Volatilities are quoted in annualized percentages. To calculate 21 week and 14 week percentages we multiply the VDAX values of August 2nd, 2001 and September 20, 2001 by $\sqrt{21/52}$ and $\sqrt{14/52}$, respectively.

The implied volatility of the DAX until the end of the year 2001 is 12.73% on August 2nd, 2001 and 22.90% on September 20, 2001. Thus, the DAX volatility estimates of the investors in our sample, especially the increase of the volatility estimate after the terror attacks seem to be reasonable. One interpretation of this result is that investors rationally expect a higher risk in the economy. Alternatively, this result can be interpreted in the way that investors expect a higher standard deviation of returns as a result of the experience of high past (absolute) returns. In addition, it is reasonable that the DAX volatility estimate is the lowest volatility estimate in both groups followed by the BASF, Deutsche Telekom, and Nemax50 volatility estimate. BASF and Deutsche Telekom are members of the DAX index which contains 30 German blue chip stocks. An index is more diversified than a single stock that is part of the index. The index therefore (usually) has a lower volatility. Furthermore, BASF is a low risk value stock and Deutsche Telekom is

[25] We also checked the robustness of all the results presented in this subsection by calculating the volatility estimate using another measure: the difference between the high forecast and the low forecast, divided by the price level and multiplied by 100. This measure is, for example, used in De Bondt (1998, Table 1, p. 839). Using this measure does not change our results.

[26] See the description of the VDAX volatility index at www.deutsche-boerse.com.

Table VII. Volatility forecasts

This table presents median volatility forecasts of the two groups of respondents for two German stock market indexes and two German blue chip stocks. Volatility forecasts are calculated as described in Section 5. In addition, the table shows historical volatilities of (non-overlapping) 21 week returns (column 3) and 14 week returns (column 4), respectively. For the Nemax50 and Deutsche Telekom, there is only a very short time series of price data available. Therefore, we calculate historical volatilities until March 2003. For the DAX, the table reports the implied volatility of the respective response date as well. These implied volatilities were calculated using the VDAX. The VDAX expresses the fluctuation range or implied volatility of the DAX index, as expected by the forward market. See Section 5 for details. Column 5 contains p-values of a two-sided Mann-Whitney test (Wilcoxon ranksum test). Null hypothesis is that the two populations are from the same distribution (volatility forecasts are equal in both groups).

		First group August 2nd, 2001	Second group September 20, 2001	p-value (Mann-Whitney)
DAX	Median across subjects	6.53%	12.39%	<0.0001
	Number of Observations	115	75	
	Historical standard deviation (January 1988-time of response)	14.65%	12.31%	
	Implied volatility	12.73%	22.90%	
Nemax50	Median across subjects	18.49%	33.74%	<0.0001
	Number of Observations	111	74	
	Historical standard deviation (January 1998–March 2003)	39.94%	41.48%	
BASF	Median across subjects	6.97%	14.43%	<0.0001
	Number of Observations	99	65	
	Historical standard deviation (January 1988–time of response)	15.65%	11.80%	
Deutsche Telekom	Median across subjects	13.00%	19.23%	<0.0001
	Number of Observations	108	73	
	Historical standard deviation (November 1996–March 2003)	35.32%	27.84%	

a high risk telecom stock which suggests that BASF stock returns should have a lower volatility than Deutsche Telekom stock returns. Nemax50, the New Market index in Germany, is a high risk segment.

Table VIII presents cross-sectional regression results on the determinants of the volatility forecasts of the investors to analyze whether investor characteristics drive the results shown in Table VII. The independent variables used in the regressions are defined in Table II. Table VIII shows that the only significant variable at the 1% level is the September 11 dummy variable (with the Nemax50 as the only exception). The low adjusted R-squared value in the Nemax50 regression, which is similar to the result in Table V, might be explained by the time series chart of the Nemax50. After years of, compared to historical German stock returns, unusually high returns until March 2000, the index dramatically dropped afterwards.

Unreported results show that the skewness of the return distribution given by the investors in our sample is unaffected by September 11. In addition, we find that investors who state higher return estimates, on average, also state higher volatility estimates. The investors in our sample, as a group, seem to understand the risk-return trade-off.

5.2. VOLATILITY FORECASTS: DISCUSSION

Our results are in line with the Graham and Harvey (2003) study. As volatility benchmarks we use several historical volatilities (volatilities of non-overlapping 21 week returns (column 3 of Table VII) and 14 week returns (column 4 of Table VII)).[27] Historical volatilities are often used as an objective volatility benchmark or an estimate for the future volatility.[28] Prior to the terror attacks the historical volatility of returns over the respective time horizons is underestimated in all four cases. This finding is in line with the overconfidence literature.[29] Overconfidence is regarded as "perhaps the most robust finding in the psychology of judgment" (De Bondt and Thaler (1995, p. 389)). Most behavioral models incorporate judgment biases into theories of financial markets by assuming that at least some market participants are overconfident in the way that they overestimate the precision of their knowledge or underestimate the variance of information signals. As a consequence, their confidence intervals for the value of a risky asset are too tight when compared to the rational benchmark. This assumption is in line with a variety of psychological studies that are often referred to as the "calibration" literature (see

[27] For the Nemax50 and Deutsche Telekom, there is only a very short time series of price data available. Therefore, we calculate "historical" volatilities, or, in other words, our volatility benchmark, until March 2003. Note, that the volatility does not drop after September 11. We calculate non-overlapping 21 week and 14 week returns for (almost) the same period. The results are similar when we calculate the standard deviation until, say, the end of 2003. The variance of the 14 week returns should be lower than the variance of the 21 week returns in any case. More generally, this information is used, for example, in variance ratio tests to test the random walk property of a time series. Without autocorrelation and under the assumption of stationarity, the ratio of the variance of a two-period return to twice the variance of a one period return should be one. See Campbell et al. (1997, p. 48 and p. 68).

[28] See, for example, De Bondt (1998), Graham and Harvey (2003), and Siebenmorgen and Weber (2004).

[29] See Glaser and Weber (2004a) and Glaser, Nöth and Weber (2004) for surveys of the overconfidence literature. The term "overconfidence" summarizes many different phenomena: investors overestimate the precision of their knowledge, their probability estimates are often not well calibrated, they overestimate their ability to do well in the future, they think that they can control and predict random tasks, and they assess themselves as above average with regard to skills when compared to others. See, for example, Barucci (2003, p. 279).

Table VIII. Determinants of volatility forecasts: Cross-sectional regressions

This table presents cross-sectional regression results on the determinants of the volatility forecasts of the investors. Volatility forecasts are defined in Section 5. The independent variables used in the regressions are defined in Table II. Absolute values of t statistics are in parentheses. * indicates significance at 10%; *** indicates significance at 1%.

	DAX	Nemax50	BASF	Deutsche Telekom
Age	−0.000005	−0.002	−0.00005	0.0002
	(0.01)	(0.18)	(0.06)	(0.17)
Experience	−0.003	0.031	0.004	0.0002
	(1.54)	(0.88)	(1.31)	(0.05)
Information	0.001	0.001	−0.0004	0.001
	(1.31)	(0.10)	(0.35)	(0.65)
ln(Turnover)	0.002	−0.124	−0.005	0.0003
	(0.34)	(1.62)	(0.85)	(0.03)
ln(Stock portfolio value)	0.003	0.025	0.003	0.004
	(0.65)	(0.38)	(0.52)	(0.51)
Gender (dummy; men = 1)	0.007	−0.097	0.004	−0.032
	(0.19)	(0.18)	(0.09)	(0.47)
High risk strategy (dummy)	−0.005	−0.149	−0.003	−0.033
	(0.30)	(0.55)	(0.16)	(0.95)
Warrant trader (dummy)	0.005	−0.004	0.001	−0.006
	(0.46)	(0.02)	(0.04)	(0.26)
Stock portfolio performance	−0.167	1.917	0.174	0.147
	(0.67)	(0.49)	(0.55)	(0.30)
September 11 (dummy)	0.055	0.232	0.055	0.105
	(4.80)***	(1.30)	(3.73)***	(4.65)***
Stock in portfolio (dummy)			0.026	0.043
			(0.96)	(1.95)*
Constant	−0.002	−0.219	−0.012	0.001
	(0.05)	(0.28)	(0.19)	(0.01)
Observations	109	107	93	104
Adjusted R-squared	0.17	0.00	0.10	0.15

Lichtenstein et al. (1982), Klayman (1999), Soll and Klayman (2004), and Griffin and Brenner (2004)). Before September 11, investors in our data set underestimate the variance of stock prices which is consistent with the assumptions of overconfidence models. However, after the crisis, the historical standard deviation of returns is overestimated in two cases (DAX, BASF). In contrast, Graham and Harvey (2003) find volatility estimates of one-year risk premiums of 6.79% prior to the terror attacks and 9.76% afterwards compared to historical standard deviations of one-year stock returns of 13.0% (1980–2000) or 20.1% (1926–2000) in the U.S.. In the cases of Nemax50 and Deutsche Telekom the historical volatility is underestimated. Note, however, the low number of past non-overlapping return observations for the Nemax50 and Deutsche Telekom used in calculating the standard deviation of returns which makes the historical standard deviation as volatility benchmark questionable in these two cases.

Glaser, Langer and Weber (2004) also find that people do not generally underestimate the variance of stock returns. They find that for short forecast horizons of only one week historical volatilities are also overestimated.

The higher volatility estimates of investors after September 11 might be a result of a rational anticipation of a higher uncertainty in the economy or a higher expected standard deviation of returns. However, a further explanation might be an anchoring and adjustment heuristic (see Tversky and Kahneman (1982)). A higher volatility might, at least in part, arise as investors first predict the value of an index or the price of a stock in the future. If they then build their confidence intervals by putting an interval with constant range around their point (or median) estimate, they will predict higher volatilities when stocks or indexes have lower nominal values as was the case after September 11.

Other reasons for deviations of forecasts in the two groups might be the different time horizons of the forecasts (21 versus 14 weeks) as both groups were asked to state end of the year prices. However, in our view, it is unlikely that the different time horizons will be a major driving force of our results. On the contrary, one would expect that, over a shorter horizon, return and volatility forecasts should, anything else equal, be *lower* for the second group. However, this is not the case. The driving forces of our results are the September 11 tragedy and the drop in share prices in the days after the terror attacks.

Similar to Table VI, we investigate this issue in greater detail using a cross-sectional regression analysis. The results are shown in Table IX. The main difference compared to the results shown in Table VI is that the September 11 dummy variable is no longer significant. The main results presented in this subsection are completely explained by past returns.

6. Results on Differences of Opinion

In this subsection, we especially focus on the level of agreement or disagreement among investors when making forecasts after large drops in share prices or

Table IX. Determinants of volatility forecasts: Cross-sectional regressions including past returns

This table presents cross-sectional regression results on the determinants of the volatility forecasts of the investors. Volatility forecasts are defined in Section 5. The independent variables used in the regressions are defined in Table II. Absolute values of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

	All investors (1)	First group (2)	Second group (3)	All investors (4)	First group (5)	Second group (6)	All investors (7)
Age	−0.000	0.001	−0.002	−0.000	0.001	−0.002	−0.000
	(0.15)	(0.47)	(0.38)	(0.13)	(0.46)	(0.38)	(0.14)
Experience	0.008	0.005	0.015	0.008	0.005	0.015	0.008
	(0.88)	(0.54)	(0.81)	(0.86)	(0.56)	(0.81)	(0.88)
Information	0.001	−0.006	0.002	0.001	−0.006	0.002	0.001
	(0.19)	(1.16)	(0.39)	(0.17)	(1.17)	(0.39)	(0.20)
ln(Turnover)	−0.035	−0.022	−0.066	−0.035	−0.022	−0.066	−0.035
	(1.74)*	(1.05)	(1.63)	(1.74)*	(1.07)	(1.62)	(1.74)*
ln(Stock portfolio value)	0.008	0.008	−0.002	0.007	0.008	−0.002	0.008
	(0.46)	(0.46)	(0.06)	(0.43)	(0.46)	(0.07)	(0.46)
High risk strategy (dummy)	−0.044	−0.059	−0.056	−0.043	−0.060	−0.055	−0.044
	(0.63)	(0.80)	(0.37)	(0.62)	(0.81)	(0.37)	(0.63)
Warrant trader (dummy)	−0.002	0.066	−0.103	−0.003	0.066	−0.103	−0.002
	(0.05)	(1.30)	(1.04)	(0.06)	(1.31)	(1.04)	(0.04)
Stock portfolio performance	0.565	1.424	0.291	0.578	1.427	0.283	0.565
	(0.56)	(1.11)	(0.17)	(0.58)	(1.12)	(0.17)	(0.56)
Return [month –6 to day –1]	−0.745	−0.535	−2.033				
	(5.68)***	(4.12)***	(4.38)***				
Return [day –10 to day –1]				−0.609	0.563	−1.356	−0.692
				(2.73)***	(0.70)	(2.81)***	(2.05)**
Return [month –6 to day –11]				−0.771	−0.379	−1.548	−0.798
				(5.98)***	(1.95)*	(4.31)***	(5.24)***
September 11 dummy							−0.023
							(0.33)
Constant	−0.150	−0.148	−0.530	−0.150	−0.107	−0.348	−0.158
	(0.86)	(0.79)	(1.32)	(0.87)	(0.56)	(0.89)	(0.90)
Observations	413	252	161	413	252	161	413
Adjusted R-squared	0.09	0.08	0.15	0.10	0.09	0.14	0.10

when interpreting publicly known events such as September 11. Does disagreement increase or decrease in these crisis situations?

The histograms shown in Figure 5 give a first impression of the level of heterogeneity of the expected median price levels in the two groups of respondents. The histogram of the second group shows, in contrast to the histogram of the first group, that the distribution of the forecasted median price levels has two separated peaks. In the first group, 75 out of 117 investors (64%) expect an increase of the

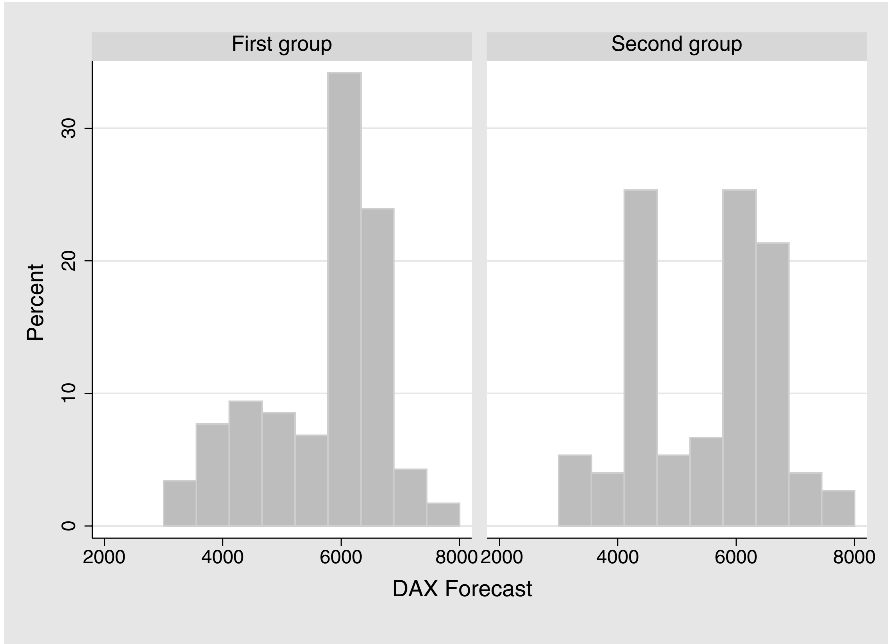

Figure 5. Histogram of the DAX index level forecasts by group.

DAX until the end of the year. After the terror attacks, 71 out of 75 investors (95%) expect an increase. These results show that it is difficult to draw conclusions about the level of heterogeneity using histograms alone.

Two measures are usually used in the literature to quantify the level of disagreement. First, we calculate simple standard deviation of return and volatility forecasts across subjects (used, for example, in Graham and Harvey (2003) as the measure of heterogeneity). Second, we also calculate another measure of differences of opinion. As in Diether et al. (2002), differences of opinion (henceforth *dop*) are calculated as the standard deviation of the forecasts divided by the respective absolute value of the mean forecast. Diether et al. (2002) analyze whether this measure of differences of opinion is related to the cross section of expected returns. They find that the higher their measure of differences of opinion (dispersion in analysts' earnings forecasts), the lower future returns of otherwise similar stocks.

In the literature, there is a discussion over which measure should be used to quantify opinion divergence (see, for example, Garfinkel (2004)). Whether a higher standard deviation is associated with a higher level of heterogeneity depends on the mean value. That is the reason why the *dop* measure as defined above is the preferred measure in the literature. However, one potential concern is that mean forecasts near zero generate very large *dop* measures (see also Garfinkel (2004, p. 12)). In the remainder of this section, we use both measures. However, in line with the literature, we argue, that our *dop* measure is the preferred measure.

Table X presents means of the mean and median return forecasts. Mean and median return forecast are defined in Subsection 4.1. Table X shows that the means of the return forecasts are similar in magnitude to the medians of the return forecasts presented in Table IV. The reason why we present the means of return forecasts in Table X (instead of the medians of the mean and median return forecast presented in Table IV) in addition to the standard deviation and our measure of differences of opinion is the fact that we scale the standard deviation by the absolute value of the mean forecast to calculate the *dop* measure.[30]

Table X shows that the standard deviation of forecasts across subjects is higher after September 11. In their survey of CFO stock return expectations, Graham and Harvey (2003) present related results by showing that past market returns are related to differences of opinion with regard to the one year risk premium estimate. High past (absolute) returns lead to higher differences of opinion as measured by the variance of forecasts across individuals.

However, when we scale the standard deviation by the absolute value of the mean forecast, Table X reports that differences of opinions *dop* concerning return forecasts are lower after the terror attacks. The differences of the *dop* measure of DAX return forecasts before and after the crisis are driven by the mean forecasts that are close to zero.

Table XI shows the mean of the volatility forecast. Volatility forecasts are defined in Section 5. The means of the volatility forecasts are similar in magnitude to the medians as presented in Table 5. The standard deviation of the volatility forecasts are higher after the terror attacks. However, when we focus on the *dop* measure, the picture is less clear. The *dop* values are similar for both groups. For the DAX and the BASF stock the *dop* measure is slightly lower after September 11. In contrast, for the stock of Deutsche Telekom the *dop* measure is slightly higher after the terror attacks. For the New Market index Nemax50, the *dop* measure is equal in both groups. Thus, differences of opinion with regard to volatility forecasts are largely unaffected by the terror attacks whereas differences of opinion concerning return forecasts are *lower* after the terror attacks.

Furthermore, another interesting finding is presented by Table X and Table XI. Differences of opinion are generally higher with regard to return (point) forecasts when compared to differences of opinion with regard to volatility forecasts. This finding is interesting as it presents an empirical test of modeling assumptions in the "differences of opinion" and the "overconfidence" literature.[31] In both types of models, investors often receive noisy signals which are the sum of two random variables: the value of the risky asset plus a random error term. Loosely speaking, "differences of opinion" models assume that investors disagree about the mean of the error term whereas investors in "overconfidence" models disagree about the

[30] We use the exact value of the standard deviation rather than the rounded values reported in Table X to calculate the differences of opinion measure.

[31] See Glaser and Weber (2004a) for a discussion of these two strands of literature.

Table X. Return forecasts: Differences of opinion

This table presents means of the mean and median return forecast. Mean and median return forecast are defined as in Subsection 4.1. Furthermore, the table shows standard deviation of return forecasts as well as the differences of opinion. Differences of opinion (*dop*) are calculated as the standard deviation of the return forecasts divided by the pespective absolute value of the mean return forecast.

			First group August 2nd, 2001	Second group September 20, 2001
DAX	Mean forecast	Mean	−0.0136	0.4360
		Standard deviation	0.18	0.29
		Differences of opinion *dop*	12.88	0.66
	Median forecast	Mean	−0.0087	0.4490
		Standard deviation	0.18	0.29
		Differences of opinion *dop*	20.19	0.65
Nemax50	Mean forecast	Mean	0.2972	0.9858
		Standard deviation	0.56	0.76
		Differences of opinion *dop*	1.89	0.77
	Median forecast	Mean	0.2878	0.9256
		Standard deviation	0.48	0.71
		Differences of opinion *dop*	1.68	0.77
BASF	Mean forecast	Mean	0.0311	0.4212
		Standard deviation	0.17	0.32
		Differences of opinion *dop*	5.58	0.75
	Median forecast	Mean	0.0340	0.4300
		Standard deviation	0.18	0.32
		Differences of opinion *dop*	5.27	0.74
Deutsche Telekom	Mean forecast	Mean	0.0862	0.5123
		Standard deviation	0.30	0.36
		Differences of opinion *dop*	3.46	0.71
	Median forecast	Mean	0.0931	0.5134
		Standard deviation	0.30	0.37
		Differences of opinion *dop*	3.21	0.71

variance of the error term.[32] Our results might be interpreted as an indication that modeling disagreement about mean returns has a better foundation in documented

[32] Note, however, that underestimation of the variance of signals also creates heterogeneity of conditional means (differing posterior beliefs) that are driven by information (signal realizations), not by differing opinions concerning the mean of the prior (such as, for example, in Varian (1989)).

Table XI. Volatility forecasts: Differences of opinion

This table presents the mean of the volatility forecast. Volatility forecasts are defined as in Section 5. Furthermore, the table shows standard deviation of volatility forecasts as well as the differences of opinion. Differences of opinion (*dop*) are calculated as the standard deviation of the volatility forecasts divided by the respective absolute value of the mean volatility forecast.

		First group August 2nd, 2001	Second group September 20, 2001
DAX	Mean	0.0743	0.1298
	Standard deviation	0.04	0.07
	Differences of opinion *dop*	0.57	0.52
Nemax50	Mean	0.2236	0.4014
	Standard deviation	0.16	0.28
	Differences of opinion *dop*	0.70	0.70
BASF	Mean	0.0911	0.1469
	Standard deviation	0.05	0.08
	Differences of opinion *dop*	0.56	0.51
Deutsche Telekom	Mean	0.1423	0.2283
	Standard deviation	0.07	0.14
	Differences of opinion *dop*	0.51	0.60

investor behavior than disagreement about the variance of returns. However, we note that this argument is speculation and needs further investigation.

7. Conclusion

This paper analyzes stock return and volatility forecasts and the level of disagreement of individual investors before and after the terror attacks of September 11. Our study contributes to the literature in the way that it provides a further not yet analyzed context in which mean return and volatility forecasts are made: the situation with an unprecedented terror attack accompanied by a high degree of uncertainty in connection with a large drop in share prices. In connection with the literature discussed above it is possible to gain a more comprehensive picture of how investors behave and how such events affect their expectations. Our main results can be summarized as follows:

1. Return forecasts are significantly *higher* after September 11 and the large drop in share prices after the terror attacks when compared to the return forecasts before the attacks. Thus, investors expect mean reversion. The large drop in stock prices is almost completely regarded as temporary rather than permanent.

2. After the terror attacks, volatility estimates are in two out of four cases *higher* than the historical volatility of returns whereas before the terror attacks historical volatilities are always underestimated. Therefore, investors are *not generally* overconfident in the way that they underestimate the variance of stock returns.
3. Differences of opinion with regard to return forecasts are *lower* after the terror attacks whereas differences of opinion concerning volatility forecasts are mainly unaffected.

The most important finding of this study is perhaps the high expected return until the end of the year 2001 of the second group of respondents. And, very striking, investors were not completely wrong: There was a strong rebound until the end of the year 2001. Perhaps, investors think that there will be a rebound - and that is the reason, why the rebound actually occurs.

However, one important point to note is that we asked for price or index levels instead of asking directly for returns. One argument in favor of asking directly for future price or index levels is that these questions are easier to understand for individual investors. However, it is possible that the framing of the question influences the forecasts obtained. Andreassen (1987, 1988) argue that the regressiveness of predictions depends (among other things) on the way investors think about past realizations of the time series. Do investors think in terms of price levels or price changes (i.e., returns)? He argues that the most representative price of the time series "35, 37, 39, 41, 43, 45" is lower than the final price. Thus, making a forecast while thinking in terms of price levels leads to mean reverting expectations. In contrast, the most representative change of the time series "+2, +2, +2, +2, +2" is "+2". Thus, thinking in terms of changes leads to a belief in trend continuation. We hypothesize that a similar mechanism might be at work for different ways of asking for forecasts. Our way of measuring return forecasts, i.e., asking for future price levels, might lead to (a higher degree of) mean reverting expectations whereas asking directly for returns might lead to a belief in trend continuation (or a lower degree of mean reverting expectations). Therefore, future research should further investigate how the framing and wording of questions and the information presented to the judges affect stock return forecasts of investors.

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