Heterogeneity of beliefs and trade in experimental asset markets

Tim A. Carle*, Yaron Lahav**, Tibor Neugebauer*, Charles N. Noussair***

*University of Luxembourg
** Ben-Gurion University of the Negev
***University of Arizona

Abstract

Revisiting the data of Haruvy et al. (2007), we investigate the relationship between traders' expectations and market outcomes. The data show that those who have high price expectations buy more frequently and submit higher bids, and those who hold low price expectations sell more frequently and submit lower bids, than average. Those indicating more accurate expectations have greater earnings. Simulations using only the belief data reproduce the pricing and transaction volume patterns observed in the market well, indicating that the heterogeneity of expectations is the key to explaining the market activity.

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1. INTRODUCTION

It has long been recognized that expectations are an important input in economic choices. One obvious example of this is asset trading, in which purchase and sale decisions are presumed to be governed, at least in part, by expectations of future prices. For example, if expectations are homogeneous as is frequently assumed in theory and individuals do not differ in terms of risk attitudes, a *no-trade theorem* typically applies (Milgrom and Stokey, 1982; Tirole 1982). On the other hand, a substantial literature suggests that the heterogeneity of expectations is the key to explaining most trades in asset markets (see the survey of Hong and Stein 2007). Varian (1992) contends that "*...just as it takes differences of opinion to make horse races, it is likely that a substantial portion of trade in actual financial markets is due to different…beliefs*".[1] Different beliefs can result from heterogeneity in information, but they can also result from differing interpretation of the same information, differences in tastes, or simply from different views about the future. Keynes (1936) highlights the distinction between tastes and beliefs in his famous 'beauty contest' metaphor, where he emphasizes the differences between tastes and beliefs about the tastes of others.[2] In their model of the beauty contest, Biais and Bossaerts (1998) conjecture that (p. 309) "…*disagreement may lead to trades in which agents with low private valuations buy the asset from agents with higher valuations, because of optimism about the resale potential of the asset*."[3] Further testable implications of the literature on heterogeneous beliefs are thus that shares are purchased and held by the more optimistic traders (Hirshleifer 1975, Harrison and Kreps 1978), that belief dispersion implies a rise of transaction volume (Varian 1989) and that price levels are greater when short sales are banned (Miller 1977).

With our analysis of experimental asset market data, we first consider the relationship between individual beliefs and decisions. Both theories of heterogeneous beliefs, as well as experimental designs that elicit beliefs and incorporate them as part

[1] Throughout the paper, we employ the terms expectation and belief synonymously.

[2] In her experimental study of the beauty contest game, Nagel (1995) suggests that differences in subjects' responses under identical information can result from heterogeneous beliefs about the other subjects' cognitive abilities.

[3] Biais and Bossaerts call these trades *controversial* since each trader thinks that the other party makes a bad deal, given their speculative valuations. Similar speculative trades are also suggested in Harrison and Kreps (1978) and Scheinkman and Xiong (2003), where the latter theoretical study links heterogeneous beliefs with overconfidence. The model of Barberis, Greenwood and Shleifer (2015) suggests that the most changes in prices may be driven by changes in beliefs.

of trading strategies (e.g., Marimon, Spear and Sunder, 1993; Hommes et al. 2005, Hommes and Lux, 2013), build on the assumption that individual expectations and actions are aligned. So far, empirical evidence supporting these conjectures is scarce and a direct test seems overdue. In non-market experiments, empirical evidence has been reported which supports the conjecture that actions are rational given beliefs, at least to some degree. Neugebauer et al. (2009) report evidence from a linear public goods game. They find that subjects' beliefs about the actions of others are highly correlated with their own actions, although their own actions are closer to equilibrium play than these beliefs. In ultimatum games, Trautmann and van de Kuilen (2014) obtain significant positive correlations between beliefs and actions using different approaches of belief elicitation. On the other hand, Costa-Gomez and Weizsacker (2008) and Rey-Biel (2009) find that subjects in 3x3 matrix games play best response to their beliefs only frequently. Lahav (2015) also finds some inconsistency between beliefs and actions in beauty contest experiments with belief elicitation. The correlation between dispersion of beliefs and activity in experimental asset markets has also been investigated in recent work that shows that manipulations of subjects' beliefs in the direction of more homogeneity lead to smaller mispricing in experimental asset markets (Kirchler, Huber and Stöckl 2012; Palan, Hedegaard and Cheung 2014).[4]

One advantage of experimental methods is that expectations can be measured directly using protocols in which individuals have an incentive to truthfully report them. In this paper, we revisit the data collected by Haruvy, Lahav and Noussair (2007), hereafter HLN. HLN elicit predictions of future prices from participants in repeated experimental asset markets with a 15-period horizon. They find that price expectations in the laboratory are formed in an adaptive backward-looking manner.[5] With repetition, the average expectation converges on the expected dividend value,

[4] A large number of experimental market studies manipulate beliefs by offering traders different pieces of information about the uncertain state of the world (see the literature survey by Sunder 1995). More recently, Hey and Morone (2004) and Palfrey and Wang (2013) report that mispricing can result in markets with noisy private or public information, respectively. In contrast to this literature, however, our analysis uses measured elicited expectations rather than manipulated expectations.

[5] Confirming empirical evidence has been reported in a recent study of naturally occurring markets by Greenwood and Shleifer (2014). They use time series of six different surveys of expectations as proxies for beliefs and investigate the correlation of market expectations with market returns. Their data reject the rational expectation hypothesis, according to which expected future returns should equal expected realized returns. Their surveys data show, like HLN, that expectations of future returns positively correlate with past returns and past price levels, and therefore correlate negatively with model-based expected returns.

but does so after the price has converged on the expected dividend value. HLN do not discuss dispersion and heterogeneity of beliefs in detail. The work reported here extends the work of HLN in view of several objectives. The first is to study heterogeneous beliefs in a market environment where subjects have identical information on the risks and returns of the asset and to consider the fundamental assumption of finance theory that subjects make trades in accordance with their expectations. In this context, we report the elicited heterogeneous beliefs both short-term and long-term and explore the qualitative updating interaction between the two. The second objective is to explore a possible connection between accurate beliefs and trading profits. The third is to test the market implications of heterogeneity of beliefs on market prices and transaction volume. The fourth objective is to study how accurately the market activity can be simulated by using belief and order quantity data only.

The rest of the paper is organized as follows: In section 2, we briefly survey the data and our statistical approach. In section 3, we report our findings. In section 4 we simulate market behavior using belief data. Section 5 concludes.

2. DATA AND PROCEDURES

2.1 The Data

In our test of heterogeneous beliefs, we analyze the experimental data of HLN, who elicited individual beliefs during six sessions of experimental asset markets in the standard single asset market design of Smith, Suchanek and Williams (1988)[6]. In each session, *n=9 subjects* participated in *M=4 repeated markets*.[7] Each market consisted of *T=15 periods* of a *call auction*. Thus, the data set includes 345 market periods.

The structure follows design 4 of Smith et al. (1988). Subjects were endowed with cash and shares. At the end of each period, a dividend was independently drawn from the set {0, 4, 14, 30} francs, each number being equally likely to be chosen. Given 15 dividend draws per market, the initial fundamental value, equal to the

[6] HLN use call market trading rules while Smith, Suchanek and Williams (1988) employ continuous double auction rules. However, according to Van Boening, Williams and Lamaster (1993), pricing behavior is not different in asset markets conducted under the two different rules. Call markets, in which there is only one uniform price for all transactions in a period, are more conducive to studying price predictions.

[7] One session had only eight subjects, and another session had only three repeated markets.

expected value of the future dividend stream of each share, was 180 francs.[8] The expected value of the initial endowment in each market was 652 francs for each subject, including shares and cash. Three subjects were endowed with one share of asset, three other subjects were endowed with two shares, and the last three subjects were endowed with three shares. Other than shares, the remainder of the initial endowment value of 652 francs was cash. Dividend payments and revenue from sales (over the course of a market) increased cash holdings while expenditures of purchases decreased them. Throughout the experiment, no borrowing was possible; asset purchases on margin and short sales were disabled.

In each period, subjects submitted one 'bid' (an offer to buy) and one 'ask' (an offer to sell) order. The 'ask' consisted of a sale price and a quantity of shares offered for sale, and a 'bid' consisted of a proposed purchase price and a quantity of shares demanded for purchase. Both quantities were required to be non-negative, but could equal zero, and proposed sale price must exceed proposed purchase price. At the end of each period, the market cleared, the market price was determined by the intersection of submitted market demand and market supply, and shares were exchanged between winning sellers and buyers at the market price. The data contain 2009 submitted bid orders and 1554 ask orders of single or multiple units. The majority of positive order submissions were for single units, including 58 percent of bids and 61 percent of asks.[9]

Cash and asset holdings were reinitialized at the same starting levels at the beginning of each of the four markets. Within a market, participants carried over cash and shares from one period to the next.

Beliefs were elicited by providing monetary incentives to subjects to reveal their expectations about the trajectory of future prices. At the beginning of each period $t = \{1, 2, \ldots, 15\}$, before submission of bids and asks for period t, each subject predicted the closing prices of both current and future periods (all periods $s \geq t$) within the current market $m = \{1, \ldots, 4\}$. Thus, the task involved 120 predicted prices per subject and market, 15 predictions of the current period (below we refer to short-

[8] To make sure that all subjects recognize the role of the expected periodic dividend as the dividend value of the asset, each subject received a table that specifies the dividend value of the asset at the end of each period.

[9] Submissions for two and three units occurred with relative frequencies 20% and 8% for bids and 20% and 11% for asks when positive quantities were submitted, respectively. Finally, 31% of bids and 39% of asks involved zero quantities when positive submissions were possible (accounting for the individual price expectations and liquidity constraints).

term beliefs) and 105 predictions of future periods (below we refer to the aggregate as long-term beliefs). Short-term beliefs were about equally often above (51%) and below (49%) the actual realized price in markets 2-4, but more often below (61%) the realized price in market 1.[10] Monetary incentives offered salient rewards to subjects for accuracy of each prediction.

At the end of the last market, subjects received their total earnings of all markets in cash. Total earnings included payment received for the prediction task, and cash balance in their possession at the end of the repetition. The cash balance depended on the collected dividends and the capital gains from trade.

Market prices in the data exhibit the bubble and crash pattern typically observed in this experimental design (see the survey by Palan 2013), starting below dividend values at the beginning of the market, increasing gradually and crossing the fundamental value after a few periods. After another few periods during which the asset price exceeds its fundamental value, it reaches a peak. The price subsequently plummets to roughly track its fundamental value in the end phase of the market. This pattern is observed in all sessions when traders are inexperienced (market 1). With increased experience in repeated markets, the magnitude of the bubble shrinks, the asset price peaks earlier and it more closely tracks its dividend value (see Figure 4 in section 4).

2.2. Measures used in the analysis

We construct a number of variables from the data. In particular, we thus organize the elicited individual expectations about future prices from each period. Individual beliefs are characterized by the price level they indicate, both in the short term, defined as the upcoming market period, and the long term, which is the average over the remaining periods in the life of the asset.

Ranked short-term beliefs: For each period, we rank subjects by their expectations on future market prices, from highest to lowest. The lowest price expectation is assigned $rank\,[.] = 1$, the second lowest $rank\,[.] = 2$, etc. In case of a draw, we assign the mid-rank. For the analysis of short-term belief in period *t*, we

[10] Short-term beliefs and long-term beliefs were 42% and 23% of times below the fundamental value, respectively. Long-term beliefs were above the actual observed price three times as often as they were below. In other words, the average long-term belief was too optimistic.

use the price-expectation rank of subject i within group g (denoting one of the experimental session 1-6) for period t in market *m*. We write i's short-term belief as

(1) $$STB_{mgit} = B_{mgit}^{mt},$$

where B_{mgit}^{mt} denotes the belief of subject i from group g during market m (denoting the current market) and period t (which denotes both the submission and forecast period). If subject i's short-term price expectation submitted in period t is largest within group *g*, we write $rank\,[STB_{mgit}] = 9$. Consequently, the large ranks indicate a high level of optimism, while the small ranks indicate less optimism about the price in the current period. The ranking procedure serves two main purposes. First, it provides a measure of optimism of beliefs that is not sensitive to the declining time trend of dividend values, as the range of ranks is constant. Second, the procedure is unbiased towards even extreme outliers (e.g., extremely high or low beliefs) as they have no effect on mean and standard deviation.

Ranked long-term beliefs: Recall that each trader submits beliefs for the current period as well to all of the remaining future periods of the current 15-period market. As we are interested in the ranked long-term beliefs, we define the long-term belief of trader i = {1, 2, .., 9} as the average deviation of the trader's beliefs from the asset value in the remaining periods as follows:

(2) $$LTB_{mgit} = \frac{1}{T-t}\sum_{k=1}^{T-t}\frac{B_{mgit}^{m,t+k} - f_{t+k}}{f_{t+k}}$$

$B_{mgit}^{m,t+k}$ denotes the subject's price forecast for the period $t+k$ ($1 \leq k \leq T-t$) submitted in the current period *t*. $T = 15$ is the total number of periods in a market and f_{t+k} is the fundamental value in the forecasted period. As with short-term beliefs, we rank the long-term beliefs and therefore write $rank\,[LTB_{mgit}] = 1$ if the $LTB_{.}$ of subject i is the lowest number within group g.

Belief dispersion: We use the coefficient of variation as a measure for current belief dispersion within a trader cohort. This measure accounts for the changing dividend value over time better than the simple standard deviation. Hence, we define the short-term belief dispersion as the ratio of standard deviation of short-term beliefs in group *g* and its average in the same period.

(3) $$BD_{mgt} = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(B_{mgti}^{m,t} - \overline{B}_{mgt}^{m,t})^2}}{\overline{B}_{mgt}^{m,t}},$$

where $\overline{B}_{mgt}^{m,t} = \sum_{i=1}^{n} B_{mgit}^{m,t} / n$ and n is the number of participants in group g. The long-term belief dispersion is defined in the same way using long-term beliefs.

Bubble measure, relative deviation: To measure bubble magnitudes, we use the Relative Deviation (Stöckl, Huber and Kirchler 2010) of the price trajectory. The Relative Deviation (RD) is calculated as follows:

(4) $$RD_{mg} = \frac{1}{T}\sum_{t=1}^{T}\frac{P_{mgt} - f_t}{\overline{f}}$$

where P_{mgt} denotes the clearing price in group g and market m, f_t is the fundamental value in period t and $\overline{f}$ is the average fundamental value across the 15 trading periods. Positive values of the measure indicate overpricing, and negative values reveal underpricing, relative to fundamentals. A low absolute value means that prices are adhering closely to fundamentals.

3. RESULTS

This section is organized into three parts. The first considers the relationship between reported expectations on the one hand and individual decisions and market behavior on the other. The second part covers the connection between the accuracy of beliefs and earnings. The third concerns the relationship between belief dispersion and market outcomes.

3.1 Individual beliefs and behavior

In this sub-section, we report a number of findings concerning the connection between individual expectations and subsequent actions. We study both short-term and long-term beliefs and show how both affect traders' buying and selling behavior. Our first observation summarizes our results on the relationship between individual expectations and purchase/sale decisions.

Observation 1. Subjects who believe that prices will be higher tend to be buyers, and subjects who believe that prices will be lower tend to be sellers, in the market. Consequently, share holdings are positively correlated with beliefs.

Support for Observation 1: Figure 1 shows subjects' net-purchases according to their ranked short-term beliefs. Net-purchases increase from low ranked short-term beliefs (less optimistic subjects) to high ranked ones (more optimistic subjects). Figure 1 suggests that optimistic subjects purchase shares from the less optimistic ones.

Figure 2 shows subjects' average share-holdings per period according to their ranked short-term beliefs. As Figure 2 shows, the more optimistic investors hold more shares than the less optimistic ones. Interestingly, both graphs are not linear. Figure 1 suggests that more optimistic traders make purchases while relatively pessimistic ones make sales. Figure 2 suggests that there is a limit to the extent of the purchases that optimists can make, perhaps due to cash constraints.

To check for statistical significance of these observations, we report GLS regression results[11] where both net-purchases (ΔS_{mgit}) and share-holdings (S_{mgit}) are the dependent variables, and the ranked short-term belief is the independent variable. The results are summarized in Table 1 for short-term beliefs and in Table 2 for long-term beliefs.

[Insert about here: Figure 1, 2 and Table 1, 2]

[11] We conduct regressions on these ranked beliefs using panel data methods. We pretest the data using the Hausman specification test (Wooldridge 2010) and choose the specification of our general least square (GLS) regression-model depending on the results of the test. If the null hypothesis of the Hausman test that a random-effect specification is the appropriate model is rejected at a 5% significance level, we report the results of the fixed-effects model. Otherwise, we report the results of the random-effects model. The GLS model accounts for group effects and is denoted as follows;

$$y_{mgit} = \alpha + x_{mgit}\beta + \eta_{mg} + \varepsilon_{mgit},$$

where α, β are the intercept and slope of the regression respectively, and the indices m, g, i, t denote the market-repetition, the session (or group), the trader, and the period, respectively. x_{mgit} is the explanatory variable (e.g., within-session rank of the subject's short-term price expectation), y_{mgit} is the dependent variable (e.g., the subject's net-purchases in period *t* of market *m*), and ε_{mgit} is an iid error-term. With the fixed-effects model, the term η_{mg} denotes the group-specific time-invariant error-term. In contrast to the fixed-effects model, the random-effects model supposes that the time-invariant error term η_{mg} in the regression equation is also i.i.d., and therefore that the two error terms are mutually independent. We estimate the GLS model using STATA.

The results reported in Table 1 clearly show that ranked short-term belief is a significant predictor of net-purchases and total share-holdings, with more positive beliefs associated with greater net-purchases. The β coefficient is significant at the 5% level in any market and across markets for either dependent variable. Long-term beliefs have a similar relationship, and are significant in markets 1, 2, and 4, for both net-purchases and total holdings, and market 3 for share holdings.

Observation 1 supports theoretical work which assumes that individual beliefs can be heterogeneous even with identical information and that more optimistic agents hold more shares in the market (e.g., Miller 1977, Harrison and Kreps 1978). The observed positive relationship between share-holdings and short-term beliefs, however, may have an endogenous element. While it can be presumed that optimistic traders increase their holdings and therefore tend to hold more units, it is possible that large shareholders become more optimistic because of wishful thinking (Forsythe, Rietz, and Ross, 1999), but we find no support of such a relationship in the data.[12]

An analogous result to observation 1 applies to the submission of bids and asks. Observation 2 reports that there is a positive relationship between beliefs and offer levels. In our analyses, we consider bids and asks of subjects who may expect a trade, that is, those whose bids exceed their beliefs and beliefs exceed their asks.[13]

Observation 2: Subjects who believe that prices will be higher submit higher bids and asks, and subjects who believe that prices will be lower submit lower bids and asks.

Support for observation 2: The analysis involves (i) an individual consistency test for each subject and (ii) a consistency test for each group and market.

(i) We conduct a Spearman rank-order correlation coefficient test on the individual data, including up to 60 short-term beliefs and up to 60 bids and 60 offers. This test on individual bids and asks is restricted to bids below and asks above the

[12] To check the 'wishful thinking' hypothesis, we test whether initial individual beliefs depend on the initial (random) endowment of shares. The GLS regression of ranked short-term beliefs on the initial share-holdings for the first period shows no significant positive effect; the t-statistic is -1.17. Thus, we do not find support that short-term beliefs are significantly influenced by initial share endowment.

[13] The considered bids and asks represent intended transactions. If, instead of the intended transactions, we consider all bids and asks in the analysis, we arrive at the same conclusions as reported here, i.e., the signs of the coefficients remain the same, but the levels of significance drop.

submitted short-term price expectation. Under the null hypothesis, the nominal short-term beliefs and the individual bids and asks are random. Our result supports the alternative hypotheses that bids and asks are positively correlated with beliefs; only for two of the 53 individual order submissions (i.e. 3.8 percent of our sample) the correlations between bids and short-term beliefs and between asks and short-term beliefs are not significant at the five percent level. The average correlation coefficients between bids and short-term beliefs, and asks and short-term beliefs, are 0.730 and 0.721, respectively. Thus, the data show that the bids and asks and the short-term beliefs of the same subject are significantly positively correlated over all periods.

(ii) Tables 3 and 4 show regression results where the dependent variable is the rank of the submitted bid or ask. The independent variables are ranked short-term (Table 3) and long-term (Table 4) beliefs. The estimates indicate a significant relationship between the submitted offer and short-term or long-term beliefs respectively.

[Insert about here: Table 3, 4]

To check the robustness of short-term and long-term beliefs as determinants in individual behavior, we include control variables that have been shown to impact beliefs. HLN suggest that beliefs are formed in an adaptive manner, influenced by past price changes. In Tables A1 and A2 in the appendix, we show that both long-term and short-term beliefs influence trading behavior even when we control for previous price changes, as well as share- and cash holdings.

A natural question to ask is whether long-term beliefs have additional predictive power for actions if one controls for short-term beliefs. Our main finding in this regard is reported as follows.

Observation 3. Short-term beliefs are better determinants of trading behavior than long-term beliefs.

Support for Observation 3: When including the short-term belief as an independent regression variable, the long-term belief is not a significant determinant of bids and asks anymore (see Table 5 and 6). These results suggest that subjects make their decisions based on their short-term expectations rather than long-term expectations. Both short-term and long-term beliefs remain significant in regressions of net-purchases and share-holdings using the pooled data from all markets.[14]

[Insert about here: Table 5, 6]

Table 6 suggests that beliefs are a more important influence on purchase than on sale decisions. Because purchases typically involve anticipation of a future action (resale), beliefs may be given greater consideration in decisions to buy. The profitability of a sale, once it is concluded, is not affected by future prices. On the other hand, even after a purchase is made, beliefs affect the perceived value of the unit that was purchased. Our results show that individual choice depends on the short-term beliefs only.

To conclude this subsection on individual beliefs and behavior, we report on the interactions between short-term and long-term beliefs. The following observation concerns the dynamics of expectation updating, i.e. how subjects adjust their long-term beliefs in light of new experiences. The sign of the deviation of their short-term belief from the observed market price seems to play a critical role. If the market turns out to set the price above (below) the subject's reported short-term expectation, the subject reacts by upward (downward) adjustment of the forecasted future price levels. The adjustment behavior of reported expectations upon arrival of new price information is quite similar for all subjects. It indicates that higher than expected returns generally lead to more optimistic forecasts. The finding is summarized in observation 4.

Observation 4: Individuals increase the price estimates in their long-term belief profile when their short-term belief has turned out to be below the realized market price and vice versa.

Support for Observation 4: We compare the short-term belief with the realized price for every individual in the period. When their short-term belief is below the realized

[14] The average individual Spearman rank-order correlation coefficient between the short-term and long-term belief over all periods is 0.51, 0.49, 0.32 and 0.39 for markets 1-4, respectively. Apparently, subjects who are optimistic for the short-term market behavior are also optimistic for the long term.

price, subjects tend to increase their reported long-term beliefs. When their short-term belief is above the realized price, subjects tend to decrease their reported long-term beliefs. This means that subjects adjust their expectation in the opposite direction of the belief deviation from prices. If the short-term belief exceeds the observed price, the long-term belief is adjusted lower, and vice versa.[15] Figure 3 describes the number of long-term belief adjustments due to deviation of short-term beliefs from market prices. In all markets, the majority of belief adjustments are in the opposite direction to the deviation between beliefs and price. Overall, 51 out of 53 subjects adjust their long-term beliefs in the majority of periods according to this rule. The result is significant as the probability of 51 or more subjects out of 53 behaving in this way due to pure chance is close to zero.

[Insert about here: Figure 3]

3.2. Beliefs and earnings

In this sub-section, we examine the relationship between earnings and predictions. We test the hypotheses that higher profits are associated with belief accuracy and with the level of optimism.

With respect to the relationship between profits and the accuracy of beliefs, there are two competing conjectures. The first is that subjects with forecasts closer to actual prices will earn higher profits. The second conjecture is that traders with predictions closer to dividend value will earn higher profits. We observe both relationships holding in the data.

Observation 5. Subjects who (accurately) forecast asset prices close to actual market prices and subjects who expect prices close to fundamentals earn higher profits.

[15] More formally, $STB_{mgit-1} - P_{mgt-1} \underset{<}{\overset{>}{=}} 0 \Rightarrow LTB_{mgit}^{mt} - LTB_{mgit-1}^{mt} \underset{>}{\overset{<}{=}} 0$, where the subindex indicates the time of belief submission, and the superindex indicates the first forecast period. This adjustment behavior is in the spirit of impulse response theory (Selten, 2004) that proposes adaptive behavior in the *direction of the ex-post best response*.

Support for Observation 5: We employ the *relative belief-price deviation*, *RBPD*, which we define as measure of the absolute difference between short-term beliefs and prices.

(5)
$$RBPD_{mgi} = \frac{1}{T}\sum_{t=1}^{T}\frac{\left|B_{mgit}^{m,t} - P_{mgit}\right|}{P_{mgit}}$$

Lower values of the relative belief price deviation indicate that short-term beliefs are on average closer to the realized prices. Correspondingly to (5), we define the measure *relative belief-value deviation*, *RBVD*, indicating how far the short-term belief differs from the dividend value.[16] The GLS regression analysis with ranked total profits across the 15 periods as the dependent variable and the ranked belief deviation measures as the independent variable is summarized in Table 7 for each measure of short-term beliefs separately. Larger deviations of short-term beliefs from both fundamentals and prices are associated with lower profits when measured across all markets, as indicated in the table by the negative coefficients. The deviation of short-term beliefs from prices has a significant negative effect on profits in market 1 and 4. Deviation of short-term beliefs from fundamentals has a significant negative effect on profits in market 1.

[Insert about here: Table 7]

Observation 5 suggests that profits are made when traders either (1) make decisions that reflect accurate forecasts of the price of the next period, or (2) trade on fundamentals. The first strategy is profitable when speculating on price changes between one period and the next. The second strategy is more profitable than average earnings in the long run. In market 1, both of these are profitable as there is a positive correlation between earnings and the adherence of beliefs to each benchmark.

3.3 Belief dispersion and market behavior

Theory suggests that heterogeneous beliefs can push up prices if short sales constraints are binding (Miller 1977), and that belief dispersion can lead to higher transaction volume (Varian 1989) as disagreement encourages trade. Our data do not

[16] We also tested the effect of short-term beliefs at the beginning of the market (belief regarding the price of period 1) on profits. We found that when inexperienced (during market 1 only), traders that were more accurate regarding the price of period 1, earned higher profits. We did not find significant effect for long-term beliefs.

support the former statement that the price increases with belief dispersion, but are inconsistent with the second conjecture that beliefs and transaction volume are positively correlated.

We measure belief dispersion in each period by means of the coefficient of variation (see equation 3). Earlier research in asset market experiments has shown that the number of transacted shares tends to decrease with repetition (Palan 2013), but belief dispersion has not been measured in this context before. However, if transaction volume is associated with belief dispersion, as suggested by Varian, then as a consequence, dispersion would decrease over time too. Indeed, we find that both belief dispersion and transaction volume do decrease as traders accumulate experience.

Observation 6. Belief dispersion declines with experience.

Support for Observation 6: In experimental asset markets, participants gain experience by participating in several consecutive markets. In the HLN data, there are four levels of experience. During the first market, participants are inexperienced. During the fourth market, participants are highly experienced. The average short-term belief dispersion decreases from 0.297 to 0.244, 0.212 and 0.174, and the average share turnover decreases from 0.145 to 0.113, 0.095 and 0.106 per period, from market 1 to 4.[17] On average, across 60 periods, the short-term belief dispersion declines by 1.96% and the transaction volume by 1.90% per period. Regressing belief dispersion and transaction volume on period number shows significant decline across periods and markets.[18] Thus, it seems as if expectations become less heterogeneous with experience.[19] Taking a second look on the averages of belief dispersion and transaction volume in the fourth market, nonetheless, it appears to us unlikely that the markets would converge to a no-trade, zero belief-dispersion market in a reasonable amount of time.

[17] There is no significant reduction in long-term belief dispersion across markets. The average long-term belief dispersion for markets 1 through 4 is 0.465, 0.493, 0.456, 0.346, respectively.

[18] T-statistics when regressing transaction volume, short-term belief dispersion and long-term belief dispersion, on market number equal -3.24[a], -2.79[a], and -1.66 respectively. When regressing on period number, the t-statistics equal -3.95[a], -2.81[a], and -4.37[a], respectively. (N=345, 345, 322).

[19] We also measured homogeneity of beliefs by counting the frequency of identical short-term (long-term) belief submissions within a period of a market by different subjects. Thus, the data would suggest no drop of belief heterogeneity.

Next, we turn the focus to the theoretical implications of the magnitude of belief dispersion on market price and transaction volume. The effect of belief dispersion on transaction volume has the expected positive sign, but its magnitude is not significant at conventional levels. When controlling for the time trend, the GLS regression of transaction volume on belief dispersion shows that belief dispersion is not a significant determinant of volume as suggested in theory (e.g., Varian 1989); the t-statistic of belief dispersion is 0.46 (N=345) in the random-effects regression of transaction volume on short-term belief dispersion and period. This result is included in the following observation.

Observation 7. Belief dispersion has no significant effect on transaction volume. Belief dispersion is associated with higher prices. The initial belief dispersion can be indicative of the later market price level.

Support for Observation 7: The regression results of transaction volume on both belief dispersion and lagged transaction volume are presented in Table 8. As the table shows, the regression coefficients are not significant for any market. Therefore, the data suggest no significant relationship between belief dispersion (both short-term and long-term) and transaction volume. Thus, we fail to support the theoretical prediction.

[Insert about here: Table 8]

In line with theory (e.g., Miller 1977), however, higher prices are associated with higher belief dispersion in the data. One possible reason for this is the fact that an increase in short-term belief dispersion is associated with a higher number of bids,[20] though not of asks. To test this, we compute the average short-term belief dispersion and the average long-term belief dispersion for each market in accordance with equation 3. For the GLS regression of relative deviation (equation 4) on belief dispersion, we thus have one observation per market, and four per session. The t-statistic for the short-term belief dispersion in this regression is 2.72^{fa}, and of long-term belief dispersion 2.80^{fa} (N=23). Thus, the data support the theory; belief dispersion appears to be a good indicator of price levels in the asset market

[20] t-statistic = 4.27^{a}.

experiment. The price level can already be anticipated in the first period because the relative deviation significantly depends on the short-term belief dispersion in the first period.[21]

This result indicates that belief dispersion is correlated with higher prices and may reflect the parameters used in our markets, which are typically applied in the literature. In the experiment, because short sales are disabled, the largest short position a pessimistic trader can take is to sell all of her holdings. On the other hand, because of the relatively high ratio of cash to current prices in the experiment, an optimistic trader typically has the capacity to take larger long positions. This means that an increase in belief dispersion would typically increase prices as suggested in the theoretical literature (Miller 1977).

Observation 8. Belief dispersion affects the relative size of price changes. The relative size of past price changes affects the belief dispersion. The latter is stronger than the former effect.

Support for Observation 8: To show the relationship between belief dispersion and price changes, we conduct a GLS regression with both belief dispersion and prior price changes as explanatory variables, and the current price change from the prior period as the dependent variable. The results are presented in Table 9, which shows that short-term belief dispersion is a significant determinant of price changes in markets 1 and 2 and in the data overall, while long-term belief dispersion is not significant in any market.

HLN show that recent past price changes affect beliefs, and establish the result for average beliefs. Here, we also find that the magnitude of prior price changes affects belief dispersion. To show this we conduct a GLS regression of the current belief dispersion on the lagged absolute price change (controlling for lagged belief dispersion as an additional explanatory variable)[22]. Table 10 shows the results for the GLS regression. The magnitude of the price change is a significant determinant of the short-term belief dispersion in each market, and of the long-term belief in markets 1, 3

[21] The GLS regression of the relative deviation on the short-term beliefs of period 1 leads to a t-statistic of 2.53[a]. The same regression analysis using the first period long-term beliefs as the dependent variable leads to a t-statistic of -0.39.
[22] Results are preserved even when the regression does not control for lagged belief dispersion.

and overall. Therefore, the data suggest that the belief dispersion is adaptive vis-à-vis the size of the price change rather than vice versa.

[Insert about here: Table 9, 10]

4. SIMULATION OF MARKET BEHAVIOR USING BELIEF DATA

In this section, we use a simulation approach to test if beliefs can be employed to predict future prices and transaction volumes. With this approach we indirectly test the validity of experimental designs (e.g., Marimon, Spear and Sunder 1993) that use belief data for market clearance rather than bids and asks. Our observations above have indicated that subjects' actions are aligned with their expectations. Subjects who are optimistic about the asset's risk and return submit bids to buy in the market and less optimistic subjects submit asks to sell. However, we have also reported that order prices and expected prices are generally not identical. So we address the question if, despite these existing discrepancies, the knowledge of the market participants' expectations is valuable information to successfully foretell the observed market behavior including its bubble and crash pattern.

The simulations implement the following thought experiment. Suppose that an observer has the full profile of the short-term belief data, and the bid and ask quantities submitted (of those who intend to trade as well as those who do not). Can the observer predict prices and quantities transacted accurately in advance? Of special interest is whether the observer can predict a market crash in advance.

In the simulation, the submitted short-term beliefs are used to generate bids and asks. For each trader *i* in period *t* of market *m* in session *g*, a bid at price STB_{mgit}, and an ask at STB_{mgit} + .01 francs are submitted. The quantities specified in *i*'s bid and ask are equal to the quantities the subject submitted in the corresponding period of the experiment. Revealed demand and supply curves are constructed from these orders and the market clears according to HLN's call market rules. The implied transactions are concluded and cash balances and asset inventories are updated accordingly. Dividends are realized and paid out at the end of each period in the same way as in the experiment.[23]

[23] However, if investors have equal beliefs and only some of the shares can be traded at the market clearing price, the traded shares are randomly determined. In case of a period without trade, the highest

Observation 10. Simulated prices (and quantities) based on the short-term belief profile resemble the actual ones observed in the experiment. A selling strategy constructed on the simulated price trajectory generates significant excessive gains.

Support for Observation 10: Figure 4 shows the resulting prices, averaged over the six simulated sessions. Table 11 records the resulting average Spearman rank correlation coefficients between simulated and observed period prices, and also the simulated and observed average transaction volumes per period. The figure and table show and suggest that the simulated prices and quantities resemble the actual ones observed in the experiment. We test the correlation of simulated and observed price trajectory against the correlation of dividend value and observed period price. The average correlation coefficient between the latter is only 0.389. The average correlation coefficient between simulation and observation is significantly larger, i.e. 0.890, and shows that the simulated price trajectory is significantly closer to the data than the theoretical benchmark. Thus, the belief data allow an observer to predict the price data quite accurately, although arguably not perfectly.

The timing of the crash is also reproduced quite well as is shown in Figure 4, except for market 3, in which the average simulated market crashed one period too late. The quantities transacted in the simulated markets are close to - though on average somewhat below - the actual observed quantities.[24]

[Insert about here: Figure 4, Table 11]

To judge the value of the simulated trajectory, in particular its value of predicting a market crash, we derive a selling strategy involving the simulated data for which we compare its returns to alternative selling strategies. A second look at Figure 4 reveals that a crash occurs shortly after the simulated trajectory surpasses the observed price trajectory. In our strategy, this surpassing of the price trajectory above the dividend value generates an event. As soon as an event has occurred, our selling

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bid price plus one unit of experimental currency is implemented as the market price, in accordance with the experimental design.

[24] The average transaction volume over all markets is not significantly different at the 10% significance level; the t-statistic of the two-tailed t-test on the overall averages is -1.947.

strategy records the next price above the dividend value as potential selling price, and the difference to the dividend value as potential gain. This potential gain is compared to the maximum potential gain (maximum price deviation from dividend value) in the same session. Our simulation-based selling strategy thus secures 0.77 of the maximum gain.

To evaluate the excess return generated by our strategy we need a good alternative model for the purpose of comparison. Our alternative model for the selling strategy is constructed on the basis of the excess demand (number of bids minus number of asks) as proposed by Smith et al. (1988).[25] This alternative excess bids model is meaningful in this environment since Smith and collaborators suggested that negative excess bids heralds the crash of the experimental asset market. So, this alternative selling strategy generates an event as soon as the excess bid is negative for the first time when price is above dividend value. The excess-bids based selling strategy achieves 0.47 of the maximum excess gains. Our simulation-based (belief-based) selling strategy thus secures significantly larger excess gains than the alternative excess-bids model.[26]

Concluding, we can say that by means of our simulation approach we have shown that the knowledge of the belief profile is valuable when we want to retrace the behavior of the market including the bubble and crash pattern. This evidence reinforces our conclusion that subjects place their bets in accordance with their expectations.

5. CONCLUSION

Theories in economics and finance build on assumptions about decision makers' beliefs. To study individual beliefs, experimental designs elicit predictions of future prices by offering salient rewards to participants for accurate predictions. Revisiting the data of Haruvy, Lahav and Noussair (2007), our study shows that individual beliefs are heterogeneous and consistent with individual trading behavior. Our study provides empirical evidence that heterogeneous beliefs result in heterogeneous actions and thus make people trade. The fundamental empirical result that traders in the asset

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[25] In fact, the lagged excess bid is a significant determinant in the unilateral GLS regression of relative price changes also in these data. Overall markets the t-statistic for the slope is 5.33[fa] in this regression.

[26] The t-statistic is 2.455[a] according to the two-tailed t-test. Relative to another alternative selling strategy that generates an event as soon as the price is above dividend value for the first time (which secures 0.14 percent of maximum) is significantly worse than these two approaches; t-statistics are 4.197[a] (simulation) and 3.317[a] (excess bids).

market act in line with their beliefs is a major contribution of our study. Net-purchases, share-holdings and submitted orders depend on subjects' short-term and long-term beliefs. Hence, we find that trade occurs because more optimistic traders purchase from less optimistic traders.

Despite the fact that theories have long suggested this relationship (e.g. Varian 1985, Bossaerts and Biais 1998), the experimental approach can be used to show empirically that the fundamental relationship between expectations (i.e., short- and long-term beliefs) and actions holds in financial asset markets and that expectations are indeed heterogeneous. With homogenous beliefs, theory predicts no trade. The no-trade theorem presumably and in particularly applies to experimental markets where no liquidity needs and no liquidity surpluses require no trading. Since beliefs are heterogeneous and subjects act in accordance with their beliefs, and given our statistical data analysis, we conclude that in the HLN asset market experiment, many transactions occur because subjects have heterogeneous beliefs. In the same way, heterogeneous beliefs should lead to transactions in experimental markets in which beliefs are not measured directly.

Theory also suggests the existence of a measurable effect of belief dispersion on transaction volume (Varian 1989) and that price bubbles increase with belief dispersion in the market for given short-sale restrictions (Miller 1977). In fact, we find that both belief dispersion and transaction volume decline over periods and markets. However, despite the aligned behavioral dynamics, the data show no significant correlation between transaction volume and belief dispersion.[27] Nonetheless, we find evidence that the mispricing increases with the measured belief dispersion.

In the field, heterogeneous beliefs can result from different types of available information, or from different interpretation of the same information. Therefore, the controlled test of homogeneous beliefs in the laboratory is meaningful. In the experiment, individuals face the same instructions and receive the same information. Under these conditions including identical information and perfect knowledge of fundamentals one would assume that the beliefs of subjects must be homogeneous, but they are not. Individual beliefs are heterogeneous in each period and market. Even with repetition, beliefs seem not to converge although belief dispersion decreases over

[27] Bossaerts and Biais (1998) investigate the correlation between belief dispersion and transaction volume in statistical simulation models. Their result does not indicate any significant correlation either.

time. As heterogeneity of beliefs persist, we find that markets are not able to homogenize expectations and do not lead to a no-trade equilibrium.

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Figure 1. Average net-purchases per market and ranked short-term belief over all markets and sessions.

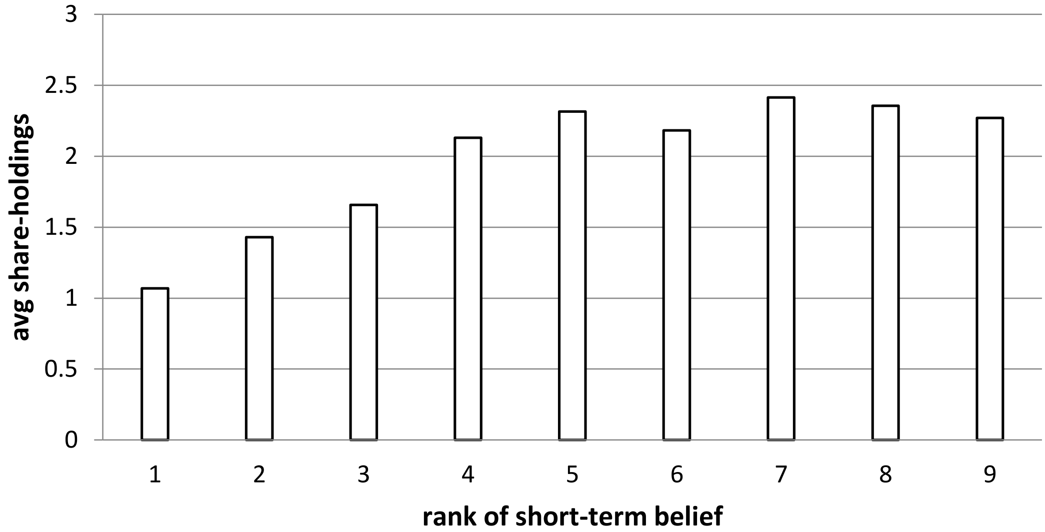

Figure 2. Average share-holdings and ranked short-term belief over all markets and sessions.

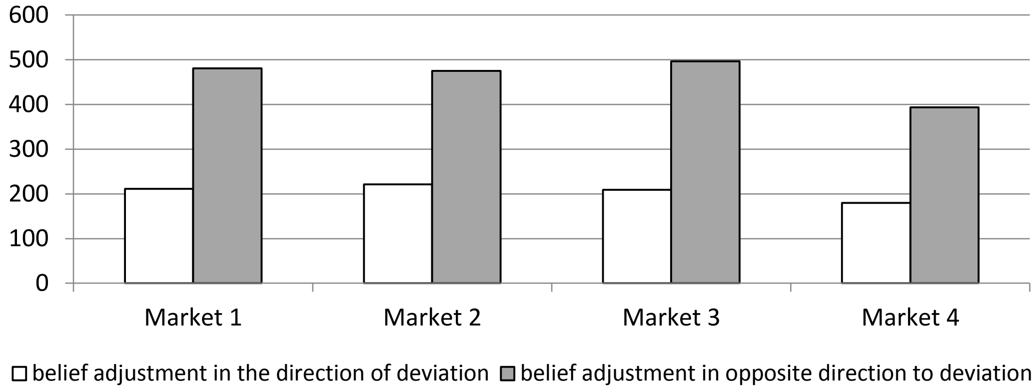

Figure 3. Number of long-term belief adjustments in the direction of and away from short-term beliefs from market prices

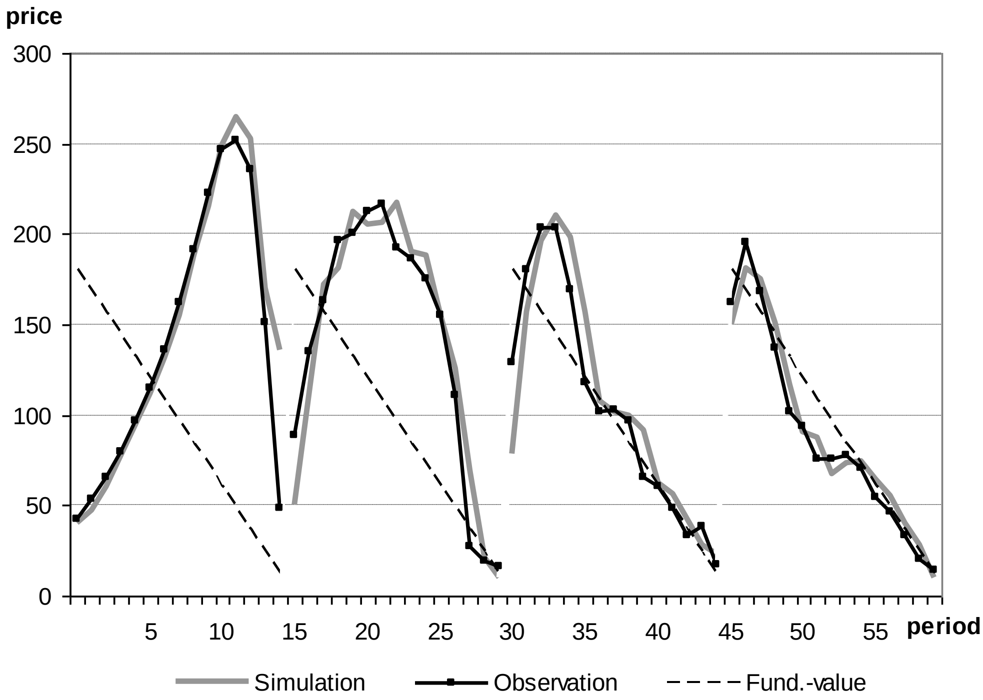

Figure 4. Simulated and observed average market price

Table 1 - GLS regression of net-purchases and share-holdings on **ranked short-term beliefs** (t-statistics in parenthesis)

	$\Delta S_{mgit} = \alpha + rank\ [STB_{mgit}]\beta$		$S_{mgit} = \alpha + rank\ [STB_{mgit}]\beta$	
	Net-purchase ($\Delta S = y$)		**Share-holdings** ($S = y$)	
	Intercept **α**	**Slope** **β**	**Intercept** **α**	**Slope** **β**
Market I	-0.26[a]	0.05[a]	1.32[a]	0.14[a]
(N=742)	(-2.81)	(3.15)	(8.53)	(5.03)
Market II	-0.25[a]	0.05[a]	1.28[a]	0.15[a]
(N=742)	(-3.55)	(3.98)	(10.43)	(6.68)
Market III	-0.12	0.02[a]	1.29[a]	0.15[a]
(N=742)	(-1.91)	(2.14)	(10.20)	(6.41)
Market IV	-0.23[a]	0.05[a]	1.39[a]	0.13[a]
(N=616)	(-3.01)	(3.38)	(8.53)	(4.37)
Overall	-0.22[a]	0.04[a]	1.32[a]	0.14[a]
(N=2842)	(-5.60)	(6.28)	(18.65)	(11.10)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 2 – GLS regression of net-purchases and share-holdings **on ranked long-term beliefs** (t-statistics in parenthesis)

$$\Delta S_{mgit} = \alpha + rank\ [LTB_{mgit}]\beta \qquad S_{mgit} = \alpha + rank\ [LTB_{mgit}]\beta$$

	Net-purchase ($\Delta S = y$)		**Share-holdings** ($S = y$)	
	Intercept α	**Slope β**	**Intercept α**	**Slope β**
Market I (N=742)	-0.29[a] (-3.03)	0.06[a] (3.42)	1.26[a] (8.15)	0.15[a] (5.57)
Market II (N=742)	-0.18[a] (-2.44)	0.04[a] (2.75)	1.39[a] (11.70)	0.13[a] (5.98)
Market III (N=742)	-0.09 (-1.43)	0.02 (1.61)	1.43[a] (11.46)	0.12[a] (5.27)
Market IV (N=616)	-0.22[a] (-2.81)	0.04[a] (3.16)	1.30[a] (8.30)	0.15[a] (5.22)
Overall [28] (N=2842)	-0.19[a] (-4.92)	0.04[a] (5.54)	1.35[a] (19.45)	0.13[a] (10.97)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

[28] Indeed, we may want to take into account liquidity restrictions so that subjects with low expectations had no shares to sell and those with high expectations had no cash to purchase shares. Considering the net-purchase when investors hold shares and when their cash holding is above the expected price we find a highly significant relationship between net-purchases and beliefs with a t-statistic of 5.33 for short-term beliefs and 2.84 for long-term beliefs.

Table 3 - GLS regression of ranked bids and ranked asks on **ranked short-term beliefs** when bids exceed beliefs and beliefs exceed asks (t-statistics in parenthesis)

$$y_{mgit} = \alpha + rank\ [STB_{mgit}]\beta$$

	Bids $[rank\ [bid\ ] = y]$		**Asks** $[rank\ [ask\ ] = y]$	
	Intercept **α**	***rank*[*STB*]** **β**	**Intercept** **α**	***rank*[*STB*]** **β**
Market I	5.19[a]	0.39[a]	1.55[a]	0.18[a]
(N=279, 151)	(23.94)	(9.04)	(4.35)	(3.40)
Market II	5.66[a]	0.30[a]	1.59[a]	0.13[a]
(N=216, 135)	(20.82)	(5.86)	(5.20)	(2.93)
Market III	6.41[a]	0.20[a]	1.62[a]	0.10
(N=181, 116)	(24.07)	(4.08)	(4.16)	(1.74)
Market IV	6.85[fa]	0.22[fa]	0.84[a]	0.23[a]
(N=125, 88)	(28.85)	(5.09)	(2.49)	(4.39)
Overall [29]	5.86[a]	0.30[a]	1.44[a]	0.16[a]
(N=801, 490)	(37.80)	(12.59)	(8.80)	(6.21)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

[29] When considering all submitted (no default) bids where investors cash holding exceed the price expectation and all submitted (no default) offers where investors hold stocks the overall t-statistic for bids is 7.38 and for asks is 4.52.

Table 4 – GLS regression of ranked bid and ranked ask on **ranked long-term beliefs when** bids exceed beliefs and beliefs exceed asks (t-statistics in parenthesis)

$$y_{mgit} = \alpha + rank\ [LTB_{mgit}]\beta$$

	Bids (*rank* [*bid*] = *y*)		**Asks** (*rank* [*ask*] = *y*)	
	Intercept **α**	**Slope** **β**	**Intercept** **α**	**Slope** **β**
Market I	5.65[fa]	0.24[fa]	1.74[a]	0.12[a]
(N=277,127)	(23.14)	(5.50)	(4.62)	(2.17)
Market II	6.24[fa]	0.16[fa]	1.67[a]	0.12[a]
(N=207,133)	(21.41)	(3.03)	(5.51)	(2.70)
Market III	7.18[a]	0.03	2.21[a]	-0.02
(N=171,105)	(22.24)	(0.48)	(6.92)	(-0.44)
Market IV	7.74[a]	0.09	1.83[a]	0.08
(N=118,83)	(28.42)	(0.66)	(5.56)	(1.21)
Overall[30]	6.48[fa]	0.14[fa]	1.87[a]	0.08[a]
(N=773,448)	(43.99)	(5.22)	(11.90)	(3.02)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

[30] When considering all submitted (no default) bids where investors' cash holding exceed the price expectation and all submitted (no default) asks where investors hold stocks the overall t-statistic for bids is 6.00 and for asks is 4.70.

Table 5. GLS regression of net-purchase, share-holdings on **ranked short-term** and **ranked long-term beliefs** (t-statistics in parenthesis)

$$y_{mgit} = \alpha + rank\ [STB_{mgit}]\beta_1 + rank\ [LTB_{mgit}]\beta_2$$

	Net-purchase *[S = y]*			**Shares** *[S = y]*		
	Intercept α	***rank[STB]*** β_1	***rank[LTB]*** β_2	**Intercept** α	***rank[STB]*** β_1	***rank[LTB]*** β_2
Market I	-0.35[a]	0.03	0.04[a]	1.08[a]	0.08[a]	0.11[a]
(N=742)	(-3.24)	(1.18)	(2.09)	(6.33)	(2.28)	(3.21)
Market II	-0.30[a]	0.05[a]	0.01	1.11[a]	0.11[a]	0.07[a]
(N=742)	(-3.70)	(3.30)	(0.58)	(8.45)	(4.57)	(2.69)
Market III	-0.14	0.02	0.01	1.13[a]	0.10[a]	0.08[a]
(N=742)	(-1.91)	(1.33)	(0.90)	(7.87)	(4.07)	(3.11)
Market IV	-0.36[a]	0.04[a]	0.03[a]	0.99[a]	0.09 [a]	0.12[a]
(N=616)	(3.74)	(2.52)	(2.26)	(5.29)	(2.90)	(4.12)
Overall	-0.28[a]	0.03[a]	0.02[a]	1.09[a]	0.10[a]	0.09[a]
(N=2842)	(-6.28)	(4.04)	(3.02)	(13.79)	(6.69)	(6.64)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 6. GLS regression of ranked bids and asks on **ranked short-term** and **ranked long-term beliefs** when bids exceed beliefs and beliefs exceed asks (t-statistics in parenthesis)

$$y_{mgit} = \alpha + rank\ [STB_{mgit}]\beta_1 + rank\ [LTB_{mgit}]\beta_2$$

	Bids *(rank [bid] = y*)			**Asks (*rank [ask] = y*)**		
	Intercept A	***rank[STB]*** β1	***rank[LTB]*** β2	**Intercept α**	***rank[STB]*** β1	***rank[LTB]*** β2
Market I	5.18[a]	0.38[a]	0.01	1.37[a]	0.18[a]	0.00
(N=277,127)	(21.62)	(7.02)	(0.12)	(3.29)	(2.34)	(0.00)
Market II	5.48[a]	0.31[a]	0.01	1.46[a]	0.07	0.09
(N=207,133)	(17.39)	(5.50)	(0.13)	(4.58)	(1.21)	(1.60)
Market III	6.59[a]	0.22[a]	-0.05	1.88[a]	-0.06	0.08
(N=171,589)	(18.53)	(3.93)	(-0.86)	(4.69)	(-1.02)	(1.38)
Market IV	6.70[fa]	0.23[fa]	0.01[f]	0.88[a]	0.22[a]	0.01
(N=118,83)	(21.27)	(5.09)	(0.14)	(2.27)	(3.87)	(0.13)
Overall	5.72[fa]	0.30[fa]	0.01[f]	1.49[a]	0.13[a]	0.01
(N=773,448)	(37.26)	(10.94)	(0.30)	(8.29)	(4.22)	(0.33)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 7 - GLS regression of rank profits on **ranked absolute relative deviation of short-term beliefs** from prices and fundamentals (t-statistics in parenthesis)

$$rank\,[profit_{mg}] = \alpha + y\beta$$

	Deviation from prices		**Deviation from dividend value**	
	Intercept α	***y*=*rank*[*RBPD*] β**	**Intercept α**	***y*=*rank*[*RBVD*] β**
Market I	7.21[a]	-0.44[a]	7.53[a]	-0.51[a]
(N=53)	(10.18)	(-3.52)	(11.05)	(-4.18)
Market II	5.72[a]	-0.14	5.82[a]	-0.16
(N=53)	(7.32)	(-1.04)	(7.47)	(-1.19)
Market III	5.65[a]	-0.13	4.86[a]	0.03
(N=53)	(7.22)	(-0.94)	(6.16)	(0.20)
Market IV	6.45[a]	-0.29[a]	6.13[a]	-0.23
(N=44)	(7.74)	(-1.96)	(7.23)	(-1.51)
Overall	6.25[a]	-0.25[a]	6.08[a]	-0.22[a]
(N=203)	(16.23)	(-3.66)	(15.67)	(-3.15)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 8. GLS regression of transaction volume on belief dispersion and lagged transaction volume (t-statistics in parenthesis)

$$vol_{mgt} = \alpha + BD_{mgt}\beta_1 + vol_{mgt-1}\beta_2$$

	Short-term beliefs			**Long-term beliefs**		
	Intercept **A**	***BD*** $_{mgt}$ β_1	***vol*** $_{mgt-1}$ β_2	**Intercept** **A**	***BD*** $_{mgt}$ β_1	***vol*** $_{mgt-1}$ β_2
Market I	2.69[fa]	0.55[f]	-0.13[f]	3.50[fa]	-0.80[f]	-0.20[f]
(N=84,78)	(6.85)	(0.86)	(-1.14)	(6.00)	(-0.92)	(-1.80)
Market II	2.55[fa]	-0.99[f]	-0.15[f]	2.24[fa]	0.41[f]	-0.15[f]
(N=84,78)	(7.94)	(-1.72)	(-1.28)	(5.94)	(0.82)	(-1.33)
Market III	1.39[a]	0.32	0.14	1.53[fa]	0.58[f]	-0.02[f]
(N=84,78)	(4.78)	(0.39)	(1.28)	(4.96)	(1.14)	(-0.18)
Market IV	1.64[a]	0.11	0.09	1.76[a]	-0.34	0.11
(N=70,65)	(4.61)	(0.08)	(0.74)	(5.49)	(-0.60)	(0.81)
Overall	1.95[fa]	-0.09[f]	0.05[f]	2.06[fa]	-0.09[f]	0.03[f]
(N=322,299)	(11.79)	(-0.26)	(0.82)	(10.74)	(-0.33)	(0.46)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 9. GLS regression of absolute value of return on belief dispersion and lag absolute value of return (t-statistics in parenthesis)

$$\frac{\left|P_{mgt}-P_{mgt-1}\right|}{P_{mgt-1}}=\alpha+BD_{mgt}\beta_1+\frac{\left|P_{mgt-1}-P_{mgt-2}\right|}{P_{mgt-2}}\beta_2 ,$$

	Short-term beliefs			Long-term beliefs		
	Intercept **α**	***BD*** $_{mgt}$ β1	$\lvert P_{t-1}-P_{t-2}\rvert/P_{t-2}$ β2	**Intercept** **α**	***BD*** $_{mgt-1}$ β1	$\lvert P_{t-1}-P_{t-2}\rvert/P_{t-2}$ β2
Market I	0.13[a]	0.15[a]	0.01	0.11[fa]	0.02[f]	0.37[fa]
(N=78,72)	(3.50)	(2.82)	(0.14)	(2.85)	(0.28)	(2.39)
Market II	0.12	1.08[a]	-0.14	0.19	-0.38	0.87
(N=78,72)	(2.04)	(5.49)	(-1.23)	(2.15)	(-2.04)	(4.32)
Market III	0.22	0.61	-0.01	0.41[a]	-0.29	0.05
(N=78,72)	(2.12)	(1.46)	(-0.02)	(3.21)	(-1.11)	(0.32)
Market IV	0.17[a]	0.44	0.02	0.17[a]	0.01	-0.03
(N=65.60)	(4.18)	(0.30)	(0.18)	(4.08)	(0.22)	(-0.22)
Overall	0.16[a]	0.48[a]	0.04	0.25[a]	-0.16	0.27[a]
(N=299,276)	(4.87)	(4.42)	(0.68)	(5.64)	(-1.98)	(3.22)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 10. GLS regression of belief dispersion on absolute value of last periods return and lag belief dispersion (t-statistics in parenthesis)

$$BD_{mgt} = \alpha + \frac{\left|P_{mgt-1} - P_{mgt-2}\right|}{P_{mgt-2}}\beta_1 + BD_{mgt-1}\beta_2$$

	Short-term beliefs			Long-term beliefs		
	Intercept **α**	$\lvert P_{t-1}-P_{t-2}\rvert/P_{t-2}$ β_1	BD_{mgt-1} β_2	**Intercept** **α**	$\lvert P_{t-1}-P_{t-2}\rvert/P_{t-2}$ β_1	BD_{mgt-1} β_2
Market I	-0.05	0.88[a]	0.45[a]	-0.05	0.46[a]	0.89[a]
(N=78,72)	(-1.17)	(5.56)	(4.88)	(-1.46)	(3.30)	(18.70)
Market II	0.10[a]	0.26[a]	0.10	0.01	0.06	0.82[a]
(N=78,72)	(2.91)	(3.82)	(0.75)	(0.29)	(0.75)	(13.30)
Market III	0.09[a]	0.13[a]	0.39[a]	-0.02	0.07[a]	0.84[a]
(N=78,72)	(2.95)	(4.14)	(2.68)	(-0.59)	(2.11)	(18.46)
Market IV	0.06[a]	0.19[a]	0.47[a]	0.02	0.06	0.68[a]
(N=65,60)	(2.36)	(2.54)	(4.03)	(0.93)	(0.74)	(14.97)
Overall	0.08[a]	0.17[a]	0.40[a]	-0.01	0.08[a]	0.84[a]
(N=299,276)	(4.82)	(5.96)	(6.90)	(-0.09)	(2.61)	(32.42)

[a] Indicates coefficient is significantly different from zero at the 1 percent level.
[f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table 11. Simulated and observed average transactions per period (in percent of float) and relative deviations

	Observation		**Simulation**	
	Relative deviation	**Transaction volume**	**Relative deviation**	**Transaction volume**
Market 1	**0.46**	14.50	**0.52**	10.37
Market 2	**0.45**	11.29	**0.47**	10.06
Market 3	**0.09**	9.51	**0.12**	9.38
Market 4	**-0.08**	10.59	**-0.05**	10.44
Overall	**0.24**	11.47	**0.28**	10.07

Appendix

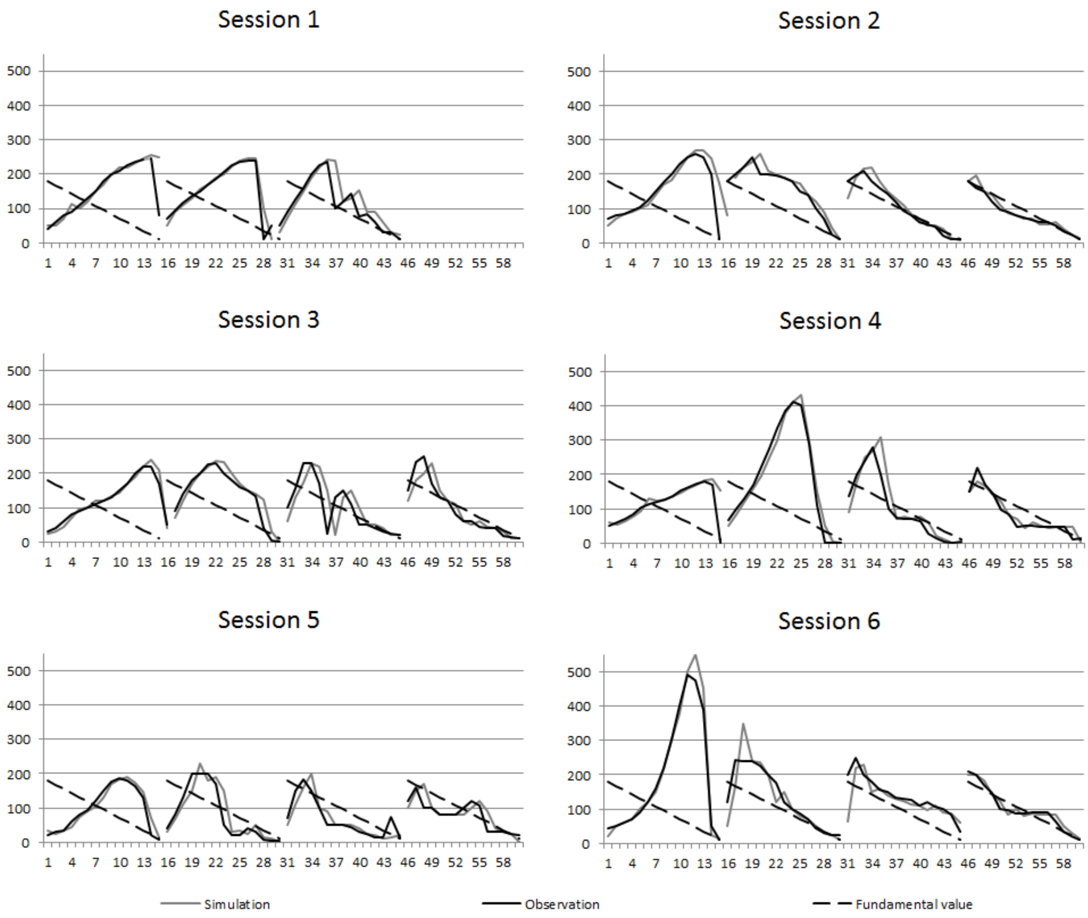

Figure A1. Realized market price per session in experimental and simulated asset market.

Table A1 - GLS regression of net-purchase, ranked bids and ranked offers with controlling for **ranked short-term beliefs**, past period price change, share and cash holdings overall markets (t-statistics in parenthesis)

$$y_{mgit} = \alpha + rank\ [STB_{mgit}]\beta_1 + (P_{mgt-1} - P_{mgt-2})\beta_2 + S_{mgit}\beta_3 + C_{mgit}\beta_4$$

	Intercept A	***rank[STB]* β1**	**Price change β2**	**Shares β3**	**Cash β4**
Net-purchase					
($\Delta S = y$)	-0.88[a]	0.02[a]	0.01	0.21[a]	0.01[a]
(N=2633)	(-15.87)	(2.28)	(0.80)	(21.32)	(12.19)
Bids					
(*rank[bid] = y*)	5.72[f a]	0.21[f a]	0.01[f a]	0.21[f a]	0.01[f]
(N=596)	(28.28)	(8.41)	(-4.41)	(6.94)	(1.73)
Asks					
(*rank[offer] = y*)	1.24[a]	0.14[a]	-0.01[a]	0.03	0.01[a]
(N=445)	(5.51)	(4.87)	(-2.70)	(0.55)	(2.82)

[a] Indicates coefficient is significantly different from zero at the 1 percent level. [f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Table A2 – GLS regression of net-purchase, ranked bids and ranked offers with controlling for **ranked long-term beliefs**, past period price change, share and cash holdings overall markets (t-statistics in parenthesis)

$$y_{mgit} = \alpha + rank\ [LTB_{mgit}]\beta_1 + (P_{mgt-1} - P_{mgt-2})\beta_2 + S_{mgit}\beta_3 + C_{mgti}\beta_4$$

	Intercept **α**	***rank[LTB]*** **β1**	**Price change** **β2**	**Shares** **β3**	**Cash** **β4**
Net-purchase					
($\Delta S = y$)	-1.02[a]	0.02[a]	0.01	0.22[a]	0.01[a]
(N=2430)	(-17.11)	(3.21)	(0.89)	(20.74)	(13.41)
Bids					
(*rank[bid] = y*)	5.81[a]	0.13[a]	-0.01[a]	0.25[a]	0.01[a]
(N=568)	(24.36)	(4.60)	(-3.58)	(7.42)	(2.51)
Asks					
(*rank[offer] = y*)	1.34[f a]	0.08[f a]	-0.01[fa]	0.11[f a]	0.01[f a]
(N=403)	(6.17)	(3.05)	(-3.27)	(2.08)	(2.42)

[a] Indicates coefficient is significantly different from zero at the 1 percent level. [f] Indicates fixed-effects regression; random-effects regression is non-indicated.

Our GLS regression approach is in line with equation (1), but instead of having the ranked beliefs as a unique explicatory variable, we add observed price change, cash and share-holding as additional variable. Applying the same conditions as above in Tables 1-6, Tables A1 and A2 recap the regression results vis-à-vis the ranked short-term beliefs and the ranked long-term beliefs, respectively. Hence, the previous significant results of short-term and long-term beliefs for trading behavior are confirmed when controlling for the price change between the prior period and the preceding period. Tables A1 and A2 reveal that although the amount of cash and share-holdings is also a significant determinant of trading behavior, both short-term and long-term beliefs are significant determinants of both net-purchase, bids and offers.