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. Finally, we confirm existing experimental evidence that high cognitive ability results in better market performance.

JEL Classification C91 · D84 · G11 · G41

Keywords Endogenous Overconfidence, Behavioral Finance, Experiment

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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 increases 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 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. Because of this independence, we obtain a "clean" measure of individual overprecision, free from any confounding market factors.

[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.

To study the dynamic nature of overprecision through time, we use our new method to elicit the overprecision of subjects at different points of the experimental market.

The findings are clear: overprecision co-moves with asset prices. When asset prices go up, overprecision rises, and when asset prices go down, overprecision falls. Moreover, larger changes in prices are met by larger changes in overprecision. Additionally, we observe that as predicted by the theory (e.g., Daniel et al., 1998; Gervais and Odean, 2001), successful traders become overprecise, but overprecise traders do not become 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, as opposed 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].*

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[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." 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:

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?*

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

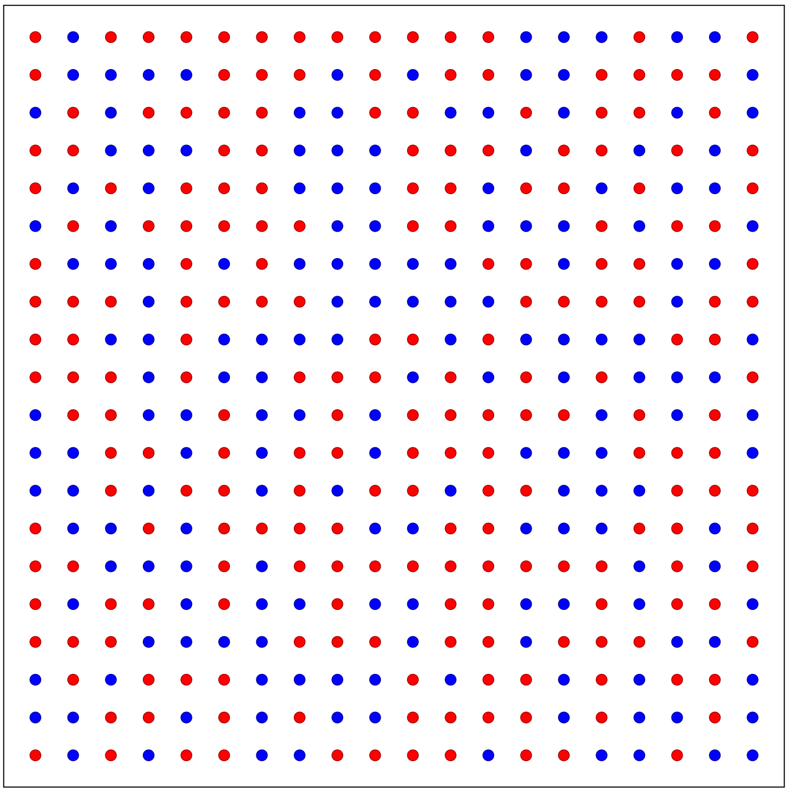

Figure 1: "Dot-Spot" Task

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.

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).[7] In 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."

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

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.[8]

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:

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

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 then ask the subjects about

[8] 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.

the number of questions they expected to have answered correctly and their expected relative ranking among all subjects in the 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).[9] Finally, we ask subjects to answer the ten-item version of the Big Five personality test suggested by Rammstedt and John (2007), as in SSW markets, extraversion and neuroticism affect the subjects' trading behavior (Oehler et al., 2018) and 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.

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 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[10] (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

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

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

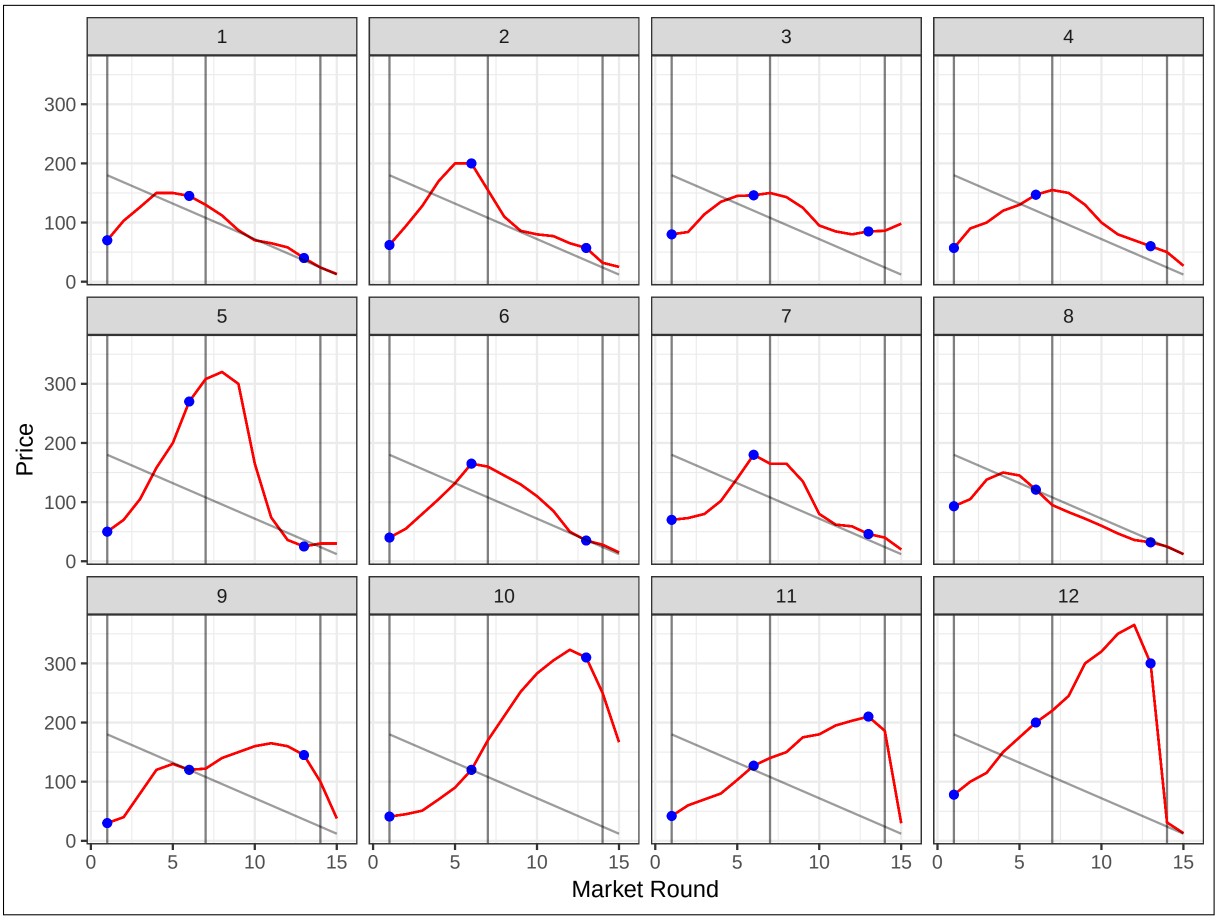

Figure 2: Equilibrium price (red line), fundamental value (solid black line), and Dot-Spot breaks (vertical black lines) for Market 1 of all sessions. To have a better understanding of the price dynamics we place blue dots at the equilibrium price immediately before the Dot-Spot task took place (i.e.,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

show the price of the asset immediately before the break.[11] From Figure 2, it is apparent that most markets show an asset price bubble, 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

[11] 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.

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[12]

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

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.[13] 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 Price*). The figure clearly shows that the overprecision of the median subject follows our hypothesized trajectory: a) it is downward trending for *Decreasing Price* sessions, b) goes up and then down in *Hump Shape* sessions, and c) is upward trending for *Increasing Price* sessions.[14]

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

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

[13] 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.

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

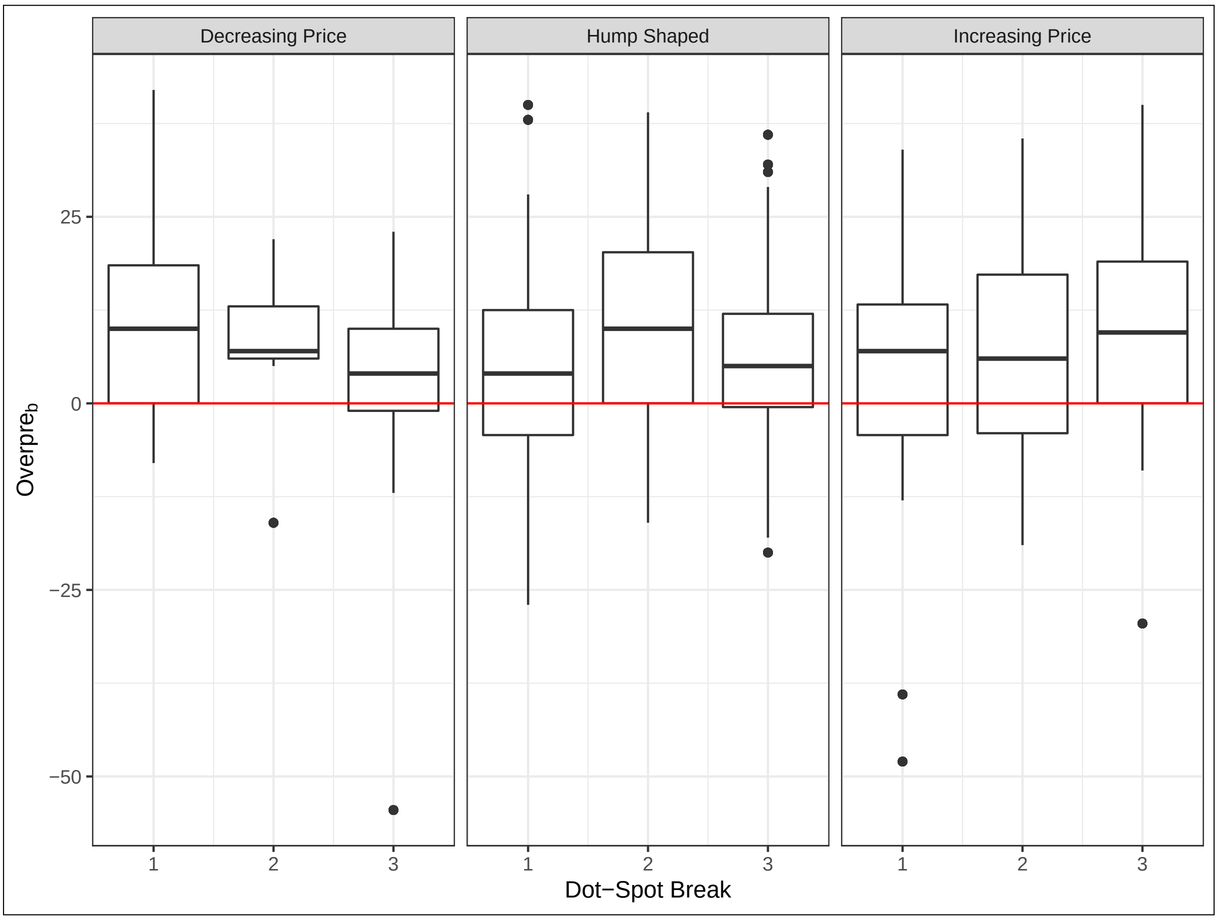

Figure 3: Box plots showing the median, 25th and 75th percentile of $Overpre_{ib}$ for each break within a session.

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 bubble bursts and prices drop.

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

	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.

fall in market prices.

Result 1: Overprecision co-moves with asset prices and 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.

In Table 2 we regress $\Delta Overpre_{(b,b')}$ on the change in asset prices and several personality measures.[15] 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 ($\Delta Price_{(1,2)} = Price_6 - Price_1$).[16] 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:

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

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

[16]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 market level.

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 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, 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

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

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.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Overpre_{(1,2)}$	$\Delta Overpre_{(1,2)}$	$\Delta Overpre_{(2,3)}$	$\Delta Overpre_{(2,3)}$	$\Delta Overpre_{(1,3)}$	$\Delta Overpre_{(1,3)}$
$\Delta Wealth_{(1,2)}$	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 market level.

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 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 ($APriceOP_i$).[17]

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 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.

[17]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.

	(1)	(2)	(3)	(4)
	Payoff	*Payoff*	*Payoff*	*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)
_cons	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 market level.

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).

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A Extra Figures and Tables

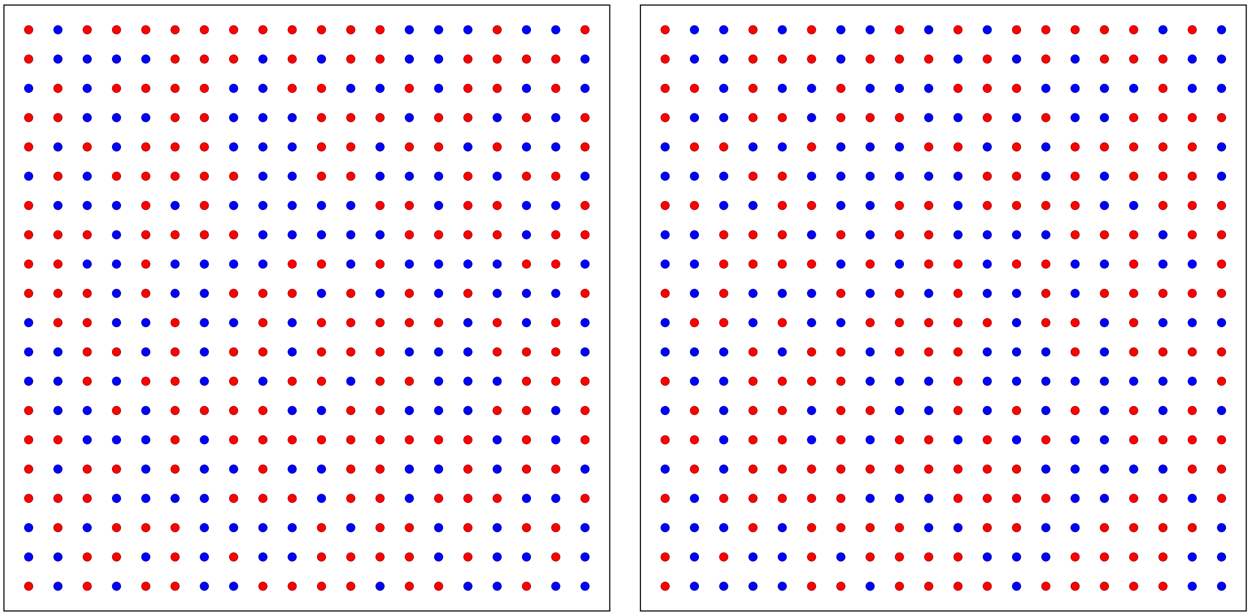


Figure 4: Two matrices with 220 red dots each, but a different dot pattern.

	(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 market level.

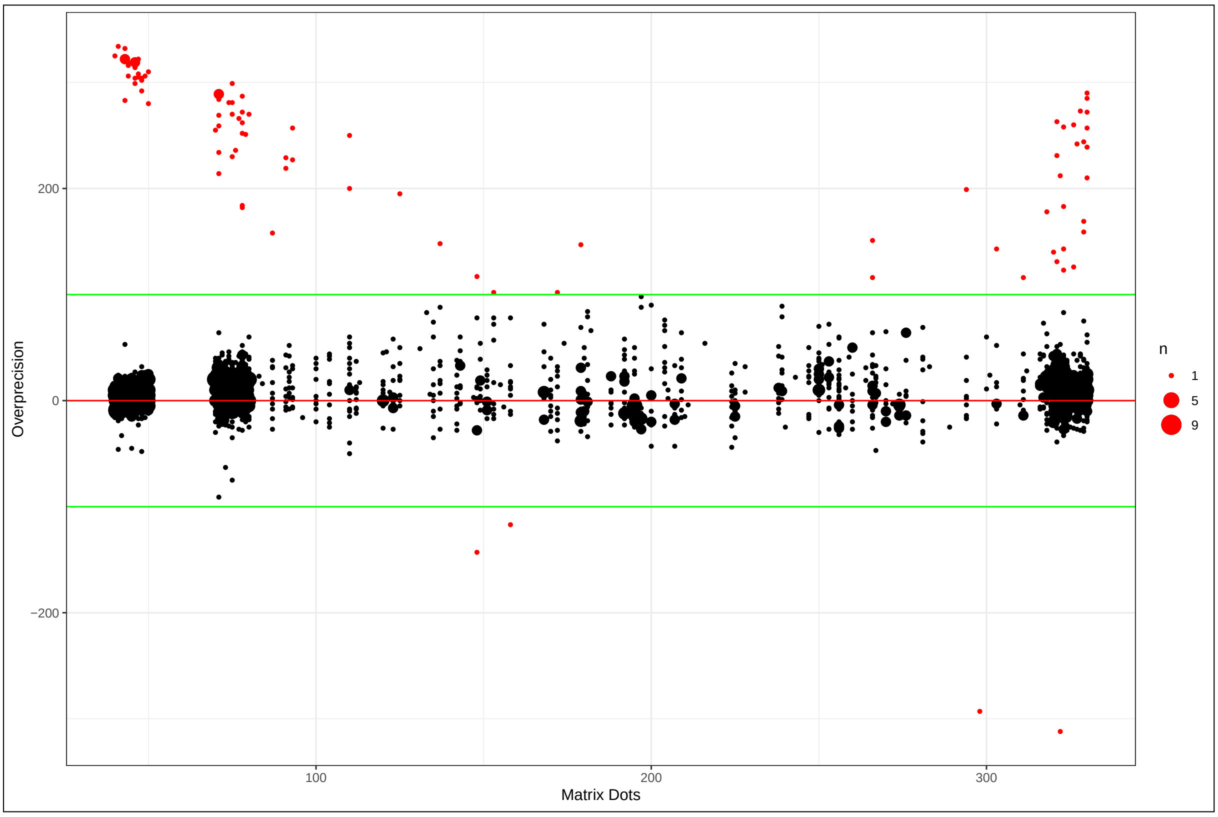
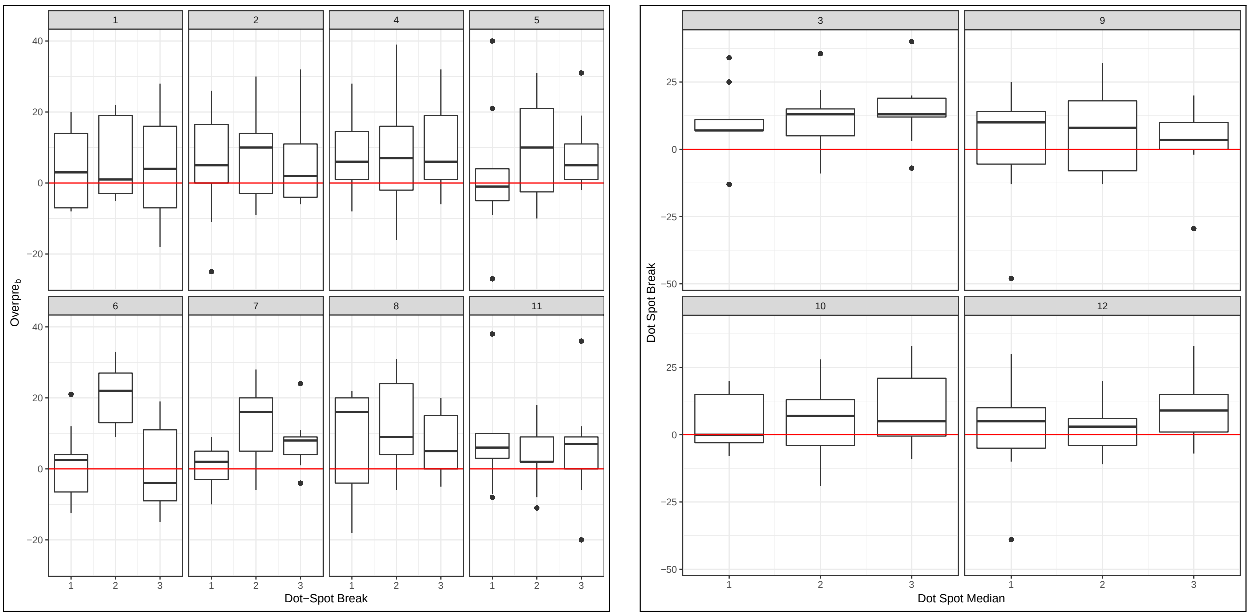


Figure 5: On the vertical axis we present the measure of overprecision for the reported number of red dots and expected error for the value of each matrix (horizontal axis). The horizontal green line is the cutoff value of 100 and -100. The horizontal red line located at 0. The values are for all matrices 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 $MDotOP_{ib}$ 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.[18] 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.

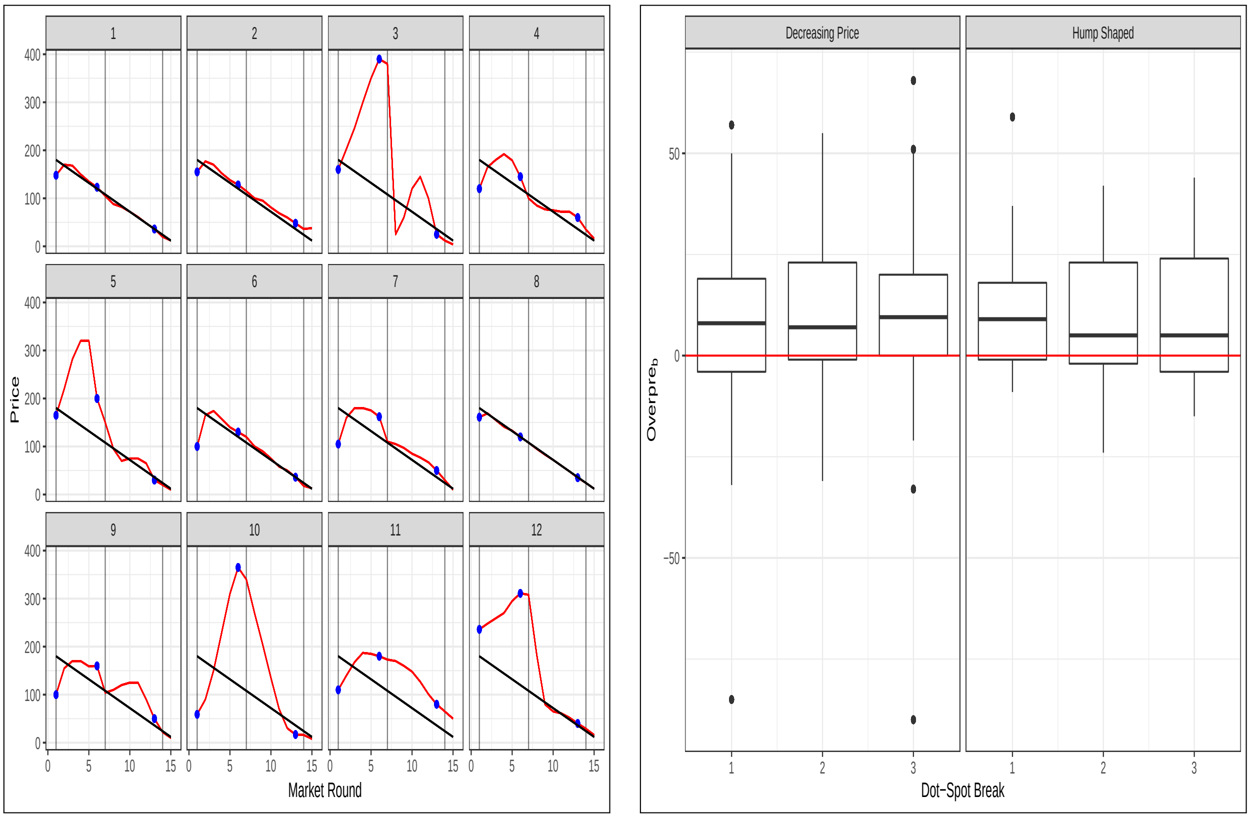
Such a result seems to confirm the thesis from Tuckett and Taffler (2008) in which holding and selling assets in an unknown ambiguous environment leads to an integration of emotional experiences to behavior. In other words, bubbles and overconfidence mostly arise in markets for exotic/unknown assets. 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.

[18] 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) $MDotOP_{ib}$ Dynamics for Market 2

Figure 8: Summary of the dynamics in Market 2.