Experiences and Asset Price Dynamics *

Steve Heinke[†] Sebastian Olschewski[‡] Joerg Rieskamp[§]

11th February 2022

Abstract

Experience effects are a promising explanation for market phenomena such as time varying risk premia. Establishing the link from experiences to behavior and the market is challenging, as prior outcomes affect several factors simultaneously. We address this issue with a laboratory investment task and compare a no-information with a full-information condition. Investment decisions are in both conditions strongly affected by experienced outcomes overriding provided information. A reinforcement model captures the observed individual behavior and allows to investigate market price dynamics. The described mechanism is relevant for theory and may serve as cognitively well founded explanation for self-enforcing market dynamics.

[*] We would like to thank XXXXXXXXXXXXX for valuable comments and discussions. We gratefully acknowledge funding from the SNF: P2BSP1$_1$88188$(Sebastian Olschewski) and CRSII5_177277 (Steve Heinke and Jörg Rieskamp). Declarations of interest: none. The WISO Experimental Lab of the Hamburg University grants the ethical approval for this study. The data and analysis code are available here: XXXXXXX$

[†] University of Basel. E-mail: steve.heinke@unibas.ch

[‡] Warwick Business School. E-mail: sebastian.olschewski@wbs.ac.uk

[§] University of Basel. E-mail: joerg.rieskamp@unibas.ch

1 INTRODUCTION

Learning about the value of one's behavior based on own experience is a fundamental cognitive regularity of adaptive organisms. Recently, this mechanism has been put forth as a driving force of investors' behavior that can in turn explain several market phenomena discussed in economics and finance (Bordalo et al. 2020; Erev et al. 2017; Lejarraga, Woike and Hertwig 2016; Malmendier 2021a, 2021b). Learning from personal experience is hard-wired in our brain, as it intensifies the neural connections and neural plasticity (Bear, Connors and Paradiso 2020; Whitlock et al. 2006). As a consequence personal experience can shape beliefs and decisions more powerful than learning from abstract provided descriptive information (Malmendier 2021b), a finding that also holds among experts (, e.g. Malmendier, Nagel and Yan 2021). The most observed patterns in decisions from experiences are a *domain specificity* of the learning, i.e. personal experiences affect behavior only in similar contexts and cannot easily be transferred to other domains; and a *recency bias*, i.e. the most recent experiences has the largest weight in the learning process.

Experienced based learning serves as explanation of pro-cyclically expectation formation and risk taking, a pattern regularly observed in surveys (Amromin and Sharpe 2014; Giglio et al. 2021; Greenwood and Shleifer 2014). One implication is, that on the subjective level the risk-aversion can remain constant while on the objective level the risk-premium of the risky assets over the risk-less return varies counter-cyclical to the economy. Thus, experienced based learning provides a rational for the counter-cyclical equity risk-premium (, see Asparouhova et al. 2015; Barberis et al. 2015; 2018; Ehling, Graniero and Heyerdahl-Larsen 2018; Fuster, Hebert and Laibson 2012; Fuster, Laibson and Mendel 2010; Malmendier, Pouzo and Vanasco 2020a; 2020b; Nagel and Xu 2021, as examples of asset pricing or dynamic macroeconomic models with experienced learning), a phenomena still under intense investigation (Campbell and Shiller 1988a, 1988b; Cochrane 2011; Shiller 1981). Moreover, in a standard model of efficient financial markets the asset price reflects all available information and investors can learn from observing the equilibrium price about the fundamental value of the asset. In these types of models the decision makers are assumed to make errors, that are independent of each other and cancel out in the aggregation process. However, experienced based learning and in particular the *recency bias* can be seen as an correlated error in the expectation formation of all market participants. When all market participants observe and experience the same prior outcome, markets might fail to serve their main purpose in aggregating information, which lowers the informational content of prices. As Hassan and Mertens 2017 point out, correlated errors in the expectation reduces the incentives to use private information when socially its most beneficial, i.e. investors rely less on their private signal about the assets value and put more emphasize on the changes in the market price. This effect increases the overall uncertainty in the financial markets as well as the economy and distorts the capital allocation, labour supply, output and consumption in the economy. Through the strong role of experience for behavior and the mechanism of correlated error, individual investor experiences can affect the economy and welfare.

To investigate and model the effect of individual experiences on market outcomes, it is important to conceptualize how investors form their expectations based on experiences and describe the mechanism affecting risk-taking behavior. Establishing such a link from individual experience effects to market outcome is nontrivial, as there are several measurement and identification problems. Most of the empirical evidence on experienced based learning and investment decisions stems from field and survey data, which established the connection between experiences or subjective beliefs and decision making in the financial and economic domain (Malmendier 2021a, 2021b). While these types of data captures a representative sample of the households in the economy, one has to make strong assumptions to infer from surveys on expectations to the actual (investment) behavior. For example, simultaneously with prior experiences a plethora of other factors are also affected, such as wealth, income and background risk, altering the available resources for risk taking. Moreover, in the market each experience contains also new information for the decision makers, altering what is rationally to be expected. Additionally, households portfolio decisions are governed by inertia (e.g. Andersen et al. 2015; Andersen, Hanspal and Nielsen 2016; Brunnermeier and Nagel 2008) and the information and option sets vary among households. Thus it remains unclear which particular experiences affected asset allocation of households. Furthermore, as experienced based learning is *domain specific* the researcher has to know the experience and circumstances made up to a particular decision situation to draw conclusions on the subsequent risk taking (, e.g. Heinke, Leuenberger and Rieskamp 2020). Consequently, if and how experience of individuals translate to market outcomes remains an open question.

We address these measurement and identification problems by conducting an incentivized laboratory investment task with experiences over several independent rounds. This gives us control over the investment options and stochastic process, while holding wealth and income constant. Thus, the objective expected value of the investment options are known. We build on the experimental paradigm of Biais et al. 2017 that allows at a later stage to draw conclusions about the price dynamics of an asset based on independent individual investor behavior. In this paradigm in each round participants are endowed with shares of a stock and enough cash to buy additional shares. In each round they submit a demand schedule indicating the quantity of shares they want to hold for a preset price range, that way we can measure the investor's preferences concerning this share much more accurately than other designs allow for. Once all demand schedules are submitted the experimenter determines randomly a price at which trade takes place by drawing from a number on a ball from a big bag. Subsequently, the experimenter throws a six-sided die, determining the liquidation value of the asset. Both random mechanisms are mechanically and transparently conducted to give participants a clear understanding of the independence of the stochastic processes. The held shares are transferred into cash according to the determined liquidation value at the end of the round and thus determine the payoff for the participant in one round. Participants play 30 independent rounds, where no wealth in cash or shares is transferred across rounds and they start every round with the same endowment. That way, we can control any wealth effects that can be present in observational data. We contrast a setting where all information about the liquidation value is provided with one where participants learn the outcome values of the liquidation value through experience.

Biais et al. 2017 make two observations for this paradigm, we take advantage of: first, the individual behavior is best described by a random utility model. This allows us to estimate for each individual a structural model consisting of reinforcement learning and a probabilistic choice rule. We use the individually estimated decision models describing the behavior of each participant best to simulate the outcome of a call market once all participant observe the same liquidation value. Second, with respect to the market price determination, Biais et al. 2017 find for this paradigm no differences in individual behavior for a call-market mechanism, matching all demand schedules to find the price with the largest trading volume, and a randomly drawn price. Therefore we use the random draw of the price to generate observations that are independent of the choices of others. In addition each participant had a different association between the number on the dice and the liquidation value reducing potential biases such as order or cohort effects. Both aspects improve the estimation of the structural model on the individual level.

Reinforcement learning is the most applied concept to model experienced based learning, and therefore the obvious choice how to incorporate experienced learning into our conceptual framework. In a nutshell, reinforcement learning assumes that decision makers keep track of the running mean of a sequence of outcomes and update it in proportion to the difference between their expected and the observed outcome (, i.e. the reward-prediction error, Sutton and Barto 2018). The main intuition is that a decision makers wants to repeat behavior which coincided with pleasure in prior situations and avoid behavior that is associated with pain. In general reinforcement learning models are successfully in predicting and explaining decisions with feedback in many situations (Lee, Seo and Jung 2012; Niv et al. 2012; O'Doherty, Cockburn and Pauli 2017; Olschewski, Diao and Rieskamp 2021; Schultz, Dayan and Montague 1997; Wunderlich et al. 2011) and are cognitively as well as neurologically well founded as the prediction error signal is observable as brain activity in humans as well as in other species (Rangel, Camerer and Montague 2008; Schultz 2015). These active brain ares are associated processing rewards, which also reacts to price changes in an investment task (Frydman et al. 2014; Frydman and Camerer 2016) and are successful in explaining individual investors behavior (see for an overview Barber and Odean 2013). Reinforcement learning explains human behavior in strategic games better than the Nash equilibrium prediction (Erev and Roth 1998; Feltovich 2000), the overweighing of more recent returns, affecting portfolio allocation and retirement savings (Rieskamp 2006; Rieskamp, Busemeyer and Laine 2003), or that investors seem to over-extrapolate from personal experience in 401(k) savings and are well described by reinforcement learning (Choi et al. 2009). Moreover, personal experience with Initial Public Offerings (IPOs) has a stronger effect on investors than warranted by rational Bayesian updating in line with reinforcement learning (Kaustia and Knüpfer 2008). The flexibility of the reinforcement learning framework allows to explain the learning of correlation among assets (Olschewski, Diao and Rieskamp 2021; Wunderlich et al. 2011), or the motivated belief formation induced during ownership of an asset (Trutmann, Heinke and Rieskamp 2021). In a static stochastic environment, as in our experiment, this mechanism leads to stronger (less) updating when the reward-prediction error is high (low).The described reinforcement learning mechanism has interesting implications, when one thinks about time varying expectation dynamics within a crises, associated with huge uncertainty and prediction errors, and the recovery phases, associated with a steady incremental change and thus small prediction errors.

We first provide evidence that learning from experience overrides provided a priori information. Participants in both conditions are affected by experienced outcome and show a *recency bias*, where the effects are stronger if the liquidation values have to be learned. This highlights the importance of taking experience into account, as even in the presence of all available information a positive (negative) experience leads to more (less) risk-taking. These findings are robust to the operationalization of experience – e.g. recent liquidation values, average observed liquidation values or observed payoffs – and several other co-variate such as age, gender, cognitive abilities, risk aversion, over-confidence, interest in study or comprehension of the instructions. These experience effects and the *recency bias* links rounds and decisions together that are technically independent.

Next, we show that the observed individual behavior can be described by a structural model where the decision maker is an expected value maximizer learning the value of holding one share of the asset with a reinforcement learning model and choose among options according to a probabilistic choice rule. We estimate this model for each participant separately. We find that the choice sensitivity parameter of participants, which reflects the choice consistency, correlates with over-confidence and task comprehension. This result is in line with its intuition interpretation. The mean learning rates are small, but significantly different from zero. Importantly, the average learning rates do not significantly differ between conditions, 0.10 (No-Info) and 0.11 (Info). This underlines the strength of personal experience over provided a priori information. We find heterogeneity in the observed learning rate among individuals, indicating that the strength of the experience effects vary across individuals. The learning rate does correlate with individual traits such as cognitive abilities, risk-preferences, age, overconfidence, and task comprehension. From these results one can conclude, that the learning rate captures an individual trait in its own right. The low level of the learning rate implies that new experiences are only incorporated partly into the learned value of the asset. Thus, only one new event will not alter the learned value of the share much. But it also implies that a lucky or bad strike of outcomes has long lasting effects on the learned value. This result is also of interest, as it might explains slow adaptation after an initially large shock, such as a financial crises. In terms of a reinforcement learning model a financial crises is a large prediction error, which leads to a downward adjustment of the expected value. As recovery processes in the economy are more incremental, the effect of a financial crises persist in the expectation and risk taking of those who went through the crises, which is in line with seminal results of Malmendier and Nagel 2011.

In our finale step, we investigate via simulations how individual experience impacts market price dynamics when all participants observe the same outcome. We take advantage of the observation of Biais et al. 2017, that the investment decisions is independent from the price mechanism in the investment task. Thus, we take the estimated models of all individuals and simulate their demand schedules if all observe the same sequence of liquidation values. While the individual noise cancels out in the aggregation process of the call-market, the experience effect in learning the assets' value systematically affects the price dynamics. The market price is higher (lower) in periods followed by a high (low) liquidation value. In sequences with multiple good (bad) draws the market price deviates from the long run mean of the rationally expected value of the asset. In markets with a high average learning rate, the asset price volatility is high. But, when the liquidation values of the asset are unknown the convergence towards the long-run mean is faster. These results imply that over- and under-valuation of the asset can persist substantially.

Our findings contribute to several strand of the literature. Close to our approach, a growing literature investigates the role of prior experiences in financial decision-making in particular. The overarching consensus is, that letting people experiencing a loss of an asset rather than a gain makes them invest less into that asset, even when they know that the stochastic process is static. This holds irrespective of the presentation format of the experiences as a trading task with pre-fixed boom or bust price paths (Cordes, Nolte and Schneider 2017; Lejarraga, Woike and Hertwig 2016), a lottery in the good or bad state (Kuhn et al. 2011; Kuhnen 2015; Kuhnen, Rudorf and Weber 2017), and priming visually (Cohn et al. 2015; Frydman and Nave 2017), or as an forecasting exercise of a stochastic process with a positive or negative trend (Kieren, Müller-Dethard and Weber 2019). Note, that a trading task with a pre-fixed price paths or lotteries in good or bad states, makes the identification of experience effects difficult, due to wealth effects or unknown stochastic processes of the price paths, which makes learning from prior outcomes a reasonable strategy. Furthermore, priming as an experimental method is sensitive to changes in experimental instructions and participants populations (Cesario 2014). Therefore it is not surprising, that the results of Cohn et al. 2015 could not be replicated with a student sample (König-Kersting and Trautmann 2018) or participants recruited via M-Turk (Alempaki, Starmer and Tufano 2019). Moreover, if the stochastic process of the priming or forecasting task is unrelated to the investment task, it remains an open question what and how people learn about the investment decision. While in our full information condition the experiences stems from the same investment decision, in Cohn et al. 2015 and Kieren, Müller-Dethard and Weber 2019 the experiences and the decision are separate tasks. This might be the reason why Kieren, Müller-Dethard and Weber 2019 do not find any experiences effects in their full information condition, opposed to Frydman and Nave 2017 and our findings. Frydman and Nave 2017 link this to a common cognitive mechanism in the belief formation for trends in a perceptual as well as a decision making task and conclude that decision makers may have a strong prior on a non-stationary model of the world, and hardly adjust the belief-formation process even-though information is given explicitly. We interpret the overriding of prior information as support for the *domain specificity* of experienced learning. Summarizing, the experimental literature shows that prior experiences affects risk taking. However, they lack to establish a close link between personal experiences, investment behavior and market outcome. Either the experiences is unrelated to the decision of interest, which leaves it open what is learned, or they have difficulties to disentangle the experiences from the wealth effect.

Our study also relates to the literature investigating that personally experienced returns on individual investment decisions. Experienced returns while invested in the stock market have a stronger effect on individual stock market participation than having the same information about previous returns through descriptive statistics (Andersen, Hanspal and Nielsen 2016; Bucher-Koenen and Ziegelmeyer 2014; Guiso, Sapienza and Zingales 2018; Hoffmann, Iliewa and Jaroszek 2017; Malmendier and Nagel 2011, 2015). Experiences also reveals and improves the own ability of good investment decisions and might affect the decision to stop trading (Seru, Shumway and Stoffman 2010). Those experience effects are stronger once investor had "skin in the game", as evidence from the field (Bucher-Koenen and Ziegelmeyer 2014; Choi et al. 2009; Guiso, Sapienza and Zingales 2018; Hoffmann and Post 2017) as well as from the lab (Hartzmark, Hirshman and Imas 2021; Kuhn et al. 2011; Kuhnen 2015; Kuhnen, Rudorf and Weber 2017; Trutmann, Heinke and Rieskamp 2021) underline. Relying on experiences can be rational, if recent returns carry new information about future returns. However, as the literature and our results indicate experienced based learning has a strong impact on investors beyond incorporating new information. Dissimilarities of the impact of descriptive statistics and feedback by experiences on risk taking have also been examined experimentally: When experiencing returns rather than knowing the return distributions descriptively before making a decision, people seem to be better in making risk-reward trade-offs (Bradbury, Hens and Zeisberger 2015, 2019; Kaufmann, Weber and Haisley 2013; Laudenbach, Ungeheuer and Weber 2019; Olschewski, Diao and Rieskamp 2021). In addition, risk taking behavior also changes from provided information to experience with respect to probability weighting (Hertwig et al. 2004; Hertwig and Erev 2009) and risk preferences (Ludvig and Spetch 2011). In most of these studies the format of information presentation varies between information provided and experience while holding the content of the information similar. However, some studies also explore the effect of experience when descriptive information about a lottery was available as well. In these cases, experiencing samples should not provide additional information. Yet, as a result, behavior seemed to be more in line with experience-based risk taking even though descriptive information was available (Erev et al. 2017; Lejarraga and Gonzalez 2011; Plonsky and Erev 2017). Thus, consistent with our results, experienced outcomes have an effect on behavior even when all statistical information is available.

Most importantly, we establish a close link between personal experience effects, cyclical risk-taking and asset price dynamics. The pro-cyclically expectation formation, leading to optimism in boom markets and pessimism during recessions leads in turn to pro-cyclical risk taking over time, which helps to understand systematic and time varying risk premium of asset classes. A large branch of explanations (Barberis, Huang and Santos 2001; Campbell and Cochrane 1999; Grossman and Shiller 1981) assumes rational Bayesian expectation formation, which implies that decision makers know in equilibrium the full probability distribution and anticipate the counter-cyclical risk-premium of stocks (Nagel and Xu 2021). In particular the latter is at odds with empirical pro-cyclical pattern of investors expectations and reinforcement learning seems to be a better suited explanation. The existence of a link between individually experienced outcome and the market is a corner stone of models trying to explain asset pricing dynamics, including high volatility, bubbles and the risk premium of asset classes, by incorporating experienced based learning (Barberis et al. 2015, 2018; Bordalo et al. 2021; Bordalo et al. 2019; Bordalo, Gennaioli and Shleifer 2018; Malmendier 2021a, 2021b; Nagel and Xu 2021). While survey evidence established the association between experiences, expectations and investment decision, as discussed above only strong assumptions allow for inferences from survey responses to actual behavior. Our findings of pro-cyclical risk taking with a experienced based learning and the short- to long-run implications for asset price dynamics give support to the mechanisms discussed in theories above. Moreover, as personal experiences overrides provided a priori information, it is plausible that the experiences effects are much stronger in the real world than implied by surveys that are less specific to individual experiences and decisions.

The remaining manuscript is structured as follows. In section 2 we conceptulize experienced based learning and its impact on the market price. Section 3 describes the experimental design. Section 4 investigates the role of prior outcomes on the subsequent decision in our task, while section 5 describes the estimation of the structural model to the observed behavior. In section 6 we simulate market outcomes with the fitted models and discuss the price dynamics. Finally, Section 7 discusses our findings and draws conclusion.

2 CONCEPTUAL FRAMEWORK

This section investigates how the experienced learning on the individual level aggregates and translates into the market price. First, we conceptualize the experienced based learning by reinforcement learning, a well established model class in cognitive psychology and neuroscience and successfully applied to economics and finance (Barber and Odean 2013; Erev and Roth 1998; Frydman and Nave 2017). In a second step we follow the insights of Biais et al. 2017 and assume bounded rational investors, who choose randomly among actions, with a larger probability on action generating a higher value. Finally, we discuss the impact on the market price dynamics.

Experienced based learning. At the beginning of round t each investor $i \in N$ is endowed with $\overline{q}$ shares of one asset. At the end of round t each share is liquidated into cash by a randomly determined liquidation value x_t. The impact of the previous liquidation value of the asset on subsequent valuations can be modeled with a reinforcement learning models: The expected value of holding one share of the asset V_t^i at time t depends on the expected value of the previous period, V_{t-1}^i, and the experienced realization x_{t-1}:

$$V_t^i = V_{t-1}^i + \gamma_i * \left(x_{t-1} - V_{t-1}^i\right), \tag{1}$$

with $\gamma_i \in [0, 1]$ as the individual learning rate. Note, two components drive the change in the expected value: first, the prediction error or surprise $\left(x_{t-1} - V_{t-1}^i\right)$, the further the experienced liquidation value x_{t-1} from the prior expected valuation V_{t-1}^i, the larger will be the change in the expected value; second the learning rate γ_i, low values mean that last experienced return x_{t-1} has only a small impact on the expected value of the asset, and vice versa. If the investor does not react on prior outcomes, we expect γ_i to be zero.

Bounded rationality with random choices. The investor i is a price-taker and states for each price, p_t, the quantity $q_t^i \in [0, q^{max}]$ desired to hold at that price. For illustrative purposes let us assume an expected value maximizer with a rational valuation function $U_i(q_t^i, p_t) = b_i + \overline{q}p_t + \left(V_t^i - p_t\right) q_t^i$, with b_i as constant capturing individual differences. This implies that if $V_t^i > p_t$ the investor wants to hold $q_t^i = q^{max}$, or if $V_t^i < p_t$ then $q_t^i = 0$. Only if $V_t^i = p_t$ the investor is indifferent between offering or demanding more shares and we assume that the desired quantity to hold is the initial portfolio $\overline{q}$.

We build on the random choice rule proposed by Luce 1959, also known as softmax rule[1]: investors decide randomly among the quantity they want to hold, with a larger probability on the quantity generating the

[1] Biais et al. 2017 apply the same framework.

highest value. Thus for each investor i exists a function $\phi_i\left[.\right]$ increasing in U_i such that the density of q_i is:

$$f_i\left(q_i, p_t\right) = \frac{\phi_i\left[U_i(q_t^i, p_t)\right]}{\sum_{q=0}^{q^{max}} \phi_i\left[(U_i(q_t^i, p_t)\right]}. \tag{2}$$

This implies that $U_i(q_t^i, p_t) > U_i(\hat{q}_t^i, p_t)$ is equivalent to $f_i\left(q_i, p_t\right) > f_i\left(\hat{q}_i, p_t\right)$ for all $(q, \hat{q}) \in [0, q^{max}]$. Intuitively, a quantity with a larger rational value U_i is more likely to be chosen. A commonly used specification of ϕ_i, which we also use later in the structural estimation, is the logit or softmax function $\phi_i = exp\left[\theta_i * U_i(q_t^i, p_t)\right]$. Note that, θ_i measures the choice sensitivity of the investor to differences in valuation (Luce 1959; McKelvey and Palfrey 1995). Thus a high θ_i value means that utility differences between the quantities translate into extreme differences in probabilities between the options. That way, if one option has a slightly higher utility than the others, the model predicts that this option will be chosen with high probability when θ is high.

Market price. In equilibrium the market price clears the market, such that the supplied shares of the asset equals the demand $\sum_{i=1}^{N} \mathbf{E}(q_t^i) = N * \overline{q}$, or

$$\sum_{i=1}^{N} \sum_{q_t^i=0}^{q^{max}} q_t^i f_i\left(q_t^i, p_t\right) = N * \overline{q}. \tag{3}$$

The market clearing price, p_t^*, will be such, that on average each investor wants to hold its initial endowment $\overline{q}$. Recall, that the individual investor i wants to hold $\overline{q}$ shares of the asset, if the market price equals the valuation of the asset. Consequently, the market clearing price p_t^* that full fills equation 3 is strongly related to the average valuation of the asset, $\frac{1}{N} \sum_{i=1}^{N} V_t^i$.

Effect of learning rate. It is obvious from the discussion above, that everything that moves the average valuation translates into the market price, as long as the average learning rate $\overline{\gamma} > 0$: a major surprise due to a large positive (negative) liquidation value , as a well as a streak of positive (negative) liquidation values leads to a higher (lower) valuation by the average investor and therefore the higher (lower) will be the market clearing price. The effect becomes larger and thus the market price will be more volatile the larger the average learning rate $\overline{\gamma}$. Moreover, any change in the fundamental value will be reflected faster in the market price, with a larger average learning rate $\overline{\gamma}$.

Note that in the experiment the stochastic processes of the liquidation value is stable. So an informed participant should not take prior experiences into account and always take the mean of the liquidation values as expected value. In this context individuals reacting less to prior experiences, γ^{low}, act as a market maker. γ^{high}-investors drive the market price up- or down, respective to their change in valuation due to prior outcomes. The valuation of γ^{low}-investors changes less and thus they provide additional demand or absorb the excess demand of γ^{high}-investors. By doing so, γ^{low}-investors bring the market price closer to its fundamental, i.e. the expected liquidation value. However, in the condition where participants have to learn the outcomes the roles revers. Participant should take prior experiences into account and have to guess initially the expected value, which we assume they do randomly and be on average in the middle of the price range (i.e. 60). In this situation individuals reacting strong to prior experiences, γ^{high}, move the market price faster to the true fundamental value.

Effect of choice sensitivity. From the market clearing condition equation 3 one can also draw conclusions on the role of the choice sensitivity parameter θ_i. Recall, a lower θ_i implies a lower sensitivity of choices to different valuations, which has two effects: on the one side, it affects $f_i\left(q_t^i, p_t\right)$ as the randomness in choices increases, reducing the informativeness and increasing the volatility of the market clearing price. On the other side, a lower θ_i means also less sensitivity to changes in the valuation. As a consequence any correlated error due to experiences effects translate less into the market price. In a market situation without any new information, this implies if θ_i is low market prices move less just due to experiences effects. However, once there is new information to learn, a lower θ_i implies also a slower adjustment process towards the new fundamental value, as the investors will react less to any changes in their valuation.

3 EXPERIMENTAL DESIGN

To examine the effect of personal experience in financial risk taking, we adopt an investment task from Biais et al. 2017. We ensured that the stochastic processes of the outcomes are intuitive and observable to the participants and non-informative about future outcomes. We also excluded wealth effects by allowing no money or asset transfers across rounds and by paying only two randomly drawn rounds out of 30. In two between-subject conditions, participants either knew, *INFO*, or did not know, *NO INFO*, the stochastic process of the outcome, which allows us to differentiate between the effect of provided information and experienced based learning about the statistical process. Drawing the market clearing price and the liquidation value randomly and individually for each participant, allows for a cleaner estimation of the structural model on the individual level. Moreover, as the price mechanism does not affect the individual behavior (Biais et al. 2017), one can use the estimated models to simulate a call market and draw inferences on the market price dynamics if all participants experience the same outcome.

Investment Task. In each round participants were initially endowed with a portfolio consisting of 300 experimental currency units, ECU, and 4 shares of a stock. The expected value, EV, of holding one share of the stock (i.e., the average liquidation value) was either low, EV=56, or high, EV 64, and consisted of six outcomes with equal probability, 1/6. The liquidation values were $27, 39, 48, 64, 73$, and 85 in the low value condition and $35, 47, 56, 72, 81$, and 93 in the high value condition. Thus the variance of the liquidation values, and thus the risk, was the same for the stocks in the low and high EV condition.

At the decision screen, Figure 1, participants saw 21 stock prices from 50 to 70 and decided how many of the stocks from zero to eight they demanded at a given price. They were thus able to invest into up to eight stocks at each price or could also sell all their stocks and receive the price for these stocks as cash. The experimenter determined the transaction price by drawing a ball from an urn filled with 21 bingo balls, with a number between 50 to 70. The number on the drawn ball was read out loud to the participants, and shown to those who were interested, before entered into the experimenter screen. Then the portfolios of all participants where updated according to the stated number of shares at the drawn transaction price.

Next, the experimenter determined the liquidation value by throwing a large die in front of all participants. The number on top of the die was read out loud and entered into the experimenter screen. The mapping between die numbers and liquidation values was random and thus different for each subject, but remained fix for each participant throughout the whole experiment. The held shares were exchanged into ECU according to the individual mapping from numbers to liquidation value. The experiment proceeded for every participant with the feedback screen on their computer, displaying the cash holdings in ECU, the amount of the liquidated shares of the stock given the thrown liquidation value also in ECU, and the sum of both ECU values, which was the payoff for this round. We had two between subjects conditions, in the *INFO* condition, participants were provided with all possible liquidation values prior to the first round. In the *NO INFO* condition, these values were not provided. In both conditions, participants knew that there were six different liquidation values that occurred with equal probability. Thus a participant in the *NO INFO* condition could expect to observe all six potential liquidation values after 15 rounds.

Additional Tasks. After the main task, participants were asked to estimate the expected value of the stock. Further, they were asked to distribute 120 points to the six observed values as well as to four decoy values according to how frequent they encountered these values. In addition, participants decided in four multiple-price lists which of two lotteries they preferred (Andersson et al. 2016; Holt and Laury 2002), and they solved four matrix puzzles (Chapman et al. 2018; Civelli and Deck 2017) to approximate their cognitive abilities (g-factor) and their overconfidence (Chapman et al. 2018). Moreover, participants assessed their own general risk preference and domain specific risk preferences (e.g. financial, health, etc.). Finally, participants answered several demographic questions including their own experience with stock investments.

Figure 1: Decision Screen (in German)

Participants state the number of stocks they want to buy for prices between 50 and 70 (only 55 until 70 is visible) by clicking on the respective ratio button (from zero to eight).

Procedure. The experiment was programmed in o-TreeChen, Schonger and Wickens 2016 and conducted at the Hamburg experimental laboratory. Participants worked on the experiment at individual computer working stations in groups of 32. Upon arrival, participants got a short standardized oral introduction and then worked at the written instructions on the computer screen at their own pace. To avoid experience effects, participants first conducted the preferences and matrix tasks lasting around 20-30minutes. Then they started with the instruction of the investment task. There were 10 comprehension questions to check participants' understanding of the task. If a question was answered incorrectly, participants received an additional explanation of the subject matter, but no participant was excluded. Participants were instructed to check all random devices themselves to rule out any doubts about the fairness of the process and the accuracy of the description. The main task was performed synchronously for the whole group. In each round participants were endowed with the same portfolio consisting of 300 ECU cash and four shares of the stock. Every participant stated for each price between 50 to 70 ECU the number of stocks they wanted to hold, between zero and eight. Only after every participant submitted their choices, the experimenter determined the transaction prices by drawing from the urn and all portfolios were update accordingly. Then, the experimenter rolled a die and the realized number determined the liquidation value and all shares in the individual portfolios were transferred into ECU accordingly. Finally, after every participant left the feedback screen, a new round started. No accumulation of prior earnings was possible. The total number of rounds was 30. At the end of the experiment, two rounds out of the 30 were randomly selected and the sum of the portfolio values in these rounds was converted into Euro (71 ECU : 1€) and paid out. In addition, participants received a bonus depending on their answers or choices for the mean estimation task, the matrices task and for the binary lottery choices. The instructions are documented in the online supplementary material S.1. and S.2., the o-tree code to run the experiment and data is available on OSF [ADD LINK].

Participants. The number of participants was determined prior to data collection. We aimed for 120 participants, resulting in 60 participants in the *INFO* and *NO INFO* condition. Due to the technical procedure of the experimental laboratory we ended up with 128 (64 per condition) participants. An experimental session lasted two hours, including organization of the group and the individual payouts. Participants came from the Hamburg experimental laboratory subject pool and our sample had a mean age of 25.93 (Mdn = 25) and an age range from 18 to 38. Sixty-seven participants identified as female and 59 as male. Participants earned a 5€ show up fee and a variable bonus of on average 23.89€ (SD = 6.34; range 15.38 to 48.94) for participating at the experiment.

	Mean	Min	Max	NO INFO	INFO
Age	25.93	18.00	38.00	26.08	25.77
Female	0.53	0.00	1.00	0.53	0.53
Instruction Quiz, % correct	42.58	20.00	70.00	41.09	44.06
Instruction comprehension (1 - 5)	3.53	1.00	5.00	3.53	3.53
Study Interest (1 - 5)	3.06	1.00	5.00	3.11	3.00
Payoff in ECU	552.11	256.00	844.00	551.12	553.09
RPMs correct (0-4)	2.78	1.00	4.00	2.75	2.81
Risk taking general (1-10)	5.19	0.00	10.00	5.12	5.25
Risk taking finance (1-10)	3.85	0.00	10.00	3.95	3.75
MPLs, % risky option chosen	51.53	0.00	70.98	52.26	50.80

Table 1: Summary statistics of the sample

Note: *Age* is self reported in years; *Female* is an indicator variable (female = 1, otherwise 0); *Instruction Quiz* are the percentage of correct answers from 10 items in the instruction quiz; *Instruction comprehension*, self reported comprehensiveness of the instructions, scale 1 (bad) to 5 (good); *Study Interest* self reported interest in study, scale 1 (no interest) to 5 (very interested); *Payoff*, final payoff in ECU from the investment task; *RPMs correct* number of solved matrix puzzles out of four Ravens Progressive Matrices style items; *Risk taking general* self reported risk taking in the general life, scale 1 (no risk taking) to 10 (very keen to take risk); *Risk taking financial* self reported risk taking in the financial domain, scale 1 (no risk taking) to 10 (very keen to take risk); *MPLs* , average % risky option chosen over four independent Multiple Price Lists for choosing risky options.

4 EXPERIENCE EFFECTS & INVESTMENT BEHAVIOR

Experiences plays a major role in sequential risk taking decisions. With our experimental design we can compare the impact of experiences and in particular *recency effects* on the risk taking when all information is available, *INFO* condition, the potential outcomes have to be learned, *NO INFO* condition. One would expect to observe an experiences effect in the latter as participants can learn something from the experiences; while in the former there is no additional information in the experiences. We start the analysis by first examining the participant's overall behavior and how the conditions affected investment into the risky stock. In a second step, we investigate the effect of prior outcomes on the demand for risky assets. We conclude this section with several robustness checks of our findings.

Investment behavior. In the *NO INFO* condition, participants demanded 3.76 (Mdn = 4, SD = 2.79) shares on average. In the *INFO* condition, this value was 3.58 (Mdn = 4, SD = 2.79), which is not significantly lower as in the *NO INFO* condition (see Table A.1 Model 1). As one would expect, participants demanded more shares when the expected value of the stock was high (M = 4.05, Mdn = 4.00, SD = 2.69), rather than low (M = 3.30, Mdn = 3.00, SD = 2.88; $p < .001$, see Table A.1 Model 2). A higher stockprice reduced the demanded quantity of the risky asset, which was less pronounced in the *INFO* condition (see Table A.1 Model 3). This means that participants in both conditions decreased their intended stocks holding as the price for the stock increased and thus the net expected value of the investment decreased. Further, separate for stocks from the low and high mean liquidation values, we observe no systematic changes in investment behavior across the 30 rounds of the experiments (see Table A.2). In addition, there was no significant interaction between experimental rounds and the info conditions. In sum, we interpret the results that participants broadly understood the task and act accordingly.

Effect of prior liquidation value. To examine the effect of prior liquidation values, we take as our dependent variable the difference in the demanded quantity of the risky asset from one round to another. This way one can easily control for individual heterogeneity among participants in their average demanded quantity. We focus on the effect of the previously experienced liquidation value on the change in the number of demanded quantity of the risky asset.

Figure 2 plots the change in demanded quantity of the risky asset on the prior experienced liquidation value for *NO INFO* condition (left) and the *INFO* condition (right). One observes for both conditions, the larger the liquidation value in the previous round, the higher the change in demanded quantity of the risky asset, or the higher the risk taking. To control and exclude further potential explanatory factors

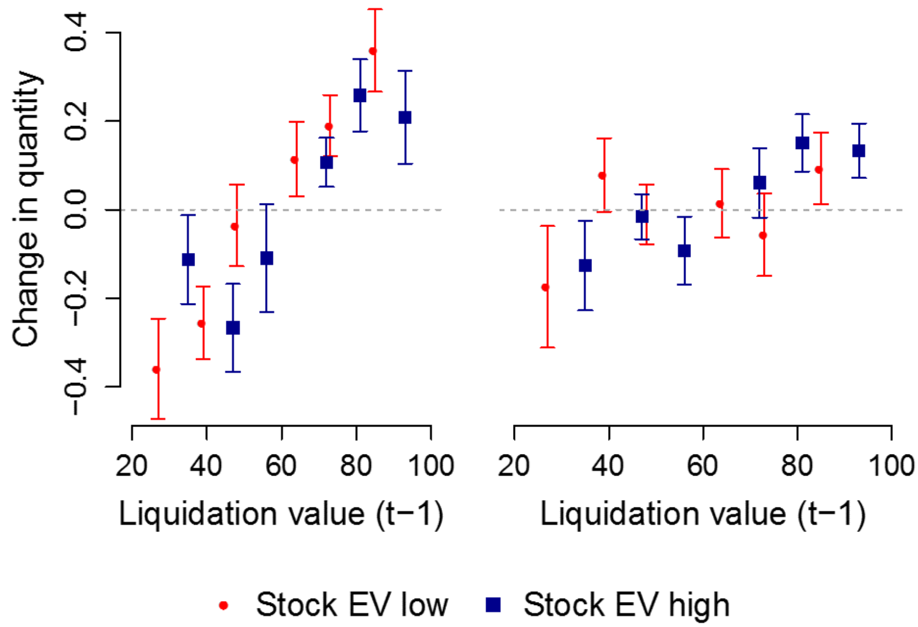


Figure 2: Prior liquidation Value and change in demanded quantity
Change in the demanded quantity (y-axis) of the risky asset from one round to the next dependent on the liquidation value of the previous round (x-axis) for the *NO INFO* condition (left) and the *INFO* condition (right). Error bars are 95% confidence intervals. The condition with a liquidation value is displayed in blue, while the low liquidation value condition is displayed in red.

we conducted panel random effect panel regressions, for the *NO INFO* and *INFO* condition separately, as well as the pooled data set to test for treatment differences. Table 2 summarizes the main results: The previously realized liquidation value of the risky asset had a significantly positive effect on the change in the number of stocks demanded in both conditions. There is also a significant negative interaction between the *INFO* conditions and the previously realized liquidation value. This means, that the effect of the previously experienced liquidation value is stronger in the *NO INFO* than in the *INFO* condition. Other than in the *INFO* condition, participants in the *NO INFO* condition gain new information from prior experiences about the underlying stock characteristics and one would expect a stronger effect of experiences. As there is a lower (0) and upper (8) bound of stock holdings, being closer to one of them might affect the possible range of the change in quantity. Therefore, we included and reported two control variables that influence this ceiling effect: First, the number of stocks demanded in the previous round which had a negative effect on the change in the number of stocks. Second, as discussed above, a higher stockprice increases the intended quantity to hold and thus the potential direction of a change. Both effects are highly significant and go into the expected direction.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Liquidation Value (t-1)	0.0102***	0.00354*	0.00972***
	(0.00169)	(0.00188)	(0.00167)
Quantity (t-1)	-0.286***	-0.228***	-0.256***
	(0.0360)	(0.0361)	(0.0255)
Stockprice	-0.0703***	-0.0644***	-0.0673***
	(0.0101)	(0.0103)	(0.00718)
Mean-High	0.0496	0.284***	0.165**
	(0.108)	(0.0915)	(0.0703)
INFO			0.276*
			(0.158)
Liquidation Value (t-1)**INFO*			-0.00557**
			(0.00247)
Constant	4.467***	4.525***	4.359***
	(0.772)	(0.783)	(0.539)
Control	Yes	Yes	Yes
Observations	38,976	37,758	76,734
R^2-overall	0.151	0.116	0.133

Table 2: Effect of previous liquidation value on change in quantity

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Liquidation Value (t-1), value at which the asset was finally liquidated in the previous round; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean-High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise. *Control Variables (omitted):* Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

Recency. The previous liquidation value has an impact on the investment choice, even if participants know about the underlying outcome distribution being independent from previous outcomes. In the following two analysis, we aim to investigate further the effect of recency – the overweighting of previous liquidation values that occurred more recently.

As first analysis we separate the effect of the average experienced liquidation values up to round $t-2$ and the last observed liquidation value on the demanded numbers of shares. Table A.3 reports the results of the corresponding regression. The effect of the average experienced liquidation values up to round $t-2$ is only significant positive in the *NO INFO* condition, with an effect size 1.5 larger than the prior liquidation value. This correspondents to the fact, that participants have to learn about the mean of the asset, which they already know in the *INFO* condition. The effect of the liquidation value of the prior period has the same sign, a similar size and significance as without controlling for the average experienced liquidation values up to round $t-2$ (compare *Liquidation Value (t-1)* coefficients from Table 2 with Table A.3). While one would expect an effect of the prior liquidation value in $t-1$ in the *NO INFO* condition, the positive and robust effect size – even-though smaller – in the *INFO* condition is interesting.

A further way to investigate the recency effect is to split the previously observed liquidation values into two parts and calculated the mean of the first and the second part starting from round 3. Recency would predict that the mean of the liqudation value from the second half of observed liquidation values is a stronger predictor for changes in investment quantities than the first half. Table A.4 shows the respective results and confirms the recency hypothesis. The effect size of the running mean of the first half of experienced liquidation values is 1.4 (*NO INFO*) to 1.7 (*INFO*) larger then the corresponding effect size of the second half. However, the experienced liquidation values are only significant predictors in the *NO INFO* condition, even-though we do not find treatment differences of the conditions once we pool the data.

Robustness. Consistent with the interpretation that the effect of the prior liquidation value indicates learning, replacing the prior liquidation values with the running mean of all previously seen liquidation values resulted in a significant predictor in both information conditions (Table A.5). In contrast to the immediate prior liquidation value, the effect of the average running mean of the experienced liquidation values was not significantly different in the two information conditions. Using the payoff of prior rounds as experienced outcome does not change the results either, but with weaker effect sizes are (Table A.6). To examine whether experienced gains or losses of the stock investment affected subsequent choices, we constructed a dummy variable that indicated whether the previous investment resulted in a net gain or loss given the selected stock price and the drawn liquidation value . Table A.7 reports a lower level of change in number of stocks for the loss domain, which is significant for the *INFO* condition or in the pooled analysis. To distinguish the effect of experience from a simple order effect, we added a round control variable to the main regression. As a result, the effect of the immediate prior liquidation value remained significant in both conditions. In addition, the effect of the previous liquidation value decreased marginal but weakly significant over time (Table A.8).

In Table A.9 we test for comprehensions effects. While the effect of the prior liquidation value became smaller and not significant once one controls for number of correct answers in the instruction quiz, it is not moderated by it. All other comprehension approximation, such as the absolute deviation of the reported mean of all liquidation values, self reported comprehension of the instruction or study interest, do not affect the level of the main effect of liquidation value of the prior round. However, a higher absolute deviation of the reported mean of all liquidation values, as well as a lower self reported comprehension of the instruction increase the main effect. Finally, the effect of the previous liquidation value on portfolio composition was not moderated by individual traits such as over-confidence, over-placement, g-factor (Table A.10), nor several measures of risk sensitivity (self reported willingness to take risks, the average estimated risk parameter for a mean-variance utility function, or stock ownership, Table A.11).

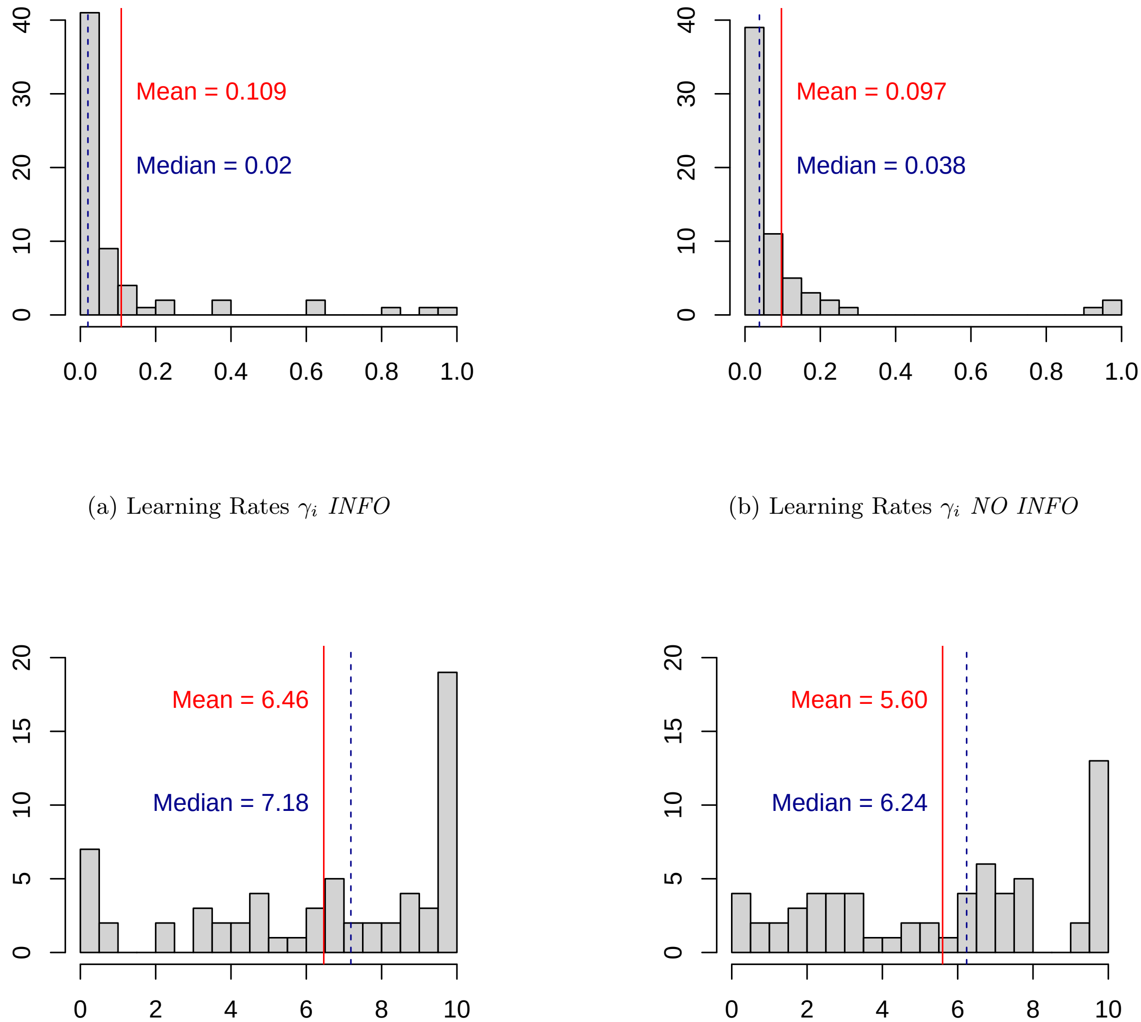
Overall, we interpret the visual as well as quantitative evidence as support for the idea that participants increase their investment into the stock the larger the realized liquidation value of the stock was in the previous round, both when they had no prior information and even when they had all information about the possible values of the stock. Moreover, more recently observed liquidation values have a stronger impact on the decision compared to outcomes observed much earlier in the task. As expected the effect of a prior liquidation values is reduced if information was available, but still significantly present. The observed experiences effects are robust to socio-demographic controls, order effects, gain-loss asymmetry, instruction comprehension or when controlling for preference. To sum up, our results are consistent with the idea that participants are affected by personal experiences even when all information about the stochastic process is available.

5 STRUCTURAL MODEL ESTIMATION

The observed experience effects on risk-taking from the prior Section 4 are captured by the conceptual framework from Section 2. In this section we first estimate the proposed structural model for each individual. In a second step, we test if the two free parameters of the model captures other than the intended individual characteristics.

Estimation. We estimated the two parameters, learning rate of the reinforcement learning model and choice consistency of the softmax choice rule as described in Section 2 from the observed demand schedules. The two free parameters of the model, learning rate γ_i and choice sensitivity θ_i, were estimated for each participant individually based on maximum likelihood and with a differential evolution algorithm in R. As initial value of the reinforcement learning model we took the true average values in the *INFO* condition and 60 ECU in the *NO INFO* condition. We grouped the resulting parameter estimates into the two experimental conditions *INFO* and *NO INFO*. The resulting individually estimated learning rates γ_i and choice sensitivities θ_i for both conditions can be seen in Figure 3.

The learning rate is the most interesting free parameter of the conceptual framework for the underlying research question. Recall that γ_i captures the updating strength due to the surprise, i.e. the differences from the expected- and observed outcome. The average learning rate estimate is $\overline{\gamma}_{INFO} = .11$ ($Mdn = .02$, $SD = 0.22$) in the *INFO* and $\overline{\gamma}_{NOINFO} = .10$ ($Mdn = .04$, $SD = .21$) in the *NO INFO* condition. Both learning rates are significantly different from 0 ($t(127) = 5.43$, $p < .001$) demonstrating that the prior liquidation values affected subsequent decisions. We also do not find a significant difference in the learning rates between the two conditions ($t(126) = .31$, $p = .756$). Note that the stochastic process in the



(a) Learning Rates γ_i *INFO*

(b) Learning Rates γ_i *NO INFO*

(c) Choice Sensitivity θ_i *INFO*

(d) Choice Sensitivity θ_i *NO INFO*

Figure 3: Histogram of individual parameter estimates.

Individual parameter estimates of the structural model as described in Section 2. The y-axis always depicts the number of participants. The red straight line represents the mean, while the blue dashed line depicts the median of the participants in the respective conditions. The parameters for the *INFO* condition are on the left panel and of the *NO INFO* condition on the right panel. Learning rate (upper row) corresponds to the individual learning rate in the reinforcement learning modelγ_i. Choice sensitivity (lower row) corresponds to the individual sensitivity of the softmax choice rule θ_i.

experimental paradigm is stationary and in the *INFO* condition there is nothing to learn from experiences. Thus, one would not expect that experiences has an impact on the valuation for the *INFO* condition. A low median learning rate of .02 suggests, that a substantial fraction of participants acts accordingly. The higher median value of the learning rate .038 for the *NO INFO* condition reflects that participants can actually learn from experiences.

In Table A.12 and Table A.13 we investigate whether the learning parameter γ_i captures behavioral differences resulting from individual traits: Woman have on average a +.01 higher learning rate, which is a highly significant effect and robust across specifications. For the remaining variables, such as age, cognitive abilities, risk-taking preferences, overconfidence, or study comprehension/interest we do not find significant effects on the learning rate. In an incentivized task we asked participants to report their expected mean of the liquidation value. This opens a further way to test the intuitive interpretation of the learning rate γ_i. For the *NO INFO* condition one would expect that a higher learning rate implies a faster learning from experiences of the true value and thus improving the final estimate. While the opposite is true for the *INFO* condition, as there is nothing to learn and a stronger learning from experiences biases the judgment. In Table A.15 we investigate the relationship of the learning rate on the error in the reported mean for both conditions. For the *NO INFO* condition there is no significant effect of the learning rate γ_i and the error in the reported mean. But for the *INFO* condition we observe that a higher learning rate γ_i leads to a larger error in the reported mean.

The choice sensitivity is the second free parameter in the conceptual framework. A higher estimated θ_i reflects a higher sensitivity of choices to different valuations and thus a less random behavior. The average estimated choice sensitivity $\overline{\theta}_{INFO} = 6.47$ ($Mdn = 7.18$, $SD = 3.43$) in the *INFO* and $\overline{\theta}_{NOINFO} = 5.62$ ($Mdn = 6.24$, $SD = 3.26$) in the *NO INFO* condition. Hence, descriptively decisions were more deterministic with respect to the utility order in the *INFO* condition than in the *NO INFO* condition. However, this difference did not reach statistical significance, ($t(126) = 1.43$, $p = .155$). From Table A.16 one can infer that the choice sensitivity γ_i is lower for woman, indicating less deterministic choices. Moreover, γ_i is unrelated to age, cognitive abilities, and risk-taking preferences. Table A.17 reports a strong correlation between overconfidence, study-comprehension, and -interest and choice sensitivity γ_i. Also the analysis of the error in the reported mean, see Table A.18, shows that a higher choice sensitivity correlates with a smaller error in the reported mean.

Summarizing we conclude: the estimated choice sensitivity parameters reflect the intuition, that a higher θ_i can be associated with less random choices. While, the learning rate γ_i does not capture individual characteristics or study comprehension, and can be interpreted as an individual trait in its own right.

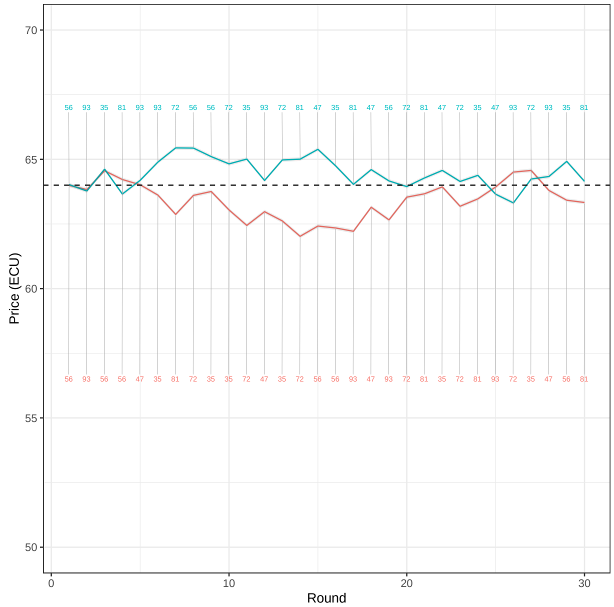
6 PRICE DYNAMICS

In a financial markets all investors observe the same realization of outcomes. Combining this with the above observed experienced based learning and *recency effect*, the asset valuation of all market participants is affected in the same direction as the prior outcomes. As a consequence, the market price is driven by a correlated biased expectation of the stock value from all investors, which will not be cancelled out in the the price formation through aggregation. Hence, the described mechanism might lead in the short run to a deviation of the market price from its long-run fundamental value.

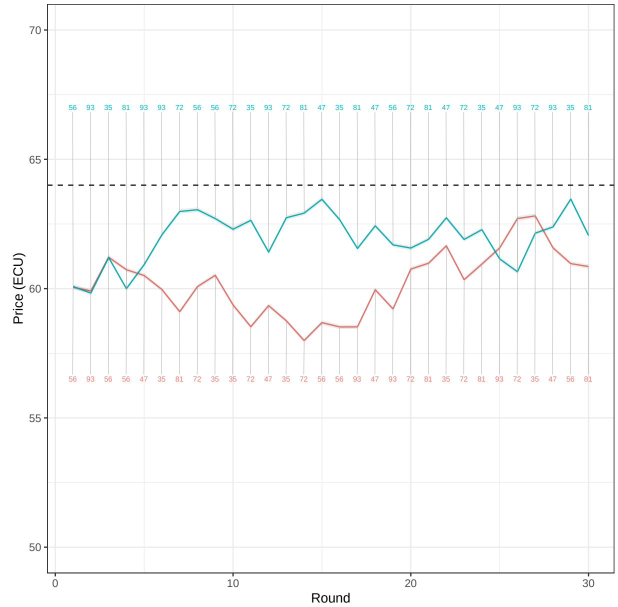
This section investigates the hypothesized market dynamics, by taking advantage of the experimental design and estimates of the structural model from Section 5. Equipped with these individually calibrated models we simulate the market price once all observe the same liquidation values and compare price dynamics in markets varying the composition of investors. Thus, we infer from structural models estimated on behavior in an individual decision task to behavior in a market setting. Sufficiency of this investigation step finds support in two crucial observations by Biais et al. 2017 within a similar experimental paradigm: first, the behavior of participants does not differ when the price is drawn randomly – as in our experimental setting – or the result from aggregating the demand schedules in a call-market. Second, participants behavior is best described by a probabilistic choice rule, as we apply it in our reinforcement learning and decision making model. These two observation are a valid foundation to analyse the impact of the experienced based learning on the market price.

Simulation of the market price. For illustrative purposes, we first calculate for each realized liquidation value path the mean and identify the 25% and 75% quartiles of the average realized liquidation values. This yields for the *INFO* and *NO INFO* conditions two separate samples of liquidation values each, with a low (LV25) or high (LV75) average in the experienced liquidation values. Note, that 50% of the liquidation paths had an even more extreme outcome. In a second step, we apply the structural model fitted for each participant separately and predict the individual demand schedule for the prices between 50 and 70 ECU given the commonly experienced liquidation value paths LV25 and LV75. In line with the structural estimation approach we take as initial value of the asset the true average values in the *INFO* condition and 60 ECU in the *NO INFO* condition. Finally we aggregate all demand schedules and determine the market price, such that it maximizes the traded quantity. Basically, we follow the procedure of a closed book sealed bid call-market, where only the market clearing price is revealed, while traders identity as well as the traded quantity are omitted. Note, that the estimated demand schedules are only pooled if the participant was in the respective condition. Everything else remains as in the experiment, i.e. the decision makers start in every round with the same initial portfolio and the stocks holdings are liquidated at the end of the round. Thus, there are no wealth or portfolio effects that are carried over to the next round, just the subjectively learned valuation of asset.

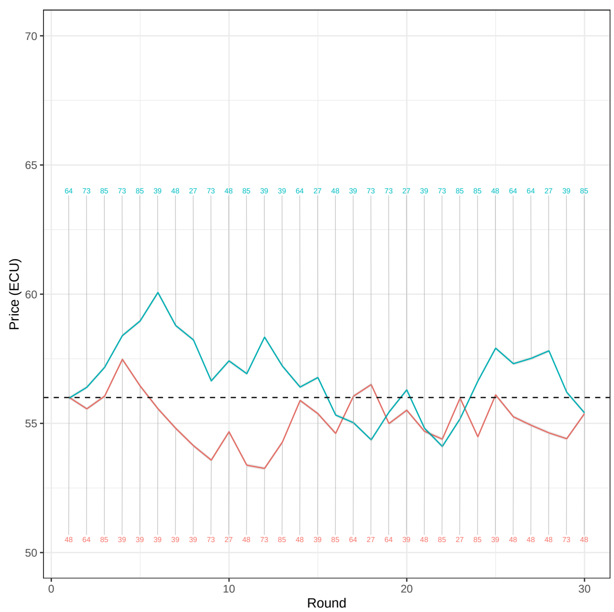
Figure 4 shows the average resulting market price dynamics of 1000 simulations for all conditions. The



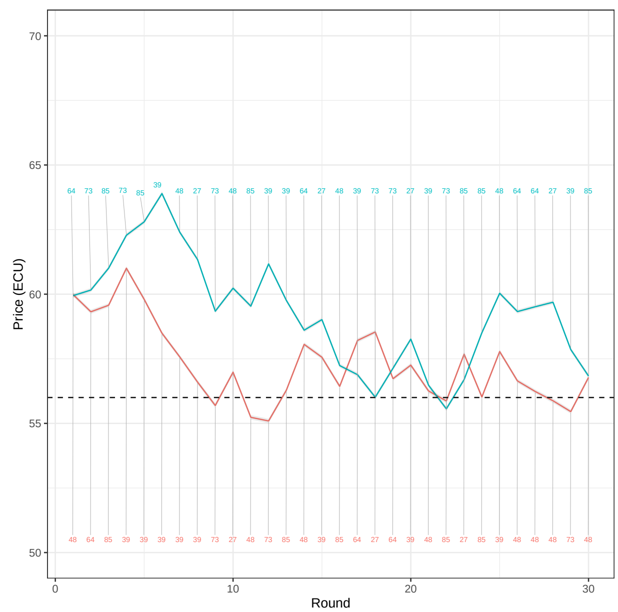
(a) High Liquidation Value and Info



(b) High Liquidation Value and No Info



(c) Low Liquidation Value and Info



(d) Low Liquidation Value and No Info

Figure 4: Simulated Market Prices in the four conditions.

This figure depicts the simulated market price in ECU (y-axis) over the rounds (x-axis). The Liquidation Value Samples $q25$ and $q75$ are the 25% and 75% quartile of the mean realized Liquidation Values. The market price of each round is labeled with the respective liquidation value drawn at the end of the round. The respective simulated market prices are displayed with bootstrapped empirical 95% interval as shadowed area around the lines. The dashed black lines represents expected value of the respective liquidation value in this condition.

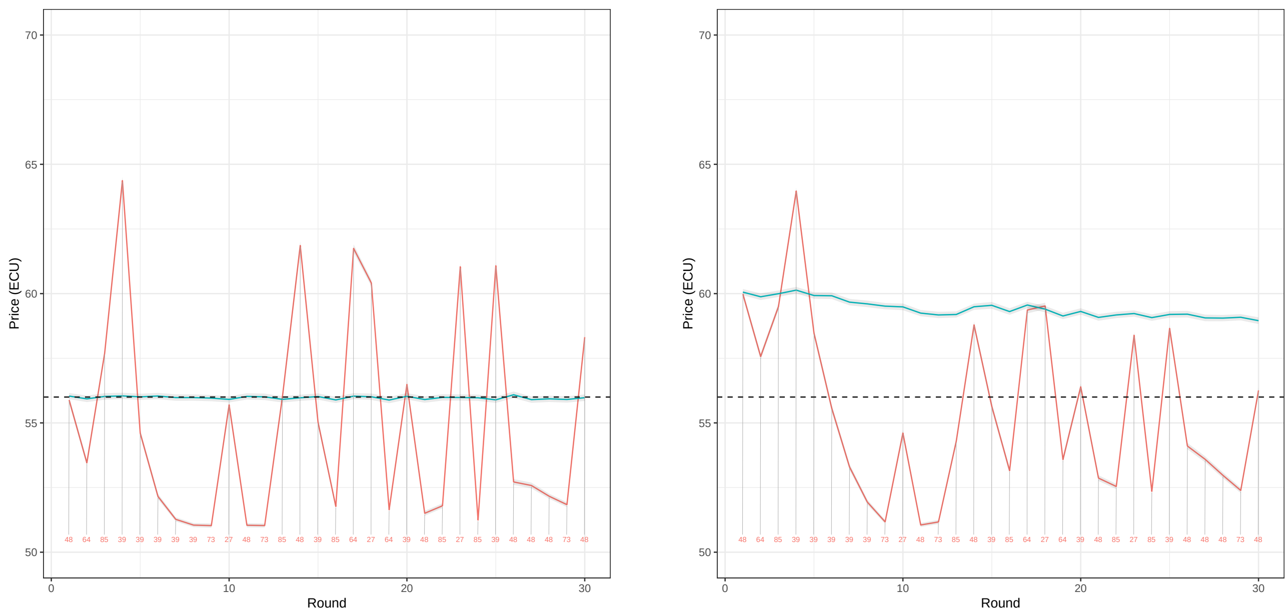
upper two graphs are the simulated market prices if the average of the Liquidation Value was high (mean = 64, dashed black line). While, the lower two graphs are for those condition with on average low Liquidation Values (mean 54, dashed black line). Graph (a) and (c) display the respective market prices if all participants are informed about the liquidation values are pooled, while Graph (b) and (d) show the conditions where the liquidation values had to be learned. The liquidation value drawn at the end of a round are displayed in each graph for each round and in the respective color. All market prices are displayed with the bootstrapped empirical 95% interval.

Experience & Price Dynamics. The market mechanism cancels out the idiosyncratic errors from the simulated demand schedule of the probabilistic choice rule, describing participants behavior best. However, due to the experienced based learning, all demand schedules are shifted towards the same direction as the prior outcome. As a consequence, the market price moves considerably away from its expected fundamental value (mean of the liquidation values). The longer a strike, the larger the deviation. This can be observed in all four graphs, independent whether participants where informed about the liquidation values or had to learn them.

The second observation is, that in the long run the market price adjusts towards the expected fundamental value. This becomes clear in the conditions where participants had to learn the potential values (Graphs (b) and (d)) and we assumed an initial asset value of 60 for each participant. Recall, that on average it takes 15 rounds to observe all six potential liquidation values and achieve full information. In the high- as well as in the low- Liquidation value *NO INFO* condition the market price remains on average below (above) the fundamental value in the final rounds. Thus in our very static and symmetric setting, participants adapt slowly to the new environment and mispricing can persist over many periods. This finding is in particular of interest for financial crises: A large and rare negative return shifts the average expected value downwards; while the recovery phase is usually associated with smaller and more common positive returns, leading to more incremental upward adjustments in the expectations and consequently prices.

Heterogeneity & Price Dynamics. To investigate the heterogeneity, we compare the market price dynamics for investors with on average a high or low learning rate γ_i. For each of the four conditions we define low (high) learning rate investors separately, as belonging to the lower (upper) tertile with size of the learning rate γ_i. To allow a clearer comparison we fixed the choice sensitivity θ_i of each individual to the mean of the *INFO* and *NO INFO* condition respectively. For each of the resulting subgroups, the market price are simulated according to the procedure described above. Figure 5 shows the resulting market prices for the two low liquidation value conditions, with the liquidation value sample as the 25% quartile of the respective mean realized liquidation values.[2] While the red line represents the market price of the participants with the high learning rate, the green line depicts the market price for markets with investors having a low learning

[2]Figure B.1 reports the remaining six visual comparisons.



(a) Info, LV_{q25}^{Low}

(b) No Info, LV_{q25}^{Low}

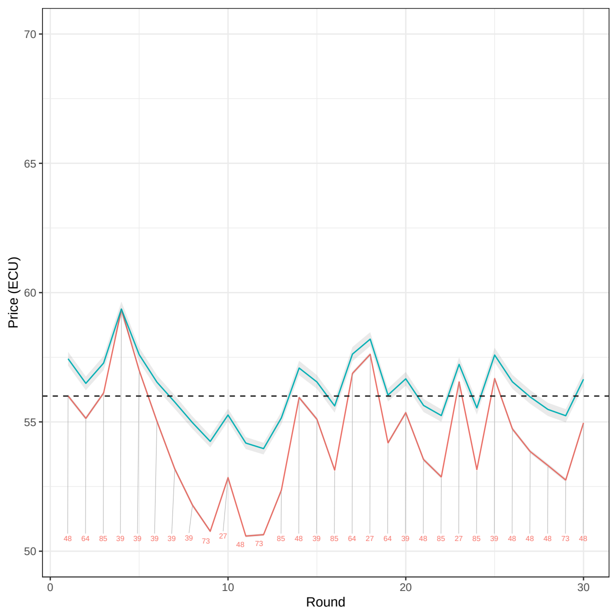
Figure 5: Price Dynamics for markets with high (red) and low (green) learning rates γ_i.
This figure depicts the simulated market price in ECU (y-axis) over the rounds (x-axis). The liquidation value sample is the 25% quartile of the mean realized liquidation values of the respective two low liquidation value condition. The choice sensitivity θ_i is fixed to the mean of the *INFO* and *NO INFO* condition respectively. The price for the simulated markets with investors having a high learning rate γ_i^H is displayed in red, while the price for the markets with investors having a low learning rate γ_i^L is displayed in green. The market price of each round is labeled with the respective liquidation value drawn at the end of the round. The respective simulated market prices are displayed with the bootstrapped empirical 95% interval as shadowed area around the lines. The dashed black lines represents expected value of the respective liquidation value in this condition.

rate.

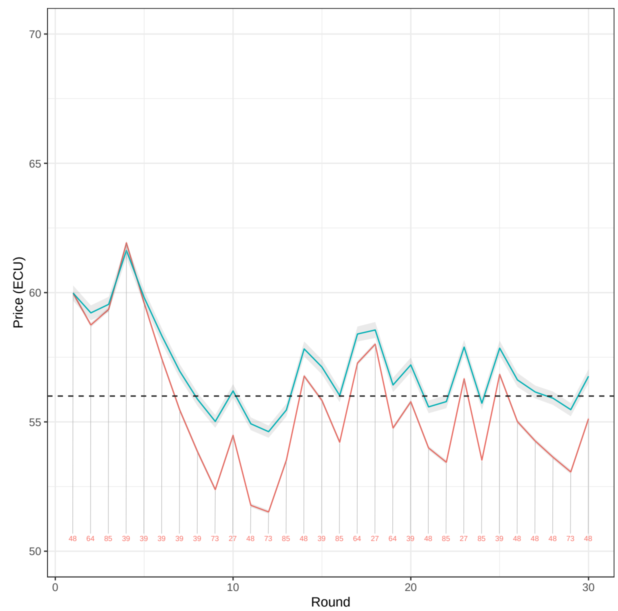
The visual inspection yields, that the average learning rate in markets is crucial for the price dynamics and price discovery process. On the one side, markets with a high (low) average learning rate depict more (less) volatile markets. Thus individuals with a low learning rate act as price stabilizer. This is however a double edged sword. If there is full information (*INFO* condition) the market price is very close (far away) to the fundamental value once the average learning rate is low (high). However, if the liquidation values have to learned (*NO INFO* condition), those markets with high average learning rate trade faster around the expected value of the asset.

As Figure 6 shows the asset price dynamics are less distinct once segregating the participants into market along the choice sensitivity θ_i. For each of the four conditions we define low (high) choice sensitivity investors separately, as belonging to the lower (upper) tertile with size of the choice sensitivity θ_i. Again, for a better comparative static we fixed the choice sensitivity γ_i of each participants to the mean of the *INFO* and *NO INFO* condition respectively. For each of the resulting subgroups, the market price are simulated according to the procedure described above.[3] A higher choice sensitivity in the markets leads to a stronger reaction

[3] Figure B.2 reports the remaining six visual comparisons.



(a) Info, LV_{q25}^{Low}



(b) No Info, LV_{q25}^{Low}

Figure 6: Price Dynamics for markets with high (red) and low (green) choice sensitivity θ_i.
This figure depicts the simulated market price in ECU (y-axis) over the rounds (x-axis). The liquidation value sample is the 25% quartile of the mean realized liquidation values of the respective two low liquidation value condition. The learning rate γ_i is fixed to the mean of the *INFO* and *NO INFO* condition respectively. The price for the simulated markets with investors having a high choice sensitivity θ_i^H is displayed in red, while the price for the markets with investors having a low choice sensitivity θ_i^L is displayed in green. The market price of each round is labeled with the respective liquidation value drawn at the end of the round. The respective simulated market prices are displayed with the bootstrapped empirical 95% interval as shadowed area around the lines. The dashed black lines represents expected value of the respective liquidation value in this condition.

to experiences, in case of the *NO INFO* condition this implies a faster convergence to the true fundamental value. Moreover, a lower choice sensitivity has two effects: first, due to the larger randomness of the choices the uncertainty of the prices increases, as one can see in the larger shaded area, the bootstrapped 95% interval ls, around the prices from markets with a low-choice sensitivity. Second, impact of the experience effect is reduced as investors react less to changes in the valuation (c.f. prices in the *INFO* condition). One can also observe a technical artefact: the average market price is closer to the average price 60. This results from a higher randomness in the choices, which pulls the overall average of observations towards the mean of the option set, an effect recently gained interest among experimenter (e.g. for behavioral risk taking methods Andersson et al. 2016; Ostrovsky-Mechera et al. 2022).

Summarizing, the market price simulations underline that the observed experienced based learning and recency effect in the behavior of participants can lead to substantial and long lasting deviations of the market price from the fundamental value of the asset in the short run. The market price adjusts towards the fundamental value in the long-run. Even though, the mispricing persist. Moreover, the average learning rate is a double edge sword. A high average learning rate leads to a higher volatility of the market price, while it also brings the prices faster to its fundamental value once the liquidation values have to be learned.

7 DISCUSSION

Personal experiences affects individuals risk taking and serves as a promising cognitively founded explanation for several market price phenomena such as time varying risk premia of asset classes (Bordalo et al. 2020; Cohn et al. 2015; Malmendier 2021a, 2021b). Once all market participants experience the same outcome, experienced based learning and the *recency bias* might introduce a error, that is small but correlated across all individuals. As a consequence the market price does not serve its main purpose to aggregate and reflect all available information. Even worse private information gets crowded out, i.e. investors rely less on their private information and put more emphasize on the changes in the market price. Thus uncertainty in financial markets and the economy increases, leading to a miss allocation of capital, labor and consumption (Hassan and Mertens 2017). Thus investigating the impact of experienced based learning on individual risk-taking and the market outcome is a relevant topic to research. Most of the studies establishing a link between prior experience and individual risk taking rely on surveys (Amromin and Sharpe 2014; Giglio et al. 2021; Greenwood and Shleifer 2014; Malmendier 2021a, 2021b). To draw from these representative field data conclusions one needs to make several assumptions, as with prior experience a plethora of other variables change as well (e.g. wealth, income...). Moreover, the *domain specificity* of experienced based learning highlights that the research needs to know which type of experience the participants made.

We circumvent these identification and measurement problems with a controlled laboratory investment task. Participant submitted over 30 independent rounds a demand schedule for an asset with an objective true value. All participants knew the stochastic process determining the liquidation value, which was executed in front of them. While in one condition participants learned the liquidation values over the course of the experiment, in the other condition participants were provided with all information about the liquidation values. We observe experience effects and a strong *recency bias* in both conditions. This highlights the strength of experience based learning, which can outweight provided information in the decision problem. Even-though we provided a full information, prior experiences affects subsequent risk taking, which is contrary to Kieren, Müller-Dethard and Weber 2019, who only observe experience effects in their ambiguity condition. We attribute these differences to the *domain specificity*, as Kieren, Müller-Dethard and Weber 2019 use a unrelated stochastic process to induce prior (task unspecific) experiences, while we use the feedback from the task to induce (task specific) experience.

Based on the individual decisions we estimate the implied structural model from our conceptual framework: a reinforcement learning agent following a risk-neutral probabilistic choice rule. There exists a heterogeneity in the first free parameter of the model: the choice sensitivity, measuring the sensitivity of differences in valuation for the actual decision. A low choice sensitivity implies more random choices. This interpretation is justified as choice sensitivity correlates with over-confidence and several comprehension measures, but not with risk-preferences, cognitive abilities, or age. Furthermore, the structural model estimation reveals that the learning rates in the info- and no-info-condition are small but different from zero and barely differ between both conditions. There exist also a considerable heterogeneity in the learning rates of the individuals. These learning rates are unrelated to individual traits such as cognitive abilites, risk-preferences, and task comprehension. We conclude, that the learning rate can be interpreted as individual trait in its own right. The small learning rates shows, that in the static stochastic environment the adaptation of a new outcome is small. However, a series of bad (good) draws as well as a large prediction error – as in a crises – leads to less (more) risk taking and has long lasting effects.

The individually estimated structural model allows us to investigate through simulations market price dynamics, once all participants observe the same liquidation value. We can also run counterfactual comparisons to isolate mechanisms. Our first observation is that the individual noise gets canceled out in the market price, and the effects of experienced based learning translates directly to the market price. Thus we find deviations in the short run from the rational objective expected value of the asset, which persist substantively. As first counterfactual analysis we manipulate the composition of market participants with respect to the learning rate. A higher average learning rate is a double edge sword to the market price dynamics. On the one side volatility increases drastically. While on the other side if there there is new information to learn, the market price converges faster to its fundamental value, even though with a high fluctuation. Markets with a high average learning rate, might markets that are populated by less experienced and probably younger investors. Such an interpretation in line a reinforcement learner, where the learning rate decrease in the length of observed outcomes, as for example in Malmendier and Nagel 2011. As a consequence young generations have a higher learning rate and markets where those trade most are more volatile, but also improve the incoproation of new information into the market price.

Note that, we implicitly ignored the second round effect of the market price as opportunity to infer the valuation from others. In our estimated reinforcement learning- and probabilistic choice model and consequently in this market price simulations, we focused on the effect of the same experienced Liquidation Value path on the market price. As some individuals extrapolate changes in the market price (, see e.g. Hefti, Heinke and Schneider 2018), the observed impact of the recency effect on the market price might be even stronger if one takes this into account. Investigating the propagation of such feedback loops through the market prices is an interesting subject for further research. In our model we can explain deviations from the expected value just due to the way experienced information is learned sequentially. That way, we do not recur to risk preferences. This relates to recent studies that model decision making under risk and uncertainty as a rational response to cognitive limitations in attention, perception, or memory (Bordalo, Gennaioli and

Shleifer 2012; Khaw, Li and Woodford 2021; Lieder, Griffiths and Hsu 2018). Moreover, we also found that participants underestimated the average return after the 30 rounds of the investment task. This confirms prior results in experience-based judgments and could indicate that participants perceive numerical information on a compressed mental number line (Olschewski et al. 2021). Future research could combine the number perception and the sequential learning aspect into a more complete model of information processing and decision making under risk and uncertainty.

In sum we are closing the gap of evidence for the hypothesized link between personal experiences and market price dynamics. Personal experience outweighs provided a priori information and affects independent subsequent decisions. Moreover, the *domain specificity* and our findings compared to similar studies, suggests that experience effects observed in the literature might be even stronger, as the specific experience made remains uncertain. We propose a parsimonious conceptual framework of experiences based learning and investor decision making, that can be estimated on the individual level and serves as basis for simulations of the market prices. As all investors experience the same market outcome the *recency bias* in the experienced based learning constitutes a small but correlated error among all market participants, which is not canceled out in the market-clearing and affects the market price dynamics. These insights shed light on how experience affects individual financial risk-taking and provide interesting implications for theories investigating asset price dynamics.

References

Alempaki, Despoina, Chris Starmer and Fabio Tufano. 2019. 'On the priming of risk preferences: The role of fear and general affect'. *Journal of Economic Psychology* 75:102137.

Amromin, Gene, and Steven A Sharpe. 2014. 'From the horse's mouth: Economic conditions and investor expectations of risk and return'. *Management Science* 60 (4): 845–866.

Andersen, Steffen, John Y Campbell, Kasper Meisner Nielsen and Tarun Ramadorai. 2015. 'Inattention and inertia in household finance: Evidence from the Danish mortgage market'.

Andersen, Steffen, Tobin Hanspal and Kasper Meisner Nielsen. 2016. 'Once Bitten, Twice Shy'. In *The 43rd European Finance Association Annual Meeting (EFA 2016).*

Andersson, Ola, Håkan J Holm, Jean-Robert Tyran and Erik Wengström. 2016. 'Risk aversion relates to cognitive ability: Preferences or Noise?' *Journal of the European Economic Association* 14 (5): 1129–1154.

Asparouhova, Elena, Peter Bossaerts, Jon Eguia and William Zame. 2015. 'Asset pricing and asymmetric reasoning'. *Journal of Political Economy* 123 (1): 66–122.

Barber, Brad M, and Terrance Odean. 2013. 'The behavior of individual investors'. In *Handbook of the Economics of Finance*, 2:1533–1570. Elsevier.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin and Andrei Shleifer. 2015. 'X-CAPM: An extrapolative capital asset pricing model'. *Journal of financial economics* 115 (1): 1–24.

— . 2018. 'Extrapolation and bubbles'. *Journal of Financial Economics* 129 (2): 203–227.

Barberis, Nicholas, Ming Huang and Tano Santos. 2001. 'Prospect theory and asset prices'. *The quarterly journal of economics* 116 (1): 1–53.

Bear, Mark, Barry Connors and Michael A Paradiso. 2020. *Neuroscience: Exploring the Brain, Enhanced Edition: Exploring the Brain.* Jones & Bartlett Learning.

Biais, Bruno, Thomas Mariotti, Sophie Moinas, Sébastien Pouget et al. 2017. *Asset pricing and risk sharing in a complete market: An experimental investigation.* Tech. rep. Toulouse School of Economics (TSE).

Bordalo, Pedro, Nicola Gennaioli, Spencer Yongwook Kwon and Andrei Shleifer. 2021. 'Diagnostic bubbles'. *Journal of Financial Economics* 141 (3): 1060–1077.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta and Andrei Shleifer. 2020. *Expectations of fundamentals and stock market puzzles.* Tech. rep. National Bureau of Economic Research.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta and Andrei Shleifer. 2019. 'Diagnostic expectations and stock returns'. *The Journal of Finance* 74 (6): 2839–2874.

Bordalo, Pedro, Nicola Gennaioli and Andrei Shleifer. 2012. 'Salience theory of choice under risk'. *The Quarterly journal of economics* 127 (3): 1243–1285.

— . 2018. 'Diagnostic expectations and credit cycles'. *The Journal of Finance* 73 (1): 199–227.

Bradbury, Meike AS, Thorsten Hens and Stefan Zeisberger. 2015. 'Improving investment decisions with simulated experience'. *Review of Finance* 19 (3): 1019–1052.

— . 2019. 'How persistent are the effects of experience sampling on investor behavior?' *Journal of Banking & Finance* 98:61–79.

Brunnermeier, Markus K, and Stefan Nagel. 2008. 'Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals'. *American Economic Review* 98 (3): 713–36.

Bucher-Koenen, Tabea, and Michael Ziegelmeyer. 2014. 'Once burned, twice shy? Financial literacy and wealth losses during the financial crisis'. *Review of Finance* 18 (6): 2215–2246.

Campbell, John Y, and John H Cochrane. 1999. 'By force of habit: A consumption-based explanation of aggregate stock market behavior'. *Journal of political Economy* 107 (2): 205–251.

Campbell, John Y, and Robert J Shiller. 1988a. 'Stock prices, earnings, and expected dividends'. *the Journal of Finance* 43 (3): 661–676.

— . 1988b. 'The dividend-price ratio and expectations of future dividends and discount factors'. *The Review of Financial Studies* 1 (3): 195–228.

Cesario, Joseph. 2014. 'Priming, replication, and the hardest science'. *Perspectives on psychological science* 9 (1): 40–48.

Chapman, Jonathan, Mark Dean, Pietro Ortoleva, Erik Snowberg and Colin Camerer. 2018. *Econographics.* Tech. rep. National Bureau of Economic Research.

Chen, Daniel L, Martin Schonger and Chris Wickens. 2016. 'oTree—An open-source platform for laboratory, online, and field experiments'. *Journal of Behavioral and Experimental Finance* 9:88–97.

Choi, James J, David Laibson, Brigitte C Madrian and Andrew Metrick. 2009. 'Reinforcement learning and savings behavior'. *The Journal of finance* 64 (6): 2515–2534.

Civelli, Andrea, and Cary Deck. 2017. 'A flexible and customizable method for assessing cognitive abilities'.

Cochrane, John H. 2011. 'Presidential address: Discount rates'. *The Journal of finance* 66 (4): 1047–1108.

Cohn, Alain, Jan Engelmann, Ernst Fehr and Michel André Maréchal. 2015. 'Evidence for countercyclical risk aversion: An experiment with financial professionals'. *American Economic Review* 105 (2): 860–85.

Cordes, Henning, Sven Nolte and Judith C Schneider. 2017. 'On the dynamics and drivers of countercyclical risk aversion'.

Ehling, Paul, Alessandro Graniero and Christian Heyerdahl-Larsen. 2018. 'Asset prices and portfolio choice with learning from experience'. *The Review of Economic Studies* 85 (3): 1752–1780.

Erev, Ido, Eyal Ert, Ori Plonsky, Doron Cohen and Oded Cohen. 2017. 'From anomalies to forecasts: Toward a descriptive model of decisions under risk, under ambiguity, and from experience.' *Psychological review* 124 (4): 369.

Erev, Ido, and Alvin E Roth. 1998. 'Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria'. *American economic review*: 848–881.

Feltovich, Nick. 2000. 'Reinforcement-based vs. belief-based learning models in experimental asymmetric-information games'. *Econometrica* 68 (3): 605–641.

Frydman, Cary, Nicholas Barberis, Colin Camerer, Peter Bossaerts and Antonio Rangel. 2014. 'Using neural data to test a theory of investor behavior: An application to realization utility'. *The Journal of finance* 69 (2): 907–946.

Frydman, Cary, and Colin F Camerer. 2016. 'The psychology and neuroscience of financial decision making'. *Trends in cognitive sciences* 20 (9): 661–675.

Frydman, Cary, and Gideon Nave. 2017. 'Extrapolative beliefs in perceptual and economic decisions: Evidence of a common mechanism'. *Management Science* 63 (7): 2340–2352.

Fuster, Andreas, Benjamin Hebert and David Laibson. 2012. 'Natural expectations, macroeconomic dynamics, and asset pricing'. *NBER Macroeconomics Annual* 26 (1): 1–48.

Fuster, Andreas, David Laibson and Brock Mendel. 2010. 'Natural expectations and macroeconomic fluctuations'. *Journal of Economic Perspectives* 24 (4): 67–84.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel and Stephen Utkus. 2021. 'Five facts about beliefs and portfolios'. *American Economic Review* 111 (5): 1481–1522.

Greenwood, Robin, and Andrei Shleifer. 2014. 'Expectations of returns and expected returns'. *The Review of Financial Studies* 27 (3): 714–746.

Grossman, Sanford J, and Robert J Shiller. 1981. 'The determinants of the variability of stock market prices'. *The American Economic Review* 71 (2): 222–227.

Guiso, Luigi, Paola Sapienza and Luigi Zingales. 2018. 'Time varying risk aversion'. *Journal of Financial Economics* 128 (3): 403–421.

Hartzmark, Samuel M, Samuel D Hirshman and Alex Imas. 2021. 'Ownership, learning, and beliefs'. *The Quarterly Journal of Economics* 136 (3): 1665–1717.

Hassan, Tarek A, and Thomas M Mertens. 2017. 'The social cost of near-rational investment'. *American Economic Review* 107 (4): 1059–1103.

Hefti, Andreas M, Steve Heinke and Frédéric Schneider. 2018. 'Mental capabilities, trading styles, and asset market bubbles: theory and experiment'. *University of Zurich, Department of Economics, Working Paper*, no. 234.

Heinke, Steve, Adrian Leuenberger and Jörg Rieskamp. 2020. 'This time is different: On similarity and risk taking after experienced gains and losses'. *Available at SSRN 3691829.*

Hertwig, Ralph, Greg Barron, Elke U Weber and Ido Erev. 2004. 'Decisions from experience and the effect of rare events in risky choice'. *Psychological science* 15 (8): 534–539.

Hertwig, Ralph, and Ido Erev. 2009. 'The description–experience gap in risky choice'. *Trends in cognitive sciences* 13 (12): 517–523.

Hoffmann, Arvid OI, Zwetelina Iliewa and Lena Jaroszek. 2017. 'Wall Street Crosses Memory Lane: How Witnessed Returns Affect Professionals' Expected Returns'.

Hoffmann, Arvid OI, and Thomas Post. 2017. 'How return and risk experiences shape investor beliefs and preferences'. *Accounting & Finance* 57 (3): 759–788.

Holt, Charles A, and Susan K Laury. 2002. 'Risk aversion and incentive effects'. *American economic review* 92 (5): 1644–1655.

Kaufmann, Christine, Martin Weber and Emily Haisley. 2013. 'The role of experience sampling and graphical displays on one's investment risk appetite'. *Management science* 59 (2): 323–340.

Kaustia, Markku, and Samuli Knüpfer. 2008. 'Do investors overweight personal experience? Evidence from IPO subscriptions'. *The Journal of Finance* 63 (6): 2679–2702.

Khaw, Mel Win, Ziang Li and Michael Woodford. 2021. 'Cognitive imprecision and small-stakes risk aversion'. *The review of economic studies* 88 (4): 1979–2013.

Kieren, Pascal, Jan Müller-Dethard and Martin Weber. 2019. 'Why so Negative? Belief Formation in Boom and Bust Markets'. *Belief Formation in Boom and Bust Markets (July 19, 2019).*

König-Kersting, Christian, and Stefan T Trautmann. 2018. 'Countercyclical risk aversion: Beyond financial professionals'. *Journal of Behavioral and Experimental Finance* 18:94–101.

Kuhn, Peter, Peter Kooreman, Adriaan Soetevent and Arie Kapteyn. 2011. 'The effects of lottery prizes on winners and their neighbors: Evidence from the Dutch postcode lottery'. *The American Economic Review* 101 (5): 2226–2247.

Kuhnen, Camelia M. 2015. 'Asymmetric learning from financial information'. *The Journal of Finance* 70 (5): 2029–2062.

Kuhnen, Camelia M, Sarah Rudorf and Bernd Weber. 2017. *The effect of prior choices on expectations and subsequent portfolio decisions.* Tech. rep. National Bureau of Economic Research.

Laudenbach, Christine, Michael Ungeheuer and Martin Weber. 2019. 'How to alleviate correlation neglect'.

Lee, Daeyeol, Hyojung Seo and Min Whan Jung. 2012. 'Neural basis of reinforcement learning and decision making'. *Annual review of neuroscience* 35:287–308.

Lejarraga, Tomás, and Cleotilde Gonzalez. 2011. 'Effects of feedback and complexity on repeated decisions from description'. *Organizational Behavior and Human Decision Processes* 116 (2): 286–295.

Lejarraga, Tomás, Jan K Woike and Ralph Hertwig. 2016. 'Description and experience: How experimental investors learn about booms and busts affects their financial risk taking'. *Cognition* 157:365–383.

Lieder, Falk, Thomas L Griffiths and Ming Hsu. 2018. 'Overrepresentation of extreme events in decision making reflects rational use of cognitive resources.' *Psychological review* 125 (1): 1.

Luce, R Duncan. 1959. 'On the possible psychophysical laws.' *Psychological review* 66 (2): 81.

Ludvig, Elliot A, and Marcia L Spetch. 2011. 'Of black swans and tossed coins: is the description-experience gap in risky choice limited to rare events?' *PloS one* 6 (6): e20262.

Malmendier, Ulrike. 2021a. 'Experience effects in finance: Foundations, applications, and future directions'. *Review of Finance* 25 (5): 1339–1363.

— . 2021b. 'Exposure, experience, and expertise: why personal histories matter in economics'. *Journal of the European Economic Association.*

Malmendier, Ulrike, and Stefan Nagel. 2011. 'Depression babies: do macroeconomic experiences affect risk taking?' *The Quarterly Journal of Economics* 126 (1): 373–416.

— . 2015. 'Learning from inflation experiences'. *The Quarterly Journal of Economics* 131 (1): 53–87.

Malmendier, Ulrike, Stefan Nagel and Zhen Yan. 2021. 'The making of hawks and doves'. *Journal of Monetary Economics* 117:19–42.

Malmendier, Ulrike, Demian Pouzo and Victoria Vanasco. 2020a. 'Investor experiences and financial market dynamics'. *Journal of Financial Economics* 136 (3): 597–622.

— . 2020b. 'Investor experiences and international capital flows'. *Journal of International Economics* 124:103302.

McKelvey, Richard D, and Thomas R Palfrey. 1995. 'Quantal response equilibria for normal form games'. *Games and economic behavior* 10 (1): 6–38.

Nagel, Stefan, and Zhengyang Xu. 2021. 'Asset Pricing with Fading Memory'. Hhab086, *The Review of Financial Studies* ().

Niv, Yael, Jeffrey A Edlund, Peter Dayan and John P O'Doherty. 2012. 'Neural prediction errors reveal a risk-sensitive reinforcement-learning process in the human brain'. *Journal of Neuroscience* 32 (2): 551–562.

O'Doherty, John P, Jeffrey Cockburn and Wolfgang M Pauli. 2017. 'Learning, reward, and decision making'. *Annual review of psychology* 68:73–100.

Olschewski, Sebastian, Linan Diao and Jörg Rieskamp. 2021. 'Reinforcement learning about asset variability and correlation in repeated portfolio decisions'. *Journal of Behavioral and Experimental Finance* 32:100559.

Olschewski, Sebastian, Ben R Newell, Yvonne Oberholzer and Benjamin Scheibehenne. 2021. 'Valuation and estimation from experience'. *Journal of Behavioral Decision Making.*

Ostrovsky-Mechera, Tehilla, Steve Heinke, Sandra Andraszewicz and Jörg Rieskamp. 2022. 'On the Presumed Link Between Cognitive Abilities and Risk-Preferences: A Meta-Analysis'. *MIMEO*: 1–71.

Plonsky, Ori, and Ido Erev. 2017. 'Learning in settings with partial feedback and the wavy recency effect of rare events'. *Cognitive Psychology* 93:18–43.

Rangel, Antonio, Colin Camerer and P Read Montague. 2008. 'A framework for studying the neurobiology of value-based decision making'. *Nature reviews neuroscience* 9 (7): 545–556.

Rieskamp, Jörg. 2006. 'Perspectives of probabilistic inferences: Reinforcement learning and an adaptive network compared.' *Journal of Experimental Psychology: Learning, Memory, and Cognition* 32 (6): 1355.

Rieskamp, Jörg, Jerome R Busemeyer and Tei Laine. 2003. 'How do people learn to allocate resources? Comparing two learning theories.' *Journal of Experimental Psychology: Learning, Memory, and Cognition* 29 (6): 1066.

Schultz, Wolfram. 2015. 'Neuronal reward and decision signals: from theories to data'. *Physiological reviews* 95 (3): 853–951.

Schultz, Wolfram, Peter Dayan and P Read Montague. 1997. 'A neural substrate of prediction and reward'. *Science* 275 (5306): 1593–1599.

Seru, Amit, Tyler Shumway and Noah Stoffman. 2010. 'Learning by trading'. *The Review of Financial Studies* 23 (2): 705–739.

Shiller, Robert J. 1981. 'Do stock prices move too much to be justified by subsequent changes in dividends?' *The American Economic Review* 71 (3): 421–36.

Sutton, Richard S, and Andrew G Barto. 2018. *Reinforcement learning: An introduction.* MIT press.

Trutmann, Kevin, Steve Heinke and Jörg Rieskamp. 2021. 'Expectation Formation and Trading Behavior: How Investment Position Interacts with Information Favorability in Investment Decisions'. *Available at SSRN.*

Whitlock, Jonathan R, Arnold J Heynen, Marshall G Shuler and Mark F Bear. 2006. 'Learning induces long-term potentiation in the hippocampus'. *science* 313 (5790): 1093–1097.

Wunderlich, Klaus, Mkael Symmonds, Peter Bossaerts and Raymond J Dolan. 2011. 'Hedging your bets by learning reward correlations in the human brain'. *Neuron* 71 (6): 1141–1152.

A INVESTMENT BEHAVIOR

VARIABLES	(1)	(2)	(3)	(4)	(5)
INFO	-0.189		1.352		1.332
	(0.241)		(1.745)		(1.746)
Stockprice			-0.253***	-0.263***	-0.251***
			(0.0184)	(0.0212)	(0.0228)
Stockprice**INFO*			-0.0257		-0.0256
			(0.0291)		(0.0292)
Mean-High		0.756***		0.961	0.942
		(0.251)		(1.742)	(1.742)
Stockprice*Mean-High				-0.00342	-0.00301
				(0.0291)	(0.0291)
Age	0.0277	0.0114	0.0277	0.0114	0.0103
	(0.0277)	(0.0296)	(0.0277)	(0.0296)	(0.0297)
Female	-0.0847	-0.104	-0.0847	-0.104	-0.105
	(0.246)	(0.238)	(0.246)	(0.238)	(0.237)
Constant	3.086***	3.042***	18.24***	18.85***	18.23***
	(0.809)	(0.765)	(1.377)	(1.526)	(1.618)
Observations	79,380	79,380	79,380	79,380	79,380
R^2-overall	0.00333	0.0197	0.331	0.347	0.349

Table A.1: Demanded Quantity of the risky asset (I)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Quantity, number of shares of the risky assets intend to held at a particular price in one round, between 0 to 8. *Independent Variables: INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean-High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) Liquidation Values Mean Low	(2) Liquidation Values Mean High
Has-Info	-0.233	0.0641
	(0.374)	(0.303)
Round	0.00281	0.00451
	(0.0128)	(0.00822)
Round*Has-Info	-0.0205	0.00818
	(0.0148)	(0.0117)
Age	0.0135	0.00949
	(0.0546)	(0.0362)
Female	0.105	-0.394
	(0.406)	(0.289)
Constant	3.099**	3.837***
	(1.526)	(1.066)
Observations	39,060	40,320
R^2-overall	0.0119	0.00717

Table A.2: Demanded Quantity of the risky asset (II)

Note: Random effects panel regressions separated for the those with a low mean (model 1) or high (model 2) of the liquidation value, with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Quantity, number of shares of the risky assets intend to held at a particular price in one round, between 0 to 8. *Independent Variables:* Has-Info, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Round, number of round the decision was taken; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Liquidation Value (t-1)	0.00993***	0.00355*	0.00934***
	(0.00173)	(0.00193)	(0.00172)
Experienced Liquidation Value (t-2)	0.0147***	0.00249	0.00809
	(0.00539)	(0.00448)	(0.00504)
Quantity (t-1)	-0.292***	-0.227***	-0.257***
	(0.0366)	(0.0372)	(0.0262)
Stockprice	-0.0729***	-0.0638***	-0.0680***
	(0.0103)	(0.0103)	(0.00729)
Mean High	-0.0533	0.275***	0.111
	(0.103)	(0.107)	(0.0752)
INFO			0.189
			(0.422)
Liquidation Value (t-1)**INFO*			-0.00496**
			(0.00251)
Experienced Liquidation Value (t-2)**INFO*			0.000826
			(0.00636)
Age	0.00741	-0.00646	-0.000392
	(0.0119)	(0.0101)	(0.00774)
Female	-0.00444	-0.0842	-0.0277
	(0.110)	(0.0701)	(0.0639)
Constant	3.835***	4.347***	3.975***
	(0.741)	(0.834)	(0.572)
Observations	37,632	36,456	74,088
R^2-overall	0.154	0.118	0.135

Table A.3: Change in demanded quantity of the risky asset (Recency I)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Liquidation Value (t-1), value at which the asset was finally liquidated in the previous round; Experienced Liquidation Value (t-2), average over all observed values at which the asset was finally liquidated up to two rounds prior to t; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise;Reported Mean Liquidation Value, reported value about the mean of liquidation values; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Experienced Liquidation Value (1st half)	0.0126***	0.00328	0.00796**
	(0.00432)	(0.00338)	(0.00382)
Experienced Liquidation Value (2nd half)	0.0180***	0.00566	0.0142***
	(0.00276)	(0.00399)	(0.00280)
Quantity (t-1)	-0.299***	-0.228***	-0.261***
	(0.0365)	(0.0371)	(0.0262)
Stockprice	-0.0745***	-0.0640***	-0.0690***
	(0.0103)	(0.0103)	(0.00732)
Mean High	-0.0943	0.256**	0.0817
	(0.103)	(0.111)	(0.0781)
INFO			0.190
			(0.483)
Experienced Liquidation Value (1st half)**INFO*			-0.000231
			(0.00479)
Experienced Liquidation Value (2nd half)**INFO*			-0.00398
			(0.00451)
Age	0.00846	-0.00633	9.18e-05
	(0.0117)	(0.0102)	(0.00777)
Female	-0.00995	-0.0796	-0.0268
	(0.110)	(0.0696)	(0.0640)
Constant	3.597***	4.187***	3.767***
	(0.757)	(0.861)	(0.585)
Observations	37,632	36,456	74,088
R^2-overall	0.151	0.116	0.132

Table A.4: Change in demanded quantity of the risky asset (Recency II)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Experienced Liquidation Value (1st/2nd half), average over all observed values at which the asset was finally liquidated in the 1st half of the observations (rounds 1 and t/2-1) or in the 2 half of the observations (rounds t/2 and t-1); Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise;Reported Mean Liquidation Value, reported value about the mean of liquidation values; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Experienced Liquidation Value	0.0285***	0.00752	0.0214***
	(0.00447)	(0.00487)	(0.00410)
Quantity (t-1)	-0.301***	-0.235***	-0.264***
	(0.0353)	(0.0379)	(0.0254)
Stockprice	-0.0741***	-0.0665***	-0.0695***
	(0.0102)	(0.0106)	(0.00721)
Mean-High	-0.0675	0.325***	0.120
	(0.110)	(0.104)	(0.0781)
INFO			0.352
			(0.397)
Experienced Liquidation Value**INFO*			-0.00696
			(0.00626)
Reported Mean Liquidation Value	-0.000325	-0.00700***	-0.00258
	(0.00191)	(0.00250)	(0.00166)
Age	0.00869	-0.00698	-0.000728
	(0.0121)	(0.00929)	(0.00763)
Female	-0.0139	-0.0870	-0.0423
	(0.113)	(0.0721)	(0.0657)
Constant	3.712***	4.835***	4.012***
	(0.776)	(0.863)	(0.590)
Observations	38,976	37,758	76,734
R^2-overall	0.151	0.118	0.131

Table A.5: Change in demanded quantity of the risky asset (Experienced Liquidation Value)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Experienced Liquidation Value, average over all observed values at which the asset was finally liquidated in the previous rounds; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise;Reported Mean Liquidation Value, reported value about the mean of liquidation values; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Payoff (t-1)	0.00204***	0.000842**	0.00195***
	(0.000347)	(0.000346)	(0.000347)
Quantity (t-1)	-0.287***	-0.228***	-0.256***
	(0.0362)	(0.0361)	(0.0256)
Stockprice	-0.0705***	-0.0643***	-0.0673***
	(0.0101)	(0.0103)	(0.00722)
Mean High	0.0630	0.287***	0.173**
	(0.107)	(0.0892)	(0.0696)
INFO			0.493*
			(0.289)
Payoff (t-1)**INFO*			-0.00100**
			(0.000495)
Age	0.00742	-0.00594	-0.000157
	(0.0121)	(0.0102)	(0.00776)
Female	0.0405	-0.0833	-0.0140
	(0.111)	(0.0724)	(0.0657)
Constant	3.947***	4.259***	3.861***
	(0.788)	(0.783)	(0.562)
Observations	38,976	37,758	76,734
R^2-overall	0.151	0.116	0.133

Table A.6: Change in demanded quantity of the risky asset (Robustness Payoff)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Payoff, portfolio value after all stocks of the asset were liquidated less the initial portfolio value; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Liquidation Value (t-1)	0.00662**	0.00186	0.00505**
	(0.00258)	(0.00303)	(0.00255)
Quantity (t-1)	-0.285***	-0.222***	-0.252***
	(0.0361)	(0.0355)	(0.0255)
Stockprice	-0.0699***	-0.0629***	-0.0663***
	(0.0100)	(0.0101)	(0.00715)
Mean High	0.0585	0.290***	0.172**
	(0.110)	(0.0948)	(0.0720)
INFO			-0.0638
			(0.271)
Liquidation Value (t-1)**INFO*			-0.00149
			(0.00361)
Loss (t-1)	-0.302	-0.692*	-0.488**
	(0.290)	(0.391)	(0.232)
Liquidation Value (t-1)*Loss (t-1)	0.000302	0.00131*	0.000593
	(0.000523)	(0.000683)	(0.000423)
Liquidation Value (t-1)*Loss (t-1)**INFO*			0.000390
			(0.000248)
Age	0.00758	-0.00599	-6.58e-05
	(0.0124)	(0.0104)	(0.00789)
Female	0.0187	-0.0880	-0.0267
	(0.111)	(0.0741)	(0.0660)
Constant	4.715***	4.538***	4.664***
	(0.827)	(0.778)	(0.600)
Observations	38,976	37,758	76,734
R^2-overall	0.152	0.117	0.134

Table A.7: Change in demanded quantity of the risky asset (Robustness Gain vs. Loss Domain)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Payoff, portfolio value after all stocks of the asset were liquidated less the initial portfolio value; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Loss (t-1), dummy variable taking on the value 1 if the realized traded price was higher then the realized liquidation value, zero otherwise; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Liquidation Value (t-1)	0.0158***	0.00889***	0.0152***
	(0.00353)	(0.00278)	(0.00352)
Quantity (t-1)	-0.287***	-0.227***	-0.256***
	(0.0359)	(0.0360)	(0.0254)
Stockprice	-0.0704***	-0.0643***	-0.0673***
	(0.0100)	(0.0102)	(0.00717)
Mean High	0.0497	0.284***	0.165**
	(0.107)	(0.0910)	(0.0700)
INFO			0.306
			(0.276)
Liquidation Value (t-1)**INFO*			-0.00572
			(0.00446)
Round	0.0210	0.0188*	0.0205
	(0.0128)	(0.0109)	(0.0128)
Liquidation Value (t-1)*Round	-0.000348*	-0.000333*	-0.000341
	(0.000211)	(0.000188)	(0.000211)
*INFO**Round			-0.00199
			(0.0167)
Liquidation Value (t-1)**INFO**Round			1.08e-05
			(0.000281)
Age	0.00771	-0.00595	2.71e-05
	(0.0122)	(0.0101)	(0.00777)
Female	0.0192	-0.0850	-0.0249
	(0.110)	(0.0718)	(0.0650)
Constant	4.127***	4.211***	4.024***
	(0.866)	(0.738)	(0.624)
Observations	38,976	37,758	76,734
R^2-overall	0.152	0.117	0.134

Table A.8: Change in demanded quantity of the risky asset (Robustness Round)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Liquidation Value, value at which the asset was finally liquidated in the previous round; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Round, number of round the decision was taken between 2-30; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) Abs Dev. Reported Mean LV	(2) Inst. Compr.	(3) Inst. Quiz	(4) Study Interest
Liquidation Value (t-1)	0.00708***	0.0190***	0.00801	0.0122***
	(0.00146)	(0.00533)	(0.00586)	(0.00425)
Quantity(t-1)	-0.256***	-0.256***	-0.256***	-0.256***
	(0.0257)	(0.0255)	(0.0255)	(0.0256)
Stockprice	-0.0673***	-0.0674***	-0.0673***	-0.0673***
	(0.00726)	(0.00719)	(0.00717)	(0.00720)
Mean High	0.173**	0.162**	0.164**	0.163**
	(0.0708)	(0.0697)	(0.0711)	(0.0701)
INFO	0.225	0.263*	0.278*	0.280*
	(0.144)	(0.155)	(0.155)	(0.158)
Liquidation Value (t-1)**INFO*	-0.00508**	-0.00869**	-0.00432	-0.00676*
	(0.00235)	(0.00429)	(0.00494)	(0.00380)
abs(Mean LV Reported - Mean LV)	-0.0117			
	(0.00818)			
Liquidation Value (t-1)*abs(Mean LV Reported - Mean LV)	0.000228*			
	(0.000126)			
Liquidation Value (t-1)*abs(Mean LV Reported - Mean LV)**INFO*	6.21e-05			
	(6.81e-05)			
Instruction Comprehension		0.114		
		(0.0760)		
Liquidation Value (t-1)*Instruction Comprehension		-0.00267**		
		(0.00127)		
Liquidation Value (t-1)*Instruction Comprehension**INFO*		0.000956		
		(0.00101)		
Instruction Quiz Correct Answers			-0.00651	
			(0.0821)	
Liquidation Value (t-1)*Instruction Quiz Correct Answers			0.000415	
			(0.00132)	
Liquidation Value (t-1)*Instruction Quiz Correct Answers**INFO*			-0.000312	
			(0.00107)	
Study Interest				0.0506
				(0.0669)
Liquidation Value (t-1)*Study Interest				-0.000800
				(0.00112)
Liquidation Value (t-1)*Study Interest**INFO*				0.000379
				(0.000968)
Age	-0.00233	0.00149	4.53e-05	0.00169
	(0.00789)	(0.00820)	(0.00764)	(0.00820)
Female	-0.0436	-0.0305	-0.0235	-0.0196
	(0.0671)	(0.0628)	(0.0681)	(0.0642)
Constant	4.562***	3.938***	4.382***	4.153***
	(0.560)	(0.583)	(0.665)	(0.597)
Observations	76,734	76,734	76,734	76,734
R^2-overall	0.135	0.134	0.133	0.133

Table A.9: Change in demanded quantity of the risky asset (Robustness Task Comprehension)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Liquidation Value (t-1), value at which the asset was finally liquidated in the previous round; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Age, self reported in years; abs(Mean LV Reported - Mean LV), absolute value of the difference between the reported mean of the liquidation value at the end of study and the actual mean of the liquidation value; Instruction Comprehension, self reported comprehension of the instructions, 1 (in-comprehensive instructions) to 5(clear instructions), mean 3.53 (SD:1.10); Instruction Quiz Correct Answers, number of correct answers from the ten instruction quiz questions, mean 7.83 (SD: 1.48); Study Interest, self reported interest in the study, 1 (no interest) to 5 (very interested), mean 4.26 (SD:0.94); Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) Over-Estimation	(2) Over-Placement	(3) Ravens Progressive Matrices
Liquidation Value (t-1)	0.00974***	0.00976***	0.0154***
	(0.00161)	(0.00166)	(0.00362)
Quantity (t-1)	-0.256***	-0.256***	-0.256***
	(0.0257)	(0.0256)	(0.0255)
Stockprice	-0.0674***	-0.0673***	-0.0674***
	(0.00721)	(0.00719)	(0.00720)
Mean High	0.182**	0.170**	0.172**
	(0.0778)	(0.0722)	(0.0719)
INFO	0.277*	0.280*	0.272*
	(0.156)	(0.156)	(0.155)
Liquidation Value (t-1)**INFO*	-0.00558**	-0.00564**	-0.00562
	(0.00245)	(0.00244)	(0.00352)
Over-Estimation	-0.0221		
	(0.0677)		
Liquidation Value (t-1)*Over-Estimation	5.59e-05		
	(0.00117)		
Liquidation Value (t-1)*Over-Estimation**INFO*	-0.000266		
	(0.000856)		
Over-Placement		-0.109	
		(0.113)	
Liquidation Value (t-1)*Over-Placement		0.00141	
		(0.00245)	
Liquidation Value (t-1)*Over-Placement**INFO*		0.000281	
		(0.00188)	
RPM correct			0.142**
			(0.0720)
Liquidation Value (t-1)*RPM correct			-0.00205
			(0.00131)
Liquidation Value (t-1)*RPM correct**INFO*			3.58e-05
			(0.00100)
Age	-0.00110	-0.000681	0.000607
	(0.00769)	(0.00814)	(0.00773)
Female	-0.0327	-0.0298	-0.0255
	(0.0659)	(0.0671)	(0.0654)
Constant	4.382***	4.372***	3.950***
	(0.548)	(0.551)	(0.588)
Observations	76,734	76,734	76,734
R^2-overall	0.133	0.133	0.134

Table A.10: Change in demanded quantity of the risky asset (Robustness Over-Confidence & IQ)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Payoff, portfolio value after all stocks of the asset were liquidated less the initial portfolio value; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Over-Estimation, difference between self assessed matrices solved and actual in the ravens progressive matrices task, mean -.27 (SD: 1.28); Over-placement, ordered variable taking on the value -1 if individuals reported to be below median in solving the ravens matrices but solved more than the median, 0 if they are correctly calibrated, and 1 if the belief solved more than the median but did not; RPM correct, number of correctly solved ravens progressive matrices from four puzzles, mean 2.78 (SD: 1.00); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) Risk General	(2) Average Risk Parameter	(3) Stock Ownership
Liquidation Value (t-1)	0.0118***	0.00784***	0.00940***
	(0.00369)	(0.00210)	(0.00164)
Quantity (t-1)	-0.259***	-0.257***	-0.257***
	(0.0260)	(0.0254)	(0.0255)
Stockprice	-0.0682***	-0.0676***	-0.0677***
	(0.00727)	(0.00714)	(0.00717)
Mean High (t-1)	0.172**	0.158**	0.156**
	(0.0694)	(0.0700)	(0.0706)
INFO	0.270*	0.272*	0.278*
	(0.156)	(0.154)	(0.164)
Liquidation Value (t-1)**INFO*	-0.00768**	-0.00664***	-0.00485*
	(0.00337)	(0.00254)	(0.00262)
Risk General	0.0442		
	(0.0392)		
Liquidation Value (t-1)*Risk General	-0.000410		
	(0.000640)		
Liquidation Value (t-1)*Risk General**INFO*	0.000398		
	(0.000478)		
Av. Risk Parameter		405.0*	
		(210.0)	
Liquidation Value (t-1)*Av. Risk Parameter		-4.597	
		(3.517)	
Liquidation Value (t-1)*Av. Risk Parameter**INFO*		-2.695	
		(2.784)	
Stock Ownership			0.0230
			(0.208)
Liquidation Value (t-1)*Stock Ownership			0.00209
			(0.00334)
Liquidation Value (t-1)*Stock Ownership**INFO*			-0.00413
			(0.00290)
Age	-0.00143	-0.000580	0.000311
	(0.00739)	(0.00777)	(0.00768)
Female	-0.00788	-0.0243	-0.0179
	(0.0677)	(0.0641)	(0.0638)
Constant	4.223***	4.564***	4.372***
	(0.568)	(0.527)	(0.550)
Observations	76,734	76,734	76,734
R^2-overall	0.135	0.134	0.134

Table A.11: Change in demanded quantity of the risky asset (Robustness Sensitivity to Risk)

Note: Random effects panel regressions with robust standard errors clustered on participants level in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Change in demanded quantity, number of shares of the risky assets intend to held at a particular price in one round less the number of shares of the risky assets intend to held at a particular price in the previous round. *Independent Variables:* Payoff, portfolio value after all stocks of the asset were liquidated less the initial portfolio value; Quantity (t-1), number of shares of the risky assets intend to held at a particular price in the previous round, between 0 and 8; Stockprice, price between 50 and 70 at which participants could state their willingness to hold between 0 to 8 shares; Mean High, dummy variable taking on the value one if the liquidation values of the participants had the high mean, zero otherwise; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Risk General, self reported willingness to take risk in general, 1 (not willing at all) to 10 (keen to take risk), mean 5.19 (SD: 2.05); Av. Risk Parameter, average estimated risk sensitivty parameter of a mean-variance utility function applied to the decisions in the four lottery decision multiple price lists, mean -.0004 (SD: .00037); Stock Ownership, dummy variable taking on the value 1 if they report to own stocks, zero otherwise, mean .19 (SD: .39); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1)	(2)	(3)	(4)	(5)
RPM correct	0.000718				
	(0.0212)				
Risk General		-0.00234			
		(0.00755)			
Stock Ownership			0.00581		
			(0.0498)		
Av. Risk Parameter				-45.93	
				(48.83)	
Age	0.000956	0.000996	0.000929	0.000945	0.000921
	(0.00435)	(0.00454)	(0.00447)	(0.00449)	(0.00445)
Female	0.101***	0.0996***	0.101***	0.0979***	0.101***
	(0.0373)	(0.0366)	(0.0364)	(0.0372)	(0.0361)
Constant	0.0293	0.0433	0.0308	0.0152	0.0322
	(0.131)	(0.112)	(0.115)	(0.120)	(0.113)
Observations	126	126	126	126	126
R^2	0.052	0.052	0.052	0.057	0.052

Table A.12: Individual learning Rate γ_i and individual traits

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Individual learning rate γ_i estimate from the structural model *Independent Variables:* RPM correct, number of correctly solved ravens progressive matrices from four puzzles, mean 2.78 (SD: 1.00); Risk General, self reported willingness to take risk in general, 1 (not willing at all) to 10 (keen to take risk), mean 5.19 (SD: 2.05); Stock Ownership, dummy variable taking on the value 1 if they report to own stocks, zero otherwise, mean .19 (SD: .39); Av. Risk Parameter, average estimated risk sensitivty parameter of a mean-variance utility function applied to the decisions in the four lottery decision multiple price lists, mean -.0004 (SD: .00037); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Instruction Quiz Correct Answers	-0.00260				
	(0.00858)				
Instruction Comprehension		-0.0164			
		(0.0167)			
Study Interest			0.0268		
			(0.0184)		
Over-placement				0.000698	
				(0.000966)	
Over-Estimation					-0.0119
					(0.0172)
Age	0.000795	0.000755	0.00293	-0.000356	0.000212
	(0.00438)	(0.00442)	(0.00465)	(0.00357)	(0.00435)
Female	0.0997**	0.0918**	0.119***	0.0944**	0.0977**
	(0.0391)	(0.0366)	(0.0410)	(0.0383)	(0.0380)
Constant	0.0566	0.0993	-0.111	0.0380	0.0824
	(0.126)	(0.106)	(0.148)	(0.108)	(0.120)
Observations	126	126	126	126	126
R^2	0.052	0.058	0.069	0.057	0.054

Table A.13: Individual learning Rate γ_i and comprehension or interest of study and over-confidence

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Individual learning rate γ_i estimate from the structural model *Independent Variables:* Instruction Quiz Correct Answers, number of correct answers from the ten instruction quiz questions, mean 7.83 (SD: 1.48); Instruction Comprehension, self reported comprehension of the instructions, 1 (in-comprehensive instructions) to 5(clear instructions), mean 3.53 (SD:1.10); Study Interest, self reported interest in the study, 1 (no interest) to 5 (very interested), mean 4.26 (SD:0.94); Over-placement, ordered variable taking on the value -1 if individuals reported to be below median in solving the ravens matrices but solved more than the median, 0 if they are correctly calibrated, and 1 if the belief solved more than the median but did not; Over-Estimation, difference between self assessed matrices solved and actual in the ravens progressive matrices task, mean -.27 (SD: 1.28); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1)	(2)	(3)	(4)
Learning Rate γ_i	18.82**			
	(8.083)			
Choice Sensitivity θ_i		-1.641***		
		(0.467)		
Instruction Quiz Correct Answers	-2.372***	-1.255	-2.421***	
	(0.734)	(0.781)	(0.754)	
Age	0.544**	0.552*	0.559**	0.675**
	(0.273)	(0.279)	(0.280)	(0.330)
female	0.872	-1.763	2.749	4.107*
	(2.212)	(2.344)	(2.372)	(2.359)
Constant	11.51	15.89*	12.58	-10.08
	(8.305)	(8.242)	(8.578)	(8.228)
Observations	126	126	126	126
R-squared	0.200	0.224	0.116	0.053

Table A.14: abs(Mean LV Reported - Mean LV) and model parameters

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* abs(Mean LV Reported - Mean LV), absolute value of the difference between the reported mean of the liquidation value at the end of study and the actual mean of the liquidation value; *Independent Variables:* Individual learning rate γ_i estimate from the structural model; Individual choice sensitivity θ_i estimate from the structural model; Instruction Quiz Correct Answers, number of correct answers from the ten instruction quiz questions, mean 7.83 (SD: 1.48); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Learning Rate γ_i	16.24	21.47**	17.59
	(14.52)	(9.538)	(14.01)
INFO			-3.849*
			(2.286)
*INFO**learning rate γ_i			2.943
			(16.60)
Instruction Quiz Correct Answers	-3.178**	-1.251	-2.232***
	(1.265)	(0.781)	(0.709)
Age	0.755	0.432*	0.543**
	(0.532)	(0.256)	(0.273)
Female	2.267	-0.271	0.890
	(3.889)	(2.064)	(2.211)
Constant	13.41	3.972	12.28
	(15.44)	(9.309)	(8.559)
Observations	64	62	126
R^2	0.179	0.318	0.216

Table A.15: abs(Mean LV Reported - Mean LV) and learning rate γ_i

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* abs(Mean LV Reported - Mean LV), absolute value of the difference between the reported mean of the liquidation value at the end of study and the actual mean of the liquidation value; *Independent Variables:* Individual learning rate γ_i estimate from the structural model; *INFO*, dummy variable taking on the value one if participants knew the potential outcomes of the liquidation values, zero otherwise; Instruction Quiz Correct Answers, number of correct answers from the ten instruction quiz questions, mean 7.83 (SD: 1.48); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1)	(2)	(3)	(4)	(5)
RPM correct	0.309				
	(0.276)				
Risk General		-0.0780			
		(0.132)			
Stock Owenership			-0.0959		
			(0.608)		
Av. Risk Parameter				366.2	
				(833.7)	
Age	-0.0231	-0.0358	-0.0385	-0.0385	-0.0383
	(0.0713)	(0.0702)	(0.0699)	(0.0704)	(0.0696)
Female	-3.123***	-3.201***	-3.150***	-3.121***	-3.147***
	(0.549)	(0.555)	(0.549)	(0.555)	(0.546)
Constant	7.402***	9.040***	8.693***	8.805***	8.670***
	(2.135)	(1.955)	(1.887)	(1.940)	(1.861)
Observations	126	126	126	126	126
R^2	0.222	0.216	0.214	0.215	0.214

Table A.16: Choice Sensitivity θ_i and individual traits

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Individual Choice Sensitivity θ_i estimate from the structural model *Independent Variables:* RPM correct, number of correctly solved ravens progressive matrices from four puzzles, mean 2.78 (SD: 1.00); Risk General, self reported willingness to take risk in general, 1 (not willing at all) to 10 (keen to take risk), mean 5.19 (SD: 2.05); Stock Ownership, dummy variable taking on the value 1 if they report to own stocks, zero otherwise, mean .19 (SD: .39); Av. Risk Parameter, average estimated risk sensitivty parameter of a mean-variance utility function applied to the decisions in the four lottery decision multiple price lists, mean -.0004 (SD: .00037); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Instruction Quiz Correct Answers	0.710***				
	(0.178)				
Instruction Comprehension		0.638**			
		(0.249)			
Study Interest			-0.0468		
			(0.252)		
Over-placement				-0.0277**	
				(0.0108)	
Over-Estimation					0.750***
					(0.250)
Age	-0.00418	-0.0319	-0.0418	0.0123	0.00655
	(0.0677)	(0.0708)	(0.0724)	(0.0725)	(0.0725)
Female	-2.749***	-2.781***	-3.178***	-2.879***	-2.923***
	(0.542)	(0.571)	(0.559)	(0.554)	(0.544)
Constant	2.020	6.056***	8.920***	8.439***	5.493**
	(2.559)	(2.136)	(2.267)	(1.832)	(2.211)
Observations	126	126	126	126	126
R^2	0.308	0.254	0.214	0.252	0.256

Table A.17: Individual choice sensitivity θ_i and comprehension or interest of study and over-confidence

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* Individual choice sensitivity θ_i estimate from the structural model *Independent Variables:* Instruction Quiz Correct Answers, number of correct answers from the ten instruction quiz questions, mean 7.83 (SD: 1.48); Instruction Comprehension, self reported comprehension of the instructions, 1 (in-comprehensive instructions) to 5(clear instructions), mean 3.53 (SD:1.10); Study Interest, self reported interest in the study, 1 (no interest) to 5 (very interested), mean 4.26 (SD:0.94); Over-placement, ordered variable taking on the value -1 if individuals reported to be below median in solving the ravens matrices but solved more than the median, 0 if they are correctly calibrated, and 1 if the belief solved more than the median but did not; Over-Estimation, difference between self assessed matrices solved and actual in the ravens progressive matrices task, mean -.27 (SD: 1.28); Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

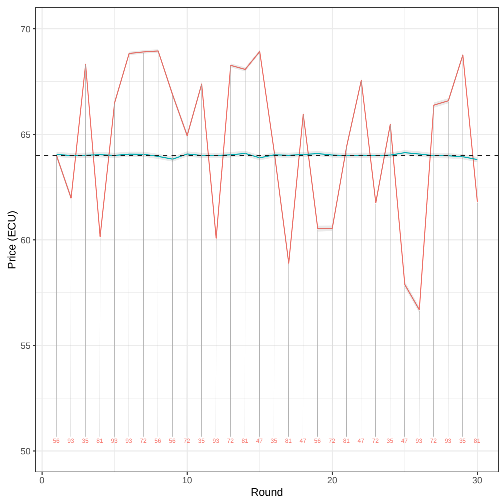
VARIABLES	(1) *NO INFO*	(2) *INFO*	(3) *POOLED*
Choice Sensitivity θ_i	-1.494*	-1.721***	-1.732**
	(0.760)	(0.620)	(0.681)
INFO			-3.665
			(6.411)
*INFO**choice sensitivity θ_i			0.250
			(0.798)
Instruction Quiz Correct Answers	-1.676	-0.769	-1.161
	(1.506)	(0.760)	(0.792)
Age	0.916	0.300	0.551*
	(0.568)	(0.231)	(0.283)
Female	0.947	-3.999	-1.528
	(3.866)	(2.916)	(2.485)
Constant	8.402	19.15**	16.61*
	(16.65)	(8.046)	(8.745)
Observations	64	62	126
R^2	0.199	0.316	0.231

Table A.18: abs(Mean LV Reported - Mean LV) and choice sensitivity θ_i

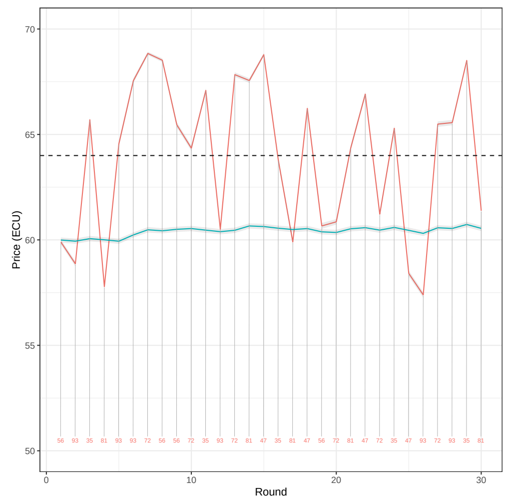
Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1 depict p-values of a two sided t-test. *Dependent Variable:* abs(Mean LV Reported - Mean LV), absolute value of the difference between the reported mean of the liquidation value at the end of study and the actual mean of the liquidation value; *Independent Variables:*
Individual choice sensitivity θ_i estimate from the structural model; Instruction Quiz Correct Answers, number of correct answers from the ten instruction quiz questions, mean 7.83 (SD: 1.48); abs(Mean LV experienced - Mean LV), absolute value of the difference between the mean of experienced liquidation values and the actual mean of the liquidation value; Age, self reported in years; Female, dummy variable taking on the value one if the participants identified themselves as female, zero otherwise.

B MARKET PRICE SIMULATION

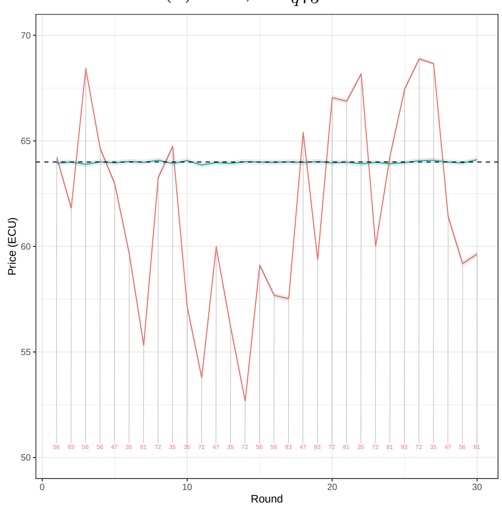
In this section, we report the additional results of simulated market prices, if all participants would have observed the same liquidation values. Basically, the market price is determined by simulated demand schedules of the participants, that are submitted to a closed book sealed bid call market. We follow the same procedure as described in Section 6.



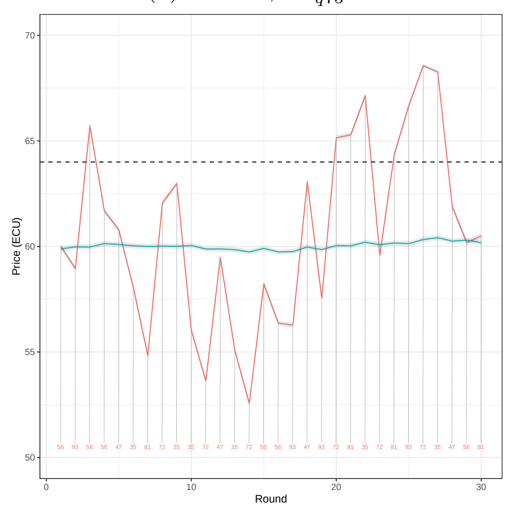
(a) Info, LV^{High}_{q75}



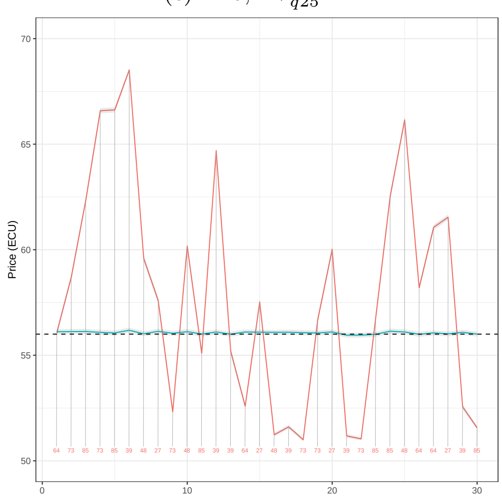
(b) No Info, LV^{High}_{q75}



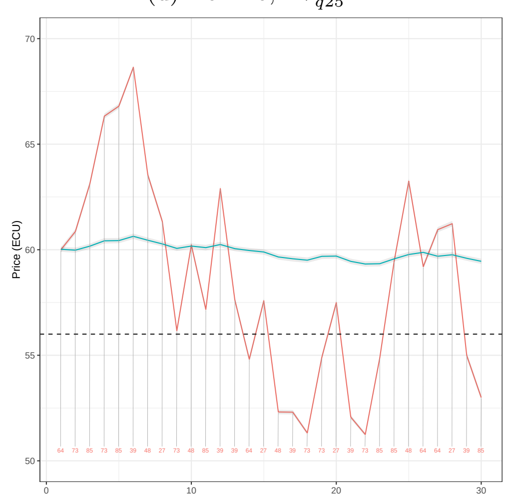
(c) Info, LV^{High}_{q25}



(d) No Info, LV^{High}_{q25}



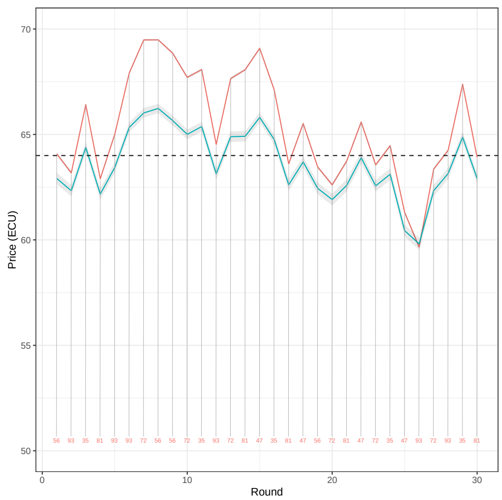
(e) Info, LV^{Low}_{q75}



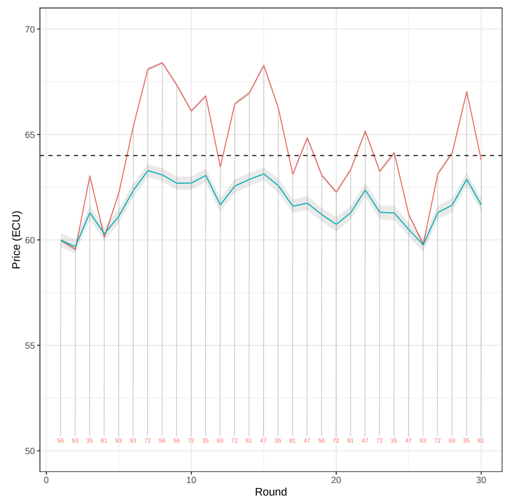
(f) No Info, LV^{Low}_{q75}

Figure B.1: Price Dynamics for markets with high (red) and low (green) learning rates $_i$.

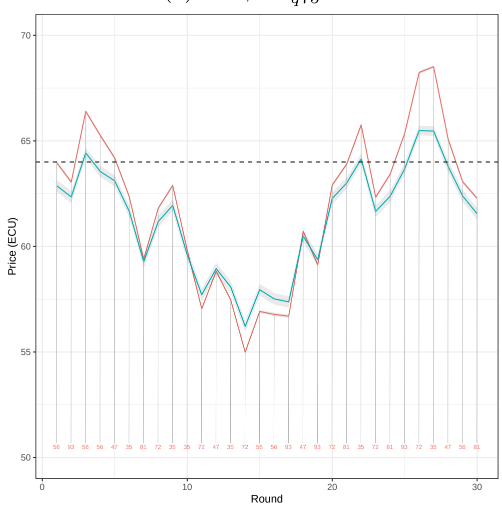
This figure depicts the simulated market price in ECU (y-axis) over the rounds (x-axis). The liquidation value samples are the q25 or q 75 (25% or 75% quartile) of the mean realized liquidation values of the respective two liquidation value condition. The price for the simulated markets with investors having a high learning rate ^H_i is displayed in red, while the price for the markets with investors having a low learning rate ^L_i is displayed in green. The market price of each round is labeled with the respective liquidation value drawn at the end of the round. The respective simulated market prices are displayed with the bootstrapped empirical 95% interval as shadowed area around the lines. The dashed black lines represents expected value of the respective liquidation value in this condition.



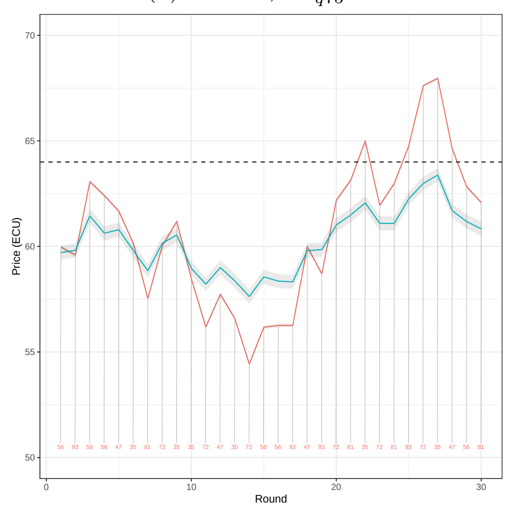
(a) Info, LV_{q75}^{High}



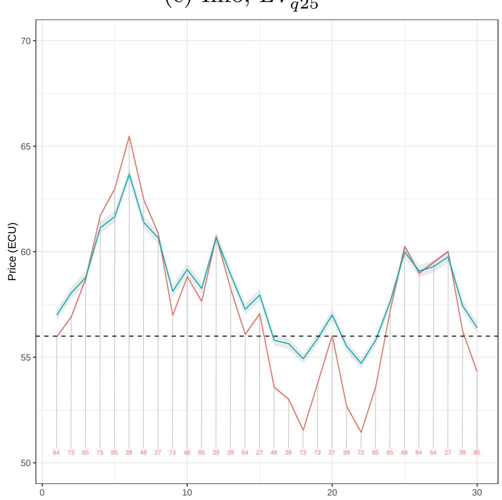
(b) No Info, LV_{q75}^{High}



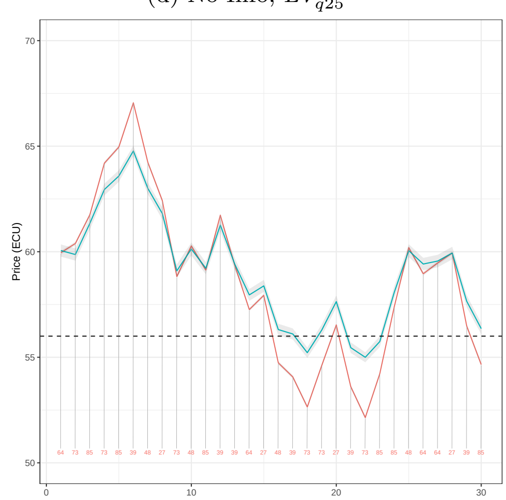
(c) Info, LV_{q25}^{High}



(d) No Info, LV_{q25}^{High}



(e) Info, LV_{q75}^{Low}



(f) No Info, LV_{q75}^{Low}

Figure B.2: Price Dynamics for markets with high (red) and low (green) choice sensitivity θ_i.

This figure depicts the simulated market price in ECU (y-axis) over the rounds (x-axis). The liquidation value samples are the q25 or q 75 (25% or 75% quartile) of the mean realized liquidation values of the respective two liquidation value condition. The price for the simulated markets with investors having a high choice sensitivity θ_i^H is displayed in red, while the price for the markets with investors having a low choice sensitivity θ_i^L is displayed in green. The market price of each round is labeled with the respective liquidation value drawn at the end of the round. The respective simulated market prices are displayed with the bootstrapped empirical 95% interval as shadowed area around the lines. The dashed black lines represents expected value of the respective liquidation value in this condition.

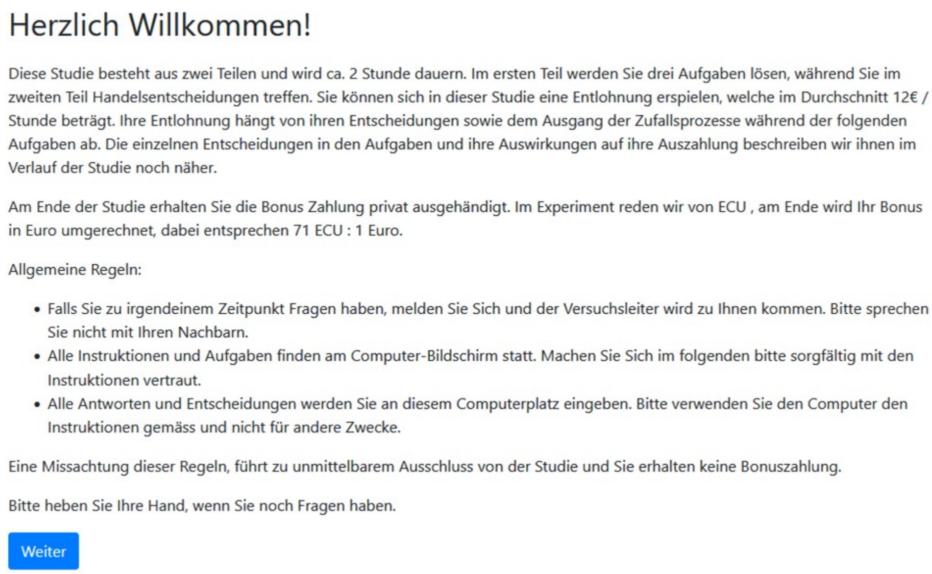
Experiences, Recency and Price Dynamics

- Online Supplementary Material -

Steve Heinke[1] Sebastian Olschewski[2] Jörg Rieskamp[3]

[1]University of Basel. E-mail: steve.heinke@unibas.ch
[2]Warwick Business School. E-mail: sebastian.olschewski@wbs.ac.uk
[3]University of Basel. E-mail: joerg.rieskamp@unibas.ch

S.1. INVESTMENT TASK - INSTRUCTIONS



Herzlich Willkommen!

Diese Studie besteht aus zwei Teilen und wird ca. 2 Stunde dauern. Im ersten Teil werden Sie drei Aufgaben lösen, während Sie im zweiten Teil Handelsentscheidungen treffen. Sie können sich in dieser Studie eine Entlohnung erspielen, welche im Durchschnitt 12€ / Stunde beträgt. Ihre Entlohnung hängt von ihren Entscheidungen sowie dem Ausgang der Zufallsprozesse während der folgenden Aufgaben ab. Die einzelnen Entscheidungen in den Aufgaben und ihre Auswirkungen auf ihre Auszahlung beschreiben wir ihnen im Verlauf der Studie noch näher.

Am Ende der Studie erhalten Sie die Bonus Zahlung privat ausgehändigt. Im Experiment reden wir von ECU , am Ende wird Ihr Bonus in Euro umgerechnet, dabei entsprechen 71 ECU : 1 Euro.

Allgemeine Regeln:

- Falls Sie zu irgendeinem Zeitpunkt Fragen haben, melden Sie Sich und der Versuchsleiter wird zu Ihnen kommen. Bitte sprechen Sie nicht mit Ihren Nachbarn.
- Alle Instruktionen und Aufgaben finden am Computer-Bildschirm statt. Machen Sie Sich im folgenden bitte sorgfältig mit den Instruktionen vertraut.
- Alle Antworten und Entscheidungen werden Sie an diesem Computerplatz eingeben. Bitte verwenden Sie den Computer den Instruktionen gemäss und nicht für andere Zwecke.

Eine Missachtung dieser Regeln, führt zu unmittelbarem Ausschluss von der Studie und Sie erhalten keine Bonuszahlung.

Bitte heben Sie Ihre Hand, wenn Sie noch Fragen haben.

Weiter

Figure S.1: Welcome Screen

Welcome to the study!

This study consists of two parts and will take about 2 hours. In the first part you will solve three tasks, while in the second part you will make trading decisions. In this study, you will be able to earn an average income of 12 Euros/hour. What you earn will depend on your decisions and the outcome of the random processes during the following tasks. The individual decisions in the tasks and their effects on your payout will be described in more detail during the course of the study.

At the end of the study you will receive the bonus payment privately. In the study, we talk about ECUs: at the end your bonus will be converted into Euros, where 71 ECUs equal 1 Euro.

General rules:

- If you have any questions at any time, please let us know and the study supervisor will come to you. Please do not talk to your neighbors.
- All instructions and tasks will take place on the computer screen. Please familiarize yourself carefully with the instructions below.
- All answers and decisions will be entered at this computer station. Please use the computer as instructed and not for any other purpose.

Failure to observe these rules will result in immediate exclusion from the study and you will not receive any bonus payments.

Please raise your hand if you have any questions.

Continue

2. Teil: Handelsentscheidungen

In diesem Teil der Studie treffen Sie mehrere Handelsentscheidungen.

Wie Sie die Handelsentscheidungen eingeben und wie diese ihre Auszahlungen beeinflussen erfahren Sie in ausführlichen Instruktionen. Zwei Probe-Runden ermöglichen Ihnen sich mit der Benutzeroberfläche vertraut zu machen. Um sicherzugehen, dass Sie die wichtigsten Teile der Instruktionen verstanden haben folgt ein Verständnisquiz. Danach beginnen die Runden mit Ihren Handelsentscheidungen welche ihre Auszahlung bestimmen können.

Bitte lesen Sie sich die Instruktionen aufmerksam durch, da jede Ihrer folgenden Entscheidungen ihre Auszahlung beeinflussen kann

Bitte heben Sie Ihre Hand, wenn Sie noch Fragen haben.

Weiter

Figure S.2: Instruction Trading

Part 2: Trading decisions

In this part of the study, you will make several trading decisions.

You will learn how to enter the trading decisions and how they affect their payouts in detailed instructions. Two trial rounds will allow you to familiarize yourself with the user interface. A comprehension quiz follows to make sure that you have understood the most important parts of the instructions. After that, the rounds begin, with your trading decisions determining your payout.

Please read the instructions carefully as each of your subsequent decisions can affect your payout. Please raise your hand if you have any questions.

Continue

Instruktionen (1/6): Entscheidungen

Die folgende Aufgabe besteht 30 unabhängige Runden. Das bedeutet, die Entscheidung in einer Runde spielt keine Rolle für die nachfolgenden Runden.

Zu Beginn jeder Runde erhalten Sie ein Budget, bestehend aus 300 ECU Bargeld und 4 Aktien.

- Jede Aktie wird am Ende einer Runde in Bargeld umgetauscht (Liquidationswert). Die Höhe des Liquidationswertes eines Wertpapiers wird erst nach Ihrer Entscheidung zufällig durch Ziehen aus einer Lotterie bestimmt (Der Prozess wird später noch genauer erklärt).
- Der Wert Ihrer Bargeldbestände bleibt unverändert bestehen bis zum Ende der Runde.

Während jeder Runde können Ihre Aktien zu einem Preis zwischen 50 und 70 ECU gehandelt werden, wobei jeder Preis mit einer gleichen Wahrscheinlichkeit eintreten kann.

Um eine Aktie zu handeln, können Sie in jeder Runde sich entscheiden, wie viele Aktien zu einem gegebenen Preis Sie gern halten wollen. Dazu geben Sie für alle Preise der Aktie zwischen 50 und 70 ECU (in ganzzahligen Schritten) an ob sie von 0 bis 8 Aktien halten wollen. Sie können also bis zu 4 Aktien kaufen oder verkaufen.

Weiter

Figure S.3: Instruction Trading 1

Instructions (1/6): Decisions

The following task consists of 30 independent rounds. This means that the decision in one round is irrelevant for the subsequent rounds.

At the beginning of each round you will be given a budget consisting of 300 ECU cash and 4 shares.

- Each share is exchanged for cash at the end of a round (liquidation value). The liquidation value of an investment is determined a random draw from a lottery after you have made your decision (the process will be explained in more detail later).
- The value of your cash balance remains unchanged until the end of the round.

During each round, your shares can be traded at a price between 50 and 70 ECU, with each price having an equal probability of occurring.

To trade a share, you can decide in each round how many shares at a given price that study supervisor to hold. To do this, specify for all prices of the share between 50 and 70 ECU (in integer steps) the number you want to hold, from 0 to 8 shares. You can therefore buy or sell up to 4 shares.

Continue

Figure S.4: Instruction Trading 2

Instructions (2/6):

Buying and selling shares By buying and selling shares, you can hold between 0 to 8 shares per round: At the beginning of the trading decision, your screen looks like the picture below.

- On the left side you see the possible price.
- The following columns represent the number of investments you want to hold at the price at the end of the period.
- The green marker indicates your selection.
- As you always hold 4 shares at the beginning, this is also the pre-selection, which you can change by ticking the corresponding boxes.

In each round you have 60 seconds to make your decision.

Example:

For a total price of 57 ECU, if you want to...

- ...hold 5 shares at the end of the period, then select the 5 investments column in row 57. So with this you buy one share when the price is realized. In this case, your shareholdings increase by one share to 5 and your cash balance decreases by 57 ECU to 243 ECU.
- ...hold 3 shares at the end of the period, then select the 3 investments column in row 57. So you sell a share when the price is realized. In this case, your shareholdings decrease by one share to 3 and your cash balance increases by 57 ECU to 357 ECU.

Continue

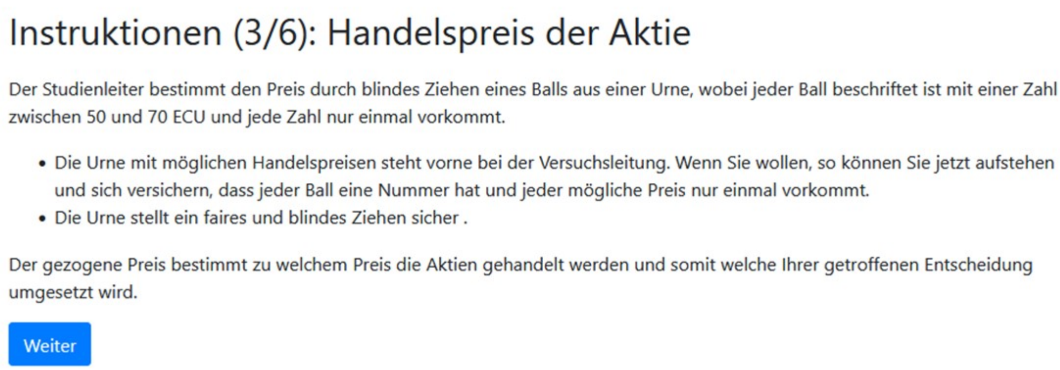


Figure S.5: Instruction Trading 3

Instructions (3/6):

Trading price of the share The study supervisor determines the price by blindly drawing a ball from an urn, each ball being labeled with a number between 50 and 70 ECU and each number occurring only once.

- The urn with possible trading prices is located at the front, with the study supervisor. If you wish, you can now step forward and make sure that each ball has a number and that each possible price occurs only once.
- The urn ensures a fair and blind draw. The price drawn determines the price at which the shares are traded and thus which of your decisions will be implemented.

Continue

Figure S.6: Instruction Trading 4

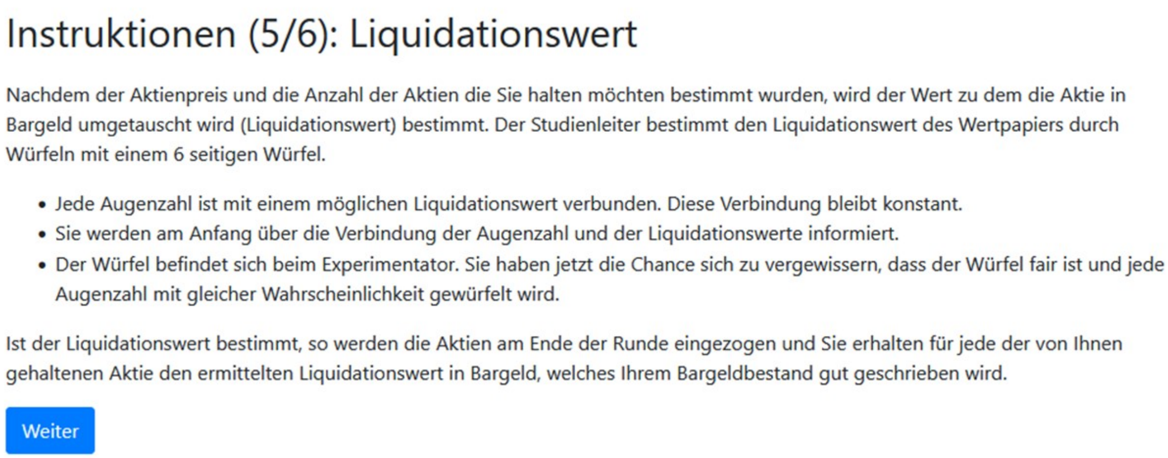
Instructions (4/6):

Trading price of a share (example) Suppose you have made the following decision as in the picture below of a particular round. The study supervisor randomly drew the price 64.

According to the picture, you previously stated that you wanted to hold 1 share at this price, i.e., to sell three shares.

This reduces your shareholdings by 3, from 4 to 1. Your cash balance increases in this round by 3 * 64 = 192 ECU from 300 to 492 ECU.

Continue



Instruktionen (5/6): Liquidationswert

Nachdem der Aktienpreis und die Anzahl der Aktien die Sie halten möchten bestimmt wurden, wird der Wert zu dem die Aktie in Bargeld umgetauscht wird (Liquidationswert) bestimmt. Der Studienleiter bestimmt den Liquidationswert des Wertpapiers durch Würfeln mit einem 6 seitigen Würfel.

- Jede Augenzahl ist mit einem möglichen Liquidationswert verbunden. Diese Verbindung bleibt konstant.
- Sie werden am Anfang über die Verbindung der Augenzahl und der Liquidationswerte informiert.
- Der Würfel befindet sich beim Experimentator. Sie haben jetzt die Chance sich zu vergewissern, dass der Würfel fair ist und jede Augenzahl mit gleicher Wahrscheinlichkeit gewürfelt wird.

Ist der Liquidationswert bestimmt, so werden die Aktien am Ende der Runde eingezogen und Sie erhalten für jede der von Ihnen gehaltenen Aktie den ermittelten Liquidationswert in Bargeld, welches Ihrem Bargeldbestand gut geschrieben wird.

Weiter

Figure S.7: Instruction Trading 5

Instructions (5/6):

Liquidation value After determining the share price and the number of shares that you would like to hold, the value at which the share will be exchanged for cash (liquidation value) is determined. The study supervisor determines the liquidation value of the investment by rolling a 6-sided die.

- Each number on the die is associated with a possible liquidation value. This association remains constant.
- You will be informed at the beginning about the association between the number and the liquidation value.
- The die is held by the study supervisor. You now have the chance to make sure that the die is fair and that each number is rolled with equal probability.

Once the liquidation value has been determined, the shares will be withdrawn at the end of the round and you will receive the determined liquidation value in cash for each of the shares you hold, which will be credited to your cash balance.

Continue

Instruktionen (6/6): Studienablauf und Auszahlung

Sie bestimmen in 30 unabhängigen Runde, wie viele Aktien Sie am Ende jeder Runde halten wollen.

Am Ende einer jeden Runde wird jede Aktie in Bargeld umgetauscht (Liquidationswert). Der Liquidationswert wird durch Würfeln eines 6 seitigen fairen Würfels bestimmt. Jede Augenzahl ist mit einem bestimmten Liquidationswert verbunden. Diese Zuordnung gilt für jede der 30 Runden. Die möglichen Liquidationswerte sind unterschiedlich. Sie werden am Anfang über die Verbindung der Augenzahl und der Liquidationswerte informiert.

Jede Runde verläuft wie folgt: Zu Beginn jeder Runde erhalten Sie ein Budget, bestehend aus 300 ECU Bargeld und 4 Aktien.

- Sie erhalten ihr Portfolio bestehend aus 300 ECU Bargeld und 4 Aktien.
- Sie entscheiden sich für jeden möglichen Preis zwischen 50 und 70 ECU wie viele Aktien Sie am Ende der Runde halten wollen.
- Der Studienleiter bestimmt den Preis durch Ziehen aus einer Urne mit 21 Kugeln, bei der jede Kugel einen Preis hat.
- Der gezogene Preis bestimmt welche der von Ihnen getroffenen Entscheidungen umgesetzt wird, d.h. die Anzahl Aktien die Sie am Ende der Runde halten werden.
- Nachdem Ihr Portfolio gemäss ihrer Entscheidung angepasst wurde, wird der Liquidationswert durch einen Würfelwurf bestimmt. Der Liquidationswert ist der Betrag zu dem jede der von ihnen gehaltenen Aktie in Bargeld umgetauscht wird.
- Der letztliche Bargeldbestand ist die Auszahlung für diese Runde.

Am Ende des Experiments werden zwei Runden für die Auszahlung ausgewählt (mit gleicher Wahrscheinlichkeit).

Weiter

Figure S.8: Instruction Trading 6

Instructions (6/6): Study procedure and payout

In 30 independent rounds, you decide how many shares you want to hold at the end of each round.

At the end of each round, each share is exchanged for cash (liquidation value). The liquidation value is determined by rolling a 6-sided fair die. Each number is associated with a specific liquidation value. This assignment applies to each of the 30 rounds. The possible liquidation values are different. You will be informed about the association between the number and the liquidation values at the beginning.

Each round proceeds as follows: At the beginning of each round, you are given a budget consisting of 300 ECU cash and 4 shares.

- You receive your portfolio consisting of 300 ECU cash and 4 shares.
- You decide for each possible price between 50 and 70 ECU how many shares you want to hold at the end of the round.
- The study supervisor determines the price by drawing from an urn with 21 balls, where each ball has a price.
- The price drawn determines which of your decisions will be implemented, i.e., the number of shares you will hold at the end of the round.
- After your portfolio has been adjusted according to your decision, the liquidation value is determined by a roll of the die. The liquidation value is the amount of cash for which each of the shares you hold will be exchanged.
- The final cash balance is the payout for that round.

At the end of the study, two rounds are selected for the payout (with equal probability).

Continue

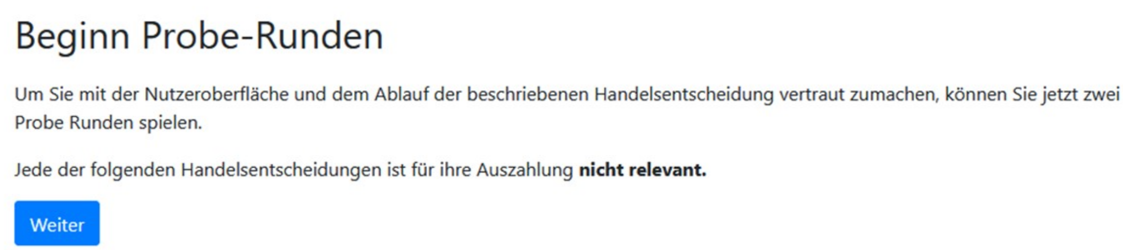


Figure S.9: Trial Rounds

Start of trial rounds

In order to familiarize yourself with the user interface and the process of the trading decision described, you can now play two trial rounds. **None of the following trading decisions is relevant to your payout.**

Continue

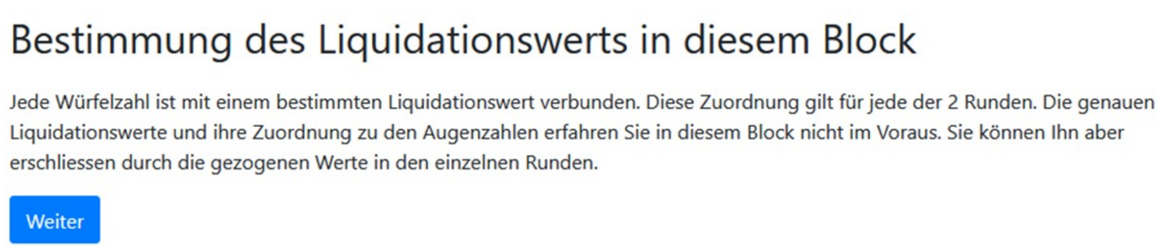
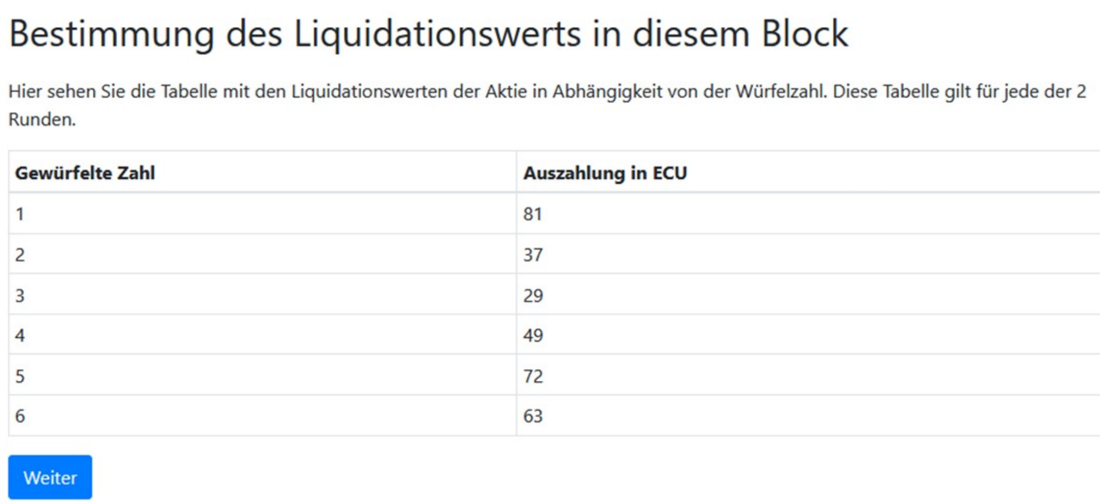


Figure S.10: Information Liquidation Value - *No Info*

Determining the liquidation value in this block

Each die number is associated with a specific liquidation value. This assignment applies to each of the 2 rounds. You will not find out in advance the exact liquidation values and their assignment to the die numbers in this block. However, you can find them out from the values drawn in the individual rounds.

Continue



Bestimmung des Liquidationswerts in diesem Block

Hier sehen Sie die Tabelle mit den Liquidationswerten der Aktie in Abhängigkeit von der Würfelzahl. Diese Tabelle gilt für jede der 2 Runden.

Gewürfelte Zahl	**Auszahlung in ECU**
1	81
2	37
3	29
4	49
5	72
6	63

Weiter

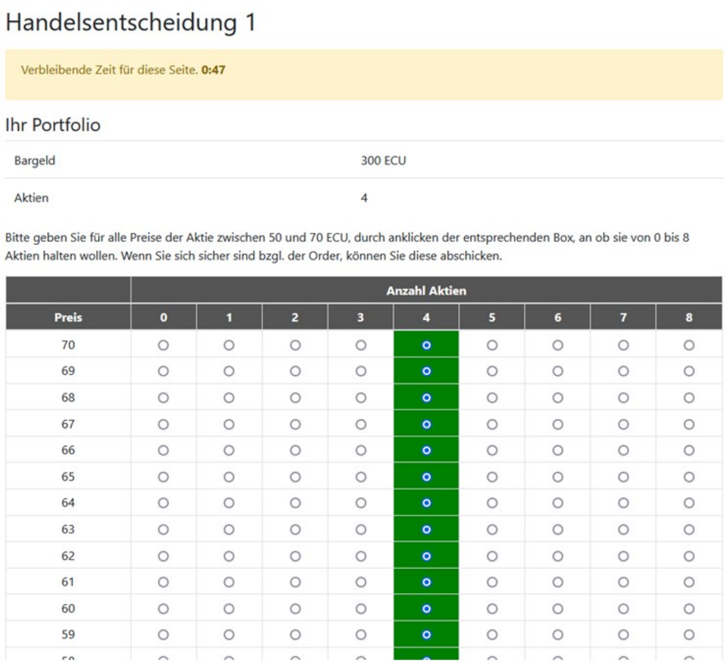
Figure S.11: Information Liquidation Value - *Info*

Determining the liquidation value in this block

Here you can see the table with the liquidation values of the share depending on the number of die. This table applies to each of the 2 rounds.

Table with column 1 "Number rolled" and column 2 "Payout in ECU"

Continue



Handelsentscheidung 1

Verbleibende Zeit für diese Seite. **0:47**

Ihr Portfolio

Bargeld	300 ECU
Aktien	4

Bitte geben Sie für alle Preise der Aktie zwischen 50 und 70 ECU, durch anklicken der entsprechenden Box, an ob sie von 0 bis 8 Aktien halten wollen. Wenn Sie sich sicher sind bzgl. der Order, können Sie diese abschicken.

	Anzahl Aktien								
Preis	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
70	○	○	○	○	●	○	○	○	○
69	○	○	○	○	●	○	○	○	○
68	○	○	○	○	●	○	○	○	○
67	○	○	○	○	●	○	○	○	○
66	○	○	○	○	●	○	○	○	○
65	○	○	○	○	●	○	○	○	○
64	○	○	○	○	●	○	○	○	○
63	○	○	○	○	●	○	○	○	○
62	○	○	○	○	●	○	○	○	○
61	○	○	○	○	●	○	○	○	○
60	○	○	○	○	●	○	○	○	○
59	○	○	○	○	●	○	○	○	○

Figure S.12: Trading Screen

Trading decision 1

Time remaining for this page. 0:47

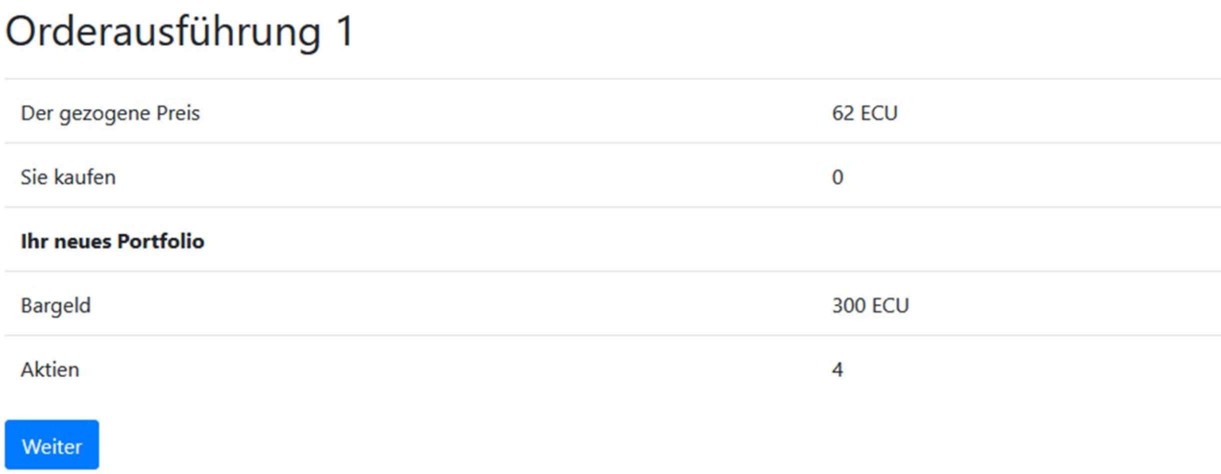
Your portfolio

Cash 300ECU

Shares 4

Please specify for all prices of the share between 50 and 70 ECU, by ticking the corresponding box, the number you want to hold, from 0 to 8 shares. If you are sure about the order, you can submit it.

Table to enter the decisions. Left column "Price", columns 2-10 "Number of shares"



Orderausführung 1

Der gezogene Preis	62 ECU
Sie kaufen	0
Ihr neues Portfolio	
Bargeld	300 ECU
Aktien	4

Weiter

Figure S.13: Order Execution Screen

Order execution 1

The price drawn 62 ECU

You buy 0

Your new portfolio

Cash 300 ECU

Shares 4

Continue

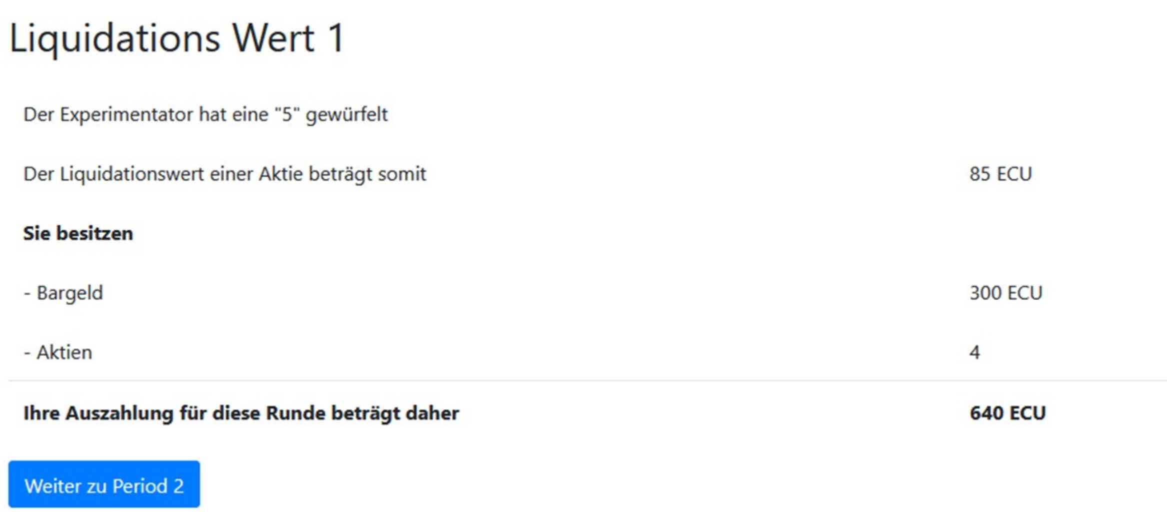


Figure S.14: Liquidation Value

Liquidation value 1

The study supervisor rolled a ”5”.

The liquidation value of a share is thus 85 ECU

You own

Cash 300 ECU

Shares 4

Your payout for this round is therefore 640 ECU

Continue to period 2

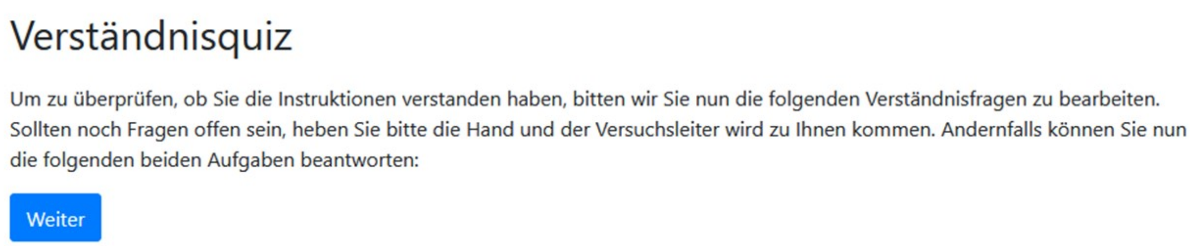
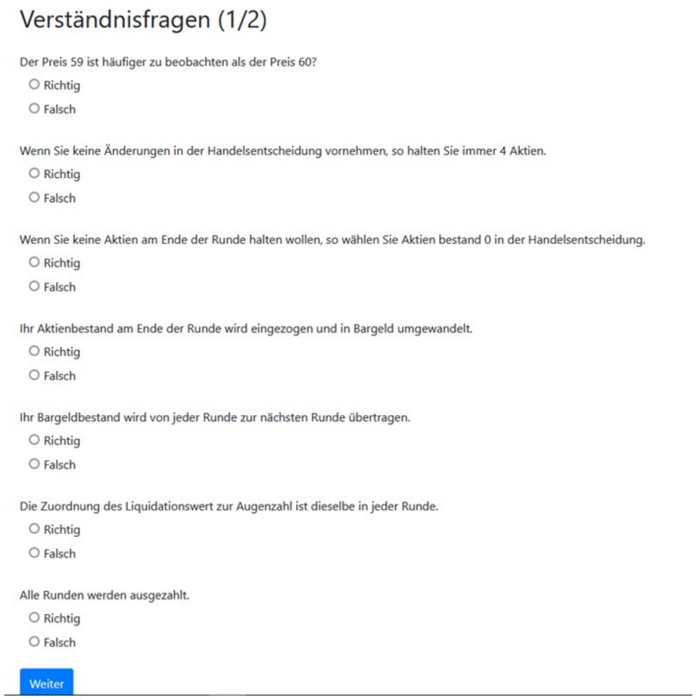


Figure S.15: Instruction comprehension Quiz

Comprehension quiz

In order to check whether you have understood the instructions, we ask you to complete the following comprehension questions. If you still have questions, please raise your hand and the study supervisor will come to you. Otherwise, you can now complete the following two tasks.

Continue



Verständnisfragen (1/2)

Der Preis 59 ist häufiger zu beobachten als der Preis 60?

- Richtig
- Falsch

Wenn Sie keine Änderungen in der Handelsentscheidung vornehmen, so halten Sie immer 4 Aktien.

- Richtig
- Falsch

Wenn Sie keine Aktien am Ende der Runde halten wollen, so wählen Sie Aktien bestand 0 in der Handelsentscheidung.

- Richtig
- Falsch

Ihr Aktienbestand am Ende der Runde wird eingezogen und in Bargeld umgewandelt.

- Richtig
- Falsch

Ihr Bargeldbestand wird von jeder Runde zur nächsten Runde übertragen.

- Richtig
- Falsch

Die Zuordnung des Liquidationswert zur Augenzahl ist dieselbe in jeder Runde.

- Richtig
- Falsch

Alle Runden werden ausgezahlt.

- Richtig
- Falsch

Weiter

Figure S.16: Comprehension questions 1

Comprehension questions (1/2)

The price 59 is observed more often than the price 60.

True

False

If you do not make any changes in the trading decision, you always hold 4 shares.

True

False

If you do not want to hold any shares at the end of the round, select 0 shares in the trading decision.

True

False

Your shareholding at the end of the round is withdrawn and converted to cash.

True

False

Your cash balance is carried forward from each round to the next round.

True

False

The assignment of the liquidation value to the number is the same in each round.

True

False

All rounds are paid out.

True

False

Continue

Figure S.17: Comprehension questions

Comprehension questions (2/2)

Assume that you have made the following trading decision.

The study supervisor has drawn the price 53. Will you buy or sell shares at that price?

Buy

Sell

How many shares will you buy or sell?

In addition, the liquidation value was determined by rolling die number 2 with 80 certainty. What is your payout in this period?

Continue

S.2. ADDITIONAL TASK DESCRIPTION

Multiple Price List Risky Lotteries. The risk elicitation consisted of four multiple price lists, each with a list of binary options, following the standard procedure (Andersson et al. 2016; Chapman et al. 2018; Holt and Laury 2002).

MPL 1: 13 binary options:

Option A: 50% 500 ECU or otherwise 0

Option B: -50, 0, 50, 100, 150, 200, 250, 300, 350, 400, 450, 500, 550

MPL 2: 11 binary options:

Option A: 50% 400 ECU or otherwise 0

Option B: -50, 0, 50, 100, 150, 200, 250, 300, 350, 400, 450

MPL 3: 10 binary options:

Option A: 50% 50 ECU or otherwise 500, 700, 800, 900, 1000, 1100, 1200, 1400, 1700, 2200 ECU

Option B: 50% 300 ECU or otherwise 500 ECU

MPL 4: 10 binary options:

Option A: 50% 20 ECU or otherwise 400, 500, 550, 600, 650, 700, 750, 950, 1350, 2150 ECU

Option B: 50% 250 ECU or otherwise 450 ECU

The corresponding variables counts the number of how often the risky option is selected.

Self-reported Risk-attitudes. To measure risk attitude, the self report Risk attitude Scale from the German Socio-Economic Panel Study (SOEP) is used. The SOEP risk scale measures risk attitudes globally and specific ones for 6 domains For further information, please consult SOEP Scales Manual, p. 59 - 61: www.diw.de/gsoep/.

Matrices puzzles. We constructed 4 matrices in the spirit of the Ravens progressive Matrices using the toolbox and procedure of Civelli and Deck 2017. These matrices approximate the cognitive abilities and were ordered in increasing difficulties. Participants had four minutes to solve all four matrices.

Overconfidence. Following Chapman et al. 2018 we asked participants after participants solved the four matrices puzzles, we asked them to estimate how many puzzles they solved correctly (overestimation) and to rank themselves among 100 randomly selected participants in this study (over-placement).

Exit Questionnaire.

Trading Strategy Stated: Open text field to expost state their strategy used.

Study Objective: Open text field to reason about the objectives of the study.

Study Interest: likert scale from 1 (not interested) to 5 (very interested)

Instruction comprehension: likert scale from 1 (not comprehensive) to 5 (very comprehensive)

Gender: 0 male, 1 female, 2 others

Year of Birth:

Highest Degree: No Degree, Secondary school leaving certificate, High School Diploma, Apprenticeship, Bachelors Degree, Masters Degree, Master's certificate, PhD or higher, others

Field of Study: Open test

Stock owenership: doe you own stocks? yes, no, do not know

Stock traded: Have you ever traded actively a stock of fund? yes, no, do not know

Stock traded last 12m: How often did you traded stocks in the last 12 months? - open text field