House of Finance
Working Paper Series

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# Thar She Blows Again: Reducing Anchoring Rekindles Bubbles

SAFE Working Paper Series No. 54

SAFE | Sustainable Architecture for Finance in Europe
A cooperation of the Center for Financial Studies and Goethe University Frankfurt

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## Non-Technical Summary

Markets play an important role in the aggregation of diverse information. Competitive markets coordinate heterogeneous relative evaluations of goods and services produced by society via transaction prices. While individual evaluations of participants in a market place are usually unobservable, competitive market prices provide signals about the aggregate fundamental value of a traded item. Whenever a market satisfies the property that transaction prices reflect fundamentals perfectly, economists refer to it as efficient or as having the *price-discovery* property. In an efficient market high prices indicate that society values a good highly, potentially fostering its supply and reducing its demand.

However, ex-ante there is no guarantee that markets fulfill their important role to accelerate price-discovery; maybe not even approximately. If mis-pricing on a market is persistently positive, i.e. if prices are above the fundamental value for an extended period of time, economists usually speak of a bubble. Bubbles are not only characterized by long periods of over-pricing but are also (at least empirically) usually associated with a significant crash of prices towards the fundamental value. As Kindleberger and Aliber (2005) put it: “Bubbles always implode”. The consequences of bubble-crash patterns, independently of the market, are usually severe. Bubbles lead to over-investment and mis-allocation of capital since the periods of increasing prices sent the wrong signal to producers. The crash, on the other hand, renders these investments unprofitable. Put differently, bubble-crash patterns in specific markets can lead to a redistribution of wealth and social turmoil which may affect the rest of the economy.

There are numerous examples for bubble-crash episodes, some of which are mentioned here. They range from the Dutch tulip-mania (1634-1637), the US-stock mania (1928-1932), the dot-com bubble (1998-2001), the uranium bubble (2004 -2008) and, most recently, the US real estate bubble (1996-2009). Although there is suggestive evidence indicating that the aforementioned episodes faced a bubble, there is no guarantee that these markets were mis-priced since the underlying fundamental values are not observable.

One way to circumvent the problem of unobservable fundamental values and to study the causes and the cures of bubbles and crashes is to utilize experimental methods. Experimental economists since Vernon Smith et al. (1988) have focused their attention on mis-pricing in experimental asset markets. Smith and his co-authors illustrate that asset prices may deviate systematically from their underlying fundamental value (FV) even in controlled laboratory environments in which the dividend distribution is common knowledge. Moreover, they show that experimental asset prices follow bubble-crash dynamics: Initially, asset prices increase beyond the fundamental value until they peak and “crash” back towards the FV. The observed price-dynamic proved to be highly replicable and persist under various experimental treatments.

Our work uses experimental methods to investigate one particular cause for the formation of bubbles in laboratory environments: visual stimuli. We show that visual stimuli induce anchoring behavior (Kahneman and Tversky (1983, 1974)) that can substantially mitigate bubble behavior. We set visual stimuli by manipulating within-period price charts used by our experimental traders. Most importantly, our evidence suggests that the visual stimulus needs to be provided only in the first period of a standard asset market experiment to affect overall price dynamics. We support our hypothesis with new experimental evidence from 22 laboratory sessions (216 subjects) and adapt existing theoretical frameworks to rationalize our findings.

Our insights suggest that trading behavior in the initial period is crucial for generating the well-established bubble-crash dynamics in experimental asset markets. Inducing an anchor at the fundamental value in the first period is sufficient to eliminate or significantly reduce bubbles in laboratory environments. If no anchor is set, standard bubble-crash patterns emerge.

Our insights further improve our understanding of stock market dynamics and suggest that setting initial prices is perhaps more important than previously believed. Stock Exchanges such as the New York Stock Exchange (NYSE) determine opening prices through pre-opening auctions. Between 8.00am and 9.30am, market makers at the NYSE collect limit orders and try to implement a market clearing price. Our findings suggest that opening prices have very important implications for subsequent intra-day price dynamics. More specifically, underpricing the asset during the pre-opening may induce severe price rallies peaking well above the assets fundamental value. Our work therefore suggests that the market structure and the price determination in pre-openings should be discussed when addressing asset market stability.

The results presented in our paper also contribute to the well-established literature on initial public offerings (IPO). Interpreting the first-period price in our experimental sessions as the IPO price of a stock, our findings suggest that mis-pricing the IPO could lead to non-trivial price dynamics. Since our experimental setup gives us more control over the “IPO price” of the stock, we can make predictions about the consequences of over- and under-pricing the asset initially.

# Thar She Blows Again: Reducing Anchoring Rekindles Bubbles*

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19th June 2014

**Abstract**

We investigate the relationship between anchoring and the emergence of bubbles in experimental asset markets. We show that setting a visual anchor at the fundamental value (FV) in the first period only is sufficient to eliminate or to significantly reduce bubbles in laboratory asset markets. If no FV-anchor is set, bubble-crash patterns emerge. Our results indicate that bubbles in laboratory environments are primarily sparked in the first period. If prices are initiated around the FV, they stay close to the FV over the entire trading horizon. Our insights can be related to initial public offerings and the interaction between prices set on pre-opening markets and subsequent intra-day price dynamics.

**Keywords**: Experimental Asset Markets, Anchoring, Bubbles
**JEL Classifications**: C90, C91, D03, G02, G12

*We gratefully acknowledge research support from the Research Center SAFE, funded by the State of Hessen initiative for research LOEWE. This project benefited from many helpful comments and suggestions. We particularly thank Carey Deck, John Duffy, Martin Götz, Michael Kirchler, Michael Kosfeld, Baptiste Massenot, Thomas Mosk, Devesh Rustagi and Ferdinand v. Siemens.

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# 1 Introduction

In a seminal paper, Smith et al. [1988] (SSW) illustrate that asset prices may deviate systematically from the underlying fundamental value (FV) even in controlled laboratory environments. Moreover, SSW show that experimental asset prices follow bubble-crash dynamics: Initially, asset prices increase beyond the fundamental value until they peak and "crash" back towards the FV.[1] The observed price-dynamics proved to be highly replicable and persist under various experimental treatments (King et al. [1993], Boening et al. [1993], Porter and Smith [1995], Caginalp et al. [1998, 2000], Dufwenberg et al. [2005], Noussair and Tucker [2006], Haruvy and Noussair [2006], Haruvy et al. [2007], Hussam et al. [2008], Williams [2008]).

We show that visual stimuli (i.e., within-period price charts) induce anchoring behavior (Kahneman and Tversky [1983, 1974]) that can substantially mitigate bubble behavior. Most importantly, our evidence suggests that the visual stimulus needs to be provided in the first period only to affect overall price dynamics. We support our hypothesis with new experimental evidence from 22 laboratory sessions (216 subjects) and adapt existing theoretical frameworks to rationalize our findings (DeLong et al. [1990], Haruvy and Noussair [2006], Duffy and Ünver [2006]).

Our insights suggest that trading behavior in the initial period is crucial for generating the well-established bubble-crash dynamics in experimental asset markets. Inducing an anchor at the fundamental value in the first period is sufficient to eliminate or significantly reduce bubbles in laboratory environments. If no anchor is set, standard bubble-crash patterns emerge, even if the fundamental value is constant over time (Noussair et al. [2001]).

To further illustrate the importance of anchors in experimental asset markets, we present data on treatments in which first-period-anchors were set at normatively irrelevant random numbers (Ariely et al. [2003]). Setting anchors at values which exceed the fundamental value, induces price-paths which initiate around the anchor and which slowly converge towards the FV from above. Setting anchors at values which are significantly smaller than the FV induces price paths, which tend to initiate below the FV, over-shoot the fundamental value and crash back to it towards the end of the trading horizon.

Our insights further improve our understanding of stock market dynamics and suggest that setting initial prices is perhaps more important than previously believed. Stock Exchanges such as the New York Stock Exchange (NYSE) determine opening prices through pre-opening auctions (Biais et al. [2000]). Between 8.00am to 9.30am, market makers at the NYSE collect limit orders and try to implement a market clearing price (Amihud and Mendelson [1987], Stoll and Whaley [1990]). Our findings suggest that opening prices have very important implications for subsequent intra-day price dynamics. However, investigating the impact of opening prices on intra-day price dynamics in field settings is difficult due to potential endogeneity concerns. Our laboratory environment provides more control over initial prices and allows us to make causal statements regarding the relationship between initial prices and subsequent price dynamics.

The results presented in this paper also contribute to the well established literature on initial public

[1]The resulting price paths therefore violate basic predictions associated with the homogeneous-beliefs, rational expectations equilibrium. The results of SSW, together with the important contributions of (e.g.) Shiller [1981], LeRoy and Porter [1981], Roll [1984], De Bondt and Thaler [1985], Mehra and Prescott [1985], Lakonishok et al. [1991, 1994] contributed to the emergence of behavioral finance (Shleifer [2000]).

offerings (IPO's, Ritter and Welch [2002], Loughrand and Ritter [2002]). Interpreting the first-period price in our experimental sessions as the IPO price of a stock, our findings suggest that mis-pricing the IPO could lead to non-trivial price dynamics. Since our experimental setup gives us more control over the "IPO price" of the stock, we can make predictions about the consequences of over- and under-pricing the asset initially.

Our results are closely related to those of Kirchler et al. [2012] (KHS, hereafter), who argue that "confusion" about the decreasing fundamental value process, coupled with an increasing cash-to-asset value (C/A) ratio, are the most important factors –if not the only factors– generating the typical bubble-crash patterns in laboratory asset markets which use the SSW-design.[2] KHS claim that environments with constant FV reduce confusion and therefore mitigate bubbles. Experiments intended to reduce this confusion by changing the notion of a "stock" to a "stock of a depletable gold mine," which served to instill the idea of a declining FV, mitigated bubble behavior.

We provide an alternative interpretation of these results. We believe that the particular features of the KHS-design generate asset prices which equal the fundamental value through increased focalism or anchoring, and not because agents are less "confused." By connecting the experimental data to the structural models of DeLong et al. [1990], Haruvy and Noussair [2006] and Duffy and Ünver [2006], we are able to distinguish between "confusion" and "anchoring". We argue that the results reported by KHS are generated by anchoring and consistent with our insights.

## 2 Experimental Design

In our laboratory environments participants traded a dividend-paying asset over a ten period trading horizon, using an experimental currency (Taler). Within each period a standard double auction trading mechanism determined bilateral trading prices. At the beginning of each experimental session half of the participants were endowed with 20 shares and 3,000 Taler. The other half received an initial endowment of 60 shares and 1,000 Taler.

Following the evidence of Kirchler et al. [2012], we implemented an environment in which the fundamental value and the C/A ratio are constant over time. That is, dividends took realizations of 5 and -5 "Taler" with equal probability of 50%. Dividend-payments/losses were collected in a separate account to keep the C/A ratio constant over time. The FV of the asset was kept constant at a value of 50 Taler over the 10 periods trading horizon, by ensuring a terminal buyback value of 50.[3]

Within each trading period we use price-charts to depict the history of transaction prices. Our within-period price plots share the same interesting features as the price charts used by KHS.

To be specific, in the first period, price-charts in the KHS-design initiate at the fundamental value of the asset. Hence, if the first trading price is above (below) the FV, subjects observe a price path which suggests that prices have "increased" ("decreased"). Moreover, after every transaction in period one, for every new offer that is made by a subject, the graph re-initiates the prices at the FV. Hence, in the first

[2]Although noise and irrationality play major roles in the formation of asset price bubbles (Smith et al. [2000], Lei et al. [2001], Smith [2010]. Black [1986], Daniel et al. [1998], Shiller [2000], Hirshleifer [2001], Lamont and Thaler [2003], Barber et al. [2009]), the type of confusion identified by KHS raises concerns about the external validity of a substantial number of asset market experiments. Similar concerns are raised by Oechsler [2010] and Oechsler et al. [2011].

[3]Just like KHS we use a Taler-Euro conversion rate of 400:1. We used identical cash and unit endowments as in the original paper.

period, subjects observe price paths which "jump" back into the FV after new offers are posted (See Figures 6a and 6b in Appendix A).

In the follow-up periods, the price plot initiates at the previous period's average price, and there is no re-initiation in the FV after every transaction as in period one. However, the scale of the y-axis is not constant across trading periods: The maximum of the y-axis is a multiple of the previous period's transaction prices, potentially channeling perceived prices towards more stable outcomes and affecting observed price dynamics.

We conjecture that these seemingly innocuous graphical interface features induce anchoring behavior and generate bubble mitigation effects. We further hypothesize that eliminating these first-period design-features will have important effects on the observed price dynamics even if the FV and the C/A ratio are constant over time.

We ran four treatments to test these conjectures and compare the price dynamics in terms of over-valuation –via the "relative deviation" (RD; Kirchler et al. [2010])– and in terms of mis-pricing – via the "relative absolute deviation" (RAD; Kirchler et al. [2010]).[4] Formulas for RAD and RD are provided in Table 11 in the Appendix.

First, we replicated the constant FV and constant C/A-ratio treatment like in KHS with the only difference that the y-axis for the within-period price chart was fixed at 250. No other component was changed in the design of KHS. That is, in the price-chart, prices were initiated in the FV (50) and jumped back into the FV after every transaction in the first period. We denote this treatment as "Anchor-T4(\=)". We will show below that this treatment generates trading prices, which mimic the trading prices of KHS. Treatment "Anchor-T4(\=)" is therefore our control treatment.

Second, we ran another treatment, denoted as "NoAnchor-T4(\=)", in which we did not initiate the real-time graphical representation of trading prices at the FV and we eliminate the re-initiation component in period one. That is, in the price-chart, prices did not jump back into the FV after every transaction in the first period. The scale of the y-axis in the price chart was again fixed at 250. Hence, the only difference between treatments "NoAnchor-T4(\=)" and "Anchor-T4(\=)" is the initiation of the price chart at the FV and the "jump-back" component in period one.[5] We show below that both treatments differ significantly in terms of the associated price dynamics.

While treatments "NoAnchor-T4(\=)" and "Anchor-T4(\=)" illustrate the difference between asset market experiments in which we set an anchor around the FV and experiments in which we do not set an anchor, they do not tell us what happens if we would try to set an anchor at a normatively irrelevant random number (Ariely et al. [2003]).

To investigate the latter question we ran two more treatments. First, we replicated treatment "Anchor-T4(\=)" with the only difference that prices were initiated at 10 Taler and prices were allowed to jump back into the value of 10 after every transaction in the first period. We denote this treatment as "Anchor10-T4(\=)". Second, we again replicated treatment "Anchor-T4(\=)" with the only difference that prices were initiated at 90 Taler and prices were allowed to jump back into the value of 90. We denote the latter treatment as "Anchor90-T4(\=)". In both treatments the scale of the y-axis in the

[4] RAD= $\frac{1}{10}\sum_{t=1}^{10}\frac{|P_t-FV_t|}{mean(FV)}$, RD= $\frac{1}{10}\sum_{t=1}^{10}\frac{P_t-FV_t}{mean(FV)}$ where $P_t$ denotes the average within period transaction price.

[5] We argue that both factors together generate an anchor towards the FV, mitigate bubbles but do not induce more systematic trading behavior.

price chart was again fixed at 250.

Table 1: Experimental Design Parameters and Characteristics

| Treatment | Sessions | Subjects | Unit Endowments | Cash Endowments | Trading Periods |
|---|---|---|---|---|---|
| "Anchor-T4(\=)" | 6 | 56 | Half 60, Half 20 | Half 1000, Half 3000 | 10 |
| "NoAnchor-T4(\=)" | 6 | 60 | Half 60, Half 20 | Half 1000, Half 3000 | 10 |
| "Anchor10-T4(\=)" | 5 | 50 | Half 60, Half 20 | Half 1000, Half 3000 | 10 |
| "Anchor90-T4(\=)" | 5 | 50 | Half 60, Half 20 | Half 1000, Half 3000 | 10 |
| Overall | 22 | 216 | | | |
| Taler-Euro Conversion Rate | | 400:1 | | | |
| Dividends | $\{-5, 5\}$ (50%) | | | | |
| Buyback value at T | 50 | | | | |

For our experiments we recruited subjects via the ORSEE system at Goethe University, Frankfurt. Just like KHS we ran six sessions of treatment "NoAnchor-T4(\=)". In four of the six sessions, 10 subjects participated. In the two remaining sessions, nine and seven subjects participated.[6] However, the two sessions with the comparatively small number of participants actually show more stable price paths than the ones in which we have exactly the same number of participants as KHS. We also ran six sessions of treatment "Anchor-T4(\=)". In each of the six sessions, 10 subjects participated. Finally, we ran five sessions of treatment "Anchor10-T4(\=)" and five sessions of treatment "Anchor90-T4(\=)". In each of the ten sessions, 10 subjects participated. The experimental design parameters and session-characteristics are summarized in Table 1.[7]

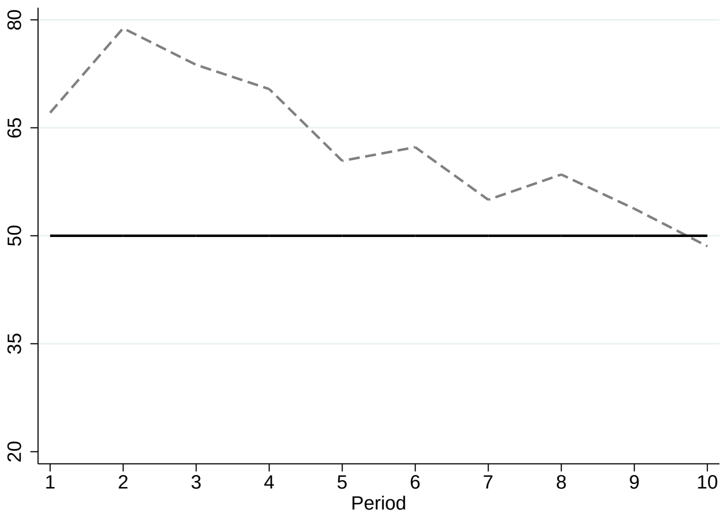
## 3 Results: Rekindling Bubbles

Figures 1a and 1b show average transaction prices under treatment "NoAnchor-T4(\=)" and treatment "Anchor-T4(\=)" respectively. Session-specific transaction prices are shown in Figures 7a - 7c in Appendix D. Note that our prices in the "NoAnchor-T4(\=)"-treatment deviate substantially from the prices observed by KHS, whereas the prices under treatment "Anchor-T4(\=)", mimic the prices observed by KHS.

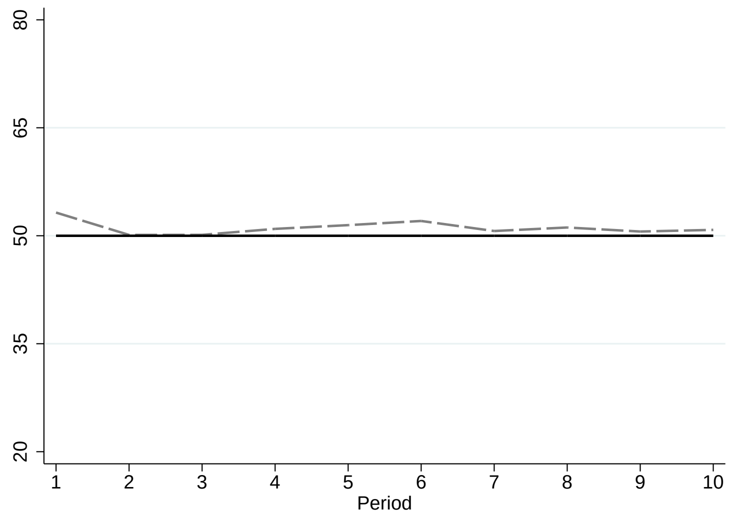
We present session-specific RAD measures for our "NoAnchor"-treatment in the first column of Table 2. The corresponding RAD-measures of KHS, denoted as T4(\=), are shown in column two. A Mann-Whitney test indicates that the median RAD in our "NoAnchor" sessions exceeds the median RAD measure of KHS significantly at a 5% level (p-value = 0.04). The difference in RD-measures between our NoAnchor-treatment and T4(\=) is not significant (p-value = 0.179; columns 3 and 4). However, given the size of the sample it is questionable whether this "insignificance" is due to the power-properties of the test. If we eliminate, for instance, the lowest or second lowest RD measure from our sessions, we

[6] On average, each session lasted 80 minutes and subjects earned on average around 15 Euros.

[7] We use the same design-parameters, materials and procedures as KHS. We accessed the zTree-software used by the authors as well as their instructions via the AEA-database. We described the cash and unit endowments above. Like KHS, we used a Taler-Euro conversion rate of 400:1. Each session lasted approximately 90 minutes (including reading instructions aloud, answering questions, test-questions and practice round). Subjects earned on average around 15 Euros in every session (includes a 5 Euro show-up feed).




(a) Average Session Prices, “NoAnchor-T4(\=)”.




(b) Average Session Prices, “Anchor-T4(\=)”.

Figure 1: Dashed Lines: Average Session Prices. Solid Line: FV.

obtain a significant difference at a 10% level.

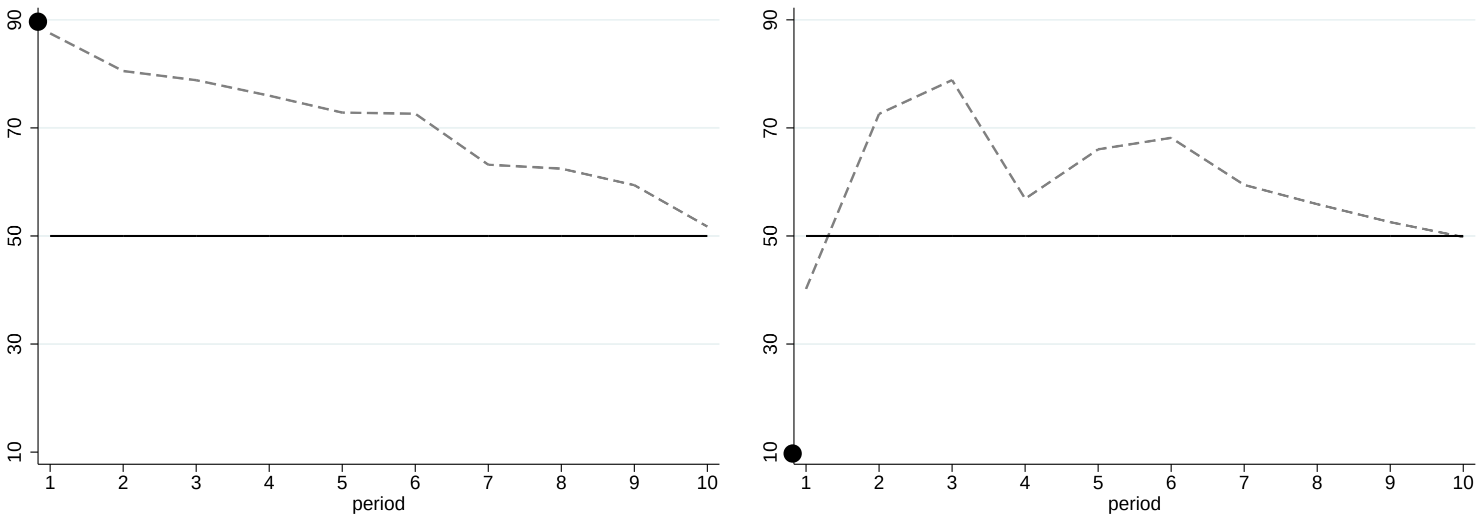
| RAD “NoAnchor-T4(\=)” | T4(\=) | RD “NoAnchor-T4(\=)” | T4(\=) | RAD “Anchor-T4(\=)” | RD “Anchor-T4(\=)” |
|---|---|---|---|---|---|
| 0.026 | 0.003 | -0.016 | -0.003 | 0.026 | 0.0005 |
| 0.051 | 0.009 | -0.001 | -0.009 | 0.029 | 0.029 |
| 0.115 | 0.008 | 0.106 | -0.008 | 0.051 | -0.003 |
| 0.058 | 0.002 | -0.053 | 0.002 | 0.031 | 0.031 |
| 0.809 | 0.086 | 0.809 | -0.086 | 0.046 | 0.045 |
| 0.923 | 0.056 | 0.820 | -0.056 | 0.042 | 0.031 |

Table 2: RAD and RD, Treatments: “NoAnchor-T4(\=)” , “Anchor-T4(\=)” and KHS .

The RAD and RD measures for our “Anchor-T4(\=)”-treatment are shown in column 5 and 6 of Table 2. First, we observe that our control treatment generates significantly less mis-pricing in comparison to our “NoAnchor”-treatment at a 10% level.[8] This is surprising since the treatments differ only in terms of the properties of the graphical interface in the first period. We do not observe significantly less over-valuation (RD). However, the average RD for our “Anchor”-treatment is 0.023, whereas the average RD for our “NoAnchor” treatment is 0.278 and therefore substantially higher. Looking at Figures 7a - 7c, we observe that the differences in the price paths across treatments are particularly pronounced in the first periods. Focusing on periods 1-6 only, we observe that both RAD and RD differ significantly across our “Anchor-T4(\=)” and “NoAnchor-T4(\=)” treatments at a 5% significance level.

Our insights from treatments “Anchor-T4(\=)” and “NoAnchor-T4(\=)” suggest that subjects are sensitive towards anchors, induced in the first period in experimental asset markets. To test whether subjects are also sensitive towards anchoring if anchors are set at normatively irrelevant numbers, we

[8] Mann-Whitney test $p - value = 0.09$.




(a) Average Session Prices, "Anchor90-T4(\=)".

(b) Average Session Prices, "Anchor10-T4(\=)".

Figure 2: Dashed Lines: Average Session Prices. Solid Line: FV. Filled Circle: Induced Anchor

induced anchors at values of 10 and 90 as described above. We hypothesize that mis-pricing (RAD) is equally severe in both treatments and that over-valuation (RD) is more severe in the "Anchor90-T4(\=)" treatment.

This is indeed what we observe. Table 3 shows session-specific RAD and RD measures for treatments "Anchor90-T4(\=)" and "Anchor10-T4(\=)". A Mann-Whitney test suggests that the RAD-measures do not differ significantly across the two treatments (p-value = 0.151) and that the RD measures in the "Anchor90-T4(\=)"-sessions are significantly higher than the RD measures in the "Anchor10-T4(\=)"-sessions (p-value = 0.095).

We observe other interesting patterns. Every single first-period average session price in the "Anchor90-T4(\=)"-treatment exceeds the asset's FV. The average first period price is 87.4 and hence very close to the anchor of 90. Moreover, four out of the five sessions in the "Anchor90-T4(\=)"-treatment initiate at high price levels and converge relatively slowly towards the FV, suggesting that the anchor is fairly persistent. The fifth session initiates at a value which exceeds the anchor and shows a pronounced bubble. We depict the average session prices for the "Anchor90-T4(\=)"-treatment in Figure 2a. Session-specific prices are illustrated in Figures 8a - 8b.

A different pattern emerges in the "Anchor10-T4(\=)"-treatment. Four out of five first-period prices in the "Anchor10-T4(\=)"-sessions initiate below the FV, ranging from 24.56 to 43.7. Most interestingly, each of these four sessions over-shoot and increase beyond the asset's FV at some point in time and converge and/or "crash" back towards the FV towards the end of the session. We depict the average session prices for the "Anchor10-T4(\=)"-treatment in Figure 2b. Session-specific prices are illustrated in Figures 8c - 8d.

Overall, we conclude that seemingly innocuous anchors can have important effects on price dynamics in experimental asset markets. In the following section we rationalize our findings in the model of Duffy and Ünver [2006] and show that anchoring behavior is responsible for the observed differences.

| RAD | | RD | |
|---|---|---|---|
| "Anchor90-T4(\=)" | "Anchor10-T4(\=)" | "Anchor90-T4(\=)" | "Anchor10-T4(\=)" |
| 1.456 | 1.078 | 1.456 | 1.039 |
| 0.142 | 0.135 | 0.142 | -0.004 |
| 0.126 | 0.095 | 0.087 | -0.087 |
| 0.183 | 0.047 | 0.182 | 0.047 |
| 0.184 | 0.031 | 0.184 | 0.009 |

Table 3: RAD and RD for "Anchor90-T4(\=)" and "Anchor10-T4(\=)"

### 3.1 Quantifying Anchoring

Duffy and Ünver [2006] (DÜ) provide a model for experimental asset markets, which incorporates anchoring behavior. DÜ model the bid and ask structure of agents in double auctions directly, with a particular focus on experimental setups. Since subjects in experimental asset markets are usually not professional stock traders, they present a parsimonious agent-based model, which captures important behavioral biases commonly observed in laboratory environments.

Although their model might not be compelling enough to capture the behavior of traders in real-world financial markets, it generates very good fits and accurate predictions for experimental asset markets, indicating that standard subject pools stick to "rule-of-thumb" trading in complex asset-market environments. Agent-based models have proven to be powerful tools in explaining phenomena observed in laboratory- and sometimes even in field environments since Gode and Sunder [1993].[9]

To keep the main body of the paper brief, we summarize the four parameters in the model $(\alpha, \kappa, \phi, S)$ and provide a full description of the model in Appendix C.

$\alpha \in [0, 1]$ is an anchoring parameter. It captures how intensely agents anchor both their bids and asks towards previous trading prices. Agents in DÜ also anchor their bids and asks towards a uniformly distributed noise term, $\epsilon_t \sim U[0, \kappa FV_t]$, with weight $1 - \alpha$. Note that the noise term has mean $\kappa FV_t/2$ and is therefore centered around a multiple of the fundamental value in period $t$.

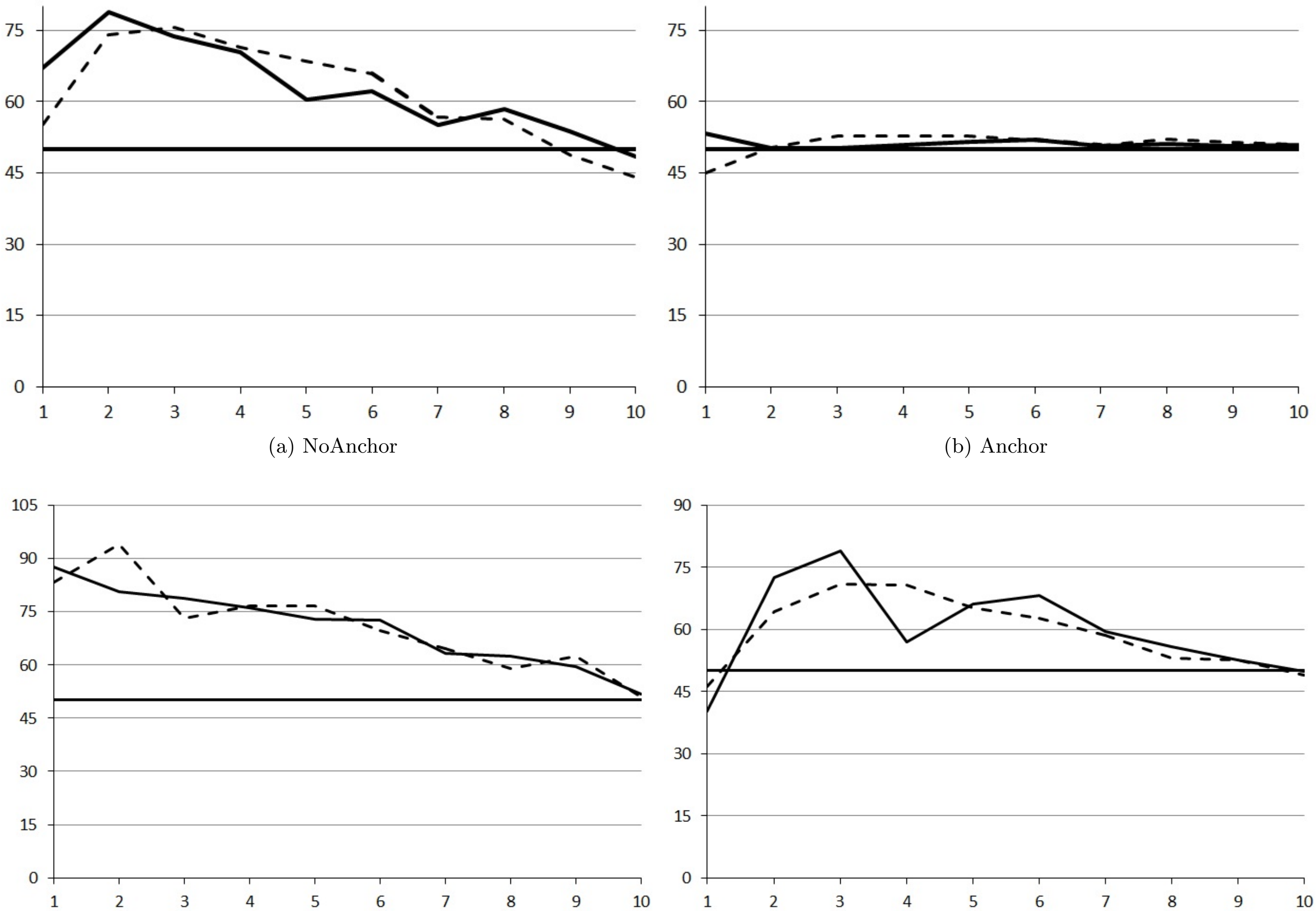
The parameter $\phi$ captures the notion of foresight. The greater is $\phi$, the quicker the agents switch from buying to selling the asset, taking the finite horizon of the experiment into account. If $\phi$ equals zero, they unsystematically buy or sell in every period with probability 1/2. The parameter $S$ keeps track of the trading volume, measuring the number of offers an agent makes in every trading period.

The model provides the basis to simulate prices and quantities for every period $t$, which will be denoted as $p_t(\alpha, \kappa, \phi, S)$ and $q_t(\alpha, \kappa, \phi, S)$.

Estimating these four parameters with our data will shed light on the extent to which agents anchor bids and asks on multiples of the fundamental value versus past prices. Examining how these estimated parameters change across treatments offers a structural and micro-founded interpretation of our results.

DÜ suggest estimating the parameters of the model by minimizing the sum of the squared deviations (SSD) between volume-weighted average experimental prices and quantities, $(\bar{p}_t, \bar{q}_t)$, and simulated prices and quantities stemming from the model, normalized by the fundamental value in period one $(FV_1)$ and

[9] For a review of the links between agent-based models and human subject experiments, see Axelrod and Tesfatsion [2006], Duffy [2006] or Hommes [2006]. Cason [1992] for example uses an agent based model to explain high efficiency levels in experimental call markets.



(a) NoAnchor (b) Anchor

(c) Anchor90 (d) Anchor10

Figure 3: Simulated Average Prices and Actual Average Prices. Dashed Lines: Simulations. Thick Lines: Actual Average Prices and Fundamental Values.

the total supply of units/shares (TSU):[10]

$$SSD(\alpha,\kappa,\phi,S)=\sum_{t=1}^{T}\left(\frac{\bar{p}_t(\alpha,\kappa,\phi,S)-\bar{p}_t}{FV_1}\right)^2+\sum_{t=1}^{T}\left(\frac{\bar{q}_t(\alpha,\kappa,\phi,S)-\bar{q}_t}{TSU}\right)^2, \quad (1)$$

The function given in (1) can be minimized with standard numerical methods.[11]

We estimate the parameters for the DÜ model using our data. Figures 3a - 3d in D illustrate the fitted values from the model and Table 4 shows the parameter estimates.

The first row in Table 4 shows the parameter estimates for our control treatment. We observe

[10] The length of the simulations is (like in DÜ) chosen to be 150. TSU is 400.

[11] In DÜ $S$ takes only discrete values. For every given $S \in \{1, 2, 3...10\}$, we used an interior-point algorithm based on Byrd et al. [2000, 1999] to find the minimizer. The global minimum was achieved by re-initiating the minimization procedure for several hundred starting points.

strong noise-anchoring ($1-\alpha \approx 0.9$), whereas the noise term is centered around the fundamental value ($\kappa \approx 2$). Under our control treatment we also observe low price-foresight ($\phi$) and therefore unsystematic purchase and sales decisions. Our estimates for the "NoAnchor-T4(\=)" treatment show less anchoring towards the fixed FV, a larger noise amplitude and an increased value for our foresight parameter $\phi$. The estimates for our "Anchor90-T4(\=)"-treatment (row 4 in Table 4) shows again more anchoring towards a multiple of the FV, which corresponds to the anchor set at 90.[12] The increase in the value of $\kappa$ for our "Anchor90-T4(\=)"-treatment is natural, since we anchor towards a multiple of the FV (90).

Table 4: Estimation Results, Own sessions.

| Treatment | $\alpha$ | $\kappa$ | $\phi$ | $S$ |
|---|---|---|---|---|
| "Anchor-T4(\=)" | 0.0910 | 2.331 | 0.0009 | 2 |
| "NoAnchor-T4(\=)" | 0.3741 | 4.832 | 0.0319 | 2 |
| "Anchor10-T4(\=)" | 0.4630 | 4.875 | 0.0307 | 2 |
| "Anchor90-T4(\=)" | 0.1140 | 5.274 | 0.021 | 2 |

Strikingly, our estimates for our "Anchor10-T4(\=)"-treatment (row 3 in Table 4) are very similar to our estimates from the NoAnchor-treatment. The latter insight suggests that behavior in experimental asset markets is similar in environments in which we set an anchor below the FV and in environments in which we set no anchor at all.

In summary, we conclude that visual stimuli provided in within-period price charts –in the first period only– have significant effects on price dynamics. Our estimation results from the DÜ model suggest that the mechanism through which those stimuli reduce bubbles is via anchoring. Our results do not only suggest that subjects are sensitive towards anchoring, but that anchors are fairly persistent. Anchoring prices towards the fundamental value in the first period, via visual stimuli, mitigates bubbles. Anchors set at levels which exceed the FV, lead to significantly more over-valuation than anchors set at levels which are below the FV.

In the following sections we argue that the same anchoring-mechanism generates the bubble-mitigation effects in the data of Kirchler et al. [2012].

# 4 Are Laboratory Asset-Price Bubbles Driven By Confusion?

The possible sources for the emergence of experimental asset price bubbles have been explored both theoretically and empirically. One branch in the literature suggests that experimental asset price bubbles emerge from the interaction of heterogeneous traders (e.g., Smith et al. [1988], Caginalp and Ilieva [2005], Ackert et al. [2006], Haruvy and Noussair [2006], Moinas and Pouget [2012], Baghestanian et al. [2012]). Another branch in the literature suggests that the observed price-dynamics are generated by subject-confusion and irrationality (e.g., Lei et al. [2001], Lei and Vesely [2009], Smith [2010], Oechsler [2010], Oechsler et al. [2011], Kirchler and Huber [2012], Kirchler et al. [2012]).

[12] To see this note that $(1-\alpha)\kappa FV/2$ –the expected price component induced by the exogenous anchor in the model– is 117.35 if $\phi = 0$.

Most recently Kirchler et al. [2012] provide intriguing evidence indicating that laboratory asset price bubbles, which emerge under the design of SSW, are primarily driven by confusion about the decreasing FV.[13]

KHS use a 2 × 2 experimental design to identify the effects of a decreasing FV and an increasing C/A ratio on the formation of bubbles in laboratory environments. In their benchmark treatment, denoted by T1(\+), KHS investigate the standard SSW environment in which the FV is declining and the C/A ratio is increasing. In their second treatment (T2(−+)) KHS keep the FV of the asset constant and increase the C/A ratio over time. In treatment T3(\=) KHS implement a double auction environment with declining FV and constant C/A ratio. In their fourth treatment (T4(−=)) the authors implement a constant FV and constant C/A environment.

For each treatment KHS present data on six experimental sessions. In each session 10 subjects participated and traded a single risky asset over a 10 period trading horizon. In each treatment half of the subjects received a cash endowment of 1000 Taler and a unit endowment of 60 shares. The other half received individual cash endowments of 3000 Taler and unit endowments of 20 shares. In treatments with declining FV the risky asset paid dividends of 0 or 10 Taler, each with a probability of 50%. In treatments with constant FV the asset paid dividends of -5 or 5 Taler, each with probability of 50%. KHS use a Taler-Euro conversion rate of 400:1.

KHS show an impressive consonance between constant FV and the emergence of bubbles. In treatments in which the FV is constant, bubbles essentially vanish. In treatments with declining FV the authors observe significant mis-pricing, measured via the "relative absolute deviation" (RAD).[14] However, only if the declining FV is coupled with an increasing C/A ratio over-valuation –measured via the "relative deviation" (RD)[15]– occurs. Formulas for RAD and RD are provided in Table 11.

The authors conclude that declining FV's coupled with increasing C/A ratios favor bubble-formation and provide additional suggestive evidence, which indicates that a declining FV fosters confusion. More specifically, the results in KHS are corroborated by a questionnaire revealing that many subjects incorrectly believed the declining FV would stay constant over time. Furthermore, KHS report that treatments, intended to reduce confusion by changing the notion of a "stock" to a "stock of a depletable gold mine," which served to instill the idea of a declining FV, mitigated bubble behavior (treatment T5($\backslash{=}_G$)).

In the following subsections we re-examine the results in KHS and offer an alternative explanation for the mechanism behind the bubble-mitigation effect reported by KHS.

### 4.1 Trader Type Distributions

In this section we investigate the individual data in KHS. We compare the trader type distributions across treatments, conjecturing that a "reduction in confusion" should be associated with a change in individual behavior and therefore in trader-type distributions. More specifically we would expect less heterogeneous trader type distributions in treatments which generate prices which are close to the homogeneous belief rational expectations equilibrium.

[13] Kirchler and Huber [2012] also attempt to identify sources for confusion among participants in laboratory asset markets and assert that instructions are particularly relevant.

[14] RAD= $\frac{1}{10}\sum_{t=1}^{10}\frac{|P_t-FV_t|}{mean(FV)}$, where $P_t$ denotes the average within period transaction price.

[15] RD= $\frac{1}{10}\sum_{t=1}^{10}\frac{P_t-FV_t}{mean(FV)}$, where $P_t$ denotes the average within period transaction price.

We determine the trader type distributions in the treatments of KHS using the model of DeLong et al. [1990] (DSSW), which consists of trend-chasers or feedback traders, fundamental traders and speculators.

Following DSSW and Haruvy and Noussair [2006] (HN),[16] the forms of the optimal demand functions, $D(\cdot)$, of trend chasers (feedback traders), fundamental traders (FV traders) and speculators are given in equations (2), (3) and (4), respectively:

$$D(p_{t-1}, p_{t-2}) = -\delta + \beta(p_{t-1} - p_{t-2}) \tag{2}$$

$$D(p_t) = -\alpha(p_t - FV_t) \tag{3}$$

$$D(p_{t+1}, p_t) = \gamma(\mathbb{E}(p_{t+1}) - p_t) \tag{4}$$

where $\delta, \beta, \alpha$ and $\gamma$ are all non-negative parameters and $\mathbb{E}(.)$ is the expectations-operator.[17]

Along the lines of HN we classify every subject (for every session separately) into one of the three types. For instance, if the change in a subjects' asset holdings has the same sign as the difference of the average transaction prices in period $t-1$ and $t-2$, that subject is classified as a trend-chaser for that particular period. Similarly, if the difference between the fundamental value of the asset in period $t$ and the average transaction price in period $t$ has the same sign as the change in a subjects' asset holdings, he or she is classified as fundamental trader in period $t$. Lastly, a subject is classified as speculator in period $t$ if the difference between the average transaction price in period $t+1$ and the average transaction price in period $t$ has the same sign as the change in a subjects' asset holdings for that period.[18]

Finally, the number of periods in which each subject belongs to every single type are counted, yielding a vector of three scores for every participant. A subject is classified as agent of the type for which he has the highest score, provided that the score is greater than or equal to 5.[19] If a subject has a maximum score lower than 5, that subject does not belong to any of the three types and is classified as "unsystematic" or noise. If a subject's maximum score is the same for two (three) types and is higher than 5, the participant is assigned a weight of 1/2 (1/3) to each type for which he has the same maximum score.

We present the overall type distributions for every treatment in Table 4 and Figure 4; The session specific type distributions are shown in Table 7 in Appendix A. First, note that the type distributions overall are very similar to the type distributions given in Table VI in Haruvy and Noussair [2006], in particular for Treatment 1, with the main exception that the fraction on non-systematic traders is overall higher in KHS.[20]

To test for differences between the type distributions we bootstrapped the p-values of the pairwise Kolmogorov-Smirnov test-statistics, correcting for the discreteness of the type-distributions (Gleser [1985], Arnold and Emerson [2011]). In every step of the bootstrap, which compared the type distribution under treatment $i$ and $j$, we generated 10,000 pseudo-samples (each of size 60) based on the individual type

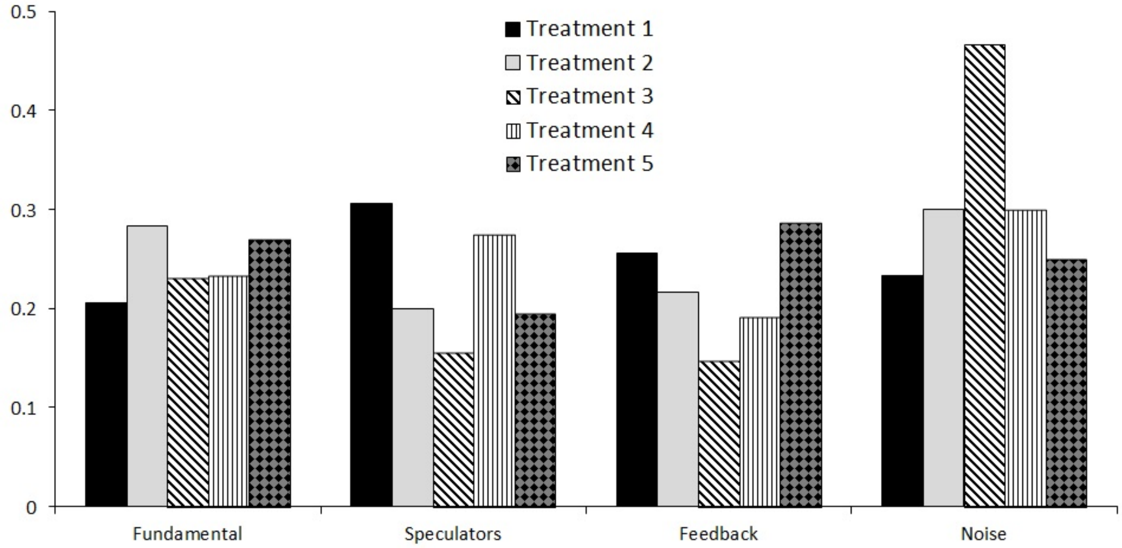
[16] See pages 1141 - 1142 in HN.

[17] Like in HN, for double auctions the prices above, $p_t$, are approximated by the average within-period transaction prices.

[18] Speculators are assumed to have perfect foresight.

[19] HN use a cutoff of 8 periods, but the trading horizon in KHS is only 10 periods, whereas it is 15 periods in HN.

[20] HN classify subjects in every period based on the assumption that changes in the asset holdings do not have the opposite sign as changes in the corresponding price (FV)-differences. Hence, if a subject neither buys or sells anything in a given period, he is classified as speculator, fundamental trader and feedback-trader in their setting. Our classification is more robust, since we demand that the changes in asset holdings have the *same* sign as the relevant differences in prices and/ or fundamental values.




| Treatment | FV-traders | Speculators | Trend-chasers | Noise | Sample Size |
|---|---|---|---|---|---|
| T1(\+) | 0.206 | 0.306 | 0.256 | 0.233 | 60 |
| T2(−+) | 0.283 | 0.200 | 0.217 | 0.300 | 60 |
| T3(\=) | 0.231 | 0.156 | 0.147 | 0.467 | 60 |
| T4(−=) | 0.233 | 0.275 | 0.192 | 0.300 | 60 |
| T5(\=$_G$) | 0.269 | 0.194 | 0.286 | 0.250 | 60 |

Figure 4 & Table 5: Trader Type Distributions by Treatment

distributions. Specifically, subject $k$ in treatment $j$ and session $s$ has an individual type distribution given by $p_{j,s,k}$ with $p^t_{j,s,k} \geq 0$ for every type $t \in \{1, 2, 3, 4\}$ and $\sum_{t=1}^{4} p^t_{j,s,k} = 1$.[21]

In every step of the bootstrap, which compared treatment $i$ and $j$, we drew for every individual a uniform random number, $u_k \sim U[0, 1]$. For treatment $j$, if $u_k \leq p^1_{j,s,k}$, individual $k$ has a trader-type 1 realization (FV-trader) for that particular draw; Whenever $u_k \leq p^1_{j,s,k} + p^2_{j,s,k}$ but $u_k \geq p^1_{j,s,k}$, individual $k$ has a type two realization (speculator) and so forth.

The generated pseudo-samples for both treatments were then used to compute the associated (again bootstrapped) p-value of the two-sample Kolmogorov-Smirnov (KS) test statistic for discrete distributions. We present the average p-values, $\bar{p}_{i,j}$, of the pairwise KS tests in Table 8 in Appendix A.

To test for significant differences, we counted the number of times the null hypothesis of equal distribution could be rejected at a 10%, 5% and 1% level. Strikingly, for none of the pairs, except the pair $(i, j) = (1, 3)$, could we reject the null hypothesis of equal distribution at a 10% level even once. For the pair (1,3), which compared the constant C/A ratio treatment to the benchmark SSW-treatment, every single p-value was below 0.1 and above 0.05, with an average p-value of 0.076. Put differently, there is no statistical evidence that the trader type distributions change across treatments, except possibly for treatment three.

Lastly, we re-applied the same method as above but replaced the KS-test with a two sample Cramer-von Mises test for discrete distributions (Choulakian et al. [1994], Lockhart et al. [2007]) and the results

[21]Whenever the HN-algorithm provides a unique type-identification for participant $k$, his individual type distribution degenerates at a certain type. For every treatment the number of non-exactly identifiable trader-types is below 10% (six subjects).

from above remain unchanged.

To test which type-fractions change from treatment one to three, we compared the marginal distributions of trader types via a standard $\chi^2$ test using again 10,000 newly generated pseudo-samples of treatments one and three. For each pair of pseudo samples we counted the number of (e.g.) FV traders in treatment one ($FV_1$) and three ($FV_3$). Letting $N_1$ ($N_3$) be the sample size under treatment one (three)[22], then under the null hypothesis of equal marginal distributions the expected number of FV-traders in treatment $i$ is $FV^e = N_i\bar{p} = N\bar{p}$,[23] where $\bar{p} = \frac{FV_1+FV_3}{N_1+N_3}$.

Based on these values, we compute for every step in the bootstrap the standard Pearson-$\chi^2$-statistic:

$$\chi^2 = \frac{(FV_1 - FV^e)^2}{FV^e} + \frac{(FV_3 - FV^e)^2}{FV^e}$$

Like with the previous test, we counted the number of times the resulting sequences of test-statistics exceeded the critical values for various significance levels. Only for the comparison of the marginal distributions of speculators and noise traders can we reject the null of equal marginal distributions across treatments. The test statistics, which compare the fraction of speculators and noise traders, exceed the 10% critical-value every single time in the bootstrap. For noise traders, the test statistics even exceed the 5% critical values every single time. The test statistics which compare FV traders and trend-chasers never exceed critical values associated with a 10% significance level.[24]

Hence, going from treatment one to three (i.e.: fixing the C/A ratio) goes hand-in-hand with a significant change in the trader type distribution, although only at a 10% level. The change is driven by a reduction in speculators and an increase in the number of unsystematic traders. None of the other treatments generate significantly different type distributions. In particular, the number of traders who condition their behavior on the fundamental value is remarkably stable across treatments. This is independent of whether the FV-process is decreasing or constant, or whether subjects trade stocks of a gold mine or not. We also do not observe an overall decrease in noisy or trend-chasing behavior across treatments involving constant FV, suggesting that the "reduced-confusion" argument, given by the authors, is not consistent with the micro-data. However, the results are consistent with the finding that an increase in the C/A ratio increases rational speculation (Caginalp et al. [1998, 2001]).

Before we discuss whether anchoring might generate the price patterns in KHS, we address one of the robustness checks presented by KHS.

#### 4.1.1 Trader Type Characteristics

KHS report individual results of a non-incentivized test in which subjects were asked to forecast the FV in the next period if the current FV is 50. Given the parameters in their experiments, the correct answers would be 45 in the decreasing FV treatments and 50 in the constant FV treatments. Using the individual type classifications from above, we again generated 10,000 pseudo-samples and compared the forecast accuracies (percentage terms) conditional on type and treatment, using a Mann-Whitney test in

[22] $N_1 = N_3 = 60$ in KHS.

[23] KHS have a fixed sample size of 60 subjects across treatments.

[24] The average test statistics to compare $FV$-traders, trend-chasers, speculators and noise traders are 0.149, 0.174, 3.417 and 4.667, respectively.

every step of the bootstrap.[25] Ex-ante, we would expect that subjects, who condition their behavior on the fundamental value of the asset during the experiment, have a better understanding of the FV process and therefore more accurate forecasts.

We present the average forecast-accuracies, conditional on type in Table 9 in Appendix A. The average p-values stemming from the pairwise Mann-Whitney comparisons are given in Table 10 in Appendix A.

The variability of the type-specific deviations are extremely small across the pseudo-samples and the null hypothesis of equal distribution cannot be rejected for most of the pairs at any reasonable significance level (less than or equal 0.1) for 90-100% of all bootstrap-repetitions. The only exception is treatment three in which fundamental traders have significantly better FV-forecast than speculators at a 10% significance level for all steps in the bootstrap.

Hence, controlling for heterogeneity, trading behavior in the experiments of KHS is overall uncorrelated with the answers subjects provided on the non-incentivized questionnaire.[26]

### 4.2 Anchoring in KHS

In this section we present an alternative anchoring-based explanation for some of the findings in Kirchler et al. [2012]. We estimate the parameters of (1) using the data of KHS.

Figures 5a - 5e show the average simulated and actual average trading prices, conditional on the estimated parameters in the model of Duffy and Ünver [2006] for every treatment. Table 6 shows the numerical values of the estimated parameters. Table 11 compares several simulated to actual bubble measures, which are frequently presented in the literature (Haruvy and Noussair [2006], Haruvy et al. [2007], Kirchler et al. [2010]).

The first row in Table 6 shows the parameter estimates under the benchmark-SSW treatment. We observe that the estimated noise-amplitude ($\kappa$) under the benchmark is numerically almost identical to the corresponding estimate provided in Duffy and Ünver [2006] (4.085), who use the data of SSW to determine the values of the parameters.[27] However, we observe more pronounced anchoring towards the FV in the data of KHS ($1-\alpha \approx 0.29$) than in the data of SSW, as determined by DÜ (0.15). As a matter

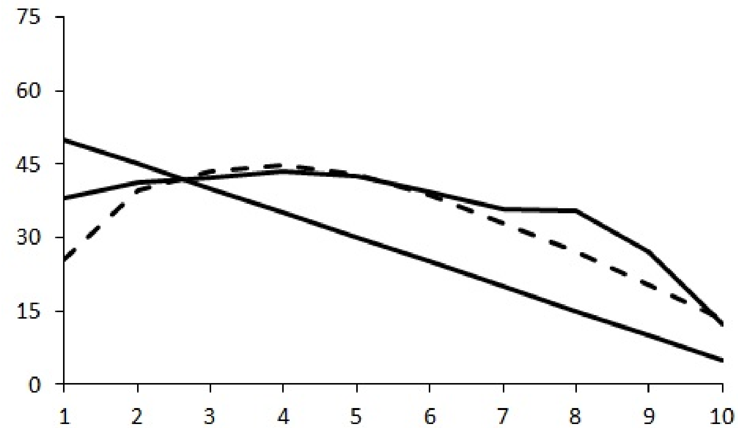
[25] For each subject we compute the forecast accuracy ($Acc_i$) as

$$Acc_i = \frac{\mathbb{E}^i(FV_2) - FV_2}{FV_2},$$

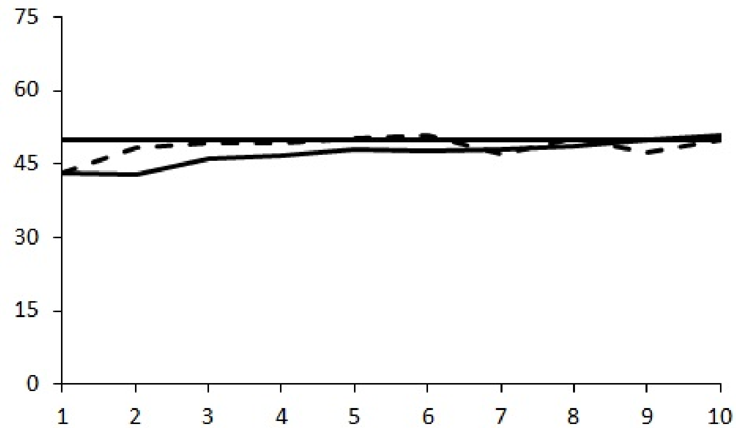
where $\mathbb{E}^i(.)$ represents the forecast of agent $i$ on the fundamental value in period 2 ($FV_2$) provided in the questionnaire. Next, we generate 10,000 pseudo samples as above and determine the average forecast error for every type and pseudo-sample.

[26] Furthermore, the authors report (see footnote 16 on page 876) that the forecasts of subjects about the FV are significantly different between treatments with constant and declining fundamental values. This assertion is not entirely complete. Focusing on treatments 1-4, the deviations between individual forecasts about the FV and the FV itself are significantly positive in treatments with declining FV. To be specific, a one-sided non-parametric sign-test on the deviations between individual forecasts and the FV gives a p-value of zero for the benchmark-SSW-treatment and a p-value of 0.0138 for treatment three. However, looking jointly at treatment two and four –which have constant fundamental values– , we cannot reject that the median of the forecast errors is significantly smaller than zero at a 5% level. To be specific, we use a simple non-parametric sign-test. The p-value of the joint test (using treatment two and four together) is 0.0328 for the two tailed test (i.e. testing the alternative that the median is unequal to zero). The p-value of the test is 0.0164 for the one-tailed test (i.e. testing the alternative that the median is less than zero). Put differently, subjects over-predict the FV in treatments with declining fundamental value and under-predict the FV in treatments with constant FV. It is not entirely clear why over-predicting the FV is a sign for confusion if the FV is decreasing, whereas under-predicting the FV in treatments in which the FV is constant is not a sign for confusion.

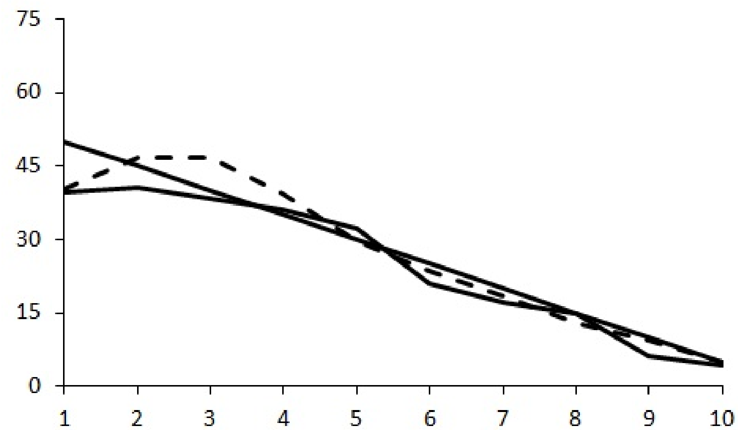
[27] See page 13 in Duffy and Ünver [2006].



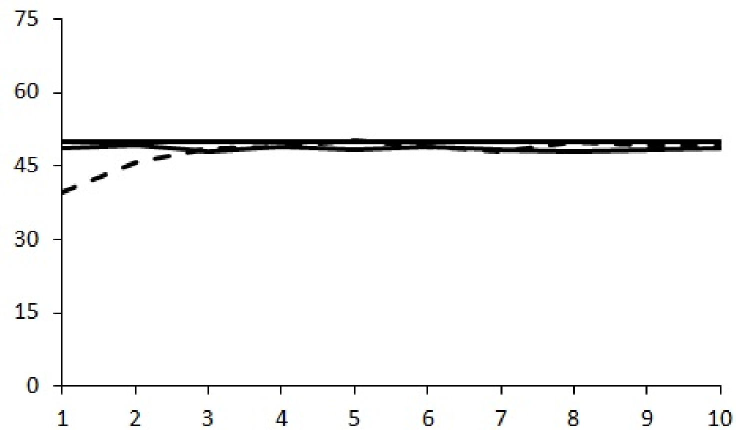

(a) Treatment T1(\+)



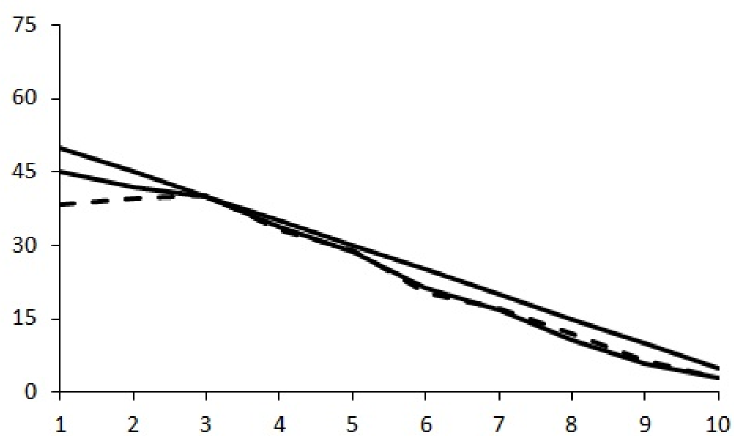

(b) Treatment T2(−+)




(c) Treatment T3(\=)




(d) Treatment T4(−=)




(e) Treatment T5($\backslash=_G$)

Figure 5: Simulated Average Prices and Actual Average Prices. Dashed Lines: Simulations. Thick Lines: Actual Average Prices and Fundamental Values.

Table 6: Estimation Results

| Treatment | $\alpha$ | $\kappa$ | $\phi$ | $S$ |
|---|---|---|---|---|
| T1(\+) | 0.7128 | 3.9851 | 0.0436 | 2 |
| T2(−+) | 0.0027 | 1.925 | 0.0083 | 2 |
| T3(\=) | 0.3381 | 3.2014 | 0.0304 | 1 |
| T4(−=) | 0.1854 | 2.1390 | 0.0014 | 2 |
| T5(\=$_G$) | 0.2108 | 2.7754 | 0.0223 | 2 |

of fact, in comparison to SSW, the anchoring towards the FV is almost twice as high for KHS.[28] Overall, going from the benchmark treatment to treatment two (constant FV, increasing C/A ratio), decreases price anchoring and increases noise-anchoring, whereas the noise term is centered around the fundamental value ($\kappa \approx 2$). It also decreases price-foresight ($\phi$) and therefore leads to less systematic purchase and sales decisions ($\phi$ decreases). A similar pattern emerges comparing the benchmark treatment to treatment four (also constant fundamental value).

Anchoring bids or asks towards a noise term, which is centered around the fundamental value, could in principle indicate more rational behavior, in which agents condition their purchase and sales decision on the FV of the asset.[29] However, the previous section has shown that the fraction of FV traders, whose behavior would be consistent with individual rationality and common knowledge thereof, is stable and unchanged across treatments.

Relative to the benchmark treatment, treatment three (constant C/A) has a similar noise amplitude ($\kappa$), subjects have similar foresight ($\phi$) and anchor their bids and asks towards the price history although less than under the benchmark. Similar, although slightly less pronounced, patterns emerge under treatment 5 (gold-framing).

We can use our estimated DÜ model to isolate the proportion of the changes in overvaluation (measured by RD)[30] and mis-pricing (measured by RAD) attributable to the specific experimental design of KHS and attributable to changes in behavior.

To disentangle design- from behavioral-effects, we first compute for every simulated treatment average RAD- and RD-measures, using the estimated parameters from Table 6. The values are given in column 2 in Table 12 and will be denoted $RD_i$ and $RAD_i$ for treatment $i$. We then fix and use the estimated parameters under the benchmark treatment (first row Table 6) and simulate the prices and quantities emerging under treatment 2-4 as described in KHS. This generates prices under the various treatments, assuming unchanged behavior relative to the SSW-benchmark. For each of those counterfactual-simulations we again compute average RD and RAD. These values are given in column three ("counterfactual") in Table 12 and will be denoted $\overline{RD}_i$ and $\overline{RAD}_i$.

We then compute the overall percentage change ($OC_i$ for treatment $i$) in the bubble-measures, relative

[28] We also observe that the estimate for $\phi$ is higher for KHS, which is related to the fact that the authors consider a trading horizon of 10 periods and SSW consider a trading horizon of 15 periods.

[29] Bossaerts et al. [2007] provide a CAPM+$\epsilon$ model, which would generate predictions, which are consistent with this view.

[30] KHS measure overvaluation via relative deviation, RD, and quantify mis-pricing via the relative absolute deviation, RAD (see Table 11 for the details on the measures).

to the benchmark treatment. For $RD$ (analogous computations are performed for $RAD$) this would be:

$$OC_i^{RD} = \frac{RD_1 - RD_i}{RD_1} \qquad i = 2, 3, 4.$$

The corresponding values are given in column four of Table 12. We also compute the percentage change between the benchmark and the counterfactual model:

$$\overline{OC}_i^{RD} = \frac{RD_1 - \overline{RD}_i}{RD_1} \qquad i = 2, 3, 4.$$

Lastly, we obtain the design-specific component ($\Delta^i_{Design}$ for treatment $i$), that contributes to the overall change in the bubble measure, as the fraction of the overall change that can be explained by the counterfactual:

$$\Delta^i_{Design} = \frac{\overline{OC}_i^{RD}}{OC_i^{RD}} \qquad i = 2, 3, 4,$$

and similarly for RAD. The behavioral components are then simply

$$\Delta^i_{Behavior} = 1 - \Delta^i_{Design} \qquad i = 2, 3, 4,$$

which are given in the last column on Table 12.

The results suggest that constant fundamental values alone contribute to a decrease in overvaluation (mis-pricing) of about 47% (46%). The remaining decrease can be attributed to the associated behavioral changes. Constant C/A ratios alone lead to a decrease in overvaluation of about 72% but lower mis-pricing only by about 44%. Behavioral changes generate the remaining mitigation effects.

Overall, the results provide suggestive evidence, indicating that constant fundamental values put a comparatively large weight on behavioral changes, identified as increased anchoring and less systematic sales and purchase decisions. Constant C/A ratios have, ceteris-paribus, a strong negative impact on overvaluation via the design channel.

We conclude that seemingly innocuous anchors can have important effects on price dynamics in experimental asset markets.[31]

Our insights suggest that if prices are initiated in the rational expectations equilibrium (e.g. via anchoring), prices stay close to the FV over the course of the entire trading horizon and bubbles tend to vanish. This observational equivalence with the price-prediction under the homogeneous beliefs rational expectations equilibrium is not generated by more rational trading behavior. If anchoring is not induced in the first period, prices tend to show standard bubble-crash patterns usually observed in laboratory asset markets, even if the FV is constant. These observations are consistent with the view that bubble-crash patterns in laboratory environments are sparked by initial price-momentum or an initial deviation from the rational expectations equilibrium. We support the latter claim with our "Anchor10-T4(\=)" and "Anchor90-T4(\=)" treatments.

[31] Our insights suggest that subtle details in the design of the graphical interface, not the graphical representation of trading prices in general, favor anchoring but do not necessarily result in more systematic trading behavior.

## 5 Conclusion

We show that setting an anchor at the FV in price charts, in the first period only, is sufficient to eliminate or to significantly mitigate bubbles in experimental asset markets. However, individual trading behavior is equally unsystematic, independently of whether we observe prices which are anchored or not. Our results further indicate that bubble-crash dynamics in laboratory environments are sparked by an initial deviation of asset prices from the homogeneous beliefs, rational expectations equilibrium. We argue that our results can be related to IPO's and the relationship between opening prices and intra-day price dynamics on stock exchanges.

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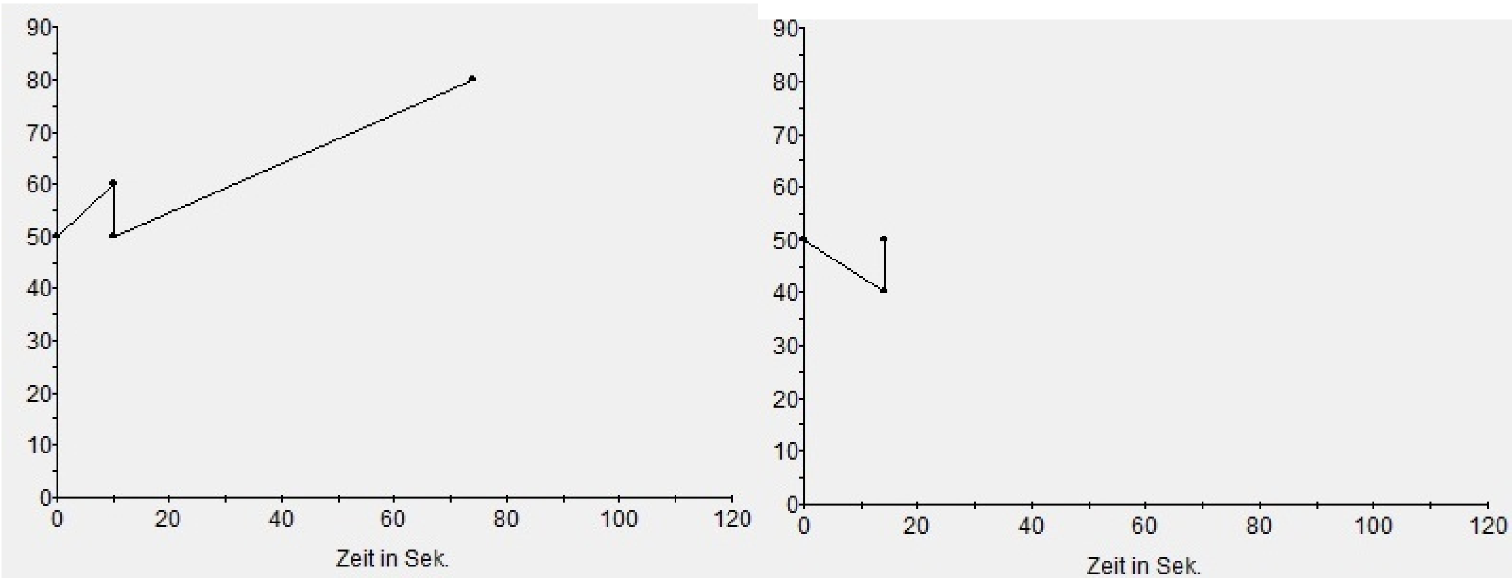
# 6 Appendix A (For Online Publication)




(a) First Price $> FV = 50$ (b) First Price $< FV = 50$

Figure 6: Price Initiation and jump-back component, KHS (Screenshots, Experimental software).

Table 7: Detailed Type Distributions

| Treatment | FV-traders | Speculators | Trend Chasers | Noise |
|---|---|---|---|---|
| 1 | 0.100 | 0.400 | 0.300 | 0.200 |
| 1 | 0.200 | 0.350 | 0.250 | 0.200 |
| 1 | 0.300 | 0.250 | 0.150 | 0.300 |
| 1 | 0.250 | 0.300 | 0.150 | 0.300 |
| 1 | 0.150 | 0.300 | 0.450 | 0.100 |
| 1 | 0.233 | 0.233 | 0.233 | 0.300 |
| 2 | 0.200 | 0.150 | 0.250 | 0.400 |
| 2 | 0.300 | 0.300 | 0.100 | 0.300 |
| 2 | 0.300 | 0.150 | 0.350 | 0.200 |
| 2 | 0.400 | 0.200 | 0.200 | 0.200 |
| 2 | 0.250 | 0.300 | 0.150 | 0.300 |
| 2 | 0.250 | 0.100 | 0.250 | 0.400 |
| 3 | 0.100 | 0.100 | 0.300 | 0.500 |
| 3 | 0.200 | 0.200 | 0.100 | 0.500 |
| 3 | 0.433 | 0.033 | 0.233 | 0.300 |
| 3 | 0.150 | 0.250 | 0.100 | 0.500 |
| 3 | 0.200 | 0.150 | 0.050 | 0.600 |
| 3 | 0.300 | 0.200 | 0.100 | 0.400 |
| 4 | 0.300 | 0.400 | 0.100 | 0.200 |
| 4 | 0.200 | 0.250 | 0.150 | 0.400 |
| 4 | 0.050 | 0.100 | 0.350 | 0.500 |
| 4 | 0.250 | 0.300 | 0.050 | 0.400 |
| 4 | 0.150 | 0.450 | 0.300 | 0.100 |
| 4 | 0.450 | 0.150 | 0.200 | 0.200 |
| 5 | 0.400 | 0.200 | 0.200 | 0.200 |
| 5 | 0.333 | 0.183 | 0.283 | 0.200 |
| 5 | 0.250 | 0.250 | 0.300 | 0.200 |
| 5 | 0.233 | 0.133 | 0.433 | 0.200 |
| 5 | 0.300 | 0.200 | 0.200 | 0.300 |
| 5 | 0.100 | 0.200 | 0.300 | 0.400 |

Table 8: Pairwise KS-tests, Bootstrapping approach

| Treatments | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | - | 0.964 | 0.076 | 0.994 | 0.896 |
| 2 | - | - | 0.374 | 0.960 | 0.991 |
| 3 | - | - | - | 0.375 | 0.117 |
| 4 | - | - | - | - | 0.719 |
| 5 | - | - | - | - | - |

Table 9: Average Forecast Accuracies Per Type and Treatment

| Treatment → | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| FV-traders | 0.073 | 0.061 | 0.056 | 0.032 | 0.053 |
| Speculators | 0.070 | 0.047 | 0.122 | 0.031 | 0.033 |
| Trend-Chasers | 0.072 | 0.054 | 0.083 | 0.039 | 0.041 |
| Noise | 0.103 | 0.033 | 0.079 | 0.044 | 0.059 |

Table 10: Pairwise Comparison Forecast Errors. P-values, Mann-Whitney Tests

| Treatment | Types | FV-traders | Speculators | Trend Chasers | Noise |
|---|---|---|---|---|---|
| 1 | FV-traders | - | - | - | - |
| 1 | Speculators | 0.985 | - | - | - |
| 1 | Trend-Chasers | 1 | 0.968 | - | - |
| 1 | Noise | 0.188 | 0.103 | 0.126 | - |
| 2 | FV-traders | - | - | - | - |
| 2 | Speculators | 0.682 | - | - | - |
| 2 | Trend Chasers | 0.777 | 0.939 | - | - |
| 2 | Noise | 0.147 | 0.278 | 0.329 | - |
| 3 | FV-traders | - | - | - | - |
| 3 | Speculators | 0.054 | - | - | - |
| 3 | Trend Chasers | 0.234 | 0.310 | - | - |
| 3 | Noise | 0.156 | 0.213 | 0.986 | - |
| 4 | FV-traders | - | - | - | - |
| 4 | Speculators | 0.899 | - | - | - |
| 4 | Trend Chasers | 0.671 | 0.602 | - | - |
| 4 | Noise | 0.859 | 0.751 | 0.873 | - |
| 5 | FV-traders | - | - | - | - |
| 5 | Speculators | 0.248 | - | - | - |
| 5 | Trend Chasers | 0.533 | 0.643 | - | - |
| 5 | Noise | 0.925 | 0.277 | 0.539 | - |

# 7 Appendix B (For Online Publication)

Table 11: Bubble Measure Comparison: Data vs. Simulations. With the exception of RPD (Relative Price Deviation), all measures are based on Haruvy and Noussair [2006], Haruvy et al. [2007] and Kirchler et al. [2010]. $P_t$ denotes the average trading price in period $t$, $q_t$ denotes the trading volume in period $t$, TSU denotes the total stock of units (400 in KHS).

| Measure | Treatment 1 | | Treatment 2 | | Treatment 3 | | Treatment 4 | | Treatment 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Data | Sim | Data | Sim | Data | Sim | Data | Sim | Data | Sim |
| Turnover= $\sum_{t=1}^{10} q_t/TSU$ | 2.060 | 1.813 | 2.318 | 1.402 | 1.435 | 1.348 | 2.094 | 1.912 | 2.195 | 1.946 |
| Amplitude= $\max_t \left\{\frac{(P_t-FV_t)}{FV_t}\right\} - \min_t \left\{\frac{(P_t-FV_t)}{FV_t}\right\}$ | 1.995 | 2.107 | 0.173 | 0.157 | 1.036 | 0.369 | 0.039 | 0.214 | 0.548 | 0.398 |
| APD= $\frac{1}{TSU}\sum_{t=1}^{10} \lvert P_t - FV_t \rvert$ | 0.285 | 0.283 | 0.099 | 0.04 | 0.210 | 0.088 | 0.034 | 0.056 | 0.108 | 0.091 |
| PD= $\frac{1}{TSU}\sum_{t=1}^{10} (P_t - FV_t)$ | 0.204 | 0.132 | -0.075 | -0.037 | -0.028 | 0.005 | -0.033 | -0.06 | -0.048 | -0.09 |
| RAD= $\frac{1}{10}\sum_{t=1}^{10} \frac{\lvert P_t-FV_t\rvert}{mean(FV)}$ | 0.414 | 0.411 | 0.079 | 0.035 | 0.305 | 0.127 | 0.027 | 0.045 | 0.157 | 0.132 |
| RD= $\frac{1}{10}\sum_{t=1}^{10} \frac{(P_t-FV_t)}{mean(FV)}$ | 0.296 | 0.192 | -0.060 | -0.029 | -0.040 | 0.008 | -0.027 | -0.044 | -0.069 | -0.130 |
| RPD= $\frac{1}{10}\sum_{t=1}^{10} \frac{\lvert P_t-FV_t\rvert}{FV_t}$ | 0.666 | 0.605 | 0.079 | 0.035 | 0.433 | 0.105 | 0.027 | 0.045 | 0.214 | 0.173 |

Table 12: Design and Behavior Decomposition

| Overvaluation: RD | | | | | |
|---|---|---|---|---|---|
| Benchmark: 0.192 (SSW- Treatment 1) | | | | | |
| Treatment | RD | Counterfactual | Overall Change | $\Delta^i_{Design}$ | $\Delta^i_{Behavior}$ |
| 2 | -0.029 | 0.087 | 1.153 | 0.473 | 0.527 |
| 3 | 0.008 | 0.060 | 0.959 | 0.717 | 0.283 |
| 4 | -0.044 | -0.124 | 1.230 | 0.895 | 0.105 |
| Mis-pricing: RAD | | | | | |
| Benchmark: 0.411 (SSW- Treatment 1) | | | | | |
| Treatment | RAD | Counterfactual | Overall Change | $\Delta^i_{Design}$ | $\Delta^i_{Behavior}$ |
| 2 | 0.035 | 0.240 | 0.914 | 0.455 | 0.545 |
| 3 | 0.127 | 0.287 | 0.690 | 0.438 | 0.562 |
| 4 | 0.045 | 0.149 | 0.891 | 0.937 | 0.063 |

# 8 Appendix C (For Online Publication)

In this section, the market environment as well as agents' behavior are described, following Duffy and Ünver [2006].

In the market environment of KHS, $N = 10$ agents interact in $T = 10$ periods and trade a single financial asset. Initially each agent $i$ is endowed with $x_0^i$ units of cash and $y_0^i$ units of the financial asset (for details on the endowment design we refer to KHS).

At the end of every period the asset pays random dividends drawn with equal probability from a commonly known support $\Theta_D$. The expected dividend is denoted as $\bar{d}$. The fundamental value of the asset in every period is common knowledge and given by

$$FV_t = \bar{d}(T - t + 1) + TV \quad \text{for} \quad t = 1, ..., T,$$

where TV denotes the terminal value of the asset. Note that the notation is sufficiently flexible to cover the decreasing, as well as the constant FV framework. Under rational expectations and risk neutrality, prices should equal the fundamental value.

In every trading period $t = 1, ..., T$ traders may either buy or sell units of the financial asset (or remain inactive). During a standard double auction, traders are allowed to submit both bids and asks, potentially for multiple units. To capture this feature in the simulations, Duffy and Ünver [2006] subdivide each trading period into $S$ submission rounds.

In each of the $s = 1, ..., S$ submission rounds a trader is either a seller or a buyer with probability $\pi_t = \max\{0.5 - \phi(t-1), 0\}$, where $\phi \in [0, 0.5/T)$. Trader $i$ in submission round $s$ and trading period $t$ can submit an ask price, $a^i_{s,t}$, for $q^i_{a,s,t}$ units of the asset if he is a seller and may submit a bid, $b^i_{s,t}$ for $q^i_{b,s,t}$ units of the asset , if he is a buyer. Bids can only be submitted if the trader has a sufficient cash balance and asks can only be submitted if the trader has a positive unit-balance. Note that in DÜ, agents can only submit bids and asks for one unit of the asset (as in the standard SSW-design). However, subjects in KHS were allowed to submit bids and asks for several units, which is why we adapted the DÜ environment. The bids in DÜ take the following form:

$$b^i_{s,t} = \min\left\{(1-\alpha)\epsilon_t + \alpha p_{t-1}, x^i_{s,t}\right\}, \tag{5}$$

where $\alpha \in [0, 1]$, $\epsilon_t \sim U[0, \kappa FV_t]$, $\kappa \geq 0$ is a parameter, $x^i_{s,t}$ denotes the current cash holdings of agent $i$, and $p_{t-1}$ is the market-clearing price in period $t-1$.[32] No bid is submitted by a buyer whenever his cash holdings are zero, i.e., if $x^i_{s,t} = 0$. The bid quantities are determined as follows:

$$q^i_{b,s,t} = \min\left\{B_i, TSU - y^i_{s,t}\right\} \qquad B_i \sim \bar{U}[0, \frac{x^i_{s,t}}{b^i_{s,t}}], \tag{6}$$

where $\bar{U}$ denotes the discrete uniform distribution, TSU is the total stock of units in the market and $y^i_{s,t}$ are the units currently held by trader $i$. If the realization of $B_i$ equals zero, that trader did not submit a bid.

Similarly, if a trader is selected to be a seller in trading round $t$ and submission period $s$, he submits an ask subject to unit holdings. His ask is of the form

$$a^i_{s,t} = (1-\alpha)\epsilon_t + \alpha p_{t-1}, \tag{7}$$

where $\alpha \in (0, 1)$ and $\epsilon_t \sim U[0, \kappa FV_t]$. No ask is submitted by the seller whenever his unit holdings are zero, i.e., if $y^i_{s,t} = 0$. The ask quantities are determined as follows:

$$q^i_{a,s,t} = A_i \qquad A_i \sim \bar{U}[0, y^i_{s,t}], \tag{8}$$

where $\bar{U}$ denotes the discrete uniform distribution and $y^i_{s,t}$ are the units currently held by trader $i$. If the realization of $A_i$ equals zero, that trader did not submit an ask.

Trading proceeds as follows (we provide a verbal description here, a technical description can be found in Duffy and Ünver [2006] and in the detailed documentation of the Matlab code provided in the

[32] DÜ assume that $p_0 = 0$.

supplemental material): In each trading round $s$ of period $t$, traders submit either bids or asks (depending on whether they are buyers or sellers), which are collected in the order book. The highest bid price is the current best bid and the highest ask is the current best ask together with the associated quantities. Orders are ranked conditional on price.

If there is currently a best ask available (see below) and a buyer submits a bid, that exceeds the current best ask (indicating that he is willing to pay more than the current best ask), trade takes place at the current best ask. If the bidding quantities exceed the associated offer-quantities (individual demand would potentially exceed individual supply at the best current ask), the second lowest ask price and the associated quantities become the best current ask offer (the entire order was filled, a new order needs to become the best current ask). Note that the trading quantities in this case are capped at the corresponding ask-quantities, not the demand quantities.[33] If the bid-quantities do not exceed the offer-quantities, (e.g.: the current best ask involves 12 units and the buyer only wants to purchase 5 units), trade takes place at the current best ask price and the bid-quantities (demand) are filled. The offer quantities are appropriately updated but the current best ask price remains unchanged (in the previous example the ask quantities are reduced to 7). If a buyer submits a bid, which does not exceed the best current ask price but is higher than all other bids in the order book, that buyers bid becomes the best current bid (price and quantity). Otherwise the bid is collected in the order book.

If there is a best current bid available and a seller submits an ask price that is lower than the best current bid price (indicating that he is willing to sell at prices below the current best ask) , trade takes place at the current best bid. If the ask quantities exceed the associated best-bid-quantities (individual supply would potentially exceed individual demand at the best current bid), the second highest bid price and the associated quantities become the best current bid offer (the entire order was filled, a new order needs to become the best current bid). Note that the trading quantities in this case are capped at the corresponding bid-quantities, not the supply quantities.[34] If the ask-quantities do not exceed the best-bid-quantities, (e.g.: the current best bid involves 12 units and the seller only wants to sell 5 units), trade takes place at the current best bid price and the ask-quantities (supply) are delivered. The best-bid-quantities are appropriately updated but the current best bid price remains unchanged (in the previous example the bid quantities are reduced to 7). If a seller submits an ask, which is not below the best current ask price but is lower than all other asks in the order book, that sellers bid becomes the best current ask (price and quantity). Otherwise the ask is collected in the order book.

After every trade, the cash and unit balances are appropriately updated. At the end of the period (after $S$ trading rounds) the cash holdings are also updated. In the standard SSW-design this would imply that:

$$x^i_{1,t+1} = x^i_{S,t} + D_t y^i_{S,t},$$

where $D_t$ is the dividend realization in period $t$. In the non-standard KHS-design, dividends were sometimes collected in a separate dividend account. In treatment two the cash-holdings were updated as

[33] If there is no second lowest ask price in the order book (no ask available), then the next submitted ask price (which is not lower than the best current bid price ), becomes the best current ask price.

[34] If there is no second highest bid price in the order book (no bid available), then the next submitted bid price (which is not higher than the best current ask price), becomes the best current bid price.

follows:

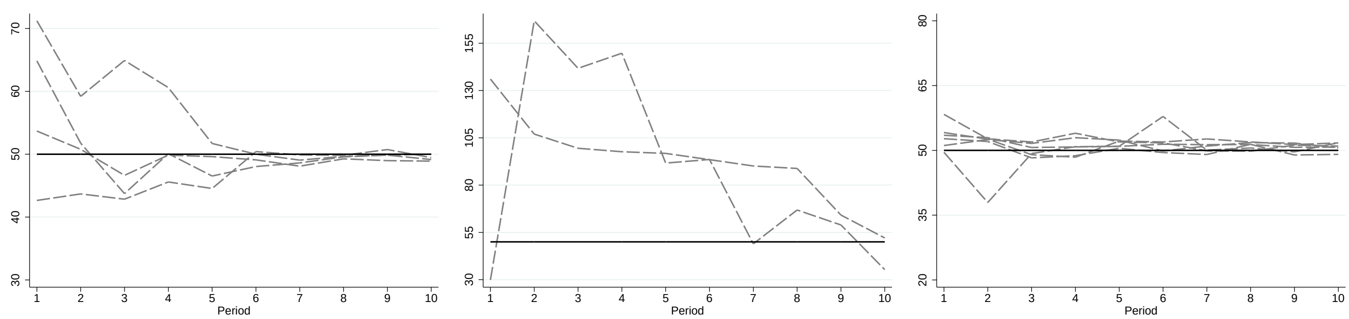
$$x^i_{1,t+1} = x^i_{S,t} + W,$$

in every period to keep the C/A ratio increasing ($W = 2000$), while the FV-process was kept constant: $\Theta_D = \{-5, 5\}$, $TV = 50$. In treatment 3 the FV process was decreasing and the C/A ratio was kept constant by updating the cash holdings as follows (again dividend payments went to a separate account):

$$x^i_{1,t+1} = x^i_{S,t} - w,$$

where $w = 200$. In treatment four the updating is trivial and self explanatory, given that the FV and the C/A ratio are kept constant.

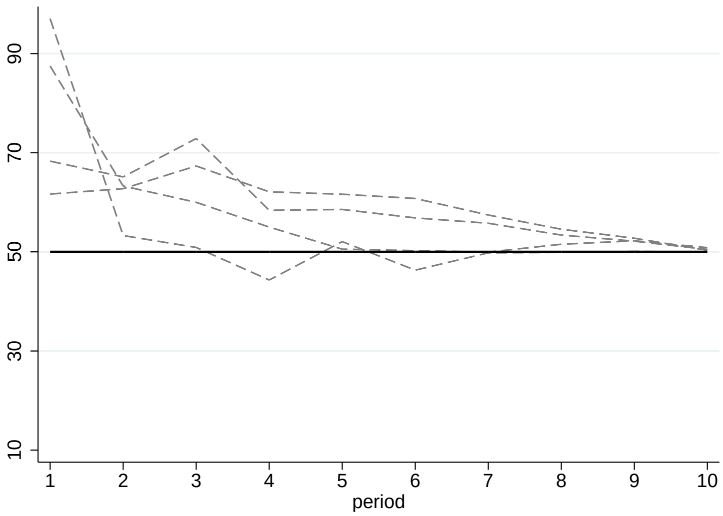
# 9 Appendix D (For Online Publication)



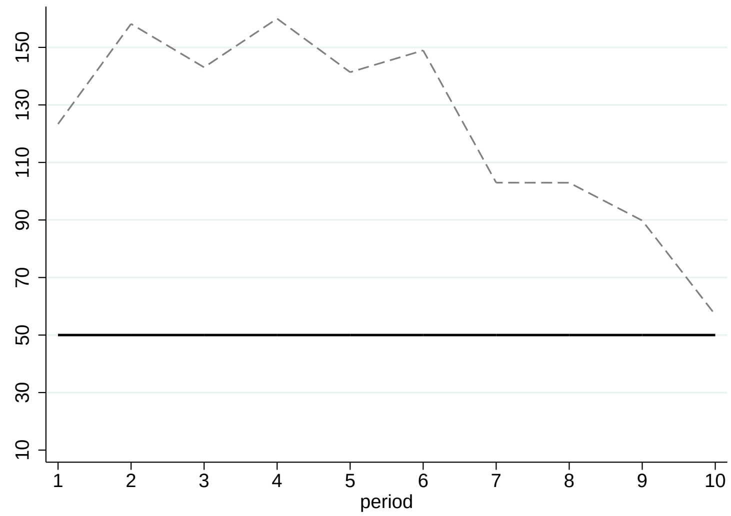

(a) Session Prices (1 - 4); NoAnchor. (b) Session Prices (5 - 6); NoAnchor. (c) Session Prices (1 - 6); Anchor

Figure 7: Dashed Lines: Session-Prices. Solid Lines: FV (50). Figures 7a - 7b: NoAnchor. Figure 7c: Anchor.

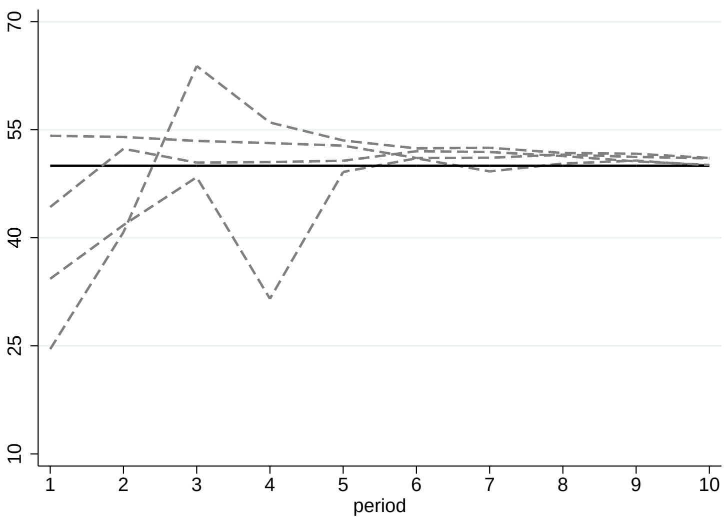
Figures 7a - 7b show the session specific, volume-weighted average transaction prices in the "NoAnchor"-treatment. Figure 7a shows prices for four of our sessions, which also include the sessions with 7 and 9 subjects. Figure 7b shows prices of 2 fairly extreme sessions under our "NoAnchor" treatment (Both sessions had 10 subjects). Figure 7c shows the price dynamics for our "Anchor"-treatments. Figures 8a - 8d show the session specific, volume-weighted average transaction prices in the "Anchor90"- and 'nchor10"-treatments.



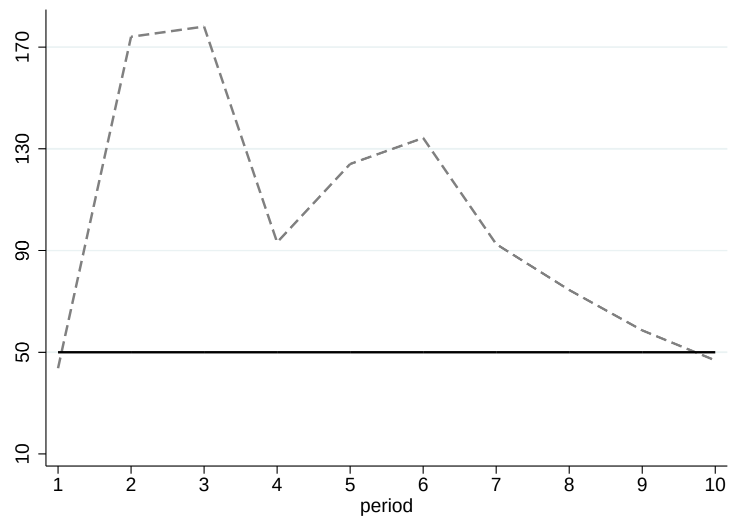

(a) 4 regular sessions: Anchor90




(b) 1 extreme session: Anchor90




(c) 4 regular sessions: Anchor10




(d) 1 extreme session: Anchor10

Figure 8: Dashed Lines: Session-Prices. Solid Lines: FV (50). Figures 8a - 8b: Anchor at 90. Figures 8c - 8d: Anchor at 10.

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