Price Dynamics and Trader Overconfidence *

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Abstract

Overconfidence is one of the most important biases in financial markets and commonly associated with excessive trading and asset market bubbles. So far, most of the finance literature takes overconfidence as a given, "static" personality trait. In this paper we introduce a novel experimental design which allows us to track different measures of overconfidence during an asset market bubble. The results show that overconfidence co-moves with asset prices and points towards a feedback loop in which overconfidence adds fuel to the flame of existing bubbles.

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1 Introduction

Traders are often overconfident about the precision of their knowledge (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 under-perform due to excessive trade (Odean, 1999; Barber and Odean, 1999) and under-diversify their portfolios (Goetzmann and Kumar, 2008), while markets populated by more overprecise traders are more volatile and result in more inflated asset prices (Scheinkman and Xiong, 2003; Michailova and Schmidt, 2016).

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

In this paper we will use an experimental asset market *à la* Smith et al. (1988) (henceforth SSW) to study whether asset prices and traders overprecision co-move. To the best of our knowledge, only two papers have studied the dynamics of overprecision in a context of changing asset prices; Kirchler and Maciejovsky (2002) and Michailova and Schmidt (2016). Both papers use SSW 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 lower in market episodes that are associated with lower asset prices. This im-

[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 beliefs to have answered 10 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 beliefs to be 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 the excitement of significant profit opportunities during asset price bubbles.

plicit evidence suggests that asset prices and the overprecision of the subjects are indeed interrelated. Yet, their design cannot rule out that such overprecision dynamics 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 (e.g., wishful thinking) (e.g., Caplin and Leahy, 2019).

In contrast, we present a novel design that allows us to disentangle the effect of asset prices on overconfidence from any confounding market factors. First, we provide a new, and simple, way to measure individual overprecision by asking subjects about the expected error of their beliefs. Second, we apply our new overprecision measure to a new task which is completely unrelated to the asset market. This design gives us a "clean" measure of overprecision free of any market biases or learning.

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), becoming wealthy makes traders overprecise, yet, becoming overprecise does not make traders wealthy. In fact, in line with ample theoretical and empirical evidence, we observe that overprecision is negatively correlated with total profits. Finally, we confirm the known result that high cognitive ability results in higher market performance (Bosch-Rosa et al., 2018; Noussair et al., 2016)..

2 Experimental Design

2.1 Asset Market

We employ a variant of the standard Smith et al. (1988) (henceforth: SSW) asset market experiment. 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 fifteen periods. At the beginning of each market, subjects receive an endowment of assets and Talers (our experimental currency) which they can use to trade.[3] At the end of each period, each asset pays a random

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

dividend of either 0, 4, 14 or 30 Talers, each with equal probability. The dividend is independent across periods. The balance of Talers and assets carries over from period to period until the end of the market (period 15) at which point the asset pays its last dividend and disappears. At the end of the experiment Talers are converted into euro 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 period, the fundamental value of the asset at period t can be easily calculated as $12 \cdot (16 - t)$. Thus, the fundamental value of the asset is monotonically decreasing with every period. To make calculations easier for our subjects, we provided them with a table showing the fundamental value of the asset for each round.

Following Haruvy et al. (2007), the market utilizes 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 they are willing to pay, and the desired quantity. Likewise, sell orders consist of a minimum selling price and the number of assets that they are willing to sell.[4] These buy and sell orders are aggregated into a supply and demand curve which determine the market-clearing price.[5] Those subjects who submitted buy orders above the market clearing price buy assets, while those that submitted sell orders below the market clearing price sell assets. In case of a tie, a "virtual" coin is flipped to determine who will trade.

2.2 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 a problematic, as subjects do not seem to understand the concept of confidence intervals and confidence intervals are hard to incentivize (Moore et al., 2016). Therefore, we propose a new, and simple, way to measure the overprecision of our subjects based on asking subjects the following two questions[6]:

[4]Subjects could not make bids that were 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 questions will be adjusted as necessary for the particular dimension of interest.

1. *Please give us your best estimate for ...*

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

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 the elicitation of confidence intervals and measures of subjective certainty, our approach is intuitive, and, importantly, can accommodate any incentivization system.

We apply our new method to elicit overprecision along two separate dimensions; (i) *price-prediction overprecision* which is the overprecision in asset price beliefs and (ii) *context-independent overprecision* which is completely unrelated to the market. 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, will mainly serve as a control for our regression analysis.

Price-Prediction Overprecision

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

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?*

To incentivize both questions, we follow Haruvy et al. (2007). Subjects get paid € 0.25, if their guess is within 10% of the realized price, € 0.10, if within 25%, € 0.05, if within 50%, and € 0 otherwise. Earnings from prices predictions are paid out *on-the-go* and can be used for asset purchases in subsequent rounds. We choose this incentivation scheme

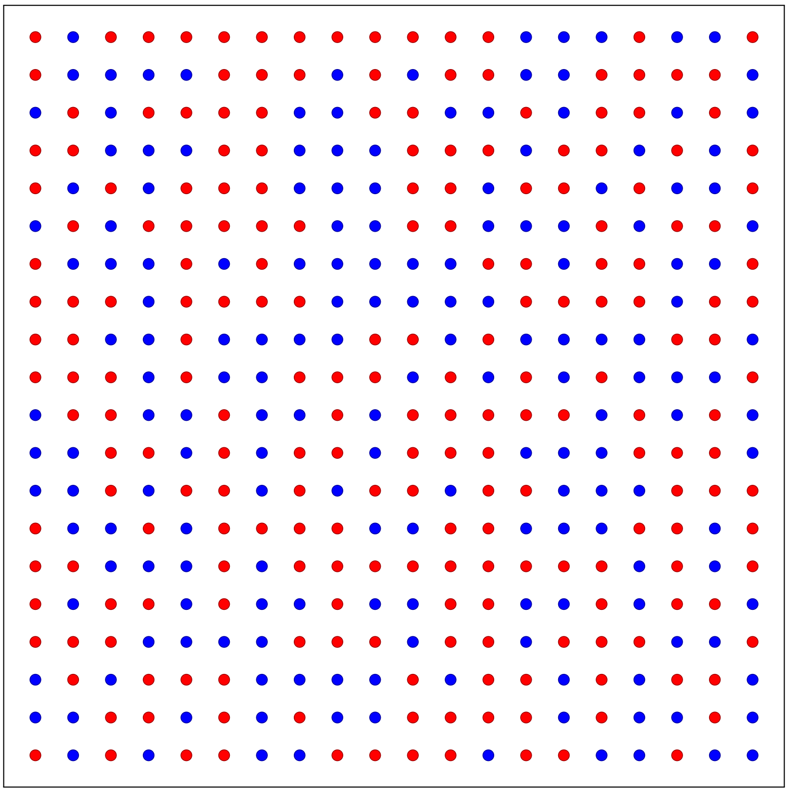

Figure 1: "Dot-Spot" Task

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 they find no evidence of any systematic bias in subjects answers. To avoid that subjects hedge between both the questions, subjects are randomly paid according to one or the other question.

Context-Independent Overprecision

To elicit 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 questions:

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?*

The incentivation scheme for these questions is analogous to the scheme for the price-prediction overprecision, with the sole difference that outcomes from the Dot-Spot, and thus the earnings, are not revealed and paid out until the completion of all markets.

We measure context-independent overprecision at three different "Dot-Spot breaks" that will 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 will be "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 will be drawn from an uniform distribution with the support of 200 ± 125 red dots. The order of the five matrices will be 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]

2.3 Control Treatment

In the control treatment, we generate 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 human subject is paired to eight computerized traders which buy and sell at fundamental value. Because of the call market rules, in all rounds, the market clearing price will be equal to the (downward sloping) fundamental value of the asset. The goal of the control treatment is to check whether there are any dynamics in overprecision (driven by, e.g., the random choice of the dot-spot matrices or the mere repetition of dot-spot tasks) in the absence of endogenous asset price dynamics.

[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 were pretty good and in 75% of our cases we are able to measure overprecision almost at the top of the bubble, and immediately after its crash.

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

2.4 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, once the two asset markets are over, subjects take part in several personality tests.

First, we elicit cognitive ability through CRT (Frederick, 2005), CRT2 (Thomson and Oppenheimer, 2016) and eCRT (Toplak et al., 2014) questions, as cognitive ability has been shown to correlate with performance in SSW markets (Noussair et al., 2016). We then ask them about the number of questions they expected to have answered correctly and their expected relative ranking amongst all subjects in the session. This gives us a measure of overestimation and overplacement, respectively, which along overprecision are the other two types of overconfidence commonly accepted in the literature (Moore and Healy, 2008).

Additionally, we elicit the risk aversion of subjects 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 size of bubbles 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 trading behavior of subjects (Oehler et al., 2018) and the size and the length of asset price bubbles (Oehler et al., 2019).

3 Results

The experiment had thirteen sessions, twelve with our baseline design and one with a downward price robustness check (see Section 2.3). A total of 117 subjects were recruited through ORSEE (Greiner, 2015). All sessions lasted approximately two hours and fifteen 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, and before the start of the experiment took part in a quiz that tested their

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

knowledge on the rules of the market, and several rounds of Dot-Spot with performance feedback.

3.1 Asset Price Dynamics and Context-Independent Overprecision

In Figure 2 we plot the market clearing price (red, solid line) and the downward sloping fundamental value (gray, solid line) for the first market of each session (for results ad analysis of the second market see Appendix C). The vertical lines denote where the Dot-Spot breaks take place and the blue dots show the price of the asset immediately before the break.[10] From Figure 2 it is apparent that most markets show an asset price bubble, as is standard in SSW markets.

More interestingly, in eight of the twelve sessions we observe that the price immediately before the second Dot-Spot break (p_6) is larger than the price at the beginning of the market (p_0), and also larger than the price before the third Dot-Spot brake (p_{13}), i.e. $p_0 < p_6 > p_{13}$. These sessions are the most interesting since their price dynamics allows us to study the full spectrum of a complete bubble-burst episode. We call these sessions, *Hump Shape* sessions.

In sessions 9 to 12, $p_0 < p_6 < p_{13}$, so we cannot study the effects that a bubble burst has on the overprecision of subjects. Yet, 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 computerized sessions with monotonically decreasing prices *Decreasing Price* sessions.

In each Dot-Spot break subjects face five different matrices. We will define the the context-independent overprecision of subject i for matrix $j \in \{1, 2, 3, 4, 5\}$ in break $b \in \{1, 2, 3\}$ as:[11]

$$DotOP_{ijb} = |RedGuess_{ijb} - RedTrue_{jb}| - ErrorGuess_{ijb}, \tag{1}$$

where $ErrorGuess_{ijb}$ is the expected error stated by the subject, $RedGuess_{ijb}$ is the guess of red dots made by the subject, and $RedTrue_{jb}$ is the correct answer. Therefore, when $DotOP_{ijb} > 0$, the larger $DotOP_{ijb}$ the more overprecise a subject is, and

[10] Notice that the first Dot-Spot break took place before the market started, so we don't 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.

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

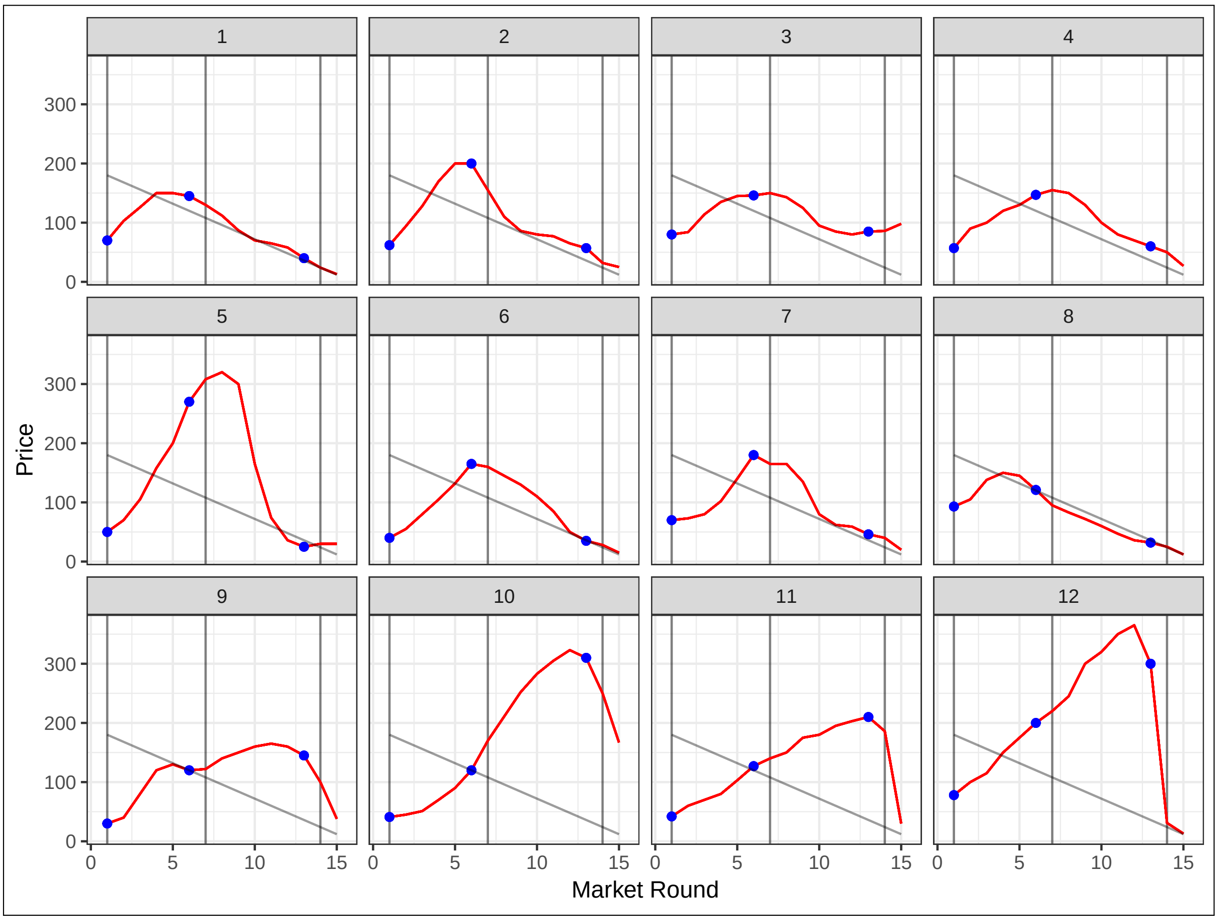

Figure 2: Equilibrium price (red line), fundamental value (solid black line), and Dot-Spot breaks (vertical black lines) for Market 1 of all sessions. To have a better understanding of the price dynamics we place blue dots at the equilibrium price immediately before the dot spot took place (i.e., p_6 and p_{13}). For the first break we place the dot on top of the first realized price (p_1)

when $DotOP_{ijb} < 0$, the smaller $DotOP_{ijb}$ is, the more *underprecise* a subject is. When $DotOP_{ijb} = 0$, then the subject is perfectly calibrated. To have a unique measure of context-independent overprecision for each Dot-Spot break b, we take the median across all $DotOP_{ijb}$ for each subject. This aggregate measure is denoted $MDotOP_{ib}$ and serves as the measure of context-independent overprecision we will use for the rest of the paper.

In Figure 3 we present the $MDotOP_{ib}$ for each break across price dynamic sub-groups (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 *Computerized* sessions b) goes up and then down in *Hump Shape* sessions, and c) it is upward trending for *Increasing Price* sessions.[12]

To test whether these differences across breaks are statistically significant, we perform

[12]We plot the individual session box plots for each session in Figure 5 of Appendix A.

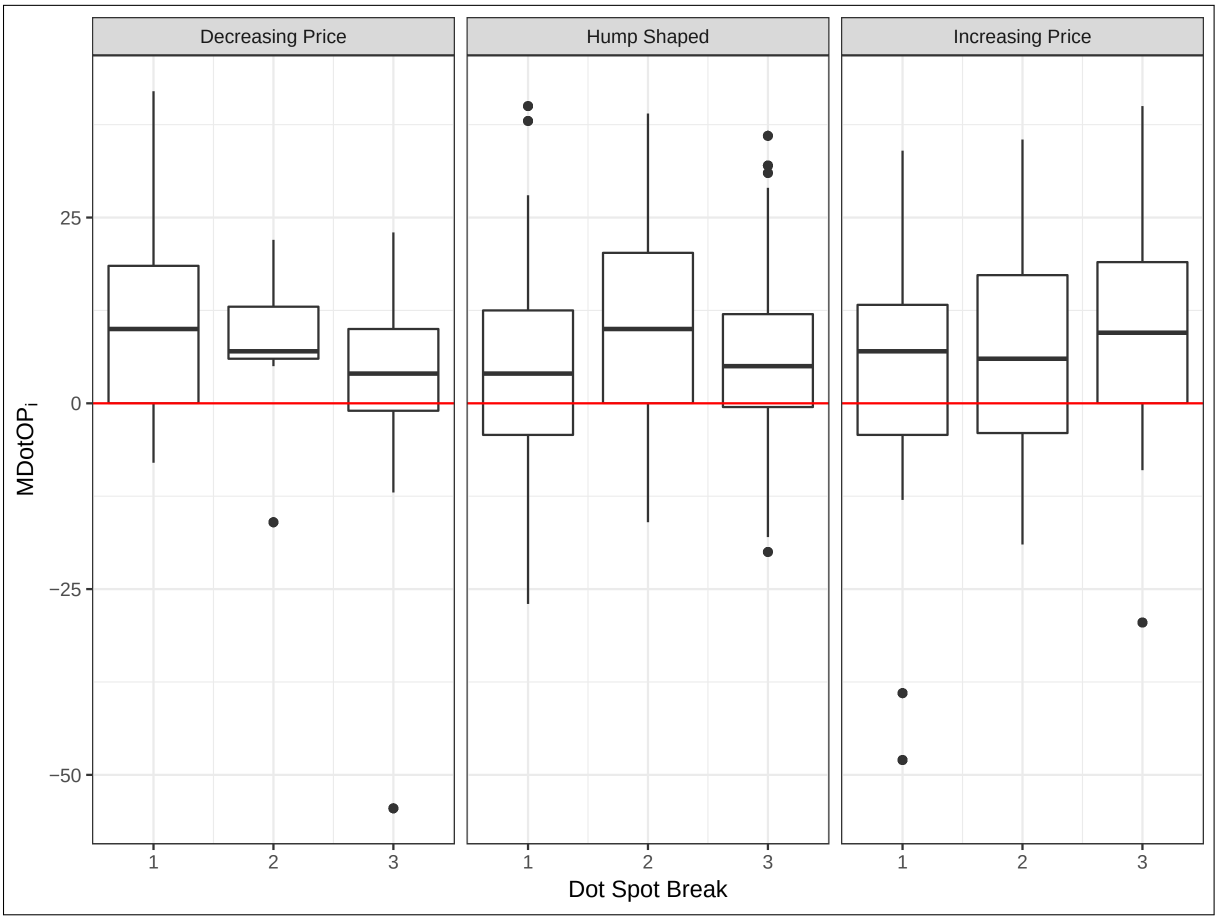

Figure 3: Box plots showing the median, 25th and 75th percentile of $MDotOP_{ib}$ for each break within a session.

a series of Wilcoxon signed-rank tests comparing $MDotOP_{ib}$ of subjects across breaks for the Hum -Shape and Increasing Price sessions. 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 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 the 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 high prices in the latter. Additionally, the lower number of observations means less power, and therefore the need of 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 sub-groups make it reasonable to associate the fall of overprecision with the fall in market prices.

	Break 1 = Break 2	Break 2 = Break 3	Break 1 = Break 3
Hump-shaped 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.

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:

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

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

In Table 2 we regress $\Delta MDotOP_{1,2}$ on the change in asset prices (Price-Difference) and several personality measures.[13] 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 ($\Delta MDotOP_{1,2}$) on the difference in price for the first and sixth round ($\Delta Price_1 = P_6 - P_1$).[14] The second model regresses the change in overprecision between the second and third Dot-Spot break ($\Delta MDotOP_{2,3}$) on the difference in price between the 13th and 6th period ($\Delta Price_2 = P_{13} - P_6$), while the third model compares the change in

[13]Notice that for ease of notation from now on we will drop the individual subject index i for $\Delta MDotOP_{b,b'}$

[14]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.

overprecision between the last and first break ($\Delta MDotOP_{1,3}$) and their corresponding price change ($\Delta Price_3 = P_{13} - P_1$).

Additionally, we introduce price-prediction overprecision POP_{itm} which is the overprecision of subject i when predicting the equilibrium price in period t of market m:

$$POP_{itm} = |PriceGuess_{itm} - PriceCorrect_{itm}| - PriceErrorGuess_{itm}. \tag{3}$$

Analogous to Equation (1) $PriceGuess_{itm}$ is the guessed price of subject i for period t in market m, while $PriceCorrect_{itm}$ is the correct price, and $PriceErrorGuess_{itm}$ the subjects expected error from guessing the price. We then aggregate the price-prediction overprecision for each subject between break to get $APOP_{i,(b,b'),m}$, where b and b' are the different breaks in market m.

The results show that price difference across Dot-Spot breaks have significant effect on the changes in the Context-independent measure of overprecision; across all three breaks, the more prices increase, the more overprecise subjects become. On the other hand, neither the accumulated price-prediction overprecision nor any of the other potential explanatory variables seem to have any effect on changes on the change of the the context-independent overperecision.

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 past success and failure of financial traders (e.g. Daniel et al., 1998; Deaves et al., 2010; Gervais and Odean, 2001). Therefore, we study the effect that past performance has on the overprecision of our experimental subjects. We proxy past performance by changes in the portfolios of the subjects between periods 1, 6, and 13 (i.e. after the first and prior to the second and third Dot-Spot break). The portfolio value of a subject i comprises her cash and her marked-to-market assets holdings at the end of trading periods 1, 6, and 13. Hence, the change in subjects i's portfolio between breaks $b' > b$ is defined as as:

$$\Delta Value_{i(b,b')} = price_{t'} * assets_{i,t'} - price_t * assets_{i,t} + cash_{i,t'} - cash_{i,t} \tag{4}$$

	(1) $\Delta MDotOP_{1,2}$	(2) $\Delta MDotOP_{1,2}$	(3) $\Delta MDotOP_{2,3}$	(4) $\Delta MDotOP_{2,3}$	(5) $\Delta MDotOP_{1,3}$	(6) $\Delta MDotOP_{1,3}$
$\Delta Price_1$	0.0480**	0.0500**				
	(0.0190)	(0.0198)				
$APOP_{1,2}$	-0.0188	-0.0178				
	(0.0138)	(0.0139)				
$\Delta Price_2$			0.0341*	0.0409**		
			(0.0161)	(0.0175)		
$APOP_{2,3}$			0.0353	0.0386		
			(0.0293)	(0.0255)		
$\Delta Price_3$					0.0220***	0.0207***
					(0.00644)	(0.00652)
$APOP_{1,3}$					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 ($\Delta MDotOP_{b,b'}$) on the change in prices across breaks ($\Delta Price_b$), the individual level accumulated price-prediction overprecision across breaks ($APOP_{b,b'}$), and personality measures. All standard errors are clustered at the market level.

where $price_t$ is the equilibrium price of the asset at round t in subject i's session, and $assets_{i,t}$ and $cash_{i,t}$ are the number of assets and cash she is holding, respectively.

The results can be found in Table 3.[15]. In it, 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 value of portfolio induces an increase (decrease) of the context-independent overprecision. Yet, this effect is not as strong as the effect that a pure change in prices has, and is inexistent for the changes in portfolio between the first and third break.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta MDotOP_{1,2}$	$\Delta MDotOP_{1,2}$	$\Delta MDotOP_{2,3}$	$\Delta MDotOP_{2,3}$	$\Delta MDotOP_{1,3}$	$\Delta MDotOP_{1,3}$
$\Delta Value_{1,2}$	0.00994**	0.0103**				
	(0.00420)	(0.00402)				
$APOP_{1,2}$	-0.0177	-0.0152				
	(0.0138)	(0.0141)				
$\Delta Value_{2,3}$			0.00637*	0.00815*		
			(0.00329)	(0.00407)		
$APOP_{2,3}$			0.0327	0.0354		
			(0.0305)	(0.0274)		
$\Delta Value_{1,3}$					0.0000325	-0.000346
					(0.00502)	(0.00540)
$APOP_{1,3}$					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 ($\Delta MDotOP_{b,b'}$) on the change in portfolio value across breaks ($\Delta Value_b$), the individual level accumulated price-overprecision across breaks ($APOP_{b,b'}$), and personality measures. All standard errors are clustered at the market level.

[15]Table 5 in the appendix shows the results of a similar exercise, but excluding for cash holdings.

Result 3: The change in value of subjects' portfolio 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.

3.3 The Impact of Overprecision on Market Performance

While wealthy traders become overprecise, overprecise traders not necessarily become wealthy. In fact, theory predicts that trader overprecision is negatively correlated with profits (e.g., 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 amount of money a subject made in the first market ($Payoff_{i,1}$) on the context-independent overprecision measured before the start of the market and the accumulated price-prediction overprecision across the whole market ($APOP_{i,m}$).[16]

The results can be found in Table 4 and show 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 in which, 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 are 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: The bigger the context-independent overprecision of a subject, the worse her performance in the asset market.

[16] $Payoff_{i,m}$ is composed by the total amount of cash a subject ends the market. Such cash can come from the initial endowment, trading, or the asset dividends, and does not include any payoffs from the price belief elicitation nor the Dot-Spot tasks.

	(1)	(2)	(3)
	Payoff	*Payoff*	*Payoff*
$MDotOP_1$	-7.684**	-7.500**	-6.152***
	(3.048)	(3.050)	(1.707)
$APOP_1$	0.0860	0.0488	-0.0436
	(0.225)	(0.249)	(0.172)
CRT	28.94***	27.10**	27.53**
	(8.956)	(11.15)	(11.22)
Male	120.8*	114.0*	118.3*
	(62.69)	(61.24)	(64.27)
Risk Aversion	78.46	45.12	49.00
	(96.73)	(115.8)	(110.3)
$\Delta MDotOP_{1,2}$			-0.643
			(2.131)
$\Delta MDotOP_{1,2}$ x $MDotOP_1$			-0.209*
			(0.0989)
Constant	364.2***	469.8	461.3
	(91.40)	(359.4)	(345.8)
N	117	117	117
adj. R^2	0.138	0.123	0.146
Big Five	No	Yes	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

Overconfidence is considered one of the most significant and pervasive cognitive biases (Kahneman, 2011; Plous, 1993). It is a well documented phenomenon among experts and professionals in business (e.g., Ben-David et al., 2013; Malmendier and Tate, 2005, 2008; Malmendier et al., 2011) and financial markets (Glaser et al., 2013; Glaser and Weber, 2007; Menkhoff et al., 2013). In finance models especially, agents are assumed to be too optimistic about the quality of their information (i.e., overprecise), which leads to excessive trading, under-diversification, and inflated markets (Odean, 1999; Goetzmann and Kumar, 2008; Scheinkman and Xiong, 2003).

Importantly, overprecision is a "dynamic" personality trait which changes endogenously with past performance of traders (Deaves et al., 2010; Hilary and Menzly, 2006; Merkle, 2017). The dynamic nature of overprecision implies a strong interdependence between overprecision and asset price dynamics such that when asset prices go up, so does the overprecision of traders (Daniel and Hirshleifer, 2015; Daniel et al., 1998; Gervais and Odean, 2001). This creates a feedback loop which potentially amplifies the adverse effects of overprecision on stock price volatility and trading volume and increases the probability of asset price bubbles.

Against this background, in this paper we study whether prices cause overprecision to co-move in an experimental asset market. To do so we introduce a new way of eliciting overprecision and implement it in a novel experimental design which allows us to disentangle the effect of prices on overprecision, free of other potential confounds.

The results are clear: overprecision is dynamic and is driven by prices. When prices go up, so does overprecision, and when prices go down, overprecision follows. This holds for markets with constant increases in price, constant decreases in price, and, crucially, for markets in which bubbles fully develop, going from fast price increases to the final bust. Our results also show a monotonic relation: the more prices increase, the more overprecision increases. Furthermore, we confirm the predictions postulated by the theory that more overprecise subjects have lower returns, and that changes in own portfolio are positively correlated to subject overprecision. Hence, while wealth increases overprecision, overprecision does not increase wealth. Finally, we also confirm known results such as the positive effects of cognitive ability on market performance (Bosch-Rosa et al., 2018; Noussair et al., 2016).

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A Extra Figures and Tables

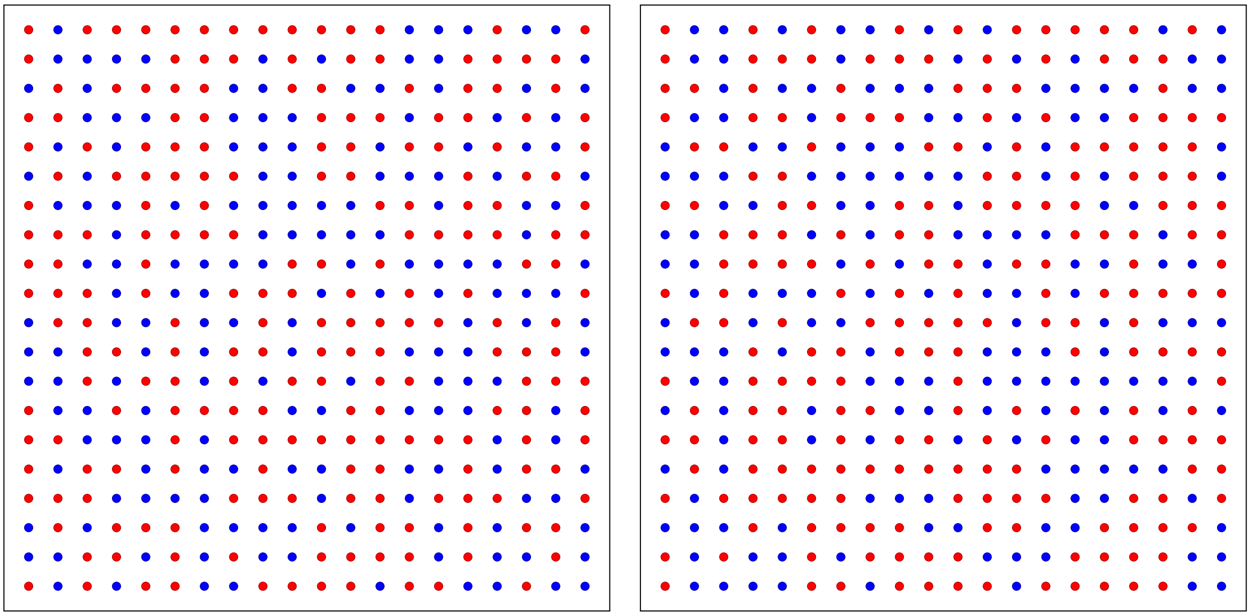
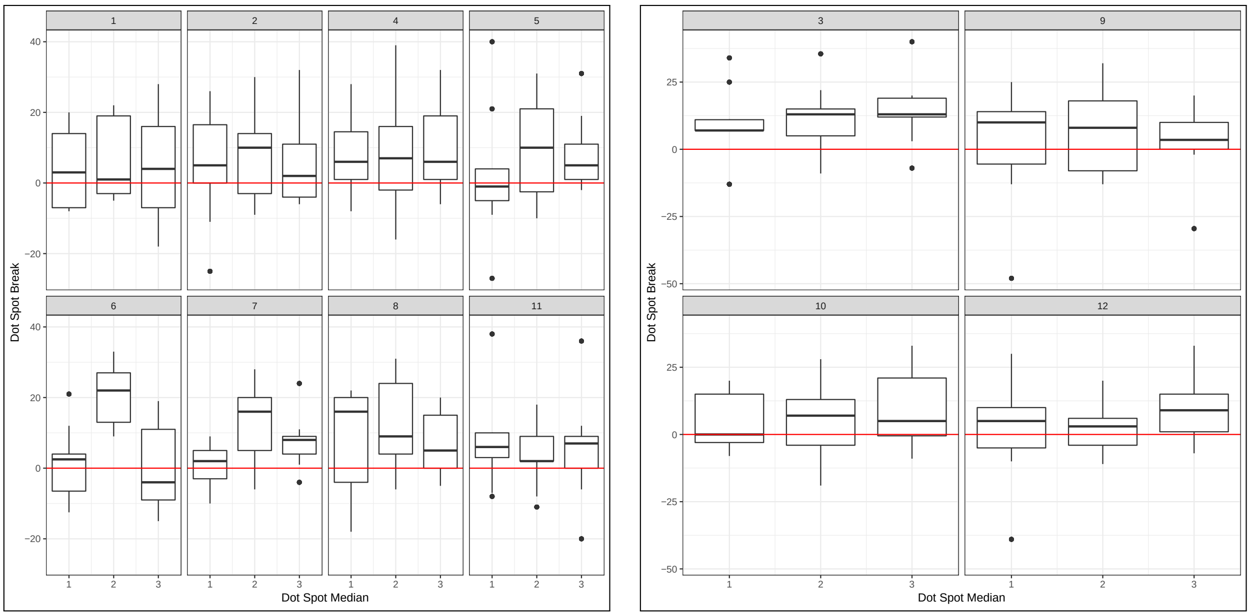


Figure 4: Two matrices with 220 red dots each, but a different dot pattern.



(a) Hump Shaped (b) Increasing Price

Figure 5: Box plots showing the median, 25th and 75th percentile of $MDotOP_{ib}$ for each break within a session

	(1) $\Delta MDotOP_{1,2}$	(2) $\Delta MDotOP_{1,2}$	(3) $\Delta MDotOP_{2,3}$	(4) $\Delta MDotOP_{2,3}$	(5) $\Delta MDotOP_{1,3}$	(6) $\Delta MDotOP_{1,3}$
$\Delta assets_{1,2}$	0.0104*	0.0103*				
	(0.00519)	(0.00542)				
$APOP_{1,2}$	-0.0142	-0.0111				
	(0.0130)	(0.0129)				
$\Delta assets_{2,3}$			0.0108**	0.0107***		
			(0.00366)	(0.00348)		
$APOP_{2,3}$			0.0400	0.0421		
			(0.0275)	(0.0251)		
$\Delta assets_{1,3}$					0.00245	0.00303
					(0.00336)	(0.00386)
$APOP_{1,3}$					0.0228*	0.0225*
					(0.0121)	(0.0125)
CRT	0.0446	0.152	-0.124	-0.209	-0.315	-0.264
	(0.450)	(0.389)	(0.558)	(0.633)	(0.558)	(0.555)
Male	-3.036	-1.126	-1.403	-2.806	-4.544	-4.259
	(3.846)	(3.443)	(2.309)	(1.998)	(2.768)	(2.758)
Risk Aversion	-0.321	-0.400	-15.11	-14.83	-15.24*	-14.61*
	(6.550)	(7.264)	(9.052)	(9.647)	(8.056)	(8.124)
Constant	4.758	-6.913	6.918	18.89	11.66	14.20
	(4.372)	(9.870)	(6.276)	(10.65)	(6.800)	(12.52)
N	117	117	117	117	117	117
adj. R^2	0.011	0.038	0.071	0.075	0.089	0.065
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 ($\Delta MDotOP_{b,b'}$) on the change in book value of share across breaks ($\Delta assets_b$), the individual level accumulated price-overprecision across breaks ($APOP_{b,b'}$), and personality measures. All standard errors are clustered at the market level.

B Risk Aversion Measure

For our regression analysis in Tables 2, 5, and 4 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 6, 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 6: 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.[17] This is clear in the left panel of Figure 7 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-Shaped.

In the right panel of Figure 7 we show the distribution of the $MDotOP_{ib}$ 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 ($MDotOP_{ib}$) across breaks. This is confirmed in Table 6 where we see that there is no difference in overprecision across the different breaks.

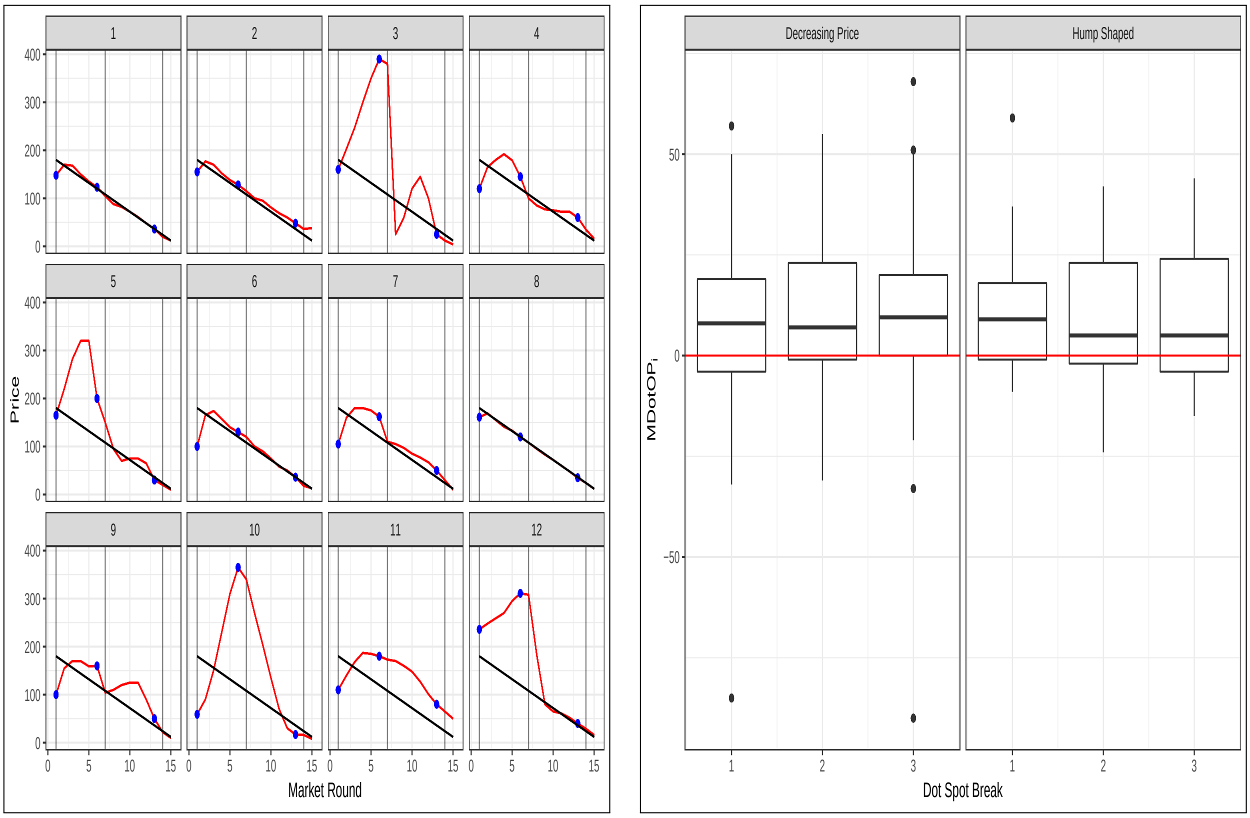
Such a result seems to confirm our the thesis from Tuckett and Taffler (2008) in which holding and selling assets in an unknown ambiguous environment leads to an integration of emotional experiences to behavior. In other words, bubbles and overconfidence mostly arise in markets for exotic/unknown assets.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

[17] 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 7: Summary of the dynamics in Market 2.