Asset Price Dynamics and Endogenous Trader Overconfidence*

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Abstract

Using a new experimental design, we show how asset prices and the overconfidence of traders co-move; when asset prices go up, overconfidence rises, and when asset prices go down, overconfidence falls. Consistent with models of endogenous overconfidence (Daniel et al., 1998; Gervais and Odean, 2001), we observe that becoming successful makes traders overconfident, yet becoming overconfident does not necessarily make traders successful. Additionally, we confirm existing experimental evidence that high cognitive ability results in better market performance.

JEL Classification C91 · D84 · G11 · G41

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1 Introduction

Traders are often overconfident about the precision of their judgment (Moore et al., 2016). Such bias is known as overprecision[1] and has important consequences in financial markets both at the individual and aggregate level. For example, overprecise traders both underperform due to excessive trade (Odean, 1999; Barber and Odean, 2001) and underdiversify their portfolios (Goetzmann and Kumar, 2008), while markets populated by overprecise traders are more volatile and result in more inflated asset prices (Scheinkman and Xiong, 2003; Michailova and Schmidt, 2016).

However, trader overprecision is not a "static" personality trait, and it changes endogenously with past success and failure (Deaves et al., 2010; Hilary and Menzly, 2006; Merkle, 2017). Models of endogenous overprecision (e.g., Daniel and Hirshleifer, 2015; Daniel et al., 1998; Gervais and Odean, 2001) imply a strong relationship of trader overprecision and asset price dynamics; overprecise traders push up asset prices, while the gains from such asset price soares spur traders' overprecision.[2] Therefore, endogenous overprecision creates a feedback loop that can give rise to hump-shaped asset price dynamics (i.e., short-term momentum and long-term reversal of asset prices), thereby amplifying stock price volatility and trading volume and increasing the probability of asset price bubbles.

In this paper we present a novel experimental design to study whether asset prices and endogenous trader overprecision co-move in a Smith et al. (1988) (henceforth SSW) experimental asset market. To do so, we first provide a new method to measure individual overprecision. We then apply our method to a task in the spirit of Caplin and Dean (2014) that is independent from the experimental asset market. The advantage of such a context-independent measure is that it gives us a "clean" measure of individual overprecision, free from any confounding market factors. To study the endogeneity of overprecision through

[1] Moore and Healy (2008) differentiate between three types of overconfidence: *overestimation* of one's true abilities, performance, or level of control (e.g., someone believes to have answered ten questions of a quiz correctly but actually only got five correct); *overplacement* of one's abilities or performance relative to others (e.g., almost everyone believes they are an above-average driver); and *overprecision* as an excessive faith in the quality of one's judgment (e.g., stating that the Dow Jones will go up by 167.38 points in the next two weeks).

[2] A related co-movement of asset prices and overprecision is postulated by (Tuckett and Taffler, 2008), who argue that the overprecision of traders changes with the emotions and excitement of significant profit opportunities during asset price bubbles.

the market cycle, we use our new method to elicit the overprecision of subjects at different points of the experimental market.

The findings are clear: overprecision is endogenous and co-moves with asset prices. When asset prices go up, trader overprecision rises, and when asset prices go down, trader overprecision falls. Moreover, larger changes in prices are met by larger changes in trader overprecision. Additionally, we observe that as predicted by the theory (e.g., Daniel et al., 1998; Gervais and Odean, 2001), successful traders become more overprecise, but overprecise traders do not become more successful. In fact, in line with theoretical (e.g., Benos, 1998; Odean, 1998; Gervais and Odean, 2001) and experimental (e.g., Biais et al., 2005) evidence, we find that trader overprecision is negatively correlated with total profits. Finally, we confirm previous studies' findings that high cognitive ability results in higher market performance (Bosch-Rosa et al., 2018; Noussair et al., 2016).

To the best of our knowledge, only two papers have studied endogenous overprecision in the context of changing asset prices, Kirchler and Maciejovsky (2002) and Michailova and Schmidt (2016). Both papers use SSW experimental asset markets to test whether the subjects' overprecision in asset price beliefs changes over the course of a bubble burst pattern. They find that, on average, overprecision is larger in market episodes that are associated with higher asset prices and is lower in market episodes associated with lower asset prices. This implicit evidence suggests that there indeed exists a relationship between asset prices and the subjects' overprecision. Yet, contrary to our experimental design, these papers cannot rule out that such changes in overprecision are driven by factors other than asset price dynamics, such as uncertainty about the asset market (e.g., Hanaki et al., 2018), learning and experience (e.g., Griffin and Tversky, 1992), or cognitive biases related to the market such as wishful thinking (e.g., Caplin and Leahy, 2019).

The paper is organized as follows. Section 2 presents our experimental design and introduces our new method to measure overprecision. Section 3 presents the results of the experiment. Finally, Section 4 concludes.

2 Experimental Design

In this section we provide our experimental design. We first describe the SSW experimental asset market. Then we introduce our novel method to measure the individual overprecision. Finally, we present the set of personality traits that we elicit from our subjects.

2.1 Experimental Asset Market

This experiment has two treatments. In the baseline treatment, asset prices are endogenous and are determined by the market participants. The goal of the baseline treatment is to test whether asset prices and overprecision co-move. By contrast, in the control treatment, asset prices are exogenous and are determined by the known fundamental value. The goal of this treatment is to control for the endogeneity that overprecision may have on asset price dynamics and thereby to test for a causal effect of asset price dynamics on overprecision.

2.1.1 Baseline Treatment

We employ a variant of the standard SSW experimental asset market. Each session consists of two consecutive asset markets with nine subjects per market. The particular market design and parametrization is based on Haruvy et al. (2007) and has subjects trading an asset for 15 periods. At the beginning of each market, subjects receive an endowment of assets and Talers[3] (our experimental currency) that they can use to trade. At the end of each trading period, each asset pays a random dividend of either 0, 4, 14, or 30 Talers, each with equal probability. The dividend is independent across trading periods. The balance of Talers and assets carries over from trading period to trading period until the end of the market (trading period 15), at which point the asset pays its last dividend and disappears. At the end of the experiment, Talers are converted into euros at a conversion rate of € 1 for every 100 Talers.

Because the market is finite and the expected dividend of the asset is the same at every trading period, the fundamental value of the asset at trading period t can be easily calculated as $12 \cdot (16 - t)$. Thus, the fundamental value of the asset is monotonically decreasing with every trading period. To make calculations easier for our subjects, we provide them with a table showing the fundamental value of the asset for each trading period.

[3]Three subjects receive three assets and 112 Talers, three receive two assets and 292 Talers, and the remaining three receive one asset and 472 Talers.

Following Haruvy et al. (2007), the market uses call market rules; all subjects simultaneously make a single buy and sell order at the beginning of each trading period. Buy orders consist of the maximum price subjects are willing to pay and the desired quantity. Likewise, sell orders consist of a minimum selling price and the number of assets subjects are willing to sell.[4] These buy and sell orders are aggregated into a supply and demand curve that determines the market-clearing price.[5] Subjects who submit buy orders above the market-clearing price buy assets, while those who submit sell orders below the market-clearing price sell assets. In case of a tie, a virtual coin is flipped to determine who will trade.

2.1.2 Control Treatment

In the control treatment, we generate SSW experimental asset markets where the price of the asset is both exogenous and certain. Following Akiyama et al. (2017) and Hanaki et al. (2018), in each market one subject is paired to eight computerized traders that buy and sell at fundamental value. Because of the call market rules, in all trading periods the market-clearing price will be equal to the downward-sloping fundamental value of the asset.

2.2 New Method to Measure Overprecision

Most previous efforts to study overprecision in asset markets are based on eliciting confidence intervals (e.g., Glaser and Weber, 2007; Kirchler and Maciejovsky, 2002). This approach, however, is problematic, as subjects do not seem to understand the concept of confidence intervals and they are hard to incentivize (Moore et al., 2016). Therefore, we propose a new, and simple, method to measure the overprecision of subjects by asking them to answer the following two items[6]:

1. *Please give us your best estimate for [variable to be estimated].*

[4]Subjects cannot make bids that are higher than their asks. Likewise, bids and asks are subject to their budget constrains and their current asset holdings.

[5]We follow the algorithm proposed by Palan (2018). The market-clearing price is defined as the volume-maximizing price. Note that in cases where there is a continuum of market-clearing prices, the mean value of the continuum is used.

[6]These items will be adjusted as necessary for the particular dimension of interest.

2. *How far away do you think your estimate is from the true answer?*

The first item allows us to measure the true estimation error. The second item measures the subjective, expected estimation error. The difference between the expected error and the true error determines the subject's overconfidence. A subject is said to be *overprecise* if the expected estimation error is smaller than the true estimation error. Analogously, a subject is said to be *underprecise* if the expected estimation error is larger than the true estimation error. Unlike eliciting confidence intervals and measures of subjective certainty, our approach is intuitive and, importantly, can accommodate any incentivization system.

We apply our new method to measure overprecision along two separate dimensions: (i) *context-independent overprecision*, which is completely unrelated to the market, and (ii) *price-prediction overprecision*, which is the overprecision in asset price beliefs. While overprecision in asset price beliefs may be confounded with other market biases (e.g., wishful thinking) or the learning that is so prevalent in SSW asset markets, the goal of the context-independent measure of overprecision is to have a clean measure of overprecision, free of any confounding factors. By completely isolating the measure of overprecision from the market, we get a transparent measure through which we can clearly identify the effect of asset price dynamics on the overprecision of subjects. Therefore, our main interest lies in the context-independent measure of overprecision. Price-prediction overprecision, on the other hand, mainly serves as a control for our regression analysis.

2.2.1 Context-Independent Overprecision

To measure context-independent overprecision, subjects take part in a task we call "dot-spot."[7] In this task, subjects are flashed for six seconds with a matrix of 20×20 red and blue dots like the one shown in Figure 1. Subjects are then asked to answer two items[8]:

1. *Please estimate the total number of red dots in the dot-spot matrix.*
2. *How far away do you think your estimate is from the true answer?*

[7] The software for the dot-spot task is available at `https://pank.eu/dotspot`.

[8] The exact German wording is: 1. Bitte schätzen Sie die Gesamtanzahl der roten Punkte in dem DotSpot Bild.; 2. Was schätzen Sie, wie weit ist Ihre Einschätzung von der wahren Antwort entfernt?

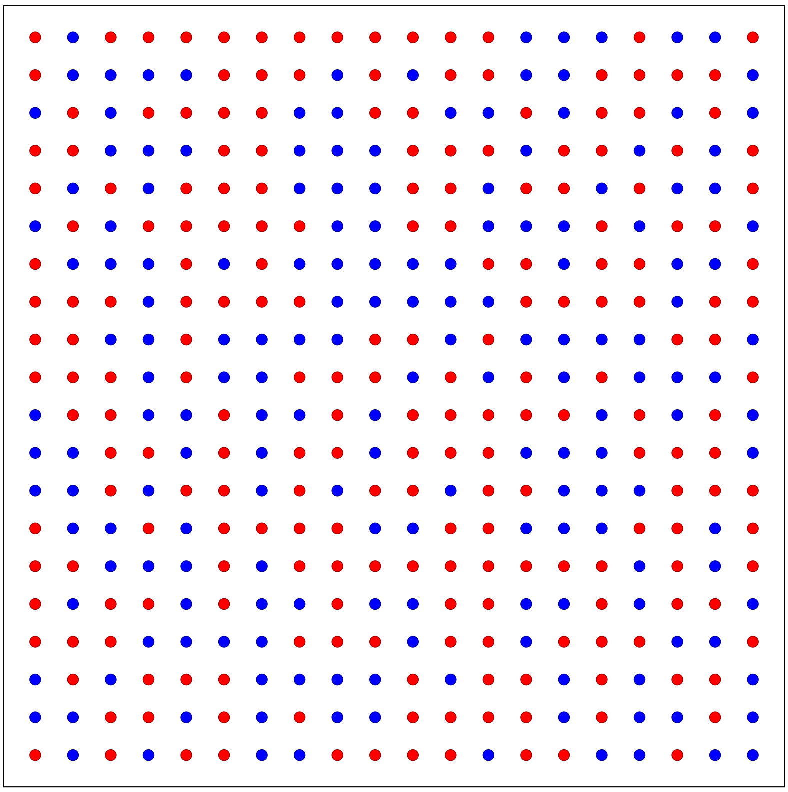

Figure 1: "Dot-Spot" Task

To incentivize both questions, we follow Haruvy et al. (2007). Subjects get paid € 0.25 if their guess is within 10% of the realized number of red dots, € 0.10 if within 25%, € 0.05 if within 50%, and € 0 otherwise. The outcomes from the dot-spot task, and thus the earnings, are not revealed and are not paid out until the end of the experiment. We choose this incentivation scheme over more sophisticated alternatives, such as the quadratic scoring rule (Brier, 1950) or the binarized scoring rule (Hossain and Okui, 2013), as Haruvy et al. (2007) show that this system is easy for subjects to understand and find no evidence of any systematic bias in subjects' answers. To avoid that subjects hedge between both questions, subjects are randomly paid according to one or the other question [9].

To study the endogeneity of overprecision, we measure context-independent overprecision at three different dot-spot "breaks" that take place before the start of each market (Break 1), after trading period 6 (Break 2), and after trading period 13 (Break 3).[10] In

[9] See Blanco et al. (2010) for a discussion on how to avoid hedging in belief elicitation contexts.

[10] One of the reasons that we decided to use SSW markets is that we could *ex ante* predict when it would be best to "interrupt" the market to get a sample of overprecision at the top of the bubble and after the bubble has exploded. Figure 2 shows that our predictions are pretty good, and in 75% of our

each of these breaks, subjects take part in five consecutive rounds of the dot-spot task. The unique context-independent measure of overprecision per subject per break is then determined by the median of all five rounds.

To make breaks comparable, in each break, three of the five matrices are "similar." Similar matrices are generated using a uniform distribution with support between 45 ± 5, 75 ± 5, or 325 ± 5 in each dot-spot break. The other two matrices are drawn from a uniform distribution with the support of 200 ± 125 red dots. The order of the five matrices are random within each break.

Importantly, while similar matrices have a similar number of dots, the disposition of these dots is different. In other words, even though the number of dots is almost identical, the distribution of the red and blue dots is unique.[11]

2.2.2 Price-Prediction Overprecision

The advantage of call market rules is that each trading period has a unique market-clearing price. This unique price allows us to elicit subjects' price beliefs and their associated price-prediction overprecision by asking the following at the beginning of each trading period:[12]

1. *Please give us your best estimate for the price of the asset in this trading period.*

2. *How far away do you think your price estimate is from the true answer?*

The incentivation scheme for these questions is analogous to the scheme for the dot-spot, with the sole difference being that earnings from prices predictions are paid out *on-the-go* and can be used for asset purchases in subsequent trading periods.

2.3 Personality Traits

The experimental literature has shown that personality traits significantly affect the behavior of subjects in SSW markets (e.g., Bosch-Rosa et al., 2018; Eckel and Füllbrunn,

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cases we can measure overprecision almost at the top of the bubble and immediately after its crash.

[11]See Figure 4 in Appendix A, which shows two similar matrices with the *exactly the same number of red dots* but with a different pattern side-by-side.

[12]The exact German wording is: 1. Bitte schätzen Sie den Handelspreis der Aktie in dieser Periode.; 2. Was schätzen Sie, wie weit ist Ihr geschätzter Preis von der wahren Antwort entfernt?

2015; Michailova and Schmidt, 2016). To control for personality traits in our data analysis, subjects take several personality tests at the end of the experiment.

First, we elicit the subjects' cognitive ability through questions from three different versions of the cognitive reflection test (henceforth CRT), the original CRT (Frederick, 2005), CRT2 (Thomson and Oppenheimer, 2016), and eCRT (Toplak et al., 2014). We do this because CRT scores have been shown to correlate with performance in SSW markets (Noussair et al., 2016; Bosch-Rosa et al., 2018). We also ask the subjects about the number of questions they expected to have answered correctly and their expected relative ranking among all subjects who participated in the same session. Their answers give us a measure of overestimation and overplacement, respectively.

Additionally, we elicit the subjects' risk aversion using a Holt and Laury (2002) multiple price list and the non-incentivized risk question from the German Socio Economic Panel ("How likely are you to take risk on a scale of 0 (not risk taking at all) to 10 (very prone to take risk)?"), as risk aversion affects the way subjects behave in SSW markets (Eckel and Füllbrunn, 2015).[13]

Finally, we ask subjects to answer the ten-item version of the Big Five personality test suggested by Rammstedt and John (2007), as extraversion and neuroticism affect the subjects' trading behavior in SSW experiments (Oehler et al., 2018) in addition to the size and length of asset price bubbles (Oehler et al., 2019).

3 Results

The experiment contained 21 sessions, 12 sessions with our baseline design and 9 sessions with our control treatment. A total of 117 subjects were recruited through the Online Recruitment Software for Economic Experiments, or ORSEE (Greiner, 2015). All sessions lasted approximately 2 hours and 15 minutes and were run at the Experimental Economics Laboratory of the Technische Universität Berlin. The experiment was programmed and conducted using oTree (Chen et al., 2016), and the dot-spot task used `D3.js` (Bostock et al., 2011). Subjects made, on average, € 26.20.

[13]For our regressions, we combine both risk measures into one single risk aversion measure. For details, see Appendix B.

Before the start of the experiment, subjects participated in a quiz that tested their knowledge on the rules of the market and in several rounds of a dot-spot task with performance feedback.

3.1 Asset Price Dynamics and Endogenous Context-Independent Overprecision

In Figure 2 we plot the endogenous market-clearing price (red, solid line) and the downward-sloping fundamental value (gray, solid line) for the first market of each session from our baseline treatment[14] (for results and analysis of the second market (Market 2), see Appendix C). The vertical lines denote where the dot-spot breaks occur, and the blue dots show the price of the asset immediately before the break.[15] From Figure 2, it is apparent that most markets develop asset price bubbles, as is standard in SSW markets.

More interestingly, in 8 of the 12 sessions, we observe that the price immediately before the second dot-spot break ($Price_6$) is larger than the price at the beginning of the market ($Price_0$) and is also larger than the price before the third dot-spot break ($Price_{13}$); i.e., $Price_0 < Price_6 > Price_{13}$. These sessions are the most interesting since their price dynamics allow us to study the full spectrum of a complete bubble burst episode. We call these sessions *Hump Shape* sessions.

In sessions 9 to 12, $Price_0 < Price_6 < Price_{13}$, so we cannot study the effects that a bubble burst has on the overprecision of subjects. However, we can still use these sessions to study whether such sustained price increases raise the level of the subjects' overprecision further. We call these sessions *Increasing Price* sessions. Finally, we call the control sessions with exogenously decreasing prices *Decreasing Price* sessions.

In each dot-spot break, subjects face five different matrices. We define the context-independent overprecision of subject i for matrix $j \in \{1, 2, 3, 4, 5\}$ in break $b \in \{1, 2, 3\}$ as[16]

$$DotOP_{ijb} = |RedGuess_{ijb} - Red_{jb}| - RedErrorGuess_{ijb}, \tag{1}$$

[14] We do not plot the control treatment since by construction, the market-clearing price equals the downward-sloping fundamental value.

[15] Notice that the first dot-spot break took place before the market started, so we do not have a price before that market. Instead we put the blue dot at the first price realized in the market immediately after the dot-spot task.

[16] To ease notation, we ignore that there are two markets in each session and drop this subindex.

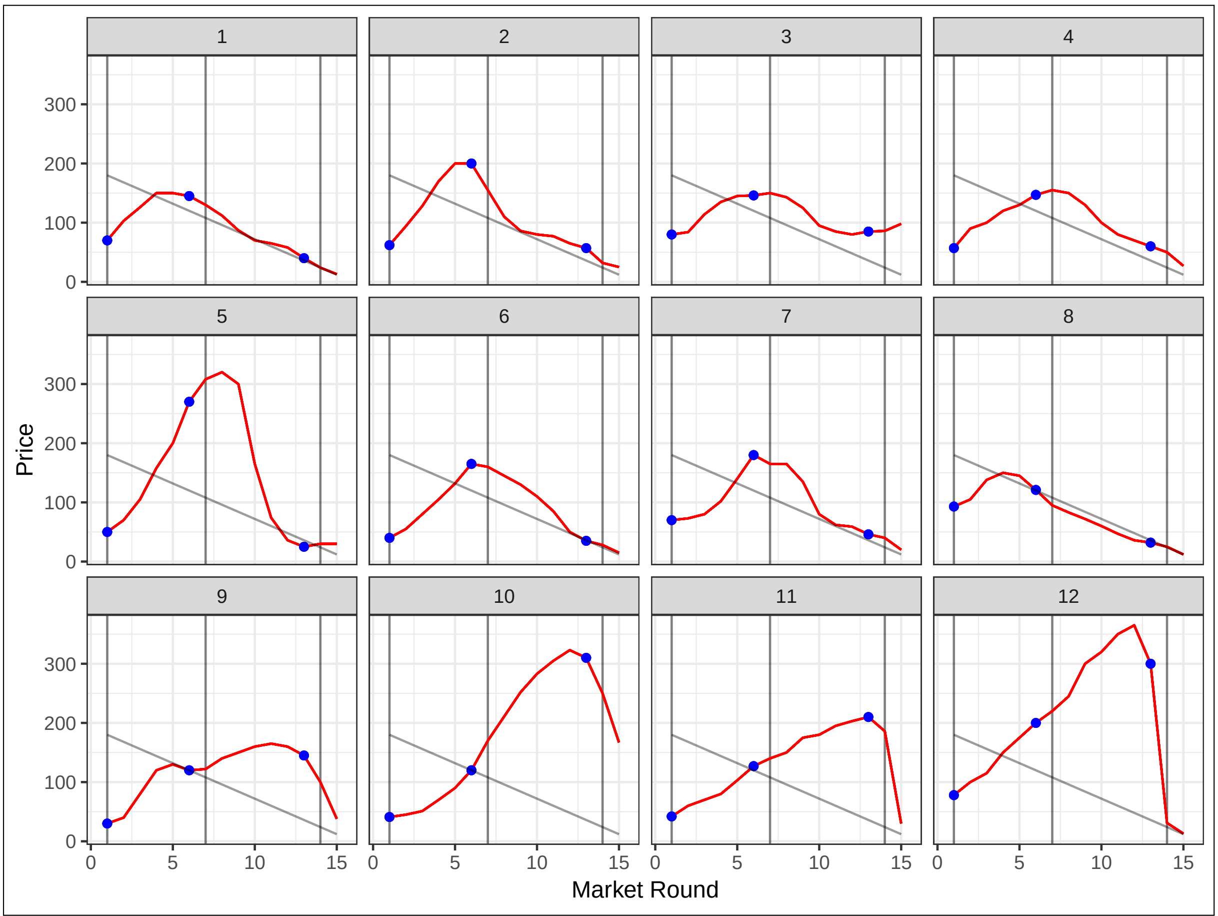


Figure 2: Equilibrium price (red line), fundamental value (solid black line), and Dot-Spot breaks (vertical black lines) for Market 1 of all sessions. To have a better understanding of the price dynamics we place blue dots at the equilibrium price immediately before the Dot-Spot task took place (i.e., $Price_6$ and $Price_{13}$). For the first break we place the dot on top of the first realized price ($Price_1$)

where $RedGuess_{ijb}$ is the guess of red dots made by the subject, Red_{jb} is the correct number of red dots, and $RedErrorGuess_{ijb}$ is the expected error stated by the subject. Therefore, with larger $DotOP_{ijb}$, the subject is more overprecise, and with smaller $DotOP_{ijb}$, the subject is less overprecise. To have a unique measure of context-independent overprecision for each dot-spot break b, we drop all values where the error is greater than 100 ($\sim$4% of all observations) and then take the median across all remaining $DotOP_{ijb}$ for each subject.[17] This aggregate measure is denoted as $Overpre_{ib}$ and serves as our main measure of overprecision.

In Figure 3 we present the distribution of $Overpre_{ib}$ for each break of Market 1 across price dynamic subgroups (from left to right, *Decreasing Price*, *Hump Shape*, *Increasing*

[17]Using 100 as our cut-off value is an ad hoc decision, but the results do not change qualitatively if we pick other values such as 150 or 200 as cutoffs. In Figure 5 of Appendix A we can clearly see how the dropped values are outliers.

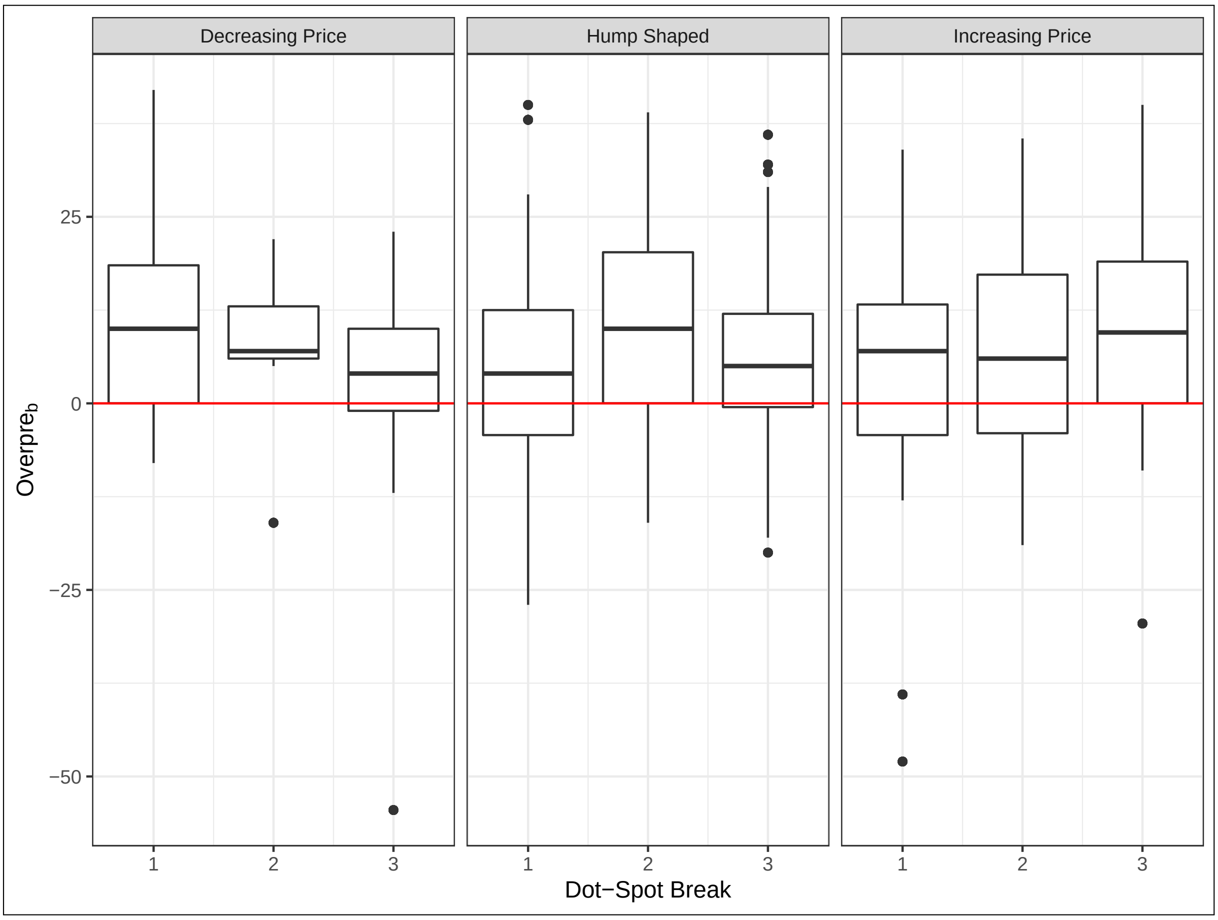


Figure 3: Box plots showing the median, 25th and 75th percentile of $Overpre_{ib}$ for each break within a session.

Price). The figure clearly shows that the overprecision of the median subject changes over the market cycle and follows our hypothesized trajectory: a) it is downward trending for the *Decreasing Price* sessions, b) goes up and then down in the *Hump Shape* sessions, and c) is upward trending for the *Increasing Price* sessions.[18]

To test whether these differences across breaks are statistically significant, we perform a series of Wilcoxon signed-rank tests comparing $Overpre_{ib}$ of subjects across breaks for the *Hump Shape*, *Increasing Price*, and *Decreasing Price* sessions, respectively. The p-values are summarized in Table 1. Our interest lies in the *Hump Shape* sessions, as they allow us to test a wider range of price effects on overprecision. In this case we see how the differences between breaks are highly significant; as prices climb, so does the context-independent overprecision. Interestingly, the effect on overprecision is reversed when the

[18]We plot the individual session box plots for each session in Figure 6 of Appendix A.

	Break 1 = Break 2	Break 2 = Break 3	Break 1 = Break 3
Hump Shape ***p*-value** (N=72)	0.001	0.010	0.198
Increasing Price ***p*-value** (N=36)	0.587	0.299	0.030
Decreasing Price ***p*-value** (N=9)	0.314	0.440	0.085

Table 1: P-values resulting from Wilcoxon matched-pairs signed-ranks test comparing the equality of matched pairs of observations across Dot-Spot task across different session sub-groups.

bubble bursts and prices drop.[19]

The results for the *Increasing Price* sessions show no differences between consecutive breaks, yet the overall trend (between the first and third break) is significant at the 5% level. This is intuitive, as the *Increasing Price* sessions have, on average, relatively lower prices in the middle break and have high prices in the latter. Additionally, the lower number of observations means less power and therefore the need for a bigger effect to detect statistical differences.

A similar story can be told when comparing the breaks in the *Decreasing Price* sessions. While the differences across breaks are, yet again, not significant at the 5% level, the trend of the measured overprecision in Figure 3, the low number of observations, and the results for the other subgroups make it reasonable to associate the fall of overprecision with the fall in market prices.

Result 1: Overprecision is endogenous and co-moves with asset prices and it carries over to out-of-context tasks.

Next, we want to quantify the effects that price dynamics have on the change in their overprecision. To do so, we define the change in context-independent overprecision as

$$\Delta Overpre_{i(b,b')} = Overpre_{ib'} - Overpre_{ib}, \tag{2}$$

where b' and b are different breaks in a market and $b' > b$. So, for example, $\Delta Overpre_{i(1,2)}$ is the change in overprecision from the first to the second dot-spot break for individual i.

[19] Notice that aggregating the observations of both *Hump Shape* and *Increasing Price* sessions when studying the changes in $Overpre_{ib}$ between the first two breaks (b_1, b_2) results in a qualitatively identical result (Wilcoxon signed-rank tests p-value = 0.003).

In Table 2 we regress $\Delta Overpre_{(b,b')}$ on the change in asset prices and several personality measures.[20] We divide the data into three different models. In the first model we regress the change in overprecision between the first and second dot-spot break ($\Delta Overpre_{(1,2)}$) on the difference in price for the first and sixth trading period ($\Delta Price_{(1,2)} = Price_6 - Price_1$).[21] The second model regresses the change in overprecision between the second and third dot-spot break ($\Delta Overpre_{(2,3)}$) on the difference in price between trading periods 6 and 13 ($\Delta Price_{(2,3)} = Price_{13} - Price_6$), while the third model compares the change in overprecision between the last and first break ($\Delta Overpre_{(1,3)}$) and their corresponding price change ($\Delta Price_{(1,3)} = Price_{13} - Price_1$).

Additionally, we introduce price-prediction overprecision $PriceOP_{it}$, which is the overprecision of subject i when predicting the equilibrium price in trading period t:

$$PriceOP_{it} = |PriceGuess_{it} - Price_t| - PriceErrorGuess_{it}. \tag{3}$$

Analogous to Equation (1), $PriceGuess_{it}$ is the guessed price of subject i for trading period t, $Price_t$ is the correct market price, and $PriceErrorGuess_{it}$ is the subjects' expected error from guessing the price. We then aggregate the price-prediction overprecision for each subject between breaks to get $APriceOP_{i(b,b')}$.

The results in Table 2 show that the price difference across dot-spot breaks have a significant effect on the changes in the context-independent measure of overprecision; across all three breaks, the more prices increase, the more overprecise a subject becomes. On the other hand, neither the accumulated price-prediction overprecision nor any of the other potential explanatory variables seem to have any effect on the changes in the context-independent measure of overprecision.

Result 2: The bigger the fluctuations in prices, the bigger the changes in overprecision.

3.2 The Impact of Past Performance on Endogenous Overprecision

A potential driving factor of endogenous overprecision is the past success and failure of traders (e.g., Daniel et al., 1998; Deaves et al., 2010; Gervais and Odean, 2001). Therefore,

[20] For ease of notation, from now on we drop the individual subject index i for $\Delta Overpre_{(b,b')}$.

[21] Again, to ease notation, we drop the session index for $\Delta Price_1$, as it follows that for each subject we use the prices of her session.

	(1) $\Delta Overpre_{(1,2)}$	(2) $\Delta Overpre_{(1,2)}$	(3) $\Delta Overpre_{(2,3)}$	(4) $\Delta Overpre_{(2,3)}$	(5) $\Delta Overpre_{(1,3)}$	(6) $\Delta Overpre_{(1,3)}$
$\Delta Price_{(1,2)}$	0.0480**	0.0500**				
	(0.0190)	(0.0198)				
$APriceOP_{(1,2)}$	-0.0188	-0.0178				
	(0.0138)	(0.0139)				
$\Delta Price_{(2,3)}$			0.0341*	0.0409**		
			(0.0161)	(0.0175)		
$APriceOP_{(2,3)}$			0.0353	0.0386		
			(0.0293)	(0.0255)		
$\Delta Price_{(1,3)}$					0.0220***	0.0207***
					(0.00644)	(0.00652)
$APriceOP_{(1,3)}$					0.0174	0.0179
					(0.0114)	(0.0117)
CRT	0.154	0.269	-0.370	-0.482	-0.329	-0.299
	(0.460)	(0.393)	(0.587)	(0.665)	(0.575)	(0.585)
Male	-2.838	-0.822	-1.489	-3.075	-4.913	-4.611
	(3.978)	(3.827)	(2.580)	(2.252)	(2.951)	(2.960)
Risk Aversion	-0.877	-1.058	-11.80	-12.24	-16.03*	-15.42*
	(7.468)	(8.087)	(8.617)	(9.511)	(8.117)	(7.982)
Constant	2.035	-10.87	7.804	20.10*	12.25	13.98
	(5.588)	(12.32)	(6.017)	(10.000)	(6.947)	(12.33)
N	117	117	117	117	117	117
adj. R^2	0.012	0.043	0.060	0.085	0.115	0.086
Big Five	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: OLS of the change of context-independent measure of overprecision ($\Delta Overpre_{(b,b')}$) on the change in asset prices across breaks ($\Delta Price_{(b,b')}$), the individual level accumulated price-prediction overprecision across breaks ($APriceOP_{(b,b')}$), and personality measures. All standard errors are clustered at the session level.

we next study the effect that past performance has on the overprecision of our experimental subjects. We proxy past performance by changes in the subjects' book value of their wealth between breaks. The book value of subject i's wealth comprises her cash and marked-to-market assets holdings at the end of the trading period. Hence, the change in the book value of subject i's wealth between breaks $b' > b$ is defined as

$$\Delta Wealth_{i(b,b')} = Price_{t'} \cdot Assets_{it'} - Price_t \cdot Assets_{it} + Cash_{it'} - Cash_{it}, \tag{4}$$

where $Assets_{it}$ and $Cash_{it}$ are the number of assets and cash subject i is holding in periods $t = 1, 6, 13$ with $t' > t$, respectively.

Table 3 shows the results. In the table, as in Table 2, we divide the data to study the three different breaks. As expected, the results show that an increase (decrease) in the book value of wealth induces an increase (decrease) of the context-independent overprecision. However, this effect is not as strong as the effect that a pure change in prices has and is nonexistent for the changes in the book value of wealth between the first and third break.

For completeness, we repeat the exercise from Table 3 but look at the changes in the book value of assets and cash holdings separately (Table 5 in Appendix A). While changes in the book value of the asset holdings significantly affect context-independent overprecision, changes in cash holdings are without significant effect (at the 5% level) on the context-independent overprecision. This shows that changes in overprecision are driven by changes in asset prices and not necessarily by wealth *per se*.

Result 3: The change in value of subjects' portfolios has a weak positive effect on the overprecision of subjects. The bigger the change in value of the portfolio, the bigger the change in overprecision. The effect is mainly driven by changes in asset prices rather than by changes in wealth per se.

3.3 Impact of Overprecision on Market Performance

While successful traders become overprecise, overprecise traders do not necessarily become successful. In fact, theory predicts that trader overprecision is negatively correlated with total profits (e.g., Benos, 1998; Odean, 1998; Gervais and Odean, 2001). To test this hypothesis, we study the effects that overprecision has on the market performance of our

	(1) $\Delta Overpre_{(1,2)}$	(2) $\Delta Overpre_{(1,2)}$	(3) $\Delta Overpre_{(2,3)}$	(4) $\Delta Overpre_{(2,3)}$	(5) $\Delta Overpre_{(1,3)}$	(6) $\Delta Overpre_{(1,3)}$
$\Delta Wealth_{(1,2)}$	0.00994**	0.0103**				
	(0.00420)	(0.00402)				
$APriceOP_{(1,2)}$	-0.0177	-0.0152				
	(0.0138)	(0.0141)				
$\Delta Wealth_{(2,3)}$			0.00637*	0.00815*		
			(0.00329)	(0.00407)		
$APriceOP_{(2,3)}$			0.0327	0.0354		
			(0.0305)	(0.0274)		
$\Delta Wealth_{(1,3)}$					0.0000325	-0.000346
					(0.00502)	(0.00540)
$APriceOP_{(1,3)}$					0.0240*	0.0240*
					(0.0121)	(0.0125)
CRT	-0.0900	0.0307	-0.317	-0.407	-0.360	-0.315
	(0.446)	(0.385)	(0.562)	(0.647)	(0.563)	(0.562)
Male	-3.973	-1.984	-1.408	-2.906	-4.503	-4.147
	(3.786)	(3.598)	(2.622)	(2.348)	(2.900)	(2.996)
Risk Aversion	-0.762	-0.721	-11.43	-11.71	-14.56	-13.72
	(6.317)	(7.070)	(8.864)	(9.852)	(8.346)	(8.277)
Constant	5.674	-8.482	5.295	17.29	11.72	13.52
	(4.516)	(11.54)	(6.086)	(11.02)	(7.052)	(13.45)
N	117	117	117	117	117	117
adj. R^2	0.006	0.035	0.024	0.035	0.086	0.060
Big Five	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: OLS of the change of context-independent measure of overprecision ($\Delta Overpre_{(b,b')}$) on the change in portfolio value across breaks ($\Delta Wealth_{(b,b')}$), the individual level accumulated price-overprecision across breaks ($APriceOP_{(b,b')}$), and personality measures. All standard errors are clustered at the session level.

	(1) *Payoff*	(2) *Payoff*	(3) *Payoff*	(4) *Payoff*
$Overpre_1$	-7.684**	-7.500**	-6.677**	-6.152***
	(3.048)	(3.050)	(2.233)	(1.707)
$APriceOP$	0.0860	0.0488	-0.000731	-0.0436
	(0.225)	(0.249)	(0.168)	(0.172)
CRT	28.94***	27.10**	29.65***	27.53**
	(8.956)	(11.15)	(9.452)	(11.22)
Male	120.8*	114.0*	122.6*	118.3*
	(62.69)	(61.24)	(65.21)	(64.27)
Risk Aversion	78.46	45.12	89.96	49.00
	(96.73)	(115.8)	(94.70)	(110.3)
$\Delta Overpre_{(1,2)}$			-0.848	-0.643
			(2.535)	(2.131)
$\Delta Overpre_{(1,2)} \times Overpre_1$			-0.197**	-0.209*
			(0.0899)	(0.0989)
Constant	364.2***	469.8	337.0***	461.3
	(91.40)	(359.4)	(105.6)	(345.8)
N	117	117	117	117
adj. R^2	0.138	0.123	0.158	0.146
Big Five	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: OLS of asset market performance on baseline context-independent overprecision, accumulated price-prediction overprecision, and other personality traits. All standard errors are clustered at the session level.

subjects. To do so, we regress the total payoff of subjects from the first market ($Payoff_i$) on their context-independent overprecision measured before the start of the market and their accumulated price-prediction overprecision across the whole market ($APriceOP_i$).[22]

Table 4 shows the results and also shows a strong and negative effect of baseline overprecision on market performance: the higher the (baseline) overprecision of a subject, the poorer she does in the asset market. Surprisingly, the accumulated price-prediction overprecision has no effect on her market returns. Such a result seems to support our

[22]The total payoff of a subject i from the first market ($Payoff_i$) is the total amount of cash the subject ends the market with. Such cash can come from the initial endowment, trading, asset dividends, and payoffs from the price belief elicitation. It does not include any payoffs from the dot-spot tasks.

experimental design where, to avoid confounds, we use the context-independent measure of overprecision to study the effects of prices on overconfidence. To study how changes in overprecision affect performance, we also introduce an interaction effect between the baseline context-independent overprecision and the change of this overprecision between the first two breaks. The result shows a modest interaction effect, suggesting that the higher the baseline overprecision, the bigger the losses explained by changes in overprecision. Finally, our results confirm the findings of Bosch-Rosa et al. (2018) and Noussair et al. (2016), showing that CRT scores are a good predictor for performance in SSW asset markets.

Result 4: Individual market performance depends negatively on a subject's context-independent overprecision and positively on their cognitive ability.

4 Conclusion

Overprecision is a "dynamic" personality trait (Deaves et al., 2010; Hilary and Menzly, 2006; Merkle, 2017). The theoretical models of Daniel and Hirshleifer (2015), Daniel et al. (1998), and Gervais and Odean (2001) suggest a strong relationship between overprecision and asset price dynamics: when asset prices go up (down), so does the overprecision of traders. This implies a feedback loop that increases stock price volatility and trading volume, thereby increasing the probability of asset price bubbles.

Against this background, we study whether changes in asset price affect the overprecision of traders in an experimental asset market. To do so, we introduce a new measure of overprecision which allows us to cleanly analyze the relationship between asset prices and endogenous overprecision. By repeatedly using this measure at different points of the market, we are able to study the effects that changes in the value of portfolios have on the endogenous overprecision of traders.

The results are clear and support the theoretical models: overprecision is endogenous and is influenced by asset price dynamics. When prices go up, so does overprecision, and when prices go down, overprecision follows. This influence holds for markets with constant increases in price and for markets where bubbles fully develop, going from fast price increases to the final bust. Moreover, our result holds for a market with exogenously given prices, confirming the theory that the overprecision of traders follows the performance of their portfolios and not vice versa (Daniel and Hirshleifer, 2015; Daniel et al., 1998; Gervais and Odean, 2001). Finally, we confirm the known result that high CRT scores result in better market performance (Bosch-Rosa et al., 2018; Noussair et al., 2016).

References

Akiyama, E., N. Hanaki, and R. Ishikawa (2017). It is not just confusion! strategic uncertainty in an experimental asset market. Cited on page 5.

Barber, B. M. and T. Odean (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics 116*(1), 261–292. Cited on page 2.

Benos, A. V. (1998). Aggressiveness and survival of overconfident traders. *Journal of Financial Markets 1*(3-4), 353–383. Cited on pages 3 and 16.

Biais, B., D. Hilton, K. Mazurier, and S. Pouget (2005). Judgemental Overconfidence, Self-Monitoring, and Trading Performance in an Experimental Financial Market. *Review of Economic Studies 72*(2), 287–312. Cited on page 3.

Blanco, M., D. Engelmann, A. K. Koch, and H.-T. Normann (2010). Belief elicitation in experiments: is there a hedging problem? *Experimental Economics 13*(4), 412–438. Cited on page 7.

Bosch-Rosa, C., T. Meissner, and A. Bosch-Domènech (2018). Cognitive bubbles. *Experimental Economics 21*(1), 132–153. Cited on pages 3, 8, 9, 19, and 20.

Bostock, M., V. Ogievetsky, and J. Heer (2011). $\mathbb{D}^3$: Data-driven documents. *IEEE Transactions on Visualization and Computer Graphics 17*(12), 2301–2309. Cited on page 9.

Brier, G. W. (1950). Verification of forecasts expressed in terms of probability. *Monthly Weather Review 78*(1), 1–3. Cited on page 7.

Caplin, A. and M. Dean (2014). Revealed preference, rational inattention, and costly information acquisition. Technical Report 19876, National Bureau of Economic Research. Cited on page 2.

Caplin, A. and J. V. Leahy (2019). Wishful Thinking. NBER Working Papers 25707, National Bureau of Economic Research, Inc. Cited on page 3.

Chen, D. L., M. Schonger, and C. Wickens (2016). otree - an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance 9*, 88–97. Cited on page 9.

Daniel, K. and D. Hirshleifer (2015). Overconfident Investors, Predictable Returns, and Excessive Trading. *Journal of Economic Perspectives 29*(4), 61–88. Cited on pages 2, 19, and 20.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998). Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance 53*(6), 1839–1885. Cited on pages 1, 2, 3, 14, 19, and 20.

Deaves, R., E. Lüders, and M. Schröder (2010). The dynamics of overconfidence: Evidence from stock market forecasters. *Journal of Economic Behavior & Organization 75*(3), 402–412. Cited on pages 2 and 19.

Deaves, R., E. Lüders, and M. Schröder (2010). The dynamics of overconfidence: Evidence from stock market forecasters. *Journal of Economic Behavior & Organization 75*(3), 402–412. Cited on page 14.

Dufwenberg, M., T. Lindqvist, and E. Moore (2005). Bubbles and experience: An experiment. *American Economic Review 95*(5), 1731–1737. Cited on page 31.

Eckel, C. C. and S. C. Füllbrunn (2015). Thar she blows? gender, competition, and bubbles in experimental asset markets. *American Economic Review 105*(2), 906–20. Cited on pages 8 and 9.

Frederick, S. (2005). Cognitive reflection and decision making. *The Journal of Economic Perspectives 19*(4), 25–42. Cited on page 9.

Gervais, S. and T. Odean (2001). Learning to be Overconfident. *Review of Financial Studies 14*(1), 1–27. Cited on pages 1, 2, 3, 14, 16, 19, and 20.

Glaser, M. and M. Weber (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review 32*(1), 1–36. Cited on page 5.

Goetzmann, W. N. and A. Kumar (2008). Equity portfolio diversification. *Review of Finance 12*(3), 433–463. Cited on page 2.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association 1*(1), 114–125. Cited on page 9.

Griffin, D. and A. Tversky (1992). The weighing of evidence and the determinants of confidence. *Cognitive Psychology 24*(3), 411–435. Cited on page 3.

Hanaki, N., E. Akiyama, and R. Ishikawa (2018). Behavioral uncertainty and the dynamics of traders' confidence in their price forecasts. *Journal of Economic Dynamics and Control 88*(C), 121–136. Cited on pages 3 and 5.

Haruvy, E., Y. Lahav, and C. N. Noussair (2007). Traders' expectations in asset markets: Experimental evidence. *The American Economic Review 97*(5), 1901–1920. Cited on pages 4, 5, and 7.

Hilary, G. and L. Menzly (2006). Does past success lead analysts to become overconfident? *Management Science 52*(4), 489–500. Cited on pages 2 and 19.

Holt, C. A. and S. K. Laury (2002). Risk aversion and incentive effects. *American economic review 92*(5), 1644–1655. Cited on page 9.

Hossain, T. and R. Okui (2013). The binarized scoring rule. *Review of Economic Studies 80*(3), 984–1001. Cited on page 7.

Hussam, R. N., D. Porter, and V. L. Smith (2008). Thar she blows: Can bubbles be rekindled with experienced subjects? *American Economic Review 98*(3), 924–37. Cited on page 31.

Kirchler, E. and B. Maciejovsky (2002). Simultaneous Over- and Underconfidence: Evidence from Experimental Asset Markets. *Journal of Risk and Uncertainty 25*(1), 65–85. Cited on pages 3 and 5.

Merkle, C. (2017). Financial overconfidence over time: Foresight, hindsight, and insight of investors. *Journal of Banking & Finance 84*, 68–87. Cited on pages 2 and 19.

Michailova, J. and U. Schmidt (2016). Overconfidence and bubbles in experimental asset markets. *Journal of Behavioral Finance 17*(3), 280–292. Cited on pages 2, 3, and 9.

Moore, D. A. and P. J. Healy (2008). The trouble with overconfidence. *Psychological review 115*(2), 502. Cited on page 2.

Moore, D. A., E. R. Tenney, and U. Haran (2016). Overprecision in judgment. *Handbook of judgment and decision making. New York: Wiley*, 182–212. Cited on pages 2 and 5.

Noussair, C. N., S. Tucker, and Y. Xu (2016). Futures markets, cognitive ability, and mispricing in experimental asset markets. *Journal of Economic Behavior & Organization 130*, 166–179. Cited on pages 3, 9, 19, and 20.

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *The journal of finance 53*(6), 1887–1934. Cited on pages 3 and 16.

Odean, T. (1999). Do investors trade too much? *American economic review 89*(5), 1279–1298. Cited on page 2.

Oehler, A., S. Wendt, F. Wedlich, and M. Horn (2018). Investors' personality influences investment decisions: Experimental evidence on extraversion and neuroticism. *Journal of Behavioral Finance 19*(1), 30–48. Cited on page 9.

Oehler, A., S. Wendt, F. Wedlich, and M. Horn (2019). Does personality drive price bubbles? *Studies in Economics and Finance 36*. Cited on page 9.

Palan, S. (2018, October 22). *GIMS – The Graz-Innsbruck Market System: User Manaul* (v8.2.1 ed.). Cited on page 5.

Rammstedt, B. and O. P. John (2007). Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german. *Journal of Research in Personality 41*(1), 203–212. Cited on page 9.

Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of political Economy 111*(6), 1183–1220. Cited on page 2.

Smith, V. L., G. L. Suchanek, and A. W. Williams (1988). Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Asset Markets. *Econometrica 56*(5), 1119–51. Cited on pages 2 and 31.

Thomson, K. S. and D. M. Oppenheimer (2016). Investigating an alternate form of the cognitive reflection test. *Judgment and Decision Making 11*(1), 99. Cited on page 9.

Toplak, M. E., R. F. West, and K. E. Stanovich (2014). Assessing miserly information processing: An expansion of the cognitive reflection test. *Thinking & Reasoning 20*(2), 147–168. Cited on page 9.

Tuckett, D. and R. Taffler (2008). Phantastic objects and the financial market's sense of reality: A psychoanalytic contribution to the understanding of stock market instability. *International Journal of Psychoanalysis 89*, 398–412. Cited on pages 2 and 31.

A Extra Figures and Tables

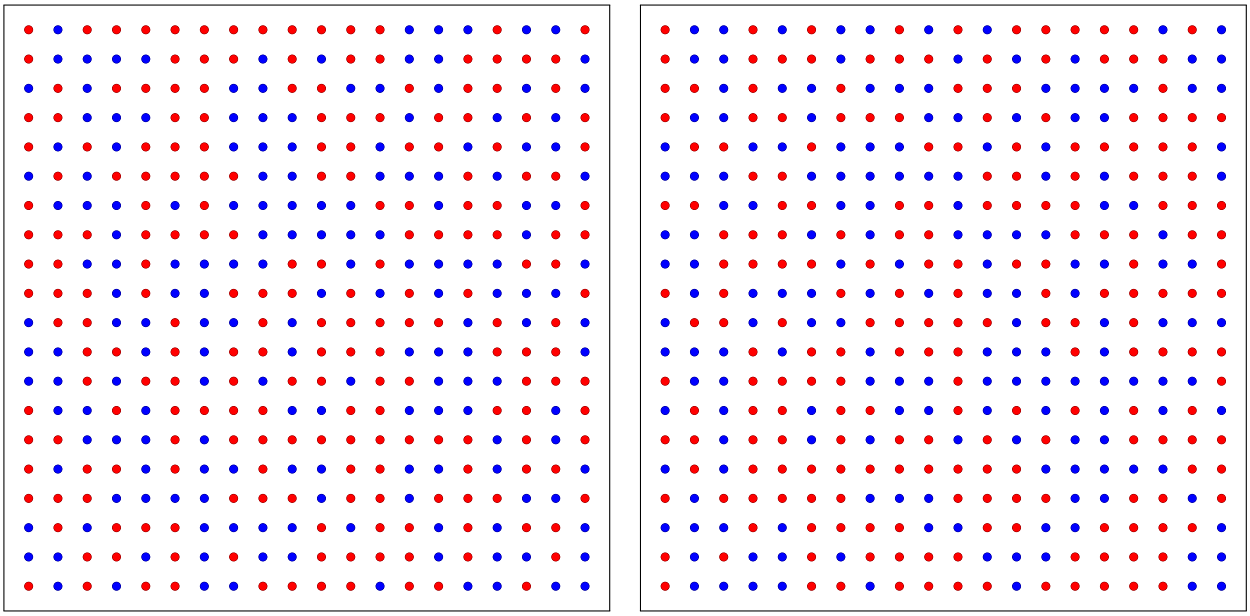


Figure 4: Two matrices with 220 red dots each, but a different dot pattern.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Overpre_{(1,2)}$	$\Delta Overpre_{(1,2)}$	$\Delta Overpre_{(2,3)}$	$\Delta Overpre_{(2,3)}$	$\Delta Overpre_{(1,3)}$	$\Delta Overpre_{(1,3)}$
$\Delta AssetsValue_{(1,2)}$	0.0136**	0.0137**				
	(0.00569)	(0.00585)				
$\Delta Cash_{(1,2)}$	0.00615*	0.00657*				
	(0.00340)	(0.00305)				
$APriceOP_{(1,2)}$	-0.0161	-0.0133				
	(0.0139)	(0.0139)				
$\Delta AssetsValue_{(2,3)}$			0.0103**	0.0114**		
			(0.00347)	(0.00391)		
$\Delta Cash_{(2,3)}$			-0.000948	0.00125		
			(0.00349)	(0.00421)		
$APriceOP_{(2,3)}$			0.0401	0.0419		
			(0.0275)	(0.0252)		
$\Delta AssetsValue_{(1,3)}$					0.00372	0.00411
					(0.00303)	(0.00357)
$\Delta Cash_{(1,3)}$					0.00362	0.00319
					(0.00418)	(0.00428)
$APriceOP_{(1,3)}$					0.0212	0.0212
					(0.0125)	(0.0128)
CRT	-0.0651	0.0530	-0.114	-0.223	-0.420	-0.354
	(0.441)	(0.374)	(0.570)	(0.654)	(0.591)	(0.591)
Male	-3.635	-1.647	-1.366	-2.877	-5.143	-4.766
	(3.817)	(3.491)	(2.305)	(2.025)	(3.189)	(3.188)
Risk Aversion	-0.141	-0.171	-15.10	-14.85	-15.08*	-14.47
	(6.365)	(7.104)	(9.039)	(9.765)	(8.231)	(8.334)
Constant	4.630	-9.008	6.896	19.07	11.76	13.50
	(4.406)	(11.05)	(6.268)	(10.82)	(6.951)	(12.00)
N	117	117	117	117	117	117
adj. R^2	0.012	0.040	0.063	0.066	0.090	0.064
Big Five	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: OLS of the change of context-independent measure of overprecision ($\Delta Overpre_{(b,b')}$) on the change in portfolio value across breaks ($\Delta AssetsValue_{(b,b')}$), the change in cash balance across breaks ($\Delta Cash_{(b,b')}$), the individual level accumulated price-overprecision across breaks ($APriceOP_{(b,b')}$), and personality measures. All standard errors are clustered at the session level.

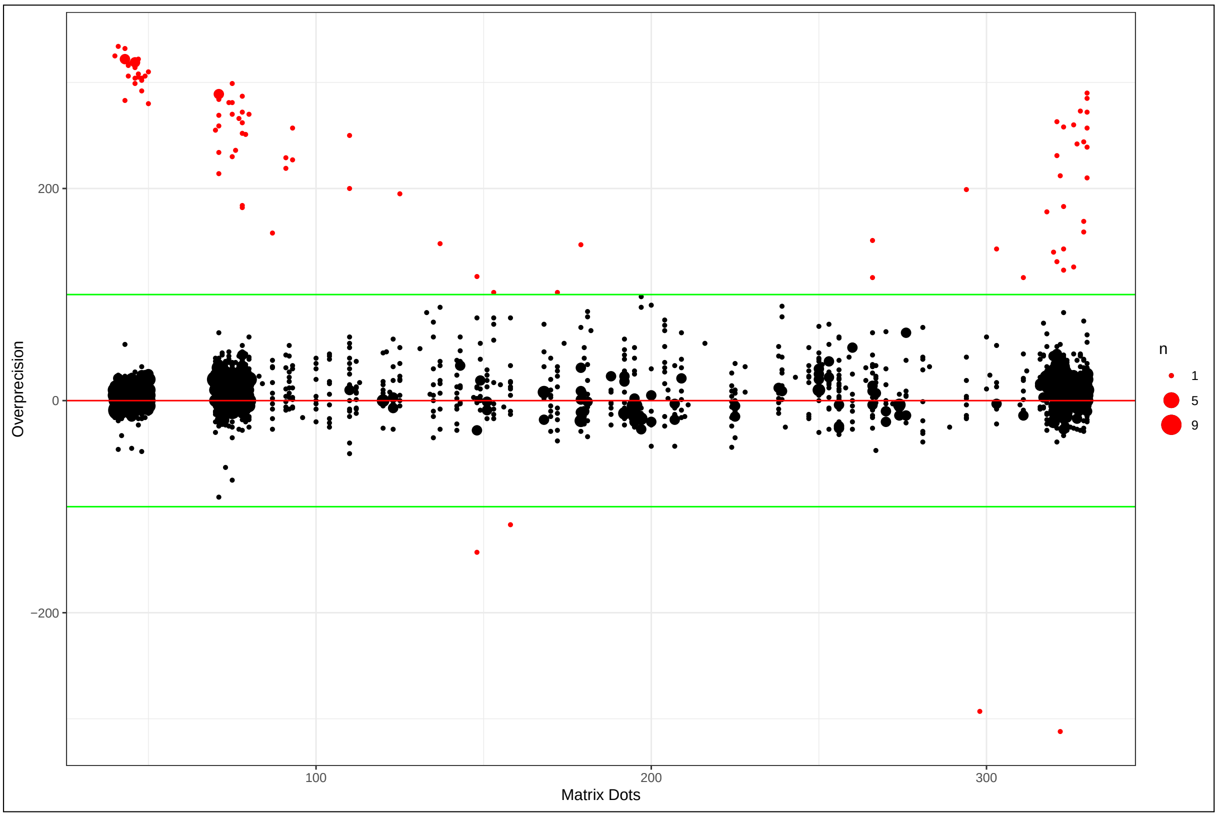
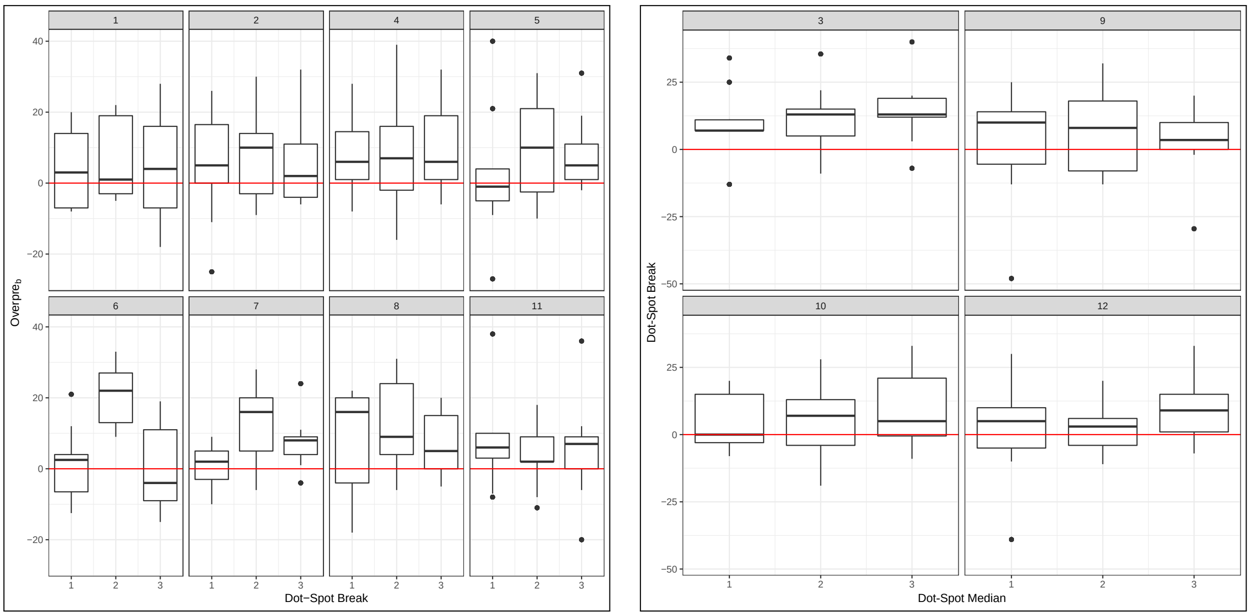


Figure 5: On the vertical axis we present the measure of overprecision for the reported number of red dots and expected error for the value of each matrix (horizontal axis). The horizontal green line is the cutoff value of 100 and -100. The horizontal red line located at 0. The values are for all matrices shown to all subjects across all breaks of both markets.



(a) *Hump Shape* (b) *Increasing Price*

Figure 6: Box plots showing the median, 25th and 75th percentile of $Overpre_b$ for each break within a session

B Risk Aversion Measure

For our regression analysis in Tables 2 to 5 we use a composite of the two risk measures we get from subjects. The first measure is the switching point from lottery A to the lottery B in a multiple price list like that in Figure 7, this gives us a value between 1 and 10 (HL_i) in which the higher the value (i.e., the later the switching point), the more risk averse a subject is. Subjects are (randomly) paid for their choice in one of the ten lottery decisions they make.

The second measure of risk aversion we gather is non-incentivized and comes from the German Socio Economic Panel. The question asks subjects: How likely are you to take risk on a scale of 0 (not risk taking at all) to 10 (very prone to take risk). The measure we get is a value between 0 and 10 (GS_i) in which the higher it is, the less risk averse a subject is.

To create the final risk aversion measure we use in our regressions we take three steps:

1. We divide each measure by 10 and 11 ($hl_i = HL_i/10$ and $gs_i = GS_i/10$, respectively), to normalize the measures.

2. We flip cardinal order of the second measure by subtracting each observation from one ($gs'_i = 1 - gs_i$). This makes the measure go from less risk averse to more risk averse.

3. We create a new measure which we call Risk Aversion (RA_i) by giving each normalized measure half of the weight ($RA_i = gs'_i/2 + hl_i/2$).

#	Option A	Option B
1	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 0% *or* EUR 0.10 with a probablity of 100%
2	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 10% *or* EUR 0.10 with a probablity of 90%
3	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 20% *or* EUR 0.10 with a probablity of 80%
4	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 30% *or* EUR 0.10 with a probablity of 70%
5	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 40% *or* EUR 0.10 with a probablity of 60%
6	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 50% *or* EUR 0.10 with a probablity of 50%
7	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 60% *or* EUR 0.10 with a probablity of 40%
8	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 70% *or* EUR 0.10 with a probablity of 30%
9	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 80% *or* EUR 0.10 with a probablity of 20%
10	Receive: EUR 2.00 for sure	Receive: EUR 4.00 with a probablity of 90% *or* EUR 0.10 with a probablity of 10%

Figure 7: Screenshot of the risk aversion multiple price list task.

C Second Market

As is typical in SSW markets, once the market is repeated prices become much closer to the fundamental value.[23] This is clear in the left panel of Figure 8 where we see how most sessions have prices that closely track the fundamental value. In fact, in Market 2 we see no session that could be labeled as *Increasing Price*, as $P_{13} < P_6$ across all sessions, while we have three that are *Decreasing Price*, and nine that are *Hump Shape*.

In the right panel of Figure 8 we show the distribution of the $\Delta Overpre_{i(b,b')}$ for each of the two types of price dynamics we find in Market 2. It is clear that there are no changes in our measure of overprecision across breaks. This is confirmed in Table 6 where we see that there is no difference in overprecision across the different breaks.

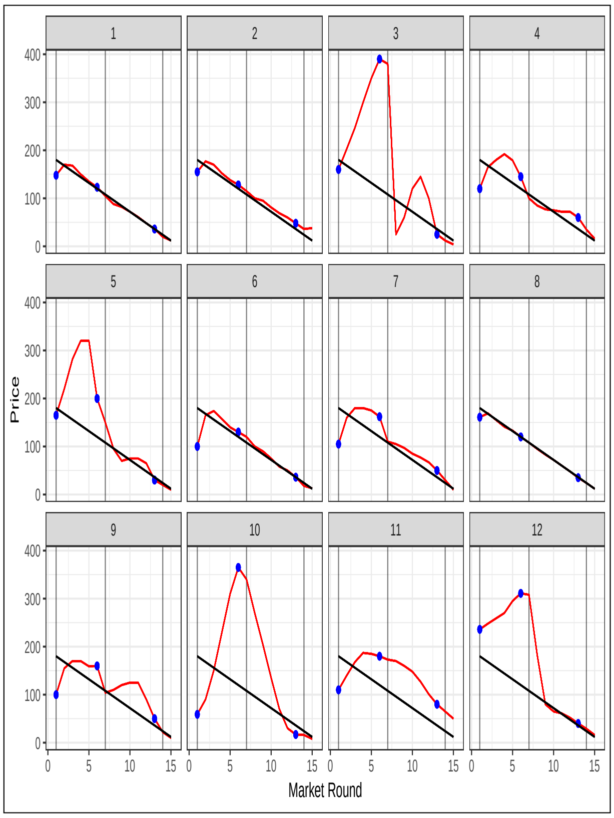
Such a result seems to confirm the thesis from Tuckett and Taffler (2008) in which holding and selling assets in an unknown ambiguous environment leads to an integration of emotional experiences to behavior. In other words, bubbles and overconfidence mostly arise in markets for exotic/unknown assets. This is a common belief and has been used to explain the Dot-Com bubble or the most recent crypto-currency craze. In the experimental literature such an approach has received support from Hussam et al. (2008) who show that experience eliminates bubbles *if the environment is held constant*.

Yet, we refrain from drawing any conclusions on this respect from our experimental design, as our setup does not allow us to cleanly disentangle the effects of individual learning from overprecision, excitement, and price dynamics. We leave this for future research.

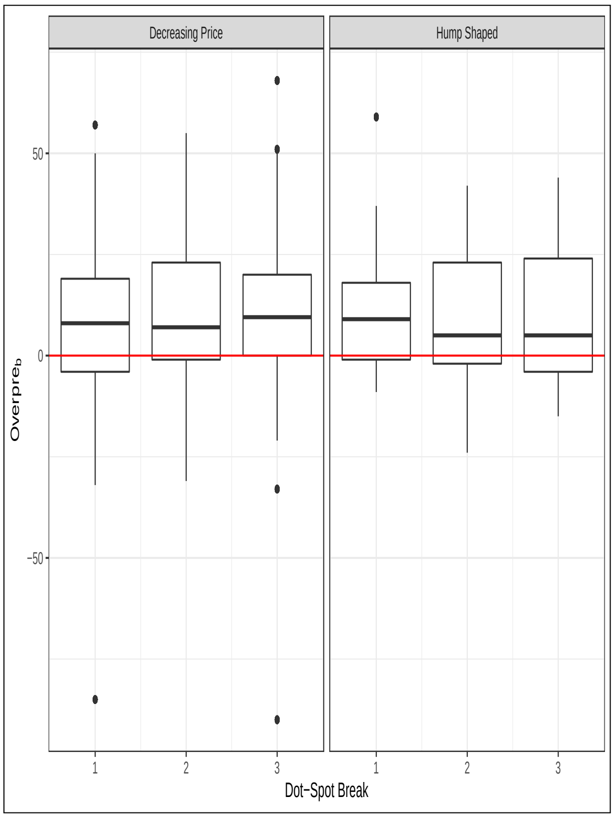
	Break 1 = Break 2	Break 2 = Break 3	Break 1 = Break 3
***Hump Shape* p-value** (N=90)	0.904	0.923	0.913
***Decreasing Price* p-value** (N=27)	0.643	0.138	0.138

Table 6: P-values resulting from Wilcoxon matched-pairs signed-ranks test comparing the equality of matched pairs of observations across Dot-Spot task across different session sub-groups for Market 2.

[23]This convergence to fundamental values is generally assumed to be due to learning (Smith et al., 1988; Dufwenberg et al., 2005; Hussam et al., 2008).



(a) Price Dynamics for Market 2



(b) $Overpre_b$ Dynamics for Market 2

Figure 8: Summary of the dynamics in Market 2.

D Instructions (translated from German)

Welcome

The experiment requires you to keep silence from now onwards. Please do not write on the instructions. For taking notes, we have provided you with pen and paper. If you have a questions, please raise your hand and we will approach you to answer them quietly. Do not ask questions aloud. If a question is relevant for all participants, we will repeat the question and answer it aloud.

During the experiment, you can't use your cellphone or any other electronic device. Please use only the specific programs and functions provided for this experiment. Please put your cellphone in silence mode and put it away.

This is an experiment on decisions in markets. In this experiment, we generate a market in which you can trade units of a fictitious asset with the other participants of this experiment. The instructions are simple. If you follow them and make good decisions you can earn a good amount of money. The money that you earn during the experiment will be paid in cash at the end.

The experiment consists of two blocks. Within each block you will take part in several parts. We will read the instructions for each part immediately before you take part in them. For Block 1 we will give you printed instructions. For Block 2, the instructions will appear directly on your screen.

Please, pay attention to the instructions in Block 1 given that you will have to answer two questions related to these. You will not be able to start playing until you answer both questions correctly.

Block 1

Block 1 is composed of two consecutive markets. Each markets lasts 15 periods, in which you can buy and sell a financial asset (which we'll call "Shares"). Each market is composed of 9 participants.

The currency in these markets is the “Taler,” and all the transactions are denominated in this currency. At the end of the experiment we will pay you one Euro for each 100 Taler in your balance.

Details of the Functioning of Markets

Before the beginning of each Market, you will be endowed with a certain amount of Taler and Shares. These endowments are not necessarily the same for every participant. In each period you can buy and sell Shares using an interface as in Figure 1.

In the upper left corner of the screen you can see how many Taler and Shares you have in your balance (in Figure 1 these quantities are covered by stars). Right beneath that, there is an interface to buy and sell Shares. If you want to buy Shares, at the beginning of the trading period, you have to make a buy order. A buy order contains the number of Shares you are willing to buy and the maximum price you are willing to pay. If you want to sell assets, you have to make a sell order. Analogous to a buy order, a sell order contains the number of Shares you are willing to sell and the minimum price you are willing to accept for each share.

Once every participant in the group has introduced their buy and sell orders, the software will automatically determine the trading price. This trading price is determined such that the number of Shares with sell orders at prices lower or equal to the trading price is equal to the number of Shares with buy orders at prices higher or equal to that price. In this way, all the participants that submitted buy orders at prices equal or higher to the trading price will buy Shares, whereas all the participants that submitted sell prices at a price equal or lower than the trading price will sell Shares.

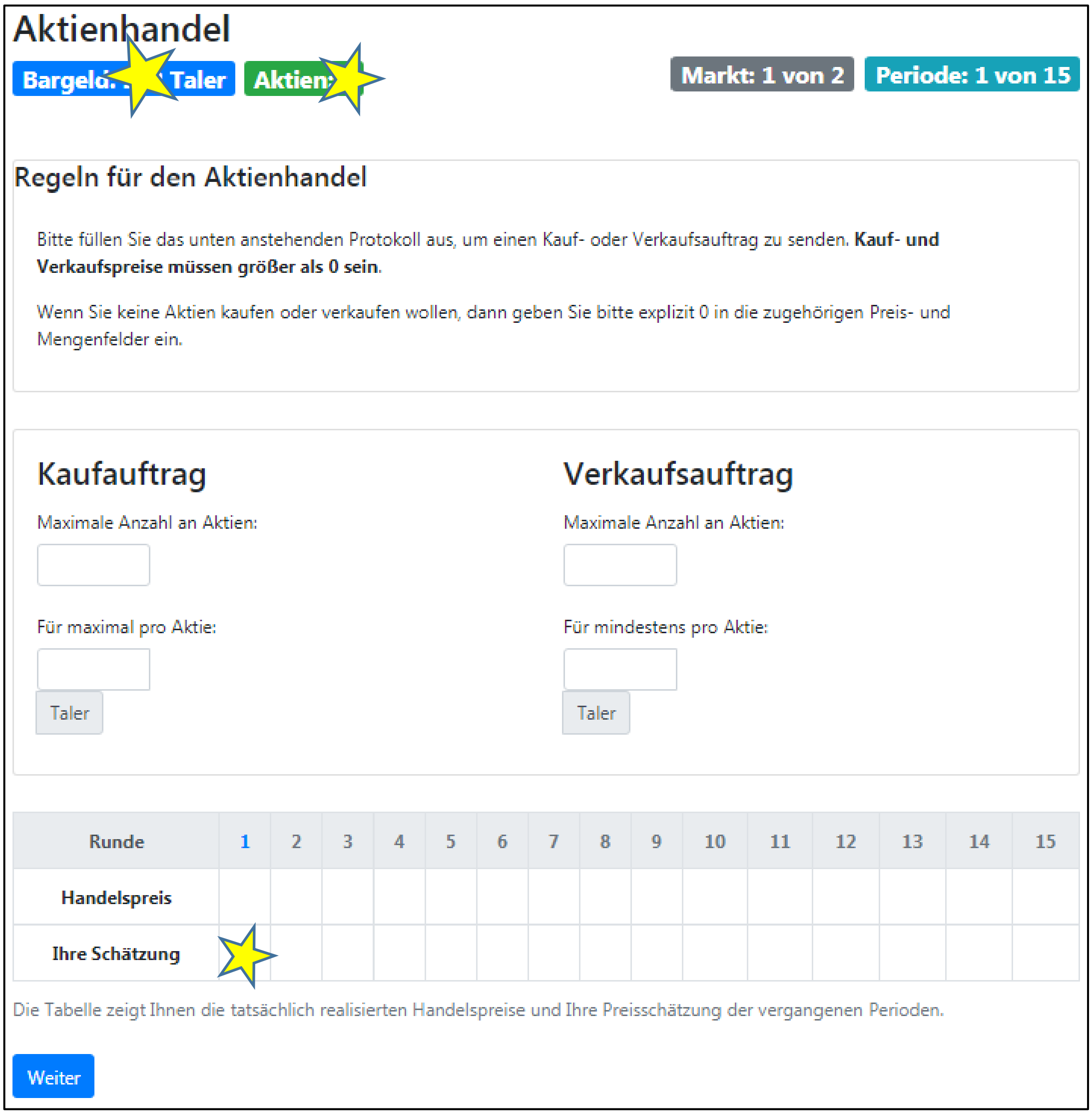


Figure 1: Trading Screen

<u>Example of the Functioning of a Market:</u> Let's suppose there are four participants:

- Trader 1 submits a buy order for one share at the price of 60 Taler.
- Trader 2 submits a buy order for one share at the price of 20 Taler.
- Trader 3 submits a sell order for one share at the price of 10 Taler.
- Trader 4 submits a sell order for one share at the price of 40 Taler.

At any price above 40, there are more units offered for sale (Traders 3 and 4) than units for purchase (Trader 1). At any price below 20, there are more units offered for purchase (Traders 1 and 2) than for sale (Trader 3). At any price between 21 and 39, there is an equal number of units offered for purchase and sale. The trading price is the average price at which there is an equal number of units offered for purchase and sale. In this case, the trading price is 30 Taler. Trader 1 buys one share from Trader 3 at the price of 30 Taler. Trader 2 buys no Shares, because her maximum buy order price (20 Taler) is below the trading price. Trader 4 does not sell any Shares, because her minimum sell order price (40 Taler) is above the trading price.

Shares

Shares have a lifetime of 15 periods. The Shares that you have purchased in one period are at your disposal at the next period. Therefore, if you happen to own 5 Shares at the end of period 1, you own the same 5 Shares at the beginning of period 2. In each period (including period 15), every share that you own pays a dividend of either 0, 4, 14, or 30 Taler. Which one out of these possibilities is paid for share will be determined by the software randomly, all with the same probability (25%). This means that the average dividend is 12 Taler. In each period, the dividend will be added to your balance in Taler and you can use it to buy Shares the next period.

At the end of the last period of the first market (period 15), each share will pay its last dividend and Market 1 closes. All your Shares will disappear and only the cash in your balance will be paid at the end of the experiment. After Market 1 finishes, Market 2 starts.

Market 2 is identical to Market 1. You will start with the same endowment of Shares and Taler that you had at the beginning of Market 1, and the group of 9 participants will be the same.

“Average Holding Value”

You have at your disposal a table called “Average Holding Value", meant to facilitate your choices. The table shows how much dividend a share pays on average (column 2), if you hold it from the current period (column 1) until the last period. The values are calculated by multiplying the average dividend, 12, with the number of periods left including the current period.

Additional Tasks

1. Price Prediction

In each period, before you make your buy and sell orders you will see a screen like that in Figure 2. On this screen we will ask you two questions:

1. Please give us your best estimate for the price of the asset in this period.
2. How far away do you think your price estimate is from the true answer?

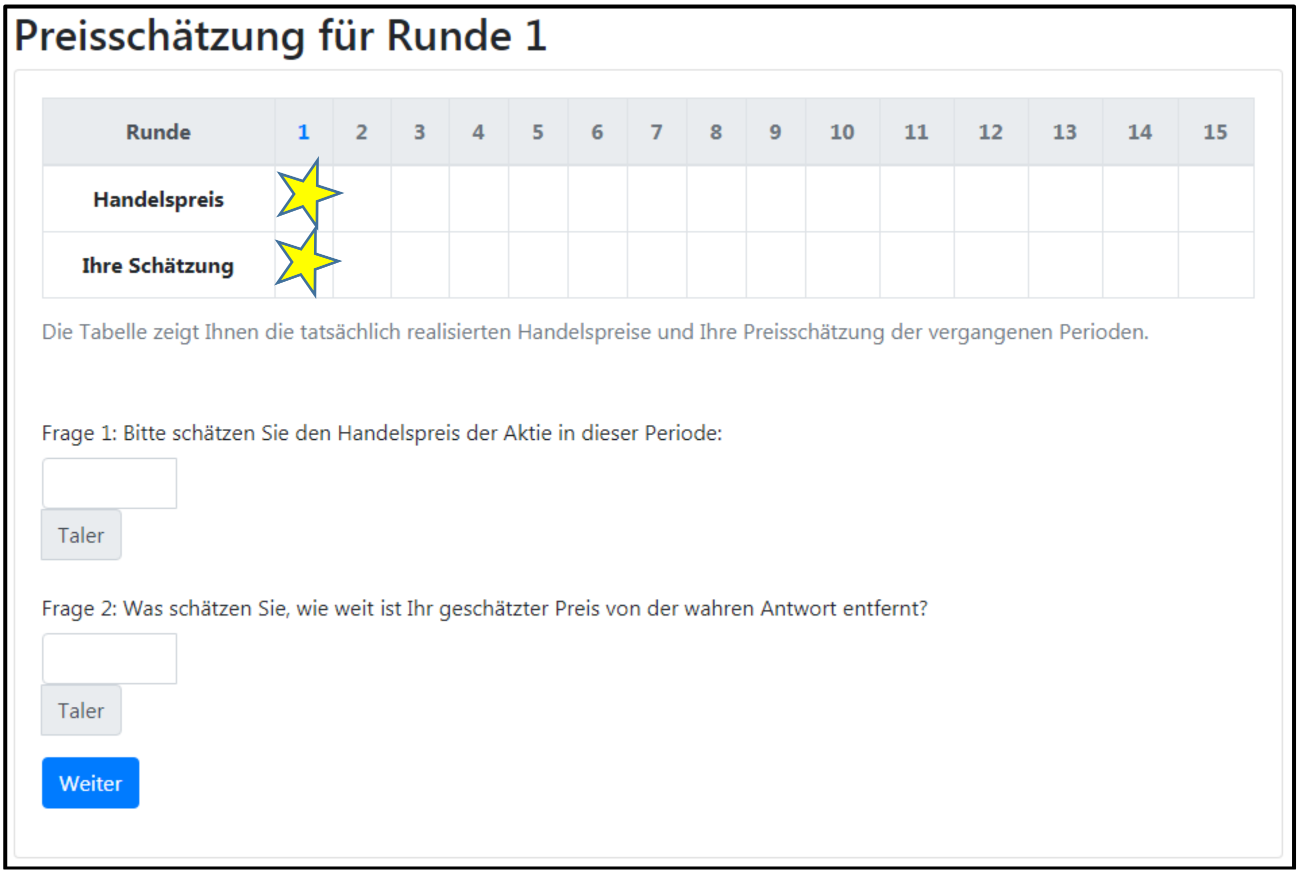


Figure 2: Price Prediction Screen

Your payoff for the two question will depend on the accuracy of your answer. The closer your answer is to the right answer, the larger your earnings will be. The earnings will be determined according to the following rule:

- 25 Taler if you are within 10%% of the true answer (both below and above)
- 10 Taler if you are within 25%% of the true answer (both below and above)
- 5 Taler if you are within 50%% of the true answer (both below and above)
- 0 Taler in any other case

Example: Suppose the true trading price is 100 Taler. If you had guessed a price between 90 and 110, then your earnings from Question 1 would have been 25 Taler. If you had guessed a price between 75 and 125 or between 50 and 150 your earnings from Question 1 would have been of 10 or 5 Taler, respectively. For any other estimated prices you would have earned 0 Taler. The same rule applies for the Question 2. Suppose you had answered 140 in Question 1. Then your estimation error is 40 Taler. If your answer to Question 2 had been between 36 and 44, your earnings from Question 2 would have been 25 Taler. If your answer to Question 2 had been between 30 and 40 or between 20 and 60, your earnings from Question 2 would have been 10 or 5 Taler, respectively.

Important: In each period, the computer randomly chooses one of the two questions to be accounted to your final earnings. Both questions have the same probability to be chosen by the computer.

2. DotSpot

In addition to trading in the market and answering to the Price Prediction task, at certain periods during the market you will take part in the "Dot Spot task". In this task we will show you 5 different matrices of 20x20 blue and red dots. Figure 3 shows an example.

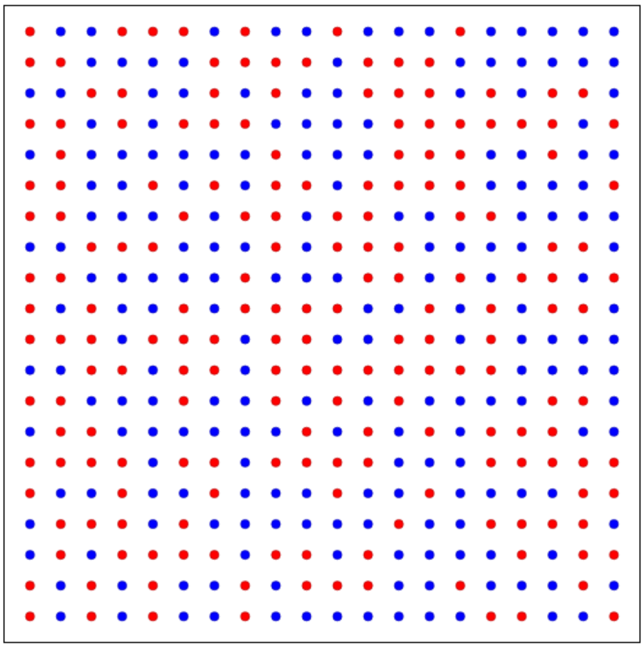


Figure 3: DotSpot Matrix

These matrices will be shown consecutively for six seconds. Your task will be to answer two questions after seeing each matrix:

1. Please estimate the total number of red dots in the Dot-Spot matrix.
2. How far away do you think is your estimate from the true answer?

Your payoff to these two questions will depend on the accuracy of your answers. The closer your answer is from the correct answer, the larger your earnings will be.

The payoff for both questions will follow the following rule:

- 25 Taler if you are within 10%% of the true answer (both below and above)
- 10 Taler if you are within 25%% of the true answer (both below and above)
- 5 Taler if you are within 50%% of the true answer (both below and above)
- 0 Taler in any other case

Example: Suppose that we show you a matrix with 200 red dots. If you had estimated between 180 and 220 red dots, then your earnings from Question 1 would have been 25 Taler. If you had estimated a value between 150 and 250 or a value between 100 and 300, then your earnings from Question 1 would have been 10 or 5 Taler, respectively. For any other estimation your earnings would have been 0 Taler. The same rule applies for the Question 2. Suppose you had answered 100 red dots in Question 1. Then, your estimation error is of 100 red dots. If your answer to Question 2 had been between 90 and 110, your earnings from Question 2 would have been 25 Taler. If you answer to Question 2 had been between 75 and 125 or between 50 and 150, your earnings from Question 2 would have been 10 or 5 Taler, respectively.

Important: For each of the matrices, the computer randomly chooses one of the two questions to be accounted to your final earnings. Both questions have the same probability to be chosen by the computer.

The DotSpot task will be held before the beginning of each market, and after the periods 6 and 13 of both markets.

Before the beginning of Block 1 of the experiment, you will participate in three practice rounds of the DotSpot task. At the end of each practice round you will receive a summary with the right answer and the hypothetical earnings. Importantly, the screen with the summary of the payoffs and results of the DotSpot task will only appear in the practice rounds. During the experiment we will not give you any information on your results on the DotSpot task.

Summary of Block 1

Block 1 consists of two consecutive markets, each lasting 15 periods. In the first period of each market, you will be endowed with a number of Shares and Taler (the experimental currency), which you can use at your will.

Each period has two parts: the estimation of the price in the current period, and the buy/sell decision of Shares. Once the transactions have been carried out, the Shares will pay a random dividend of 0, 4, 14 or 30 Taler, each with the same probability. Afterwards, a new period starts.

Before each market and at the end of periods 6 and 13, you participate in the DotSpot task. In this task, we will show you several matrices of 20 x 20 red and blue dots for 6 seconds.

Your task is to guess the number of red points in the matrix, as well as the distance between your answer and the true answer.

Average Holding Value

Actual Period	Average Holding Value
1	180
2	168
3	156
4	144
5	132
6	120
7	108
8	96
9	84
10	72
11	60
12	48
13	36
14	24
15	12

Block 2 (on screen only)

Block 2 has four different parts. We will provide you with the instructions for each part immediately before it starts. Unlike Block 1, we will not give you a printed copy of the instructions. Instructions will only appear on your screens. If you have any questions, please raise your hand. If not, please continue by clicking the 'next' button.

Part 1 of Block 2 (on screen only)

In this part of Block 2 we will present you with several questions that you must answer. The questions will appear on three consecutive screens. Each screen has between 3 and 4 questions. You have 5 minutes per screen to answer all the questions, and we will pay you 25 Taler for each correct answer.

In each screen you must "validate" your answers by clicking in ‘next’ before the 5 minutes pass. This action will validate your answers and will take you to the next screen. Take into account that once you click ‘next’ you will not be able to go back. If the 5 minutes pass and you have not clicked ‘next’, the computer will automatically move you to the next screen and will count your questions as wrong.

After the third screen finishes, you will pass to Part 2 of Block 2.

Part 2 of Block 2 (on screen only)

In the next screen we will ask you to make 10 decisions. Each decision will consist of picking a lottery with a certain probability or a fixed amount of money.

Please choose the option that you like the most of each of the lotteries. The computer will randomly select which one of the 10 lotteries your final payoff will be based on.

Part 3 of Block 2 (on screen only)

In the next screen you will find 10 brief descriptions of different personality features. Please indicate for each of these descriptions how well each one of them matches your personality (for example, "totally agree" or "totally disagree").

Part 4 of Block 2 (on screen only)

This is the last part of the experiment. Please fill in the following questionnaire.