

SPECULATION AND PRICE INDETERMINACY IN FINANCIAL MARKETS:
AN EXPERIMENTAL STUDY

By

Shinichi Hirota, Juergen Huber, Thomas Stöckl and Shyam Sunder

May 2018

COWLES FOUNDATION DISCUSSION PAPER NO. 2134



COWLES FOUNDATION FOR RESEARCH IN ECONOMICS
YALE UNIVERSITY
Box 208281
New Haven, Connecticut 06520-8281

<http://cowles.yale.edu/>

Speculation and Price Indeterminacy in Financial Markets: An Experimental Study*

Shinichi Hirota[†] Juergen Huber[‡] Thomas Stöckl[§] Shyam Sunder^{**}

May 31, 2018

Abstract

To explore how speculative trading influences prices in financial markets we conduct a laboratory market experiment with speculating investors (who do not collect dividends and trade only for capital gains) as well as dividend-collecting investors. We find that in markets with only speculating investors (i) price deviations from fundamentals are larger; (ii) prices are more volatile; (iii) the “mispricing” is likely to be strategic and not irrational; (iv) mispricing increases with the number of transfers until maturity; and (v) speculative trading pushes prices upward (downward) when liquidity is high (low).

Keywords: Experimental finance; speculation; rational expectations; price efficiency; price bubbles; overlapping generations; backward and forward induction.

JEL-Classification: C91; G11; G12.

* We thank Kohei Kawamura and participants at the Yale School of Management Faculty Workshop, seminars at Tinbergen Institute, Aoyamagakuin, Hitotsubashi, the Experimental Finance Conference 2014 and 2016, NFA meeting 2015, London School of Economics, and Barcelona GSE Summer Forum 2016 for helpful comments. Financial support from the Austrian National Bank (OeNB grant 14953, Huber), JSPS KAKENHI (Grant Number 26590052, Hirota), UniCredit (Modigliani Research Grant, 4th edition, Stöckl) and Yale University (Sunder) are gratefully acknowledged. The experimental data are available from the authors.

[†] School of Commerce, Waseda University, 1-6-1 Nishiwaseda, Shinjuku, Tokyo, 169-8050, Japan; shirota@waseda.jp.

[‡] Department of Banking and Finance, University of Innsbruck, Universitaetsstrasse 15, 6020 Innsbruck, Austria; juergen.huber@uibk.ac.at.

[§] MCI Management Center Innsbruck, Universitaetsstrasse 15, 6020 Innsbruck, Austria; thomas.stoeckl@mci.edu.

^{**} Yale School of Management, 165 Whitney Avenue, New Haven, Connecticut, 06511, USA; shyam.sunder@yale.edu.

1. Introduction

Speculators are short-term participants in financial markets focused on capital gains. Their valuation of a security depends on future price expectations which are sensitive to noisy information, higher order expectations, and even recent price changes. Therefore, in a market populated by speculators, stock prices can be susceptible to excess volatility and bubbles (Keynes 1936, Shiller 2000, Stiglitz 1989). Standard finance theory, however, does not associate these phenomena with speculation. Even short-term speculators are assumed to form rational expectations of future prices; they form iterated expectations from near to distant future generations and conduct backward induction to arrive at the present value of the security. In the resulting rational expectation equilibrium (REE) prices are equal to fundamental values (Adam and Marcet 2011, Brealey et al. 2014, Tirole 1982).

The REE outcomes depend on the assumption of common knowledge of rational expectations among all generations of investors (Cheung et al. 2014, Smith et al. 1988, Sutan and Willinger 2009): investors not only form rational expectations themselves, but also believe that all subsequent generations of investors also do the same. However, common knowledge of rationality among agents is rarely achieved in practice (Aumann 1995, Geanakoplos 1992). In experimental studies backward induction often fails due to a lack of common knowledge of rationality in several types of games, such as the centipede game (McKelvey and Palfrey 1992), bargaining games (Johnson et al. 2002), and the beauty contest game (Nagel 1995, Camerer 2003).

Given this background, the assumption of common knowledge of rational expectations among generations of investors is too strong to hold in practice. Without it, short-term speculators should have difficulty in backward induction and prices should no longer be anchored to the fundamental value and may wander away.

In this paper, we examine whether speculation causes price indeterminacy in financial markets. We conduct a laboratory experiment because it is not possible to distinguish capital gains-focused speculative trading from non-speculative trading in field data. Even if we can identify speculative trading and its effect on price volatility, it is difficult to know whether it arises from investors' difficulty in forming rational expectations.¹ Furthermore, the fundamental value of the security to serve as a benchmark for measuring mispricing is rarely identifiable in the field.² We therefore chose the experimental approach where we can control the presence of speculating investors, focus on the feasibility of rational expectations, and define the asset's fundamental value in the laboratory.

Although there have been numerous asset market experiments, the question whether speculation causes price volatility or bubbles remains unresolved. In the most commonly used design, introduced by Smith et al. (1988), price bubbles have been observed frequently and some researchers (including Smith et al. 1988) interpreted the bubbles as a result of speculative trading on others' irrationality. However, in their experimental setting, it is difficult to judge whether the bubbles occur due to the traders' speculation or their confusion about the fundamental value. Indeed, Lei et al. (2000) repeated that experiment but prevented speculation by forbidding re-sales. They still observed bubbles and concluded that bubbles in their setting occur due to traders' confusion (see also Kirchler et al. 2012).³

¹ Theoretical literature suggests several possible reasons why short-term speculation could cause security prices to deviate from the fundamental values. First, the rational bubble literature shows that when securities with infinite maturity are traded in a market populated by short-term speculators, price bubbles can emerge as the REE (e.g., Blanchard and Watson 1982, Tirole 1985). In a second class of models speculation induces prices to deviate from fundamentals due to future investors' noisy beliefs or asymmetric information (Abreu and Brunnermeier 2003, Allen et al. 2006, De Long et al. 1990a, 1990b, Dow and Gorton 1994, Froot et al. 1992, Scheinman and Xiong 2003). We should point out that both these classes of models, as well as standard finance theory, utilize the rational expectation hypothesis. Even the second class of models assume that *at least* the current investors form rational expectations of future prices by considering how current and future prices are determined by future investors' beliefs.

² Xiong and Yu (2011) is a notable exception. They examine the case of a dozen put warrants traded in China that went so deep out of money in 2005-2008 that their fundamental values were practically zero. They show that warrants traded at prices significantly above zero which they characterize as bubbles.

³ Akiyama et al. (2017) and Cheung et al. (2014) manipulate traders' information regarding the rationality of others in the Smith et al. (1988) setting. They find that uncertainty over the rationality of others is responsible for a substantial part of the mispricing. This suggests that speculation on other's irrationality is a potential cause

Hirota and Sunder (2007) and Moinas and Pouget (2013) conducted experiments that are directly related to speculation in financial markets. In their bubble game experiment, Moinas and Pouget (2013) present evidence counter to standard finance theory on speculation. They show that subjects often buy the security at prices exceeding its fundamental value even when bubbles are (theoretically) ruled out by backward induction. They also find that the propensity for a subject to buy increases with the number of steps of iterated reasoning needed for backward induction. These results indicate that the lack of common knowledge of rationality might be an important driver of speculation. However, in their experiment we cannot know whether and how speculative trading affects price formation since the security price is exogenously given by the experimenter. In Hirota and Sunder (2007), price bubbles emerge in a treatment where investors receive the expected next period price (predicted by a separate set of subjects) as liquidation value at the end of a market session. Their result shows that when investors face *impossibility* of backward induction, their speculation induces security prices to deviate from the fundamental value. In the present paper, we take a step further and examine whether short-term speculation causes price deviation from the assets' fundamental value in a market where REE (through investors' backward induction) is *theoretically feasible*, but calls for a controlled number of steps of iterated reasoning.

To this end, we introduce a newly designed set of experimental security markets, building on earlier asset market experiments such as Hirota and Sunder (2007), Moinas and Pouget (2013), and Smith et al. (1988). Our design has two unique defining features. First, a single kind of simple securities is traded in the market. Each security pays only one (terminal) non-stochastic common knowledge dividend ($D = 50$) at the end of the final period of the session. Second, the market has an overlapping generations structure, where only the first generation is endowed with securities (see Figure 1).⁴ All subsequent generations of investors

of price volatility and bubbles.

⁴ Marimon and Sunder (1993) use an overlapping generations structure for their experiment on money and infla-

enter endowed with cash but no securities; they buy securities from the (overlapping) “older” generation, and then sell them to the next “younger” generation, before exiting the market. Only the investors of the very last generation collect the dividend at the end of the final period, and these are called “dividend-collecting investors”. All other generations exit the market before receiving any dividend, trading the security only for capital gains; these traders are labeled “*speculating investors*”.⁵

This design creates speculating investors (who trade only for capital gains without ever collecting dividends), allowing us to examine the effect of speculative trading on price formation. We compare price deviation from the assets’ fundamental value in markets with dividend-collecting investors to markets with only speculating investors. We also vary the number of entering generations (and hence the number of transfers of security among generations of investors) to explore its effect on price formation. Furthermore, our choice of the single non-stochastic common knowledge dividend paid to holders of the security at the end of the final period leaves little room for doubt or confusion in the mind of any subject that the fundamental value of the security is indeed 50.⁶

Standard finance theory predicts that even in a market populated by speculating investors, the market price of this security should be close to the fundamental value of 50 throughout, since 50 is the price at the REE at which each generation of investors arrive through backward induction. However, our experimental results show that with speculating investors in the market, transaction prices deviate substantially from 50. Specifically, we find that (i) in

tion. Deck et al. (2014) design an overlapping generation structure for the asset market experiment in a Smith et al. (1988) setting. Their experiment focuses on the effect of money injection on prices, accompanied by the entry of new generations. They do not examine the effect of speculative trading.

⁵ In their models, Allen et al. (2006) call these investors “short-lived investors” and Froot et al. (1992) call them “short-horizon speculators.”

⁶ Also note that our experimental setting excludes two factors—infinite maturity and heterogeneity of dividend expectations—that are also supposed to cause prices to deviate from fundamentals in theoretical models (Blanchard and Watson 1982, Tirole 1985, Allen et al. 2006, De Long et al. 1990a, 1990b, Dow and Gorton 1994, Froot et al. 1992). By doing so, we examine if the deviation between prices and fundamentals may be rooted in more basic investors’ difficulty of forming common knowledge of rational expectations. Still, prices above and below 50 can be considered rational under certain assumptions, as we will argue in the hypotheses section.

periods with only speculating investors present prices are more likely to depart from fundamentals, compared to prices in periods in which dividend-collecting investors are present; (ii) volatility of prices is higher when only speculating investors are present; (iii) the “mispricing” is likely to be strategic rather than irrational; (iv) prices are more likely to depart from fundamentals as the securities change hands among speculating investors more often over their 16 period life (i.e., the holding period of speculating investors shrinks and more steps of iterative reasoning are called for); v) speculative trading pushes prices upward (downward) when liquidity is high (low), i.e., higher liquidity provided through higher cash endowments in the market raises prices above the fundamental value and prices fall short of the fundamental value in low-liquidity sessions. These laboratory results do not support the REE prediction made by standard finance theory, but suggest that speculation leads to price bubbles (positive as well as negative; the direction driven mostly by liquidity) and higher price volatility.

The paper is organized as follows. Section 2 describes the experimental design and procedures. Section 3 presents the hypotheses to be tested in the laboratory. Section 4 reports experimental results and Section 5 discusses the implications and presents concluding remarks.

2. Design of the experiment

Setup and treatments

Each market session in the experiment consists of 16 trading periods of 120 seconds each and is populated by investors (who buy and sell securities), and predictors (who are tasked with predicting at the beginning of each period the average transactions price for the period).

We differentiate investors into two classes by implementing an overlapping generations structure shown in Figure 1. At any time there are two generations in the market. The security traded has a maturity of 16 periods and pays a single, common knowledge terminal

dividend, $D = 50$, at the end of Period 16 only to its holders from the last generation, referred to as “dividend-collecting investors”. All other generations of investors do not collect any dividend. They are called “speculating investors,” and trade the security only for capital gains. Any securities these investors hold at the time of their exit are worthless.⁷

(Figure 1 about here)

The experiment has a 4x2 design (see Table 1) in which the first treatment (number of entering generations until maturity of the security) takes four different values and the second treatment (liquidity) takes two values. By varying the number of entering generations (1, 2, 4, and 8), we manipulate the number of periods with only speculating investors and the level of difficulty (number of iterative steps) for each generation of investors to arrive at REE through backward induction. Figure 1 illustrates that in Treatment T1 dividend-collecting investors (G1) are present in all 16 periods of the market session. In T2, T4, and T8 some periods have only speculating investors active in the market (periods 1-8 in T2, periods 1-12 in T4, and periods 1-14 in T8) and in other periods dividend-collecting investors (the last generation) are also present in the market (periods 9-16 in T2, periods 13-16 in T4 and periods 15-16 in T8).

The liquidity treatment varies the initial cash-to-asset value ratio (commonly referred to as C/A-ratio, that is the amount of cash available to trade securities in the economy divided by the total fundamental value of all securities) for H (=10) and L (=2).⁸ Treatments are denoted as T_{xy} with $x \in \{1, 2, 4, \text{ or } 8\}$ indicating the number of entering generations and $y \in$

⁷ This dividend structure is far simpler than Smith et al. (1988) where the security pays numerous (period-by-period) stochastic dividends generating a declining fundamental value. We chose this simpler dividend structure in order to minimize the chances of subjects’ confusion and to gather data from markets populated only by speculating investors. Smith et al.’s (1988) design makes it difficult to create speculating investors (who do not receive dividends and trade only for capital gains) in the overlapping-generations structure. In addition, our design of the security (a single lump sum common knowledge dividend without uncertainty) differs from previous experimental studies featuring constant fundamental values (Porter and Smith 1995, Smith et al. 2000, Noussair et al. 2001, Kirchler et al. 2012, Stöckl et al. 2015, all of which yield efficient pricing).

⁸ A higher C/A-ratio allows investors to take additional risk in trading the security. In H (L) treatments each individual investor initially holds an amount of cash that is twice (0.4 times) the total fundamental value of all assets in the market. While the C/A-ratio is deliberately high in H treatments, a C/A-ratio of 2 in L treatments ensures that investors are able to make transactions at reasonable frequencies. See Kirchler et al. (2012), Noussair and Tucker (2014), and references therein on the effects of cash endowments on mispricing.

{H or L} indicating high and low-liquidity treatments. In multiple sessions within each treatment the market structure (number of investors, number of securities and cash endowment of an entering generation) remains unchanged over the 16 periods.

(Table 1 about here)

To keep the total number of subjects within reasonable limits we recruit 18 subjects for each session.⁹ In every period, two generations (ten subjects in total, five in each generation) are active investors, while the other eight (five in T1) subjects are “predictors”. When an investor generation exits the market, five subjects are randomly chosen from the pool of eight predictors to form the newly entering generation for the next period, and the exiting generation joins the pool of predictors. Subjects stay in this pool for two or more periods. This rotating mechanism allows each generation of investors to gain experience and understanding of the environment without significantly interfering with the purpose of the experiment (see Lim et al. 1994, Marimon and Sunder 1993). Since subjects cannot know whether and when they will reenter the market, it is virtually impossible for their current behavior to be influenced by their anticipations of any future re-entries.

Security and cash endowments

Only the initial generation of investors (G0) is endowed with units of the security at the beginning of period 1. All other generations (G1 up to G8) are initially endowed with cash but no securities. They can use their cash to buy securities from the ‘older’ generation, then sell the securities to the next ‘younger’ generation and exit the market, just when another generation enters (or the session ends).¹⁰ This design ensures that even in T1, where G0 and

⁹ In treatment T1 we invited only 15 subjects instead of 18 since no rotation is needed. Ten subjects trade through all 16 periods and the other five act as ‘predictors’ (to be explained below).

¹⁰ Remember, that the cash endowment of an entering generation is ten (two) times the amount needed to buy all securities at their terminal dividend value in H (L) treatments. The amount of cash going out of the market with the exiting subjects will, of course, vary with each generation change and will be equal to the cash endowments of the entering subjects only by chance.

G1 are present for all 16 periods each security needs to be traded at least once (from a member of G0 to a member of G1) to realize its dividend.

(Table 2 about here)

To equalize the per period trading ‘workload’ across treatments, security and cash endowments are varied so as to keep the expected number of transactions for the entire 16-period session fixed at 160, independent of the number of generations (see Table 2 for details on parameter selection in each treatment). To ensure that the total number of securities in the experimental market stays constant throughout the session, any securities in the hands of exiting investors are distributed at zero cost to randomly chosen members of the entering generation. This arrangement ensures that no buyer is forced to buy a security at a price unacceptable to him/her, and the sellers have an incentive to sell their securities before exiting the market.¹¹

Trading mechanism

The trading mechanism used is a continuous double auction with open order book, opportunity to cancel a bid or ask before it is accepted, single-unit trades, and shorting constraint (no negative holdings of cash or securities allowed at any time). The single unit trades help homogenize the amount of trading “workload” per period across treatments. All cash and security balances are carried over to the following period until the investor exits. Investors can buy and sell securities freely as long as neither their cash nor the security holdings become negative. Each trading period lasts for 120 seconds with a digital wind-down clock on the trading screen. Earnings accounts are shown on a history screen at the end of each period (see Appendix A for details).

Investor payoff

¹¹ One may argue that the pressure on the exiting generation to sell its securities at the risk of forfeiture may create a downward pressure on market prices. As shown in the results section, prices in the low-liquidity treatments tend to be below the fundamental value, but not in the high-liquidity treatments. Therefore, the downward-pressure hypothesis has some validity, but is not a consistent explanation of all observed data.

The final earnings of each member of the last generation of investors are calculated as [number of securities in their hands at the end of Period 16] \times [terminal dividend of 50] + [cash holdings at the end of Period 16]. The final earnings of all other generations of investors are equal to their [cash holdings at time of exit]. Any unsold securities in the hands of these investors are forfeited, and randomly distributed in integer units among the members of the incoming generation at zero cost.¹² The final earnings of investors are converted to euros at a pre-announced rate and paid out.¹³

Predictors' task and payoff

Of the 18 subjects (15 subjects in T1), eight (five in T1) act as predictors in each period. At the beginning of each period, they are required to submit a prediction of the average transaction price of that period. This price prediction is not disclosed to the market until trading is over at the end of the period to prevent influencing investors' behavior.¹⁴ Predictors' earnings depend on the precision of their forecast. They earn 140 units of cash for a perfect forecast with one unit deduction for each unit of error (subject to zero minimum). The amount earned was later exchanged to Euros at a rate of 133:1. Hence, roughly one euro could be earned per prediction round.

Implementation

¹² During 48 sessions, a total of 970 securities were forfeited across 768 periods. This was mostly due to holders being unable to sell at a price acceptable to them. Forfeiture rates markedly increased with the number of generation changes and ranged from 1.1 percent of shares in T1H to 23 percent in T8L. See Appendix D for more information.

¹³ The conversion is done at a predetermined rate announced at the outset. We use different rates for the first, transition, and last generations and the low/high-liquidity treatments to ensure identical expected euro payouts. See Table 2 for details.

¹⁴ We deliberately separate predictor's role from investor's role in each period to eliminate the possibility that eliciting price prediction from investors induces some bias in their trading behavior in the same period. Such strategic behavior is unlikely to motivate trades in real-world markets, but might bias our experimental results. Previous literature suggests that eliciting beliefs and forecasts in the laboratory can change the subjects' behavior (see Schotter and Treviono 2014 for a survey). In particular, Bao et al. (2013) show the experimental evidence on cobweb economy that REE is less likely to be attained when subjects are asked to play the forecasting role and make decisions simultaneously.

The experiment was conducted at the Innsbruck-EconLab using z-tree (Fischbacher, 2007) in autumn 2013 with a total of 828 University of Innsbruck students (bachelor and master students from different fields). We ran 48 sessions in total (eight treatments of six sessions each). Most subjects had participated in other economics experiments earlier, but none participated in more than one session of the present study. Subjects were recruited using ORSEE by Greiner (2004).

At the beginning of each session subjects had 15 minutes to read the common knowledge instructions (with their understanding tested through a written questionnaire, see Appendix B for details). This was done to minimize the possibility of experimenter bias. Any questions occurring in this phase were answered privately. Afterwards the trading screen was explained in detail, followed by a questionnaire and two trial periods to allow subjects to become familiar with the environment, investor and prediction tasks, and mapping from experimental actions and events to their payoffs, and to test their comprehension.¹⁵ In both trial periods all subjects played dual roles of investor and predictor. As an example, instructions for treatment T2L, along with screen shots, are provided in Appendix A. Each session lasted approximately 90 minutes. Calculations of period as well as cumulative earnings are shown to subjects on the history screen at the end of each period (see Appendix A for details). At the end of a session earnings of each subject are calculated as described above, converted into euros, and paid to the subjects in private.¹⁶

3. Theory and Hypotheses

In this section we present theoretical considerations examining whether or not speculating investors induce price indeterminacy in our laboratory markets. In Section 3.1 we show that prices are equal to the fundamental value (terminal dividend) in a market with dividend-

¹⁵ We implemented this procedure to minimize mispricing due to subjects' confusion or misunderstanding.

¹⁶ There was no fixed payment for the subjects. The average and standard deviation of actual earnings of the subjects across treatments are shown in Appendix C.

collecting investors. In Section 3.2 we argue that in a standard security pricing model REE assures prices equals to the fundamental value even in a market with only speculating investors. In Section 3.3 we (partly) relax REE assumptions discussing the feasibility of the REE in our laboratory markets. In Section 3.4 we derive a set of hypotheses to be evaluated with the data generated in the experiment.

3.1 Pricing in a market with dividend-collecting investors

We start with examining price formation in markets with dividend-collecting investors in our laboratory sessions. For illustrative purposes, we discuss investors' behavior and security prices in a T4 market (see Figure 1). The same argument applies to other treatments (T1, T2, and T8). To simplify, we divide the 16 periods in T4 into four series of markets. In Market 1 traders of G0 and G1 interact (periods 1-4), in Market 2 traders of G1 and G2 interact (periods 5-8), in Market 3 traders of G2 and G3 interact (periods 9-12), and in Market 4 traders of G3 and G4 interact (periods 13-16). Only traders belonging to G4 are dividend-collecting investors, while traders of G0 to G3 are speculating investors who exit the market before the security pays its dividend D .

In Market 4 where dividend-collecting investors (G4) are present, the equilibrium price P_4 of the security is equal to the terminal dividend D due to the G4's arbitrage transactions (assuming perfect competition):

$$P_4 = D = 50. \tag{1}$$

The prediction that price is equal to the security's fundamental value also holds for markets in other treatments when dividend-collecting investors are present (periods 1-16 in T1, period 9-16 in T2, and periods 15-16 in T8).¹⁷

¹⁷ One may argue that the theoretical equilibrium price is not necessarily equal to 50 in the market with dividend-collecting investors. The argument would be as follows: dividend-collecting investors (e.g., G4 in T4) would buy the security if the price is below 50 and non-dividend-collecting investors (e.g., G3 in T4) would sell the security if the price is above 0 (because they cannot receive the dividend). Hence the equilibrium price lies

3.2 Rational Expectation Equilibrium (REE) in a market with only speculating investors

Next, we examine price formation in a market with only speculating investors. The standard security pricing model argues that REE assures prices to be equal to the fundamental value. To see this, we consider Market 3 (periods 9-12) where G2 and G3 are present. For this situation the price of the security, P_3 , depends on G3's expectation of the price in Market 4:

$$P_3 = E_3 (P_4). \quad (2)$$

Standard security pricing models claim that speculating investors form rational expectations of future prices through backward induction: G3 rationally expect P_4 to be given by (1):

$$E_3 (P_4) = 50. \quad (3)$$

Therefore,

$$P_3 = 50. \quad (4)$$

In Market 2 (periods 5-8) where G1 and G2 are present, the price of the security, P_2 , depends on G2's expectation of the price in Market 3.

$$P_2 = E_2 (P_3). \quad (5)$$

G2 rationally expect P_3 using (4),

$$E_2 (P_3) = 50. \quad (6)$$

Thus, $P_2 = 50$ holds. Repeating this process one more stage, we get $P_1 = 50$.

This step completes the derivation of the REE yielding $P_1 = P_2 = P_3 = P_4 = 50$. Prices in markets with only speculating investors (P_1 , P_2 , and P_3) are equal to those in a market with dividend-collecting investors (P_4). This argument also applies to other treatments (T2 and T8), predicting that price is 50, irrespective of the presence or absence of speculating and

in the range of [0, 50]. This argument, however, is not theoretically valid. In our experimental design, since the total number of the securities outstanding is limited (e.g., 40 in T4) and total cash held by investors is twice (4,000 in T4L) or ten times (20,000 in T4H) as much as total fundamental value of the securities outstanding ($40 \times 50 = 2,000$ in T4), there is excess demand for securities at prices below 50. This indicates that $p = 50$ is the competitive equilibrium price in the market with dividend-collecting investors.

dividend-collecting investors in the market. Therefore, the standard security pricing model predicts that, even in a market populated by speculating investors, the price of the security with fixed maturity is determined through investors iteratively forming rational expectations through backward induction, and prices are equal to the security's fundamental value.

3.3 Feasibility of REE

The result of the standard security pricing model presented above critically depends on two assumptions. First, speculating investors form rational expectations of future sales prices, knowing that future generation of investors exhaust arbitrage opportunities. For example, this assumption implies that traders of G3 form rational expectations of P_4 (equation (3)) since they not only have the cognitive ability to surmise the behavior of Market 4, but also believe that traders of G4 conduct perfect arbitrage in a frictionless market to realize $P_4 = 50$ (equation (1)). However, it is not clear that this assumption holds in practice. For example, G3 may expect that in Market 4 some traders of G4 may be reluctant to buy the security at P_4 slightly less than 50, since the profit potential from conducting such arbitrage transactions is small. Furthermore, G3 may expect that G4 in low-liquidity markets might be willing to engage in arbitrage transactions but experience a lack of liquidity to conduct a sufficient number of buy transactions.¹⁸ In contrast, G3 themselves have a strong incentive to sell the security in Market 4 because they must exit the market without receiving any dividend. The combination of a weak demand and strong supply side implies a lack of salience around the REE prediction and thus generates the possibility of $P_4 < 50$.¹⁹ Anticipating this lack of sali-

¹⁸ Theoretical models argue that market frictions such as borrowing and short-sales constraints may prevent perfect arbitrage (Allen et al. 1993 and Scheinkman and Xiong 2003). Both laboratory markets and markets in the field have such frictions, and traders cannot post an infinite number of buy and sell orders or engage in an infinite number of transactions. For example, in T4L, a trader of G3 with initial cash of 800 can only afford to purchase up to 16 shares (out of total 40) at prices near 50.

¹⁹ For instance, assume that price is 49 in Market 4. A trader of G4 (the final generation) can realize a profit of 1 by purchasing one security. In contrast, a trader of G3 (the penultimate generation) can obtain 49 profit by selling a share, as his/her security holdings are forfeited without compensation at the end of Market 4. Thus, we might reasonably expect traders of G3 to be far less patient than traders of G4 for prices near 50 because traders

ence of $P_4 = 50$, G3 may buy the security in Market 3 only if $P_3 < 50$ (or sell the security even if $P_3 < 50$), which makes REE's result of $P_3 = 50$ (equation (4)) infeasible.

Second, REE assumes that it is common knowledge among all generations of investors that speculating investors form rational expectations. This assumption implies that investors must not only form rational expectations themselves, but also believe that all subsequent generations of investors also do the same. In T4, traders of G2 form rational expectation of P_3 (equation (6)) by believing that traders of G3 also form rational expectation of P_4 . Furthermore, traders of G1 form rational expectation of P_2 , not only believing that traders of G2 also form rational expectation of P_3 , but also believing that traders of G2 believe that traders of G3 form rational expectation of P_4 . This common knowledge assumption of rational expectations, however, may not hold in practice. For example, traders of G2 may believe that some traders of G3 do not form rational expectations ($E_3(P_4) = 50$) and that they form the expectation, $E_3(P_4) > 50$. In high-liquidity markets, this expectation would cause P_3 to rise above 50 in Market 3. Anticipating this, traders of G2 buy the security at $P_2 > 50$ in Market 2 by backward induction. Further, if traders of G1 expect these price realizations, we would observe $P_1 > 50$ in Market 1 as well.

Therefore, considering the two abovementioned restrictive assumptions for REE that may not hold in practice, it is possible that P_1 , P_2 and P_3 may not be in line with REE predictions (50) and get unhinged from the fundamental value in T4. This pricing pattern may also occur in a market with only speculating investors in other treatments (periods 1-8 in T2 and period 1-14 in T8). Moreover, this argument opens the possibility that price formation is different between markets with only speculating investors and markets with dividend-collecting investors.

of G3 have far greater returns depending on the realization of trade. Therefore, it is not at all unreasonable to expect trades for prices below 50 in Market 4.

3.4 Hypotheses

As discussed in Sections 3.1 and 3.2, in standard security pricing models the nature of investors (dividend-collecting vs. speculating) does not affect the formation of security prices. In a market with dividend-collecting investors, arbitrage and competition drives prices towards the value of the terminal dividend (50); even in a market with speculating investors their formation of rational expectations of future prices through backward induction and resulting REE keeps prices equal to 50 as well.

In past security market experiments, precise correspondence between transaction prices and fundamental values is rare.²⁰ The observed deviations are often attributed to noise trading arising from subjects' gradual and imperfect learning, confusion and irrationality.²¹ We expect some transaction price noise to be present in our laboratory markets as well. However, we consider that the magnitude of price deviations due to noise trading does not vary much across markets. Therefore, we pose the following null hypothesis from REE in standard security pricing models:

***Hypothesis I₀:** Deviations of prices from the fundamental value are the same during periods when only speculating investors are present compared to periods when dividend-collecting investors are also present in the market.*

In contrast, in Section 3.3., we also considered the possibility that prices in a market with only speculating investors may become unhinged from REE. Speculating investors may not form rational expectations of future prices due to the lack of salience of future equilibrium and/or lack of common knowledge of rational expectations among all generations of investors.

²⁰ See e.g. Plott and Sunder (1982, 1988), and Smith et al. (1988) and the large follow-up literature reviewed in Palan (2013).

²¹ This is true even when the security traded has a simple dividend structure, e.g., in Smith et al. (2000), Lei et al. (2001), and Kirchler et al. (2012). However, none of these papers features overlapping generations of investors.

In that case, prices are more likely to depart from the fundamental value in a market with only speculating investors. This possibility leads us to the following alternative hypothesis:

Hypothesis I_A: Deviations of prices from the fundamental value are larger during periods when only speculating investors are present compared to periods when dividend-collecting investors are also present in the market.

Next, we shall examine whether, for a security of a given maturity, the number of security transfers across generations (and hence the length of investors' maximum holding period) influences pricing. In the four treatments of our experiment the security always has the same time to maturity (16 periods) and pays the same terminal dividend, but the number of security transfers across generations till maturity of the security are different (one in T1, two in T2, four in T4, and eight in T8).²² According to standard security pricing models (REE), price paths should not differ across the four treatments; investors of each generation should form rational expectations through backward induction and prices at all times should equal the fundamental value. However, we argue that the formation of speculating investors' rational expectations may be difficult due to lack of common knowledge of rational expectations among all generations of investors. In particular, as the number of generations till maturity increases, the number of periods with only speculating investors increases, and failure to form common knowledge rational expectations and departure of prices from the fundamentals become more likely. We set up the following null and alternative hypotheses:

Hypothesis II₀: For a security of a given maturity, the magnitude of deviation of prices from the fundamental value is not affected by the number of security transfers across generations.

²² The maximum holding periods of security for each generation are different among the four treatments. For example, the maximum holding periods for G1 are 16 in T1 and T2, eight in T4, and four in T8. Note that these are only the maximum and not the actual holding periods, because an investor of generation G1 in T4, for example, may choose to wait till period 3 to buy a security and sell it in period 5 and thus hold it only for two periods. Henceforth, we refer to the maximum holding periods simply as "holding periods".

***Hypothesis II_A:** For a security of a given maturity, the magnitude of deviation of prices from the fundamental value increases with the number of security transfers across generations (as the length of investors' holding periods becomes shorter).*

In many models, one of the key assumptions is absence of friction in markets. One of the most relevant frictions in markets is liquidity constraint. To examine whether this factor plays a role in pricing the security in our markets, we vary the total amount of cash in a market by a factor of five (see Tables 1 and 2). In standard finance theory (REE), the amount of liquidity should not affect prices, as it does not change the security's fundamentals. However, prior experimental evidence suggests that liquidity significantly affects security prices: prices are often higher when liquidity is higher either through initial cash endowments or conditions which influence the C/A-ratio.²³ We explore whether the amount of liquidity, measured by the C/A-ratio, influences the price levels and price deviations from fundamentals in our markets. We set up the following null and alternative hypotheses:

***Hypothesis III₀:** Prices will be the same irrespective of the C/A-ratio in the market.*

***Hypothesis III_A:** Prices will be different in markets with different C/A-ratios.*

Past experimental asset market prices tend to exhibit significant within-period variation. However, we do not know if the volatility of price changes will be the same when only speculating investors or when also dividend-collecting investors are present. In our laboratory, as the fundamental value is constant (50), REE predicts no price variation and thus no price volatility, irrespective of the kinds of traders present in the market. However, when REE assumptions do not hold, speculating investors may engage in short-term trading on the expectation of the future price changes even within a period, and prices become more volatile dur-

²³ See, e.g., Ackert et al. 2006, Breaban and Noussair 2014, Caginalp et al. 1998, Caginalp et al. 2001, Caginalp and Ilieva 2008, Deck et al. 2012, Haruvy and Noussair 2006, King et al. 1993, Kirchler et al. 2012, Noussair et al. 2012, and Porter and Smith 1995.

ing periods with only speculating investors compared to periods with dividend-collecting investors. This leads to the following null and alternative hypotheses:

Hypothesis IV₀: Volatility of price changes is the same during periods when only speculating investors are present compared to periods when dividend-collecting investors are also present in the market.

Hypothesis IV_A: Volatility of price changes is higher during periods when only speculating investors are present compared to periods when dividend-collecting investors are also present in the market.

4. Results²⁴

4.1 Evolution of prices

Figures 2 and 3 give a descriptive illustration of dynamic evolution of transaction prices in our experiment for each of the six independent sessions (mean transaction prices by period in thin grey lines) and the fundamental value (red bold line) for high-liquidity treatments (T1H, T2H, T4H, and T8H) and low-liquidity treatments (T1L, T2L, T4L, and T8L), respectively.²⁵ Note that the fundamental value – the terminal dividend of 50 – is constant across all periods throughout our experiment. The thick blue line with hollow circular markers is the average of six sessions in each panel.

(Figures 2 and 3 about here)

²⁴ In this Results section we only present analyses directly related to the hypotheses formulated in Section 3.4 and the formation of price expectations. In Appendix D we provide additional analyses on forfeiture rates of securities (D.1), the concentration of security holdings among traders (D.2), and price predictions (D.3).

²⁵ We dropped two transactions that occurred at prices above 800 from the analyses; the first transaction was at 999 in period 9 of a T2H market and it was one of 64 transactions in that period; it was probably a keyboard error made under heavy/fast trading. The second observation was a price of 900 in period 16 of a T2H market, and it was the only transaction in that period; it was probably caused by boredom because there had been no transactions in period 15. We repeated the analyses without dropping these two outliers and confirmed that the results were qualitatively unchanged. Note that no session ended before period 16. The two sessions appearing to have ended early did not see transactions (although several bids and asks) in the periods before the end of the market.

Figure 2 for high-liquidity sessions shows that in T1H markets (the upper left panel) when the dividend-collecting generation (G1) is always present, prices are usually close to fundamentals (50) throughout the session. While prices are relatively high in period 1, they tend towards fundamentals with time (except in one session), and they converge to the fundamental value in the last period (Period 16) in four of the six markets. This result is consistent with results of earlier experimental studies with constant fundamental values which report that prices tend to converge to fundamentals (Porter and Smith 1995, Smith et al. 2000, Noussair et al. 2001, Kirchler et al. 2012, Stöckl et al. 2015).²⁶ In contrast, in treatments T2H, T4H, T8H, where many periods without dividend-collecting generations exist, deviations of prices from fundamentals are greater and more persistent. Usually prices appear to only converge towards fundamentals once the dividend-collecting investors (of the last generation) enter the market.

The low-liquidity sessions depicted in Figure 3 exhibit a similar tendency of more inefficiency in periods with only speculating investors active. While prices are close to fundamentals in periods with dividend-collecting investors (of the last generation) present, they deviate from fundamentals in periods with only speculating investors present. In all periods in T1L, periods 9-16 in T2L, periods 13-16 in T4L, and periods 15-16 in T8L, where the respective (dividend-collecting) last generation is present, prices are close to or converge to near the fundamental value. Prices significantly deviate from the fundamentals in other periods.

Visual inspection therefore suggests that (i) price formation is different between periods in which dividend-collecting investors (of the last generation) are present and periods with only speculating investors present, and that (ii) the same securities (with the same divi-

²⁶ Comparable to earlier studies, convergence is noisy, which suggests that arbitrage is far from perfect even in the last period. In a few sessions in Figures 2 and 3, we observe that the mean prices (grey line) are above 50 in the last period (Period 16). This indicates that some traders bought the security above 50 even in the last period. Two reasons can be considered. One is that the trader believes that he/she can resell the security to others at a higher price during the last period (120 seconds), the other is that they did not fully understand the game.

end and the same maturity) exhibit different price paths across the four treatments. These results are inconsistent with the prediction of REE and appear to reject hypotheses I_0 and II_0 in favor of I_A and II_A for high as well as low-liquidity treatments. In addition, while price deviations from the fundamental value tend to be positive in the high-liquidity treatment (Figure 2), they tend to be negative for the low-liquidity sessions (Figure 3). This observation favors rejecting the null hypothesis III_0 in favor of alternative III_A .

A closer look at Figures 2 and 3 reveal some interesting details. First, in Figure 2 (high-liquidity treatments) prices tend to start at particularly high levels and price bubbles occur in early periods in most sessions. Second, in Figure 3 (low-liquidity treatments), there is a substantial price drop within the periods where the 2nd-to-last generation and the 3rd-to-last generation interact (periods 1-8 in T2L, periods 9-12 in T4L, periods 13-14 in T8L) and where the 3rd-to-last generation and the 4th-to-last generation interact (periods 5-8 in T4L, and periods 11-12 in T8L). Both these observations, price bubbles in high-liquidity treatments and price drops in low-liquidity treatments, are counter evidence to REE and are discussed in detail later.

4.2 Analyses of price deviations from the fundamental value

To examine hypotheses I and II econometrically we calculate deviations of prices from the fundamental value applying a measure of mispricing per period. In the recent experimental security market literature, the degree of mispricing is usually measured by Relative Absolute Deviation (*RAD*) proposed by Stöckl et al. (2010);

$$RAD = \frac{1}{N} \sum_{t=1}^N |P_t - F_t| / |\bar{F}| \quad (7)$$

where $|P_t - F_t|$ is the deviation of the (volume-weighted) mean price from the fundamental value in period t , $|\bar{F}|$ is the absolute average fundamental value in the session, t denotes peri-

od number, and N stands for the total number of periods. RAD measures the average level of mispricing across all periods of the session.

As we wish to compare the degree of price deviations among periods even within a session (e.g., between the periods with dividend-collecting investors and those with only speculating investors), we propose *Period-RAD*, a measure of mispricing per period.

$$Period-RAD = |P_t - F_t|/F_t \quad (8)$$

In our experiment, $F_t = 50$ throughout the session, and *Period-RAD* is

$$Period-RAD = |P_t - 50|/50. \quad (9)$$

We calculated *Period-RAD* for each of 16 periods in 24 high-liquidity sessions (six sessions \times four treatments) and 24 low-liquidity sessions.²⁷

(Table 3 about here)

The two panels of Table 3 show the six-session average of *Period-RAD* for each period of the high and low-liquidity treatments. Periods with dividend-collecting investors (the last generation) present are shaded in grey and those with only speculating investors present are white. The periods in which the same two generations trade have a bold border. In both Panels A (high-liquidity session) and B (low-liquidity session), we find that (for a given period sequence number) *Period-RAD* is almost always larger in markets with only speculating investors (white cells) than in periods with dividend-collecting investors (grey cells). Figure 4 shows the average *Period-RAD* for each period sequence number, comparing the markets with dividend-collecting investors (e.g., Period 1 in T1) with those with only speculating investors (e.g., Period 1 in T2, T4, and T8), in high (Panel A) and low liquidity (Panel B) sessions, respectively. We observe that for all period sequence numbers in high and low liquidity

²⁷ We excluded three periods from the sample of high-liquidity sessions: period 16 in Market 5 of T1H and period 15 in Market 5 of T2H had no transactions and period 16 in Market 5 of T2H had only the outlier transaction price of 900. We also deleted three periods for the low-liquidity sample (periods 11 and 13 in Market 3 in T1L and period 14 in Market 3 of T8L since they had no transactions). These deletions reduced the sample size for each liquidity treatment to 381. The resulting average of *Period-RAD* is 0.735 (with a standard deviation of 0.908) across all high-liquidity sessions and 0.333 (with a standard deviation of 0.304) for the low-liquidity sessions.

treatments (14 high and 14 low liquidity period sequence numbers), the average *Period-RAD* across markets with only speculating investors is larger than the one across markets with dividend-collecting investors. This observation corroborates that for any given period sequence number, price deviations from fundamentals are larger in markets with only speculating investors compared to those in markets with dividend-collecting investors. On average, price deviations differ by a factor of 2.45 (4.06) under high (low) liquidity.

(Figure 4 about here)

Table 4 confirms these observations. It compares the average *Period-RADs* across all periods with dividend-collecting investors (0.401 in H and 0.140 in L) with periods populated only by speculating investors (1.024 in H and 0.502 in L). The respective differences (0.623 in H and 0.362 in L) are large in absolute terms and statistically significant at the 1% level for each liquidity treatment (two-sided t-test).²⁸ The Null hypothesis I_0 (that the presence of speculating investors does not impact price deviations) can be rejected in favor of the alternative I_A (that the presence of speculating investors increases mispricing). The REE hypothesis does not hold in our laboratory markets, although theoretically, the REE would seem to be an obvious outcome in this simple market environment.

(Table 4 about here)

We can conjecture that when the number of future generations who will enter the market until the security matures is higher, prices are more likely to deviate from REE level (50). The reason is that speculating investors should have greater difficulty in forming rational expectations by conducting backward induction over a larger number of generations.²⁹ To

²⁸ Note that *Period-RADs* are not independent across periods within a session. We dealt with this dependence by regressing *Period-RAD* on the dummy variable which takes a value of one for periods with only speculating investors and checking whether the coefficient of the dummy is statistically significant using standard error adjusted for clusters (sessions). The coefficients are significant for both H and L treatments. As an additional robustness check, we added the period number (1-16) to the above regression to control for the learning effect of the subjects within a session. We also confirmed that the dummy for periods with only speculating investors is significant for both H and L treatments.

²⁹ Moinas and Pouget's (2013) experimental result shows that subjects are more likely to buy the security at higher prices than fundamentals as the number of steps of iterated reasoning needed for backward induction.

examine the effect of the number of the remaining entering generations till maturity on the degree of mispricing, we calculated averages of *Period-RAD* across periods with only speculating investors, conditional on the number of yet-to-enter generations until maturity (for example, one in periods 1-8 in T2, periods 9-12 in T4, and periods 13-14 in T8; two in periods 5-8 in T4 and periods 11-12 in T8).

(Figure 5 about here)

The resulting average *Period-RADs* are given in Figure 5, which shows that the averages of *Period-RAD* are high even when the number of remaining security transfers across generations is one (0.677 in H and 0.546 in L liquidity sessions), and both are significantly different from 0.401 (in H) and 0.140 (in L) in the presence of dividend-collecting investors. This finding suggests that speculating investors have some difficulty in forming rational expectations even when only one future generation is left. This difficulty may arise from investors' limited cognitive ability and/or investors' doubt about the next generation's conducting perfect arbitrage. Taken together, these observations suggest that the assumption of rational expectations used in standard finance theory to derive REE may not hold even in this simple laboratory market.

To evaluate Hypothesis II, we use the data presented in Table 5. We see that the number of security transfers across generations till maturity of the security (inverse of the length of investors' holding periods) affects the deviation of the security price from fundamentals. We calculated the average of *Period-RAD* for T1, T2, T4, and T8, respectively, and compared them across these four treatments. Average *Period-RAD* in the high-liquidity treatments is the smallest (0.421) in T1, 0.586 in T2, 0.739 in T4, and the largest (1.187) in T8 (see Panel A of Table 5), which are mostly statistically different from each other (see panel B in Table 5 which provides the difference in Average *Period-RAD* across treatments). The pattern is similar in the low-liquidity treatments, though with lower numbers. We conclude that given the

maturity of the security, the higher the number of future security transfers across generations of investors, the greater the deviation of prices from fundamentals. This result rejects Hypothesis II_0 in favor of alternative II_A .

(Table 5 about here)

4.3 Liquidity supply and mispricing

With Hypothesis III we explore whether liquidity supply in the market affects overall mispricing and the price level. Visual inspection of Figures 2 and 3 already gives a tentative answer, as prices tend to be above the fundamental value in the high-liquidity sessions, but below the fundamental value in the low-liquidity sessions.

To assess the direction of price deviations from fundamentals, we replace the relative absolute deviation measure (*Period-RAD*) used in the preceding subsection by the relative deviation measure (*Period-RD*):

$$\textit{Period-RD} = (P_t - 50)/50 \quad (10)$$

where P_t is the mean price of period t . *Period-RD* is an analog of *RD* (Relative Deviation), proposed by Stöckl et al. (2010) which measures the average level of gross (not absolute) price deviations from fundamental values across all periods throughout the session. The resulting average of *Period-RD* across all markets with high-liquidity is positive (0.534, meaning an average overvaluation by 53.4% of the fundamental value), but negative (−0.222, thus meaning an average undervaluation by 22.2% of the fundamental value) across all low-liquidity sessions; the difference (0.756) is statistically significant at the 1% level (two-sided t-test).³⁰ This result rejects hypothesis III_0 in favor of alternative III_A , reinforcing the visual impression from Figures 2 and 3.

³⁰ This overpricing is consistent with the findings of the previous literature on security market experiments: in a market with investors who can receive dividends (corresponding to dividend-collecting investors in our experiment), a larger C/A-ratio is associated with greater positive mispricing (see, Palan (2013) for a survey).

(Table 6 about here)

Note that the liquidity effect on prices is larger when there are only speculating investors in the market. Analyzing the data in more detail, Table 6 compares average *Period-RD* in periods with dividend-collecting investors present to those with only speculating investors. In high-liquidity sessions, the average *Period-RD* across periods with dividend-collecting investors is 0.295 (significantly different from zero at the 1% level, two-sided t-test), which indicates that prices are on average 29.5% higher than the fundamental value. On the other hand, the average *Period-RD* across periods with only speculating investors is much higher (0.741) and the difference (0.446) is statistically significant at the 1% level (two-sided t-test). This suggests that with high-liquidity, speculating investors amplify the magnitude of overpricing. As seen in Section 3.3, if speculating investors have difficulty in forming rational expectations of future prices, they (e.g. traders of G2) may buy the security at prices over 50 if they expect to find future buyers (e.g. some traders of G3) who may purchase the securities at even higher prices with the hope of subsequent price increases. This “hot potato” game is more likely to occur in the high-liquidity (H) treatments where traders have more cash on hand.^{31, 32} We conjecture that this hot potato game among speculating investors causes positive price deviations from fundamentals to persist over time in H treatments.^{33, 34}

In the low-liquidity sessions, the average of *Period-RD* when dividend-collecting investors are present is -0.087 , which is small but significantly negative (significantly different from zero at the 1% level, two-sided t-test). This value indicates that the security prices be-

³¹ In fact, in H treatments, each trader (e.g., with 4,000 of cash in T4H) could buy up all the securities (e.g., 40 in T4H) even at a price of 100.

³² Additional evidence in this regard is provided in Appendix D.2 and D.3. In D.2 we report that the concentration of securities (SC) is significantly higher in H treatments than in L treatments in T1, T2, and T8. In addition, SC increases over the course of the experiment, indicating a stronger concentration of securities among fewer subjects. In D.3 we report that not only prices in the first period but also the predicted first-period prices are above 50 in all (24) sessions in H treatments.

³³ This hot potato interpretation is consistent with De Marino et al. (2013) who report that subjects with high theory of mind have an increased propensity to ride bubbles.

³⁴ We could also argue that even dividend-collecting investors (the last generation) may participate the hot potato game as well, which causes positive price deviations in their presence in H treatments (see positive price deviations in the upper-left cell in Table 6 and the upper-left panel (T1H) in Figure 2).

low 50 are not completely driven to fundamentals by the purchases of the dividend-collecting investors (the last generation). This imperfect arbitrage may be due to dividend-collecting investors not having strong incentive to buy securities at prices slightly lower than 50, nor having sufficient cash to buy securities at this level of liquidity (C/A -ratio = 2).³⁵ In addition, the average *Period-RD* when only speculating investors are present is -0.340 , which is significantly less than -0.087 at the 1% level (two-sided t-test), indicating that with low liquidity, investors' short-term speculation magnifies the undervaluation.³⁶ We conjecture that this might be caused by speculating investors' fear of future market illiquidity. As seen in Section 3.3, speculating investors (e.g., traders of G3), who expect the dividend-collecting investors' (e.g., G4's) arbitrage not to be perfect, may fear that they cannot sell securities around 50, or may be forced to dump them in fire sale prices. This would induce them to trade at prices below 50.³⁷ This is more likely to occur in L-treatments than in H-treatments, when each dividend-collecting investor does not have sufficient cash to conduct perfect arbitrage in L treatments.³⁸

Figure 6 presents *Period-RD* classified by the number of subsequent generations to enter the market. In the high-liquidity treatments (Panel A), when this number is two or more,

³⁵ Note that there is a no-borrowing constraint in the experiment.

³⁶ For robustness checks on the results of Table 6, we regressed *Period-RD* on the dummy variable which takes a value of one for periods with only speculating investors and confirmed that the coefficient of the dummy is statistically significant using standard error adjusted for clusters (sessions) for both H and L treatments. We also add the period number (1-16) to the above regression to control for the learning effect of the subjects. The result shows that while the dummy for periods with only speculating investors become insignificant for H treatments, it is still significant for L treatments.

³⁷ This conjecture is supported by theoretical analyses of financial liquidity crises by Bernardo and Welch (2004) and Morris and Shin (2004). They point to speculating investors selling securities expecting future market declines, and causing price drops. It is also consistent with an empirical study by Cella et al. (2013) who find that during episodes of market turmoil, short-term investors sell more than long-term investors, and stocks held mostly by short-term investors experience larger price drops than stocks held mostly by long-term investors. In addition, Morris and Shin's (2004) model predicts a V-shaped pattern in prices around the liquidity crisis; after the crisis, prices go back to fundamentals through the long-term investors' arbitrage transactions. Cella et al. (2013) also report that stocks held mostly by short-term investors experienced large price reversals after the turmoil. These V-shaped price paths from theoretical and empirical studies are also observed in our low-liquidity sessions. In Figure 3, in T2L, T4L, and T8L markets, prices tend to decline when there exist only speculating investors, but they generally recover and converge to fundamentals once dividend-collecting investors (the last generation) enter the market.

³⁸ In L treatments, each traders (e.g., with 800 of cash in T4H) could not buy up all the securities (e.g., 40 in T4H) at prices above 20.

Period-RDs are significantly different from periods with dividend-collecting investors, indicating that prices are higher than in the periods with dividend-collecting investors. This seems to suggest that in high-liquidity treatments speculating investors participate in a “hot potato” game when at least two future generations enter the market (i.e., when at least one entering generation of speculating investors is left ³⁹). Moreover we find that *Period-RD* tends to increase with the number of generations left, indicating that hot potato game is more likely to occur when traders are further away from the terminal generation. In low-liquidity treatments (Panel B), five out of seven values of the *Period-RDs* are significantly smaller (more negative) than the *Period-RD* in the periods with dividend-collecting investors. Note that the difference is statistically significant even when the number of entering generations is one (i.e., when the following generation is the group of dividend-collecting investors). This confirms our conjecture that speculating investors’ fear of future market illiquidity and price drops tends to keep the prices below the fundamentals.

From these observations it appears likely that mispricing here is mainly strategic and not just error by speculating investors. Overpricing in high-liquidity treatments occurs due to investors’ “buy low and sell high” strategy; undervaluation in low-liquidity treatments occurs due to their anticipation of low price in the future. These strategies arise not from REE, but from the difficulty of forming (common knowledge of) rational expectations.

(Figure 6 about here)

4.4 Volatility of prices

To estimate within-period price volatility, we calculate for each period the standard deviation of log-returns (*VOLA*) using (11) (here $RET_t = \ln(P_t/P_{t-1})$; \overline{RET} : mean of log returns in period p ; T = number of transactions in period p).

³⁹ Note that the when the remaining number of entering generations is two, the number of entering generation of speculating investors left is only one, since the final generation is the dividend-collecting investors,

$$VOLA = \frac{1}{N} \sum_{p=1}^N \sqrt{\frac{1}{T} \sum_{t=1}^T (RET_t - \overline{RET})^2} \quad (11)$$

Table 7 compares average period-*VOLA* across all periods with dividend-collecting investors (0.135 in H and 0.091 in L) with periods populated only by speculating investors (0.222 in H and 0.266 in L), and the differences (0.086 in H and 0.175 in L) are large in absolute terms and statistically significant at the 1% level for each of the two treatments (two-sided *t*-tests). These results indicate that speculating investors introduce a higher level of price volatility to the market even within a period. When dividend-collecting investors are present, volatility is significantly lower. The null hypothesis IV_0 (that the presence of speculating investors does not impact price volatility) can be rejected in favor of the alternative IV_A .

(Table 7 about here)

4.5. Formation of Expectations

Lastly, we investigate formation of price expectations and examine whether it differs between markets with dividend-collecting investors and markets with only speculating investors. Since the dividend-collecting investors would focus on the known fundamental value, their presence in the markets should readily bring the investor expectations close to this value. In contrast, in a market with only speculating investors, investors would have difficulties in arriving at expectations of future prices through backward induction due to lack of common knowledge of rational expectations among all generations of investors. To compare the accuracy of price expectations between the two kinds of markets, we calculated the absolute deviations of expected prices (EP) from realized prices (P), normalized by prices, $\text{abs} (EP-P)/P$. During the experiment, we collected from the predictors the data on their expectation of mean transactions prices at the beginning of each period.⁴⁰ The cross-sectional average of the pre-

⁴⁰ We rely on predictors' estimates in the analysis of expectation formation because they have no incentive other than to predict as accurately as they can. Since the market information sets of the investors and predictors are

dictors' price expectations is used for EP, and the average realized price of the period is used as P. Table 8 presents a comparison of the average of abs (EP-P)/P between periods with dividend-collecting investors and periods with only speculating investors. We see that both for high- as well as low-liquidity markets, the average of abs (EP-P)/P in periods with only speculating investors is significantly higher than that in periods with dividend-collecting investors. This indicates that price expectations are less accurate when only speculating investors are present, than when dividend-collecting investors are also present.⁴¹

(Table 8 about here)

If speculating investors have difficulties in forming rational expectations of future prices through backward induction, how else do they form their expectations? We use the price predictions data to try to address this question. We postulate two simple models of the price expectation formation process; one is the fundamental model and the other is the trend model (Hirota and Sunder 2007). The fundamental model assumes that investors form expectations of future prices based on backward induction from the deviation of prices from the fundamental value of the security.

$$E_t(P_{t+1}) = P_t + \alpha(F_t - P_t) \tag{12}$$

where P_t is price of the security at time t , F_t is the fundamental value, $E_t(P_{t+1})$ is investor's expectation at time t of price at time $t+1$, and $\alpha (> 0)$ is the adjustment coefficient. With this model, investors expect future price appreciation (depreciation) if the fundamental value, F_t , is higher (lower) than the current price, P_t . In this model any $\alpha > 0$ is consistent with the fundamental model, with $\alpha = 1$ corresponding to perfect and instantaneous rational expectation formation supposed by the standard security pricing models, $E_t(P_{t+1}) = F_t$ in any period t .

identical, there is no *a priori* reason to believe that the predictions of the two sets of subjects would be different.
⁴¹ In Appendix D.3, we report that the price predictions are less accurate (prices are harder to predict) when a higher number of generations remain; consequently, prices are harder to predict at the beginning of the session compared to the later periods.

On the other hand, the trend model assumes that investors form their expectations about the future price through forward induction or extrapolation based on recently observed price changes (it thus captures momentum).

$$E_t(P_{t+1}) = P_t + \beta(P_t - P_{t-1}) \quad (13)$$

where P_{t-1} is the price at $t-1$. In this model if $\beta > 0$, recent price increases (decreases) cause investors to expect further price increases (decreases) in the future; if $\beta < 0$, recent price increases (decreases) cause investors to expect future price decreases (increases). With this model, investors' expectation of the future prices are based on recent price movements, irrespective of the fundamental value of the security.

We can combine (12) and (13) into a more general specification for expectation formation:

$$E_t(P_{t+1}) = P_t + \alpha(F_t - P_t) + \beta(P_t - P_{t-1}) \quad (14)$$

This combined model allows for the possibility that investors use some combinations of backward induction from fundamentals and forward induction from recent prices.

Rearranging terms, (12), (13) and (14) become

$$E_t(P_{t+1}) - P_t = \alpha(F_t - P_t) \quad (15)$$

$$E_t(P_{t+1}) - P_t = \beta(P_t - P_{t-1}) \quad (16)$$

$$E_t(P_{t+1}) - P_t = \alpha(F_t - P_t) + \beta(P_t - P_{t-1}) \quad (17)$$

where $F_t = 50$ (the terminal dividend) throughout all periods in all sessions in the experiment.⁴²

The cross-sectional average of the predictors' price expectations (for the following period) is used for $E_t(P_{t+1})$, and the average price of the previous period and the one before

⁴² Hommes et al. (2005) investigate the price expectation formation in asset market experiments. They report that about half of participants follow the linear autoregressive predictions with two lags (AR (2) prediction) which can be interpreted as a trend following strategy (trend extrapolators or contrarians). Using our notation, AR(2) prediction is expressed as $E_t(P_{t+1}) = \gamma + \beta_1 P_t + \beta_2 P_{t-1}$ and it becomes our trend model (equation (9)) when $\gamma = 0$, $\beta_1 + \beta_2 = 1$, and $\beta_2 = -\beta$.

that are used as P_t and P_{t-1} , respectively. We estimated equations (15), (16) and (17) using ordinary least squares regression with constant terms. We used data from the periods with and without dividend-collecting investors for each of high and low-liquidity treatments. Table 9 shows the estimation results.

Overall, we find that the coefficient of $(F_t - P_t)$ in the fundamental (FUND) model ranges from 0.070 to 0.401, which is significantly more than zero but less than one (at 1% level). These findings show that the perfect rational expectation formation ($E_t(P_{t+1}) = F_t$) is not supported, not only in periods with only speculating investors but also in periods with dividend-collecting investors.⁴³

Although the data reject the instantaneous rational expectation formation, it reveals that the fundamental value of the security plays a role of anchor to the expectation of future price in markets with dividend-collecting investors. If we first look at the results of high-liquidity sessions (upper half of Table 9), we find that in periods with dividend-collecting investors, backward induction from fundamental values fits the data better than the forward induction from recent prices. The coefficient of $(F_t - P_t)$ is significantly positive (0.197) in the fundamental (FUND) model, but the coefficient of $(P_t - P_{t-1})$ is not significant in the trend (TREND) model. In the combined (COMBINED) model, only the fundamental factor $(F_t - P_t)$ is statistically significant. These results suggest that in the presence of dividend-collecting investors, the fundamental value of the security not only determines the transaction prices but also affects the future price expectations. Arbitrage transactions of dividend-collecting investors enable market participants to expect that future prices will converge to the fundamentals.

(Table 9 about here)

In contrast, the data from periods in which only speculating investors are present support the trend model better than the fundamental model. In these periods, the coefficient of

⁴³ This result is consistent with the empirical results reported by Greenwood and Shleifer (2014). They show that expectations of investors captured by the surveys are not at all the expectations obtained from REE models.

$(F_t - P_t)$ in the FUND model shrinks (to 0.109) to remain marginally significant. However, it becomes much smaller (0.078) and insignificant in the combined (COMBINED) model. On the contrary, the coefficient of $(P_t - P_{t-1})$ is -0.301 and -0.270 in the trend (TREND) model and the combined (COMBINED) model, respectively, and both are statistically significant at the 1% level. These results suggest that in a market with only speculating investors, investors tend to form their expectations of future prices on the basis of recently observed prices through forward induction, and not on the basis of the fundamental value through backward induction. Also, the negative coefficient of $(P_t - P_{t-1})$ shows that market participants expect price reversals; a price rise of 1 from the previous period lowers the expectation of next period price by about 0.3.⁴⁴

We observe the same tendency in the results for low-liquidity sessions (in the lower half of Table 9). For periods with dividend-collecting investors, the coefficient of $(F_t - P_t)$ is significantly positive in both the fundamental (FUND; 0.401) and the combined (COMBINED; 0.419) models. For the periods with only speculating investors, the coefficient of $(P_t - P_{t-1})$ is significantly negative in both trend (TREND; -0.162) and combined (COMBINED; -0.180) models.⁴⁵ These results confirm that the expectations about future prices are formed based on the fundamentals (through backward induction) in a market with dividend-collecting investors, and are based on recent price changes (through forward induction) in a market with only speculating investors.

⁴⁴ While this pattern of reversal in expectations has been observed in some experimental markets (Bao, et al. 2012, 2013), it is in a sharp contrast to the momentum (extrapolative) expectations reported in other experimental markets (Haruvy et al. 2007, Hirota and Sunder 2007, and Hommes et al. 2005).

⁴⁵ $(F_t - P_t)$ is also significant in the fundamental and combined models, albeit with much smaller estimated coefficients (0.070 and 0.065) as compared to the periods with dividend-collecting investors (0.401 and 0.419). We can infer that the trend model is better supported over the fundamental model in periods with only speculating investors for low as well as high-liquidity sessions.

5. Discussion and Concluding Remarks

This paper proposes, and empirically tests in the laboratory, the idea that security prices tend to deviate from fundamental values when markets are populated by speculating investors. In such markets, investors' expectations about the future cash flows beyond their own personal holding periods are not relevant and therefore ignored; they are replaced in trading decisions by expectations about the future prices. Standard finance theory, however, assumes that even in such markets speculators form iterated rational expectations of future prices through backward induction and prices tend toward the fundamental value constituting the rational expectations equilibrium (REE). We conjecture that this assumption cannot be met in practice, causing prices to deviate from fundamentals and become indeterminate in financial markets populated by speculating investors.

We conduct an asset market experiment with an overlapping generations structure where all investors have identical common knowledge beliefs about the fundamental value of the security. Our laboratory results show that (i) in periods with only speculating investors present prices are more likely to depart from fundamentals compared to prices in periods in which dividend-collecting investors are present; (ii) volatility of prices is higher when only speculating investors are present; (iii) the "mispricing" is likely to be strategic, not irrational; (iv) prices are more likely to depart from fundamentals when the securities changed hands among speculating investors more often over their 16 period life (i.e., the holding period of speculating investors shrank); and (v) speculative trading pushes prices upward (downward) when liquidity is high (low), i.e., higher liquidity provided through higher cash endowments in the market raises prices above the fundamental value and prices fall short of the fundamental value in low-liquidity sessions. These laboratory results do not support the REE prediction made by standard finance theory for this environment, but suggest that speculation leads to price bubbles (positive as well as negative with the sign driven mostly by liquidity).

Given our results, it is reasonable to think that price indeterminacies and bubbles in markets outside the laboratory may arise from the presence of speculating investors. The mechanism for the price bubbles observed in the laboratory is unlike the mechanisms suggested in the extant theoretical literature – rational bubbles models (e.g. Blanchard and Watson 1982, Tirole 1985) and heterogeneous belief models (e.g. Abreu and Brunnermeier 2003, Allen et al. 2006, DeLong et al. 1990a, 1990b, Dow and Gorton 1994, Froot et al. 1992, Scheinkman and Xiong 2003). We find that even in these simple laboratory markets (the security pays a single non-stochastic common knowledge terminal dividend at the end of its 16-period life), it is difficult for speculating investors to form common knowledge rational expectations of future prices. Since securities traded in real financial markets have more complex features (such as uncertainty, information asymmetries, and heterogeneous beliefs regarding future cash flows), we conjecture that common knowledge of rationality among investors is even less likely to hold in the field and investors face even greater challenges in forming rational expectations. It appears that building theories by relaxing the assumption underlying rational expectations is one way to explain the price volatility and indeterminacy in financial markets (see, e.g., Adam and Marcet 2011).

In some earlier experiments financial markets converged to the static REE (Plott and Sunder 1982, 1988) in which traders are able to infer the current state of the world from the observed market phenomena. In contrast, the REE examined in our markets is *dynamic* and inter-generational; investors' expectations of future prices are formed by iterated expectations and backward induction over generations. Arriving at this dynamic REE is implausible since it requires investors to have not only extraordinary cognitive ability but also its common knowledge among all generations of investors.

Several implications emerge from this study. First, greater inefficiency, pricing anomalies, and the so-called “behavioral” phenomena which cause security prices to depart from

fundamentals are more likely to be observed when markets are populated with mostly speculating investors. Second, the excess price volatility in real stock markets reported by previous empirical studies (e.g., LeRoy and Porter 1981, Shiller 1981) may be caused by the existence of speculative investors. This observation raises the empirical question of whether stock price volatility is larger in periods and markets with more speculative investors. Third, securities with longer maturities are more prone to price indeterminacy. Given investors' holding periods, as the maturity becomes longer, the number of trading generations that hold the security between the present and the maturity date increases, and it becomes more difficult for investors to form rational expectations by backward inducting through multiple iterations, and prices tend to deviate more from the fundamentals. Fourth, the securities with longer durations are more likely to deviate from the fundamentals.⁴⁶ As the duration of a security increases, investors receive a smaller portion of its value from cash flow within their holding periods and a larger fraction of their valuation depends on more-difficult-to-anticipate capital gains (future prices). Fifth, prudent monetary policy would matter for the stabilization of security prices. These data show that the level of liquidity influences volatility and deviation of prices from fundamentals in markets with speculating investors. This finding implies that controlling the stock of money and credit are important for stabilizing not only the real economy but also security prices when markets are dominated by speculating investors. Sixth, to the extent security prices are destabilized by speculating investors, it is possible to develop an argument to support higher tax rates on short-term capital gains. However, effectiveness of policies for suppressing price bubbles and indeterminacy is a subject for future exploration.

⁴⁶ Duration is the weighted average time of a security's cash flows.

References

- Abreu, D. and Brunnermeier, M. K. (2003) Bubbles and Crashes, *Econometrica*, 71, 173-204.
- Ackert, L. F., Charupat, N., Church, B. K., and Deaves, R. (2006) Margin, Short Sell, and Lotteries in Experimental Security Markets, *Southern Economic Journal*, 73, 419-436.
- Adam, K. and Marcet, A. (2011) Internal Rationality, Imperfect Market Knowledge and Security Prices, *Journal of Economic Theory*, 146, 1244-1252.
- Akiyama, E., Hanaki, N., and Ishikawa, R. (2017) It Is Not Just Confusion! Strategic Uncertainty in an Experimental Asset Market, *Economic Journal*, 127, F563-F580.
- Allen, F., Morris, S., and Postlewaite, A. (1993) Finite Bubbles with Short Sale Constraints and Asymmetric Information, *Journal of Economic Theory*, 61, 206-229.
- Allen, F., Morris, S., and Shin, H. S. (2006) Beauty Contests and Iterated Expectations in Security Markets, *The Review of Financial Studies*, 19, 719-752.
- Amershi, A. H. and Sunder S. (1987) Failure of Stock Prices to Discipline Managers in a Rational Expectations Economy, *Journal of Accounting Research*, 25, 177-195.
- Aumann, R. J. (1995) Backward Induction and Common Knowledge of Rationality, *Games and Economic Behavior*, 8, 6-19.
- Bao, T., Hommes, C., Sonnemans, J., and Tuinstra, J. (2012) Individual Expectations, Limited Rationality and Aggregate Outcomes, *Journal of Economic Dynamics and Control*, 36, 1101-1120.
- Bao, T., Duffy, and Hommes, C. (2013) Learning, Forecasting and Optimizing: An Experimental Study, *European Economic Review*, 61, 186-204.
- Bernardo, A. E. and Welch, I. (2004) Liquidity and Financial Market Runs, *Quarterly Journal of Economics*, 119, 135-158.
- Blanchard, O. J. and Watson, M. W. (1982) Bubbles, Rational Expectations and Financial Markets. *Crisis in the Economic and Financial Structure*, Wachtel, H. M. (Ed.), Lexington Books, 295-315.
- Breaban, A. and Noussair, C. N. (2014) Fundamental Value Trajectories and Investor Characteristics in a security Market Experiment, CentER Working paper No. 2014-010.
- Brealey, R. A., Myers, S. C., and Allen, F. (2014) *Principles of Corporate Finance*, (11th ed.), McGrawHill, Berkshire.
- Caginalp, G., Porter D. and Smith V. (1998) Initial Cash/Security Ratio and Security Prices: an Experimental Study, *PNAS USA*, 95, 756-761.

- Caginalp, G., Porter D. and Smith V. (2001) Financial Bubbles: Excess Cash, Momentum and Incomplete Information, *The Journal of Psychology and Financial Markets*, 2, 80–99.
- Caginalp, G. and Ilieva, V. (2008) The Dynamics of Investor Motivations in Security Bubbles, *Journal of Economic Behavior and Organisation*, 66, 641-656.
- Camerer, C. (2003) *Behavioral Game Theory: Experiments in Strategic Interaction*, Princeton University Press, Princeton.
- Cella C., Ellul A., and Giannetti M. (2013) Investors' Horizons and the Amplification of Market Shocks, *The Review of Financial Studies*, 26, 1607-1648.
- Cheung, S. L., Hedegaard, M., Plan, S. (2014) To See is to Believe: Common Expectations in Experimental Asset Markets, *European Economic Review*, 66, 84-96.
- Deck, C., Porter, D. and Smith, V. L. (2014) Double Bubbles in Security Markets with Multiple Generations, *Journal of Behavioral Finance*, 15, 79-88.
- DeLong, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990a) Noise Investor Risk in Financial Markets, *Journal of Political Economy*, 98, 703-738
- DeLong, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990b). Positive Feedback Investment Strategies and Destabilizing Rational Speculation, *The Journal of Finance*, 45, 379-395.
- De Martino, B., O'Doherty, J.P., Ray, R., Bossaerts, P. and Camerer, C. (2013) In the Mind of the Market: Theory of Mind Biases Value Computation during Financial Bubbles, *Neuron*, 79(6), 1222–1231.
- Dow, J. and Gorton, G. (1994) Arbitrage Chains. *The Journal of Finance*, 49, 819-849.
- Fischbacher, U. (2007) z-Tree: Zurich Toolbox for Ready-made Economic Experiments, *Experimental Economics*, 10, 171-178.
- Froot K.A., Scharfstein D.S., and Stein J.C. (1992) Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation, *The Journal of Finance*, 47, 1461-1484.
- Geanakoplos, J. (1992) Common Knowledge, *Journal of Economic Perspectives*, 6, 53-82.
- Greiner, B. (2004) Forschung und wissenschaftliches Rechnen 2003, An Online Recruitment System for Economic Experiments. GWDG Bericht 63. Gesellschaft fuer Wissenschaftliche Datenverarbeitung, Goettingen, 79-93.
- Greenwood, R. and Shleifer, A. (2014) Expectations of Returns and Expected Returns, *The Review of Financial Studies*, 27, 714-746.

- Haruvy, E. and Noussair C. (2006) The Effect of Short Selling on Bubbles and Crashes in Experimental Spot Security Markets, *The Journal of Finance*, 61, 1119–1157.
- Haruvy, E., Lahav, Y., and Noussair, C. (2007) Traders' Expectations in Asset Markets: Experimental Evidence, *The American Economic Review*, 97, 1901-1920.
- Hirota, S. and Sunder, S. (2007) Price Bubbles sans Dividend Anchors: Evidence from Laboratory Stock Markets, *Journal of Economic Dynamics and Control*, 31, 1875-1909.
- Hommes, C. (2011) The Heterogeneous Expectations Hypothesis: Some Evidence from the Lab, *Journal of Economic Dynamics and Control*, 35, 1-24.
- Hommes, C., Sonnemans, J., Tuinstra, J., and van de Velden, H. (2005) Coordination of Expectations in Asset Pricing Experiments, *The Review of Financial Studies*, 18, 955-980.
- Johnson, E. J., Camerer, C., and Sen, S. (2002) Detecting Failures of Backward Induction: Monitoring Information Search in Sequential Bargaining, *Journal of Economic Theory*, 104, 16-47.
- Keynes, J. M. (1936) *The General Theory of Employment, Interest and Money*. London: Macmillan and Co. limited
- King, R., Smith, Williams, A. V. and van Boening, M. (1993) The Robustness of Bubbles and Crashes in Experimental Stock Markets, *Nonlinear Dynamics and Evolutionary Economics*, Oxford University Press, M., Day, R. and Chen, P. (Eds.), 183-200.
- Kirchler, M.; Huber, J. and Stöckl, T. (2012) That She Bursts: Reducing Confusion Reduces Bubbles, *The American Economic Review*, 102, 865-883.
- Kleinlercher, D. and Stöckl, T. (forthcoming) On the provision of incentives in finance experiments, *Experimental Economics*.
- Lei, V., C., Noussair, N., and Plott, C. R. (2001) Nonspeculative Bubbles in Experimental Security Markets: Lack of Common Knowledge of Rationality vs. Actual Irrationality, *Econometrica*, 69, 831-859.
- LeRoy, S. F., and Porter, R. D. (1981) The Present-Value Relation: Tests Based on Implied Variance Bounds, *Econometrica*, 49, 555-574.
- Lim, S.S., Prescott, E.C., and Sunder, S. (1994) Stationary Solution to the Overlapping Generations Model of Fiat Money: Experimental Evidence, *Empirical Economics*, 19, 255-277.
- Marimon, R. and Sunder S. (1993) Indeterminacy of Equilibria in a Hyperinflationary World: Experimental Evidence, *Econometrica*, 61, 1073-1107.

- McKelvey, R. D. and Palfrey, T. R. (1992) An Experimental Study of the Centipede Game, *Econometrica*, 60, 803-806.
- Miller, M., Modigliani, F., 1961. Dividend Policy, Growth and the Valuation of Shares, *The Journal of Business*, 34, 411-433.
- Moinas, S. and Pouget, S. (2013) The Bubble Game: An Experimental Study of Speculation, *Econometrica*, 81, 1507-1539.
- Morris, S. and Shin, H. S. (2004) Liquidity Black Holes, *Review of Finance*, 8, 1-18.
- Nagel, R. (1995) Unravelling in Guessing Games: An Experimental Study, *The American Economic Review*, 85, 1313-1326.
- Noussair, C., Richter, G. and Tyran, J.-R. (2012) Money Illusion and Nominal Inertia in Experimental Security Markets, *Journal of Behavioral Finance*, 13, 27-37.
- Noussair, C., Robin, S. and Ruffieux, B. (2001) Price Bubbles in Laboratory Asset Markets with Constant Fundamental Values, *Experimental Economics*, 4, 87-105.
- Noussair, C., Tucker S. (2014) Cash inflows and bubbles in asset markets with constant fundamental values. Working paper.
- Palan, S. (2013) A Review of Bubbles and Crashes in Experimental Security Markets, *Journal of Economic Surveys*, 27, 570-588.
- Plott, C. and Sunder, S. (1982) Efficiency of Experimental Security Markets with Insider Information: An Application of Rational-Expectations Models, *Journal of Political Economy*, 90, 663-698.
- Plott, C. R. and Sunder S. (1988) Rational Expectations and the Aggregation of Diverse Information in Laboratory Security Markets, *Econometrica* 56, 1085-1118.
- Porter, D. P. and Smith, V. L. (1995) Futures Contracting and Dividend Uncertainty in Experimental Security Markets, *The Journal of Business*, 68, 509-541.
- Scheinkman, J. A. and Xiong, W. (2003) Overconfidence and Speculative Bubbles, *Journal of Political Economy*, 111, 1183-220.
- Schotter, A. and Trevino, I. (2014) Belief Elicitation in the Laboratory, *Annual Review of Economics*, 6, 103-128.
- Shiller, R. J. (1981) Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Economic Review*, 71, 421-436.
- Shiller, R. J. (2000) *Irrational Exuberance*, Princeton University Press, Princeton, New Jersey.
- Smith, V. L. (1962) An experimental study of competitive market behavior, *The Journal of*

Political Economy, 70, 111-137.

Smith, V. L., Suchanek, G. L., and Williams, A. W. (1988) Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Security Markets, *Econometrica*, 56, 1119–1151.

Smith, V., van Boening M. and Wellford C. (2000) Dividend Timing and Behavior in Laboratory Security Markets, *Economic Theory*, 16, 567–583.

Stiglitz, J. E. (1989) Using Tax Policy to Curb Speculative Short-term Trading, *Journal of Financial Services Research*, 3, 101-115.

Stöckl, T.; Huber, J. and Kirchler, M. (2010) Bubble Measures in Experimental Security Markets, *Experimental Economics*, 13, 284-298.

Stöckl, T.; Huber, J. & Kirchler, M. (2015) Multi-period Experimental Asset Markets with distinct fundamental value regimes, *Experimental Economics*, 18, 314-334.

Sutan, A. and Willinger, M. (2009) Guessing with Negative Feedback: An Experiment, *Journal of Economic Dynamics and Control*, 33, 1123-1133.

Taylor, M. P. and H. Allen (1992) The Use of Technical Analysis in the Foreign Exchange Market, *Journal of International Money and Finance*, 11, 304-314.

Tirole, J. (1982) On the Possibility of Speculation under Rational Expectations, *Econometrica*, 50, 1163-1181.

Tirole, J. (1985) Security Bubbles and Overlapping Generations, *Econometrica*, 53, 1071-1100.

Xiong, W. and Yu, J. (2011), The Chinese Warrants Bubble, *The American Economic Review*, 101, 2723-2753.

Table 1: Treatment overview

		Liquidity	
		HIGH (C/A-ratio=10)	LOW (C/A-ratio=2)
No. of entering generations	1	T1H	T1L
	2	T2H	T2L
	4	T4H	T4L
	8	T8H	T8L

Table 2: Treatment parameterization

Treatment	T1H	T1L	T2H	T2L	T4H	T4L	T8H	T8L
Market setup								
Number of generations	2	2	3	3	5	5	9	9
Terminal dividend D	50	50	50	50	50	50	50	50
Initial no. securities/investor G_0	32	32	16	16	8	8	4	4
Initial no. of securities/ G_1 - G_8	0	0	0	0	0	0	0	0
Total securities outstanding	160	160	80	80	40	40	20	20
Total value of securities	8,000	8,000	4,000	4,000	2,000	2,000	1,000	1,000
Initial cash/investor G_0	0	0	0	0	0	0	0	0
Initial cash/investor G_1 - G_8	16,000	3,200	8,000	1,600	4,000	800	2,000	400
Total cash	80,000	16,000	40,000	8,000	20,000	4,000	10,000	2,000
Cash-to-asset value ratio (C/A-ratio)	10	2	10	2	10	2	10	2
Invited subjects ($3n+3$)	15 ^a	15 ^a	18	18	18	18	18	18
Participating subjects	90	90	108	108	108	108	108	108
Exchange rates (taler/€)								
Generation 0 (G_0)	100	100	100	100	100	100	100	100
Transition generations			500	100	500	100	500	100
Last generation	1,000	200	1,000	200	1,000	200	1,000	200
Predictors	133	133	133	133	133	133	133	133
Expected payout/subject (€)	16	16	16	16	16	16	16	16

Notes: The following parameters are identical across all treatments: Number of investors/generation (5); number of active generations (2); active investors (10 investors); period length (120 sec.); total number of periods (16); number of markets per treatment (6); number of expected transactions (160).

^a In treatments T1L and T1H we invited 15 subjects instead of 18 as no subject pool for future generations is needed. Ten subjects were investors, and five served as predictors.

Table 3: Average *Period-RAD* by Treatment and Period

Panel A: High-liquidity Sessions

Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
T1	1.423	0.582	0.354	0.293	0.329	0.301	0.321	0.390	0.374	0.382	0.396	0.303	0.323	0.286	0.387	0.259
T2	1.825	1.016	0.310	0.406	0.467	0.536	0.541	0.477	0.676	0.865	0.705	0.313	0.232	0.468	0.232	0.179
T4	1.552	1.471	1.342	1.038	1.182	0.960	0.798	0.499	0.697	0.509	0.470	0.559	0.325	0.210	0.167	0.040
T8	1.879	1.249	1.373	1.392	1.409	1.498	1.177	0.991	1.108	1.082	1.607	1.733	1.019	0.647	0.550	0.273

Panel B: Low-liquidity Sessions

Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
T1	0.226	0.139	0.106	0.098	0.077	0.101	0.103	0.138	0.152	0.158	0.147	0.070	0.084	0.083	0.085	0.085
T2	0.596	0.425	0.299	0.278	0.503	0.685	0.743	0.760	0.342	0.352	0.222	0.146	0.071	0.053	0.085	0.115
T4	0.385	0.489	0.495	0.543	0.517	0.527	0.556	0.653	0.535	0.530	0.511	0.459	0.341	0.163	0.110	0.052
T8	0.527	0.214	0.249	0.398	0.315	0.313	0.355	0.499	0.446	0.584	0.628	0.741	0.663	0.679	0.230	0.066

Notes: Cells shaded grey are periods where the last, dividend-collecting generation of investors is present. In the other periods (no shading) only speculating investors are present.

Table 4: Comparison of Average *Period-RAD* between Periods with Dividend-collecting Investors and Periods with only Speculating Investors

	(1) Periods with dividend-collecting investors present	(2) Periods with only speculating investors	Difference (2)-(1)
High liquidity Session (Treatment H)	0.401 (177)	1.024 (204)	0.623***
Low liquidity Session (Treatment L)	0.140 (178)	0.502 (203)	0.362***

Notes: Sample size is in parentheses. *** indicates that the difference is statistically significant at 1% level by two-sided t-test.

Table 5: Comparison of Average *Period-RAD* between Treatments with High and Low Liquidity.

Panel A: Average *Period-RAD* by Treatments

Treatment	T1	T2	T4	T8
High-liquidity session (H)	0.421 (95)	0.586 (94)	0.739 (96)	1.187 (96)
Low-liquidity session (L)	0.116 (94)	0.355 (96)	0.429 (96)	0.429 (95)

Notes: Sample size is in parentheses.

Panel B: Differences between Average *Period-RAD* across Treatments

High-liquidity Session (H)			
	T2	T4	T8
T1	0.165*	0.318***	0.766***
T2		0.153	0.601***
T4			0.448***
Low-liquidity Session (L)			
	T2	T4	T8
T1	0.239***	0.313***	0.313***
T2		0.075	0.074
T4			0.000

Notes: Two-sided t-test significance levels * (10%), ** (5%) and *** (1%).

Table 6: Comparison of Average *Period-RD* between Periods with Dividend-Collecting Investors and Periods with only Speculating Investors

	(1) Periods with dividend-collecting investors present	(2) Periods with only speculating investors	Difference (2)-(1)
High-liquidity session (Treatment H)	0.295 (177)	0.741 (204)	0.446***
Low-liquidity session (Treatment L)	-0.087 (178)	-0.340 (203)	-0.253***

Notes: *** indicates that the difference is statistically significant at 1% level by two-sided t-test.

Table 7: Comparison of Average *Period-VOLA* between Periods with Dividend-Collecting Investors and vs. Periods with only Speculating Investors

	(1) Periods with dividend-collecting investors present	(2) Periods with only speculating investors	Difference (2)-(1)
High-liquidity session (Treatment H)	0.135 (172)	0.222 (203)	0.086***
Low-liquidity session (Treatment L)	0.091 (176)	0.266 (201)	0.175***

Notes: *** indicates that the difference is statistically significant at 1% level by two-sided t-test.

Table 8: Comparison of Average $\text{abs}(EP-P)/P$ between Periods with Dividend-Collecting Investors and Periods with only Speculating Investors

	(1) Periods with dividend-collecting investors present	(2) Periods with only speculating investors	Difference (2)-(1)
High-liquidity session (Treatment H)	0.157 (177)	0.372 (204)	0.215***
Low-liquidity session (Treatment L)	0.107 (178)	0.433 (203)	0.326***

Notes: *** indicates that the difference is statistically significant at 1% level by two-sided t-test.

Table 9: Price Expectations Model Estimates

High-liquidity Session	Periods with dividend-collecting investors			Periods with only speculating investors		
	FUND	TREND	COMBINED	FUND	TREND	COMBINED
Const.	1.672** (0.622)	-0.709 (1.595)	1.733** (0.620)	4.159** (1.895)	-2.611* (1.310)	0.515 (1.449)
(F _t - P _t)	0.197*** (0.043)		0.211*** (0.053)	0.109* (0.061)		0.078 (0.057)
(P _t - P _{t-1})		0.020 (0.031)	0.067 (0.044)		-0.301*** (0.049)	-0.270*** (0.043)
N	173	167	167	186	168	168
F	20.96	0.42	8.09	3.19	37.71	25.16
Prob.	0.000	0.522	0.002	0.092	0.000	0.000
adj. R2	0.38	0.00	0.39	0.14	0.30	0.36
Low-liquidity Session	Periods with dividend-collecting investors			Periods with only speculating investors		
	FUND	TREND	COMBINED	FUND	TREND	COMBINED
Const.	-2.275*** (0.684)	1.054 (0.737)	-2.543** (0.742)	-0.804 (0.524)	-0.248 (0.399)	-1.636** (0.671)
(F _t - P _t)	0.401*** (0.092)		0.419*** (0.096)	0.070*** (0.017)		0.065** (0.024)
(P _t - P _{t-1})		-0.088 (0.079)	-0.016 (0.031)		-0.162* (0.081)	-0.180** (0.074)
N	171	162	162	186	168	168
F	19.36	1.26	10.10	16.25	3.95	5.82
Prob.	0.000	0.274	0.001	0.001	0.063	0.012
adj. R2	0.43	0.01	0.43	0.08	0.08	0.13

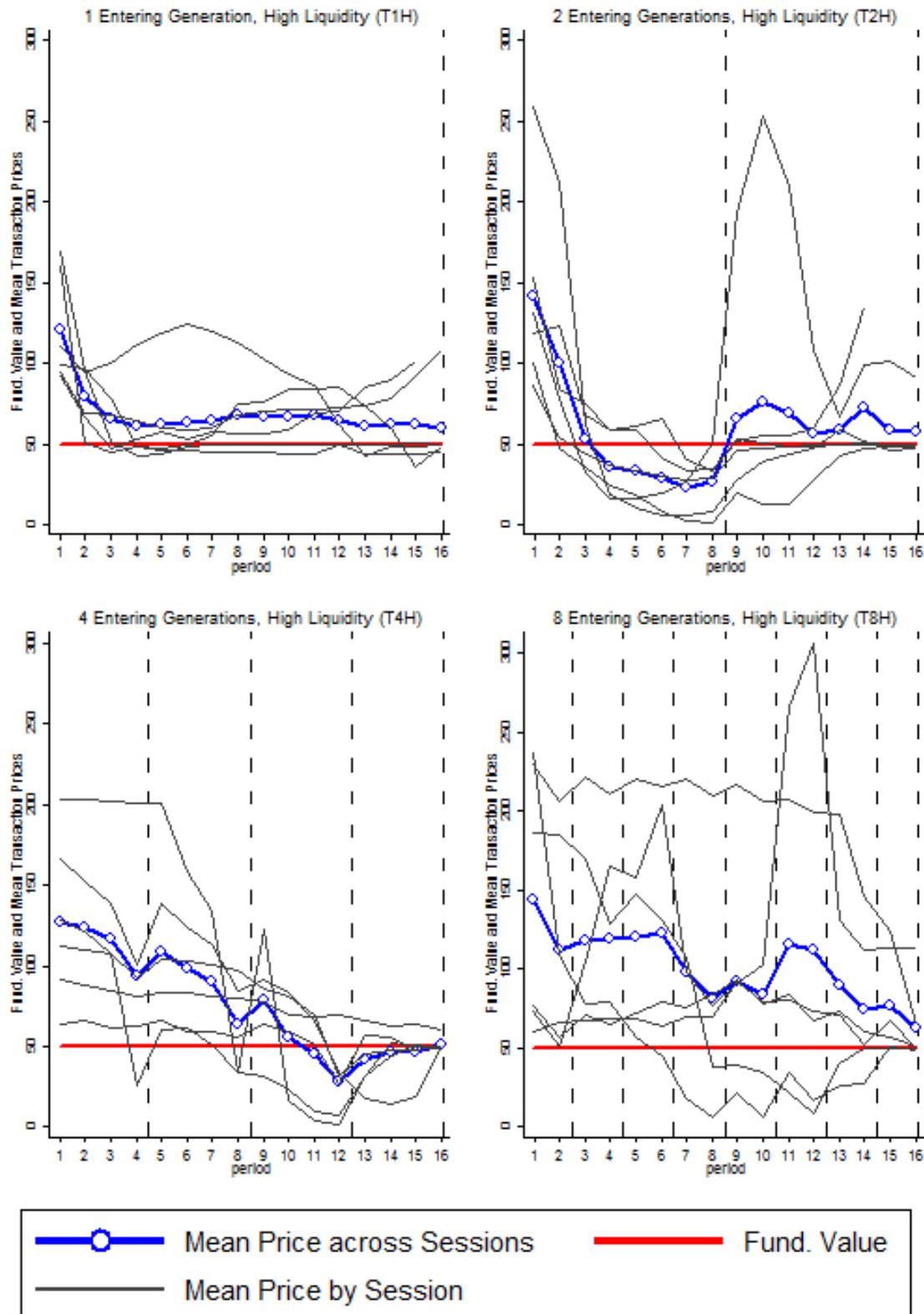
Notes: Standard errors clustered by session in parenthesis. Significance levels: * (10%), ** (5%) and *** (1%).

Figure 1: Overlapping generations

Treatment	Period # of Subjects	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	End of 16
		T1	5	G0														
5	G1																	D
T2	5	G0																
	5	G1																
	5									G2								D
T4	5	G0																
	5	G1																
	5					G2												
	5									G3								
	5														G4			D
T8	5	G0																
	5	G1																
	5			G2														
	5				G3													
	5						G4											
	5								G5									
	5										G6							
	5												G7					
	5															G8		D

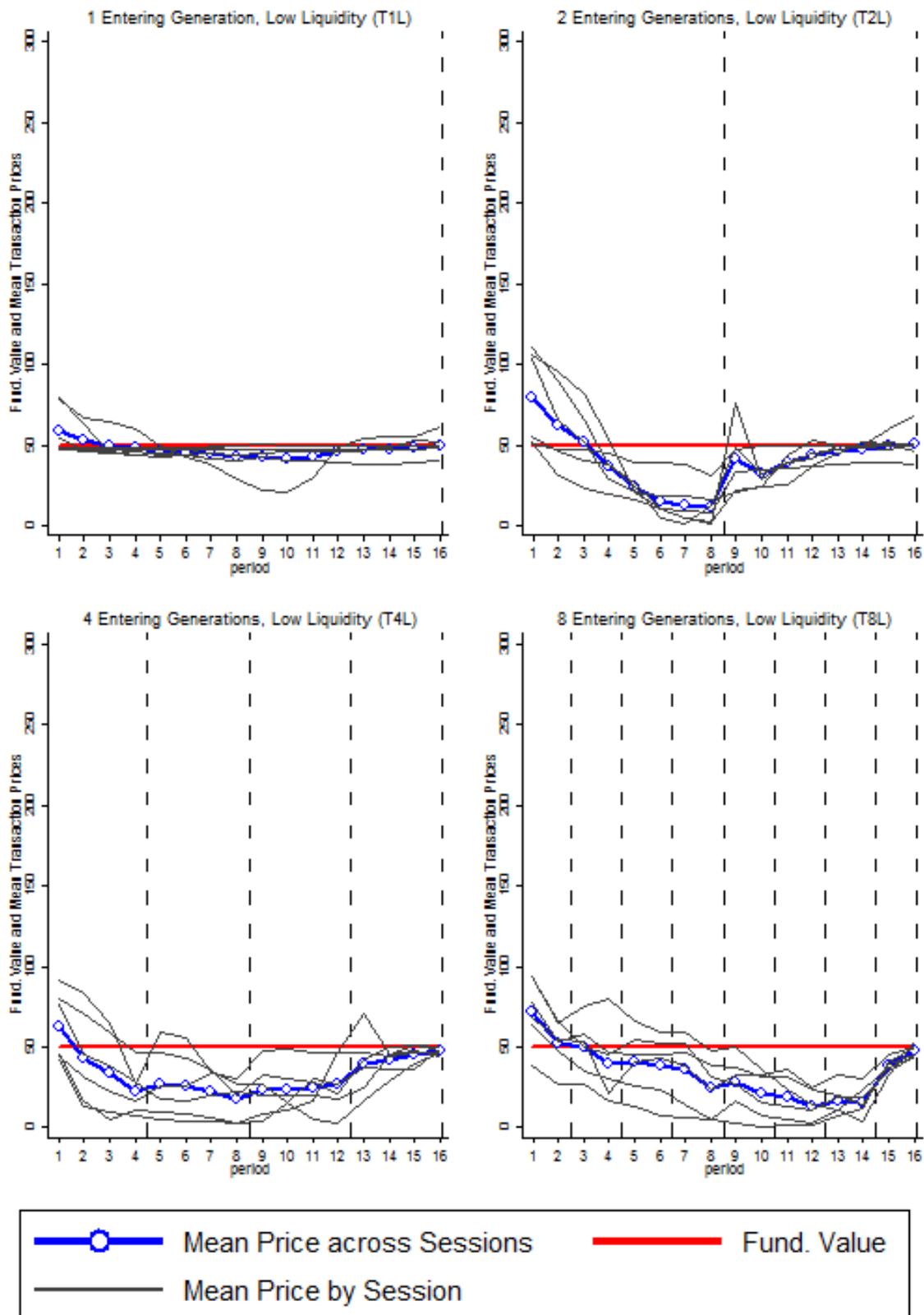
Notes: D means that the last generation of investors receives terminal dividends (50) at the end of Period 16.

Figure 2: Period-wise Average Transaction Prices in High-liquidity Treatments.



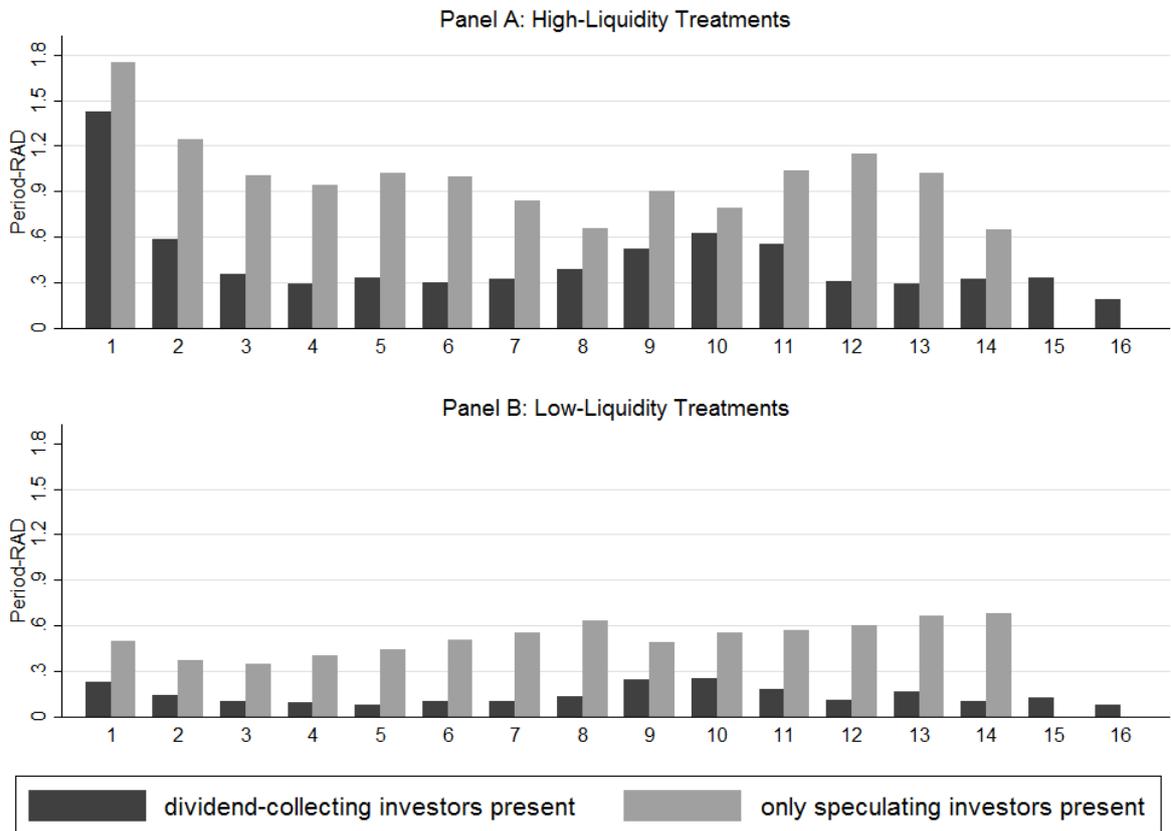
Notes: Volume-weighted mean prices from six individual sessions (grey lines), mean prices across the six individual sessions (blue bold line with hollow circles) and Fundamental Value (red bold straight line) by period on vertical axis. Broken vertical lines mark the entry/exit points of overlapping generations of investors. Each panel is identified by treatment: T1H, T2H, T4H, and T8H.

Figure 3: Period-wise Average Transaction Prices in Low-liquidity Treatments.



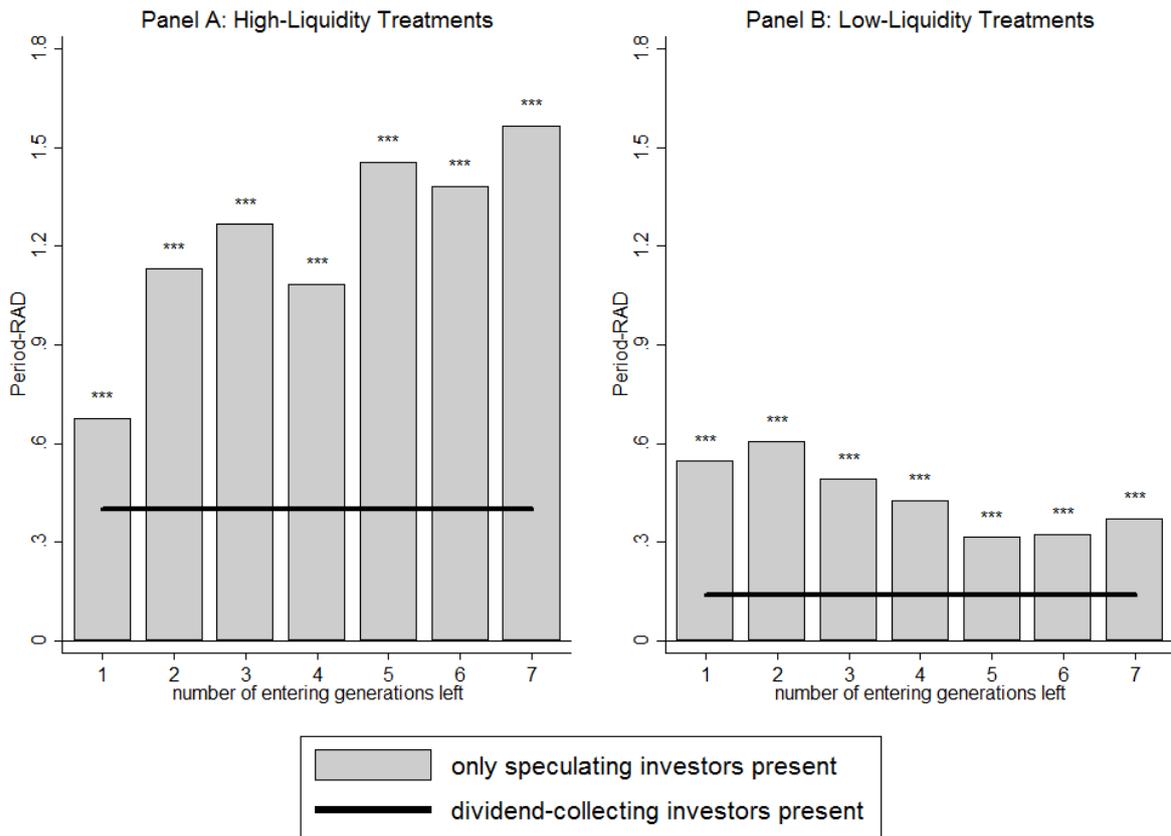
Notes: Volume-weighted mean prices from six individual sessions (grey lines), mean prices across the six individual sessions (blue bold line with hollow circles) and Fundamental Value (red bold straight line) by period on vertical axis. Broken vertical lines mark the entry/exit points of overlapping generations of investors. Each panel is identified by treatment: T1L, T2L, T4L, and T8L.

Figure 4: Average *Period-RAD* for each period number: Comparison between the markets with dividend-collecting investors and those with only speculating investors.



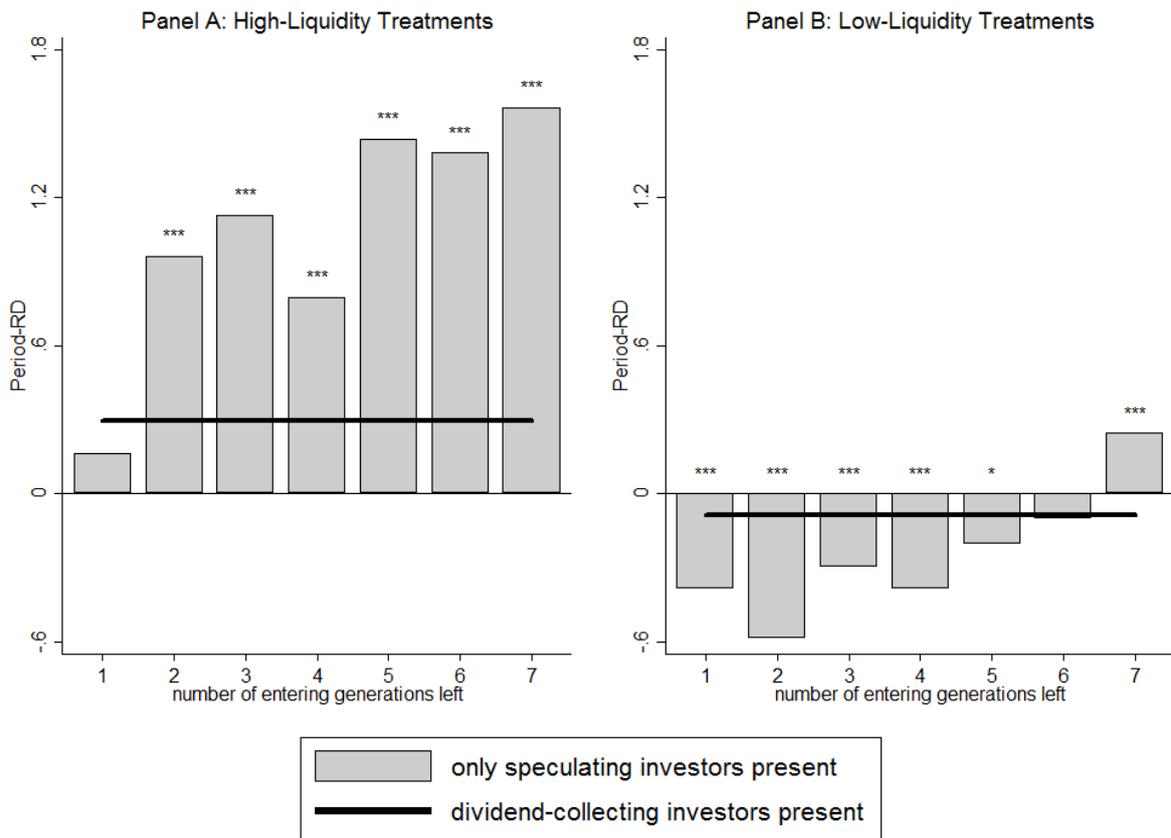
Notes: In periods 15 and 16 dividend-collecting investors are present in all treatments (see, Table 3). Therefore only black bars are shown for these two periods.

Figure 5: Average *Period-RAD* Conditional on the Number of Future Entering Generations



Notes: Grey shaded bars represent values based on periods where only speculating investors were present. The black bold line represents periods where dividend-collecting investors were present. ***, **, or * indicates that the average *Period-RAD* across periods where only speculating investors were present is significantly different at 1%, 5%, or 10% level, respectively, from the average *Period-RAD* across periods with dividend-collecting investors (two-sided t-test).

Figure 6: Average *Period-RD* Conditional on the Number of Entering Generations



Notes: Grey shaded bars represent values based on periods where only speculating investors were present. The black bold line represents periods where dividend-collecting investors were present. ***, **, or * indicates that the average *Period-RD* across periods where only speculating investors were present is significantly different at 1%, 5%, or 10% level, respectively, from the average *Period-RD* across periods with dividend-collecting investors (two-sided t-test).

Appendix A: Instructions of the experiment⁵²

We welcome you to this experimental session and kindly ask you to refrain from talking to each other for the duration of the experiment. Please follow the instructions given by the experimenter. If you have any questions regarding the procedure or the instructions of the experiment, contact one of the supervisors by raising your hand and your question will be answered privately. Violation of instructions risks forfeiting all your earnings.

General Instructions

This is an experiment in market decision making. The instructions are simple, and if you follow them carefully and make good decisions, you will earn more money.

In this session, we conduct a market experiment in which you can trade a security we shall call “shares”. You are a member of a cohort of 18 subjects. The composition of this cohort remains constant throughout the experiment. You will participate in the market as an active investor (“investor”) only in some, not all, periods. If you do not actively participate in the market you will be asked to make certain predictions about the market.

The process of assignment to the trading role in the market will be described shortly. This session consists of a total of 16 periods and trading in each period lasts for 120 seconds.

Your total earnings from participating in the market as a investor and from the prediction task, denoted in taler throughout the experiment, will be converted into Euros and paid to you in cash at the end of the session. The more taler you earn, the more Euros you will take home.

Course of the experimental session

Market experiment

Instructions to the experiment and explanation of the trading mechanism

2 trial periods (not relevant for payment) and questionnaire

Market experiment

Private payment

⁵² Instructions are for T2L. Instructions for other treatments and German translations used in Innsbruck EconLab are available from the authors upon request. Trading screens are identical across treatments (except parameter values).

Active market participants

Assignment process

Figure 1 illustrates the assignment process in the session. At the beginning of Period 1, five subjects will be randomly assigned to Cohort 1 while another five will be randomly assigned to Cohort 2. Members of these two cohorts will participate in trading in Periods 1 to 8. The remaining eight subjects will constitute the “pool” and its members will participate in the prediction task (see below), not in trading, in these periods.

At the end of Period 8, five of the eight members of the pool are randomly chosen to form Cohort 3 who enters the market beginning Period 9; members of Cohort 2 stay in the market; and members of Cohort 1 leave the market to join the pool.

The pool always has eight members who predict, and the market always has a total of 10 members (5 from each of the two cohorts) who trade. After period 8, the “old” cohort 1 leaves the market, and the new Cohort 3 enters. Note that your entry and exit from the market (i.e., which cohort you will be a part of) will be determined by a random (but fair) program.

Figure 1

Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Cohort 1	Active	Pool														
Cohort 2	Active															
Cohort 3	Pool	Active														

Share value

At the end of the session (period 16), any shares in the hands of the members of Cohort 3 will pay a dividend of 50 taler per unit, while the shares held by cohort 2 will not pay a dividend. The shares do not pay any other dividends in earlier periods and are worthless after paying the dividend at the end of Period 16 to members of Cohort 3.

Endowments and payment

Cohort 1 will enter the market at the beginning of Period 1 with an endowment of 16 shares in the hands of each member and no cash. When they exit the market at the end of Period 8, any remaining shares in their hands are worthless. When cohort 1 exits, any unsold shares

(worthless to them) will be distributed among randomly chosen members of the entering cohort at no cost.

Cohort 2 will enter the market at the beginning of period 1 with an endowment of 1.600 taler each and no shares. They may use these talers to buy any number of shares they wish to. Again, when they exit the market at the end of Period 16, any remaining shares in their hands are worthless.

Cohort 3 also enters the market with 1.600 talers each and will be able to use these talers to buy any shares they wish to during periods 9-16. At the end of Period 16, any shares remaining in their hands pay a dividend of 50 taler each, which is added to their taler holdings.

When Cohort 1 and 2 leave the market their taler holdings will be converted into EURO at the following exchange rates: **Cohort 1 and 2:** 100 taler = 1 Euro; **Cohort 3:** 200 taler = 1 Euro.

Trading

Trading will take place through a double auction (see Figure 2, explained in detail later on by the instructor). As a buyer you can submit as many bids as you wish, each for a single share, provided that you have enough cash to pay if your bids are accepted. Buying a share reduces your cash balance by the purchase price. Similarly, as a seller you can submit offer prices at which you are willing to sell each of the shares you own. You can accept any offer submitted by others if you have the cash to pay; and you can accept any bid from others if you own a share. If a bid or ask is accepted, a transaction is recorded at the bid/ask price. Prices are determined only by the bids, asks and acceptances submitted by the investors in the market. Note that neither your share nor the taler inventories are allowed to fall below zero. Outstanding bids and offers can be canceled at any time without cost. All bids and asks are automatically cancelled at the end of a period.

Figure 2: Trading screen

The trading screen is divided into several functional areas:

- Top Bar:** Shows 'Periode 1 von 16' and 'Verbleibende Zeit [sec]: 118'.
- Participant Info:** 'Ihre Rolle: Händler', 'Marktaustritt nach Periode: 8', 'Aktien: 16', 'Taler: 0'.
- Order Management:**
 - 'Eig K-Gebote' and 'Eig VK-Gebote' tables with 'LÖSCHEN K-Gebot' and 'LÖSCHEN VK-Gebot' buttons.
 - 'K-Gebot' and 'VK-Gebot' input fields with 'KAUFGEBOT' and 'VERKAUFGEBOT' buttons.
 - 'K-Gebote' and 'VK-Gebote' order books with 'VERKAUF' and 'KAUF' buttons at the bottom.
- Market Data:** 'Kurs 0.00' and a 'Price-Chart of current period' showing price over time (0-120 seconds).
- Callouts:**
 - Investor:** Information about your task (investor), period you leave the market, current Share and taler holdings.
 - Predictors:** Information about your task (predictor) and your forecast.
 - Current Market Price (of Stock):** Points to the 'Kurs 0.00' display.
 - Price-Chart of current period:** Points to the line graph.
 - Summary tables of your own BIDS and ASKS:** Points to the 'Eig K-Gebote' and 'Eig VK-Gebote' tables.
 - BID:** enter the price you are willing to pay for one unit. Trade does not take place until another participant accepts your bid!!!
 - ASK:** seller's analogue to BID - see above.
 - List of all BIDS:** from all investors - your own bids are written in blue. The bid with blue background is always the most attractive, yielding the highest revenues for the seller.
 - List of all ASKS:** from all investors - your own asks are written in blue. The ask with blue background is always the most attractive, because it is the cheapest for the buyer.
 - SELL:** You sell one unit, given the price with the blue background.
 - BUY:** You buy one unit, given the price with the blue background.

Market predictions

At the beginning of each period participants who do not actively participate in the market are asked to predict the average of the prices at which shares will be traded during that period. Those participants will be able to monitor the market. At the end of each period, their prediction will be compared to the actual average trading price. The more accurate the prediction, the more talers they earn.

Each period, you will earn 140 taler minus the absolute value of your prediction error. For example, suppose, you predict a price of PP and the actual average trading price is AP, you have a prediction error of $|PP-AP|$, and your prediction earnings will be 140 minus $|PP-AP|$.

Taler will be converted into EURO at an exchange rate of 133 taler = 1 Euro. You have 30 seconds to enter your prediction. If you do not enter a prediction value in time or your earnings would be negative, you will earn 0 Euro.

At the end of each period you see a History Screen (Figure 3) for 15 seconds providing you with cumulative information.

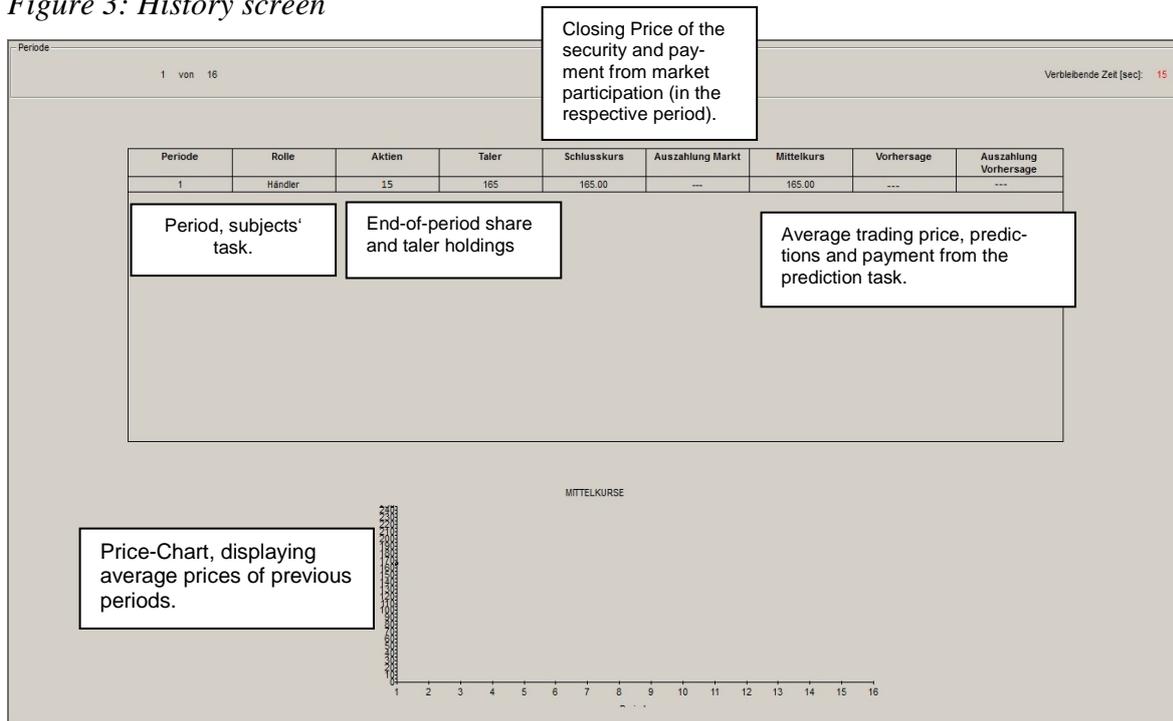
Important information

- No interest is paid for taler holdings.
- Each trading period lasts for 120 seconds.
- You have 30 sec. to enter your prediction.
- The session ends after 16 periods.
- Offers to buy/sell shares can be placed in the range from 0 to 999 taler (with at most one decimal places).
- Members of Cohort 3 (and only this cohort) receive a dividend of 50 talers per share for their holdings at the end of Period 16. Shares are worthless thereafter.
- Use the full stop (.) for decimal.

Trial periods

Before the actual session starts, there will be two trial periods to familiarize you with the trading mechanism. Each participant will be an active investor split into two cohorts. Members of Cohort 1 receive 4 shares and no taler, while members of Cohort 2 receive 400 taler and no shares. The security pays a dividend of 50 to members of Cohort 2. In contrast to the main experiment, you will also make predictions about the average trading price. Trial periods have no influence on your Euro earnings!

Figure 3: History screen



Your payment from the experiment

Your payment from the experiment equals the sum of earnings from participation in the market plus the sum of earnings from the prediction task. This amount will be paid to you in cash.

$$\text{Your payment} = \text{Sum of earnings from market experiment} + \text{Sum of earnings prediction tasks}$$

Appendix B: Questionnaire for understanding (correct answers in italic font).

1. How many trading periods are there during the session? *16*
2. For how many seconds does one trading period last? *120 sec*
3. If you buy a share for 350 taler, what happens to your cash balance? (i) *My cash balance decreases by 350.* (ii) *My cash balance increases by 350.* (iii) *Nothing happens to my cash balance.*
4. If you sell a share for 350, what happens on your cash balance? (i) *My cash balance decreases by 350.* (ii) *My cash balance increases by 350.* (iii) *Nothing happens to my cash balance.*
5. Can you buy a share when you do not have enough cash to pay for the purchase? *Yes/No.*
6. Can you sell a share when you do not have a share? *Yes/No.*
7. What are the two ways of buying a share? (i) *Submit a bid or accept an open offer to sell (ask).* (ii) *Submit an offer (ask) or accept an open offer to buy (bid).* (iii) *Submit a bid or accept an open offer to buy (bid).* (iv) *Submit an offer (ask) or accept an open offer to sell (ask).*
8. What are the two ways of selling a share? (i) *Submit a bid or accept an open offer to sell (ask).* (ii) *Submit an offer (ask) or accept an open offer to buy (bid).* (iii) *Submit a bid or accept an open offer to buy (bid).* (iv) *Submit an offer (ask) or accept an open offer to sell (ask).*
9. You are a member of cohort 2. How are your taler converted into real euros? (i) *Exchange rate of 50 (100) taler to 1 Euro.* (ii) *Exchange rate of 100 (500) taler to 1 Euro.* (iii) *Exchange rate of 200 (1000) taler to 1 Euro. Values in parenthesis for high cash treatments. Correct answers vary by treatment.*
10. Are you allowed to talk, use email, or surf the web during the session? *No.*
11. Your role is “predictor”: You predict a price which is 8 taler less than the actual average price of the period. What is your profit (in taler)? *$140-8=132$*
12. You are a member of cohort 1 and you will leave the market at the end of that period. What is the value of the shares you are holding at the end of the period? (i) *Shares have a value 50.* (ii) *Shares have a value of 0.* (iii) *Shares have a value of 200.*

Appendix C: Subjects' earnings across treatments

In Table C1 we provide information on subjects' average earnings in each treatment (column total earnings). We furthermore split earnings into parts originating from the investor task (column investor earnings) and parts originating from the predictor task (column predictor earnings). To put these numbers into perspective, we report the average number of periods subjects had that role in the corresponding treatment in parenthesis.

Table C1: Subjects' average earnings by treatment

Treatment	Total earnings		Investor earnings		Predictor earnings	
	average	s.d.	average	s.d.	average	s.d.
T1L	16.04	1.60	15.85 (16.00)	1.93	16.42 (16.00)	0.32
T2L	15.40	3.38	10.17 (10.67)	5.29	9.58 (9.85)	3.34
T4L	15.39	2.64	8.49 (8.89)	3.11	6.90 (7.11)	1.62
T8L	15.75	1.72	8.79 (8.89)	1.90	6.95 (7.11)	0.96
T1H	17.63	4.57	18.75 (16.00)	5.24	15.39 (16.00)	0.57
T2H	15.46	3.38	10.96 (10.67)	5.19	8.76 (9.85)	3.16
T4H	16.57	3.22	9.87 (8.89)	3.97	6.70 (7.11)	1.71
T8H	15.52	2.33	9.36 (8.89)	2.37	6.16 (7.11)	1.35

Notes: The numbers in parenthesis indicate the average number of periods subjects had that role in the corresponding treatment.

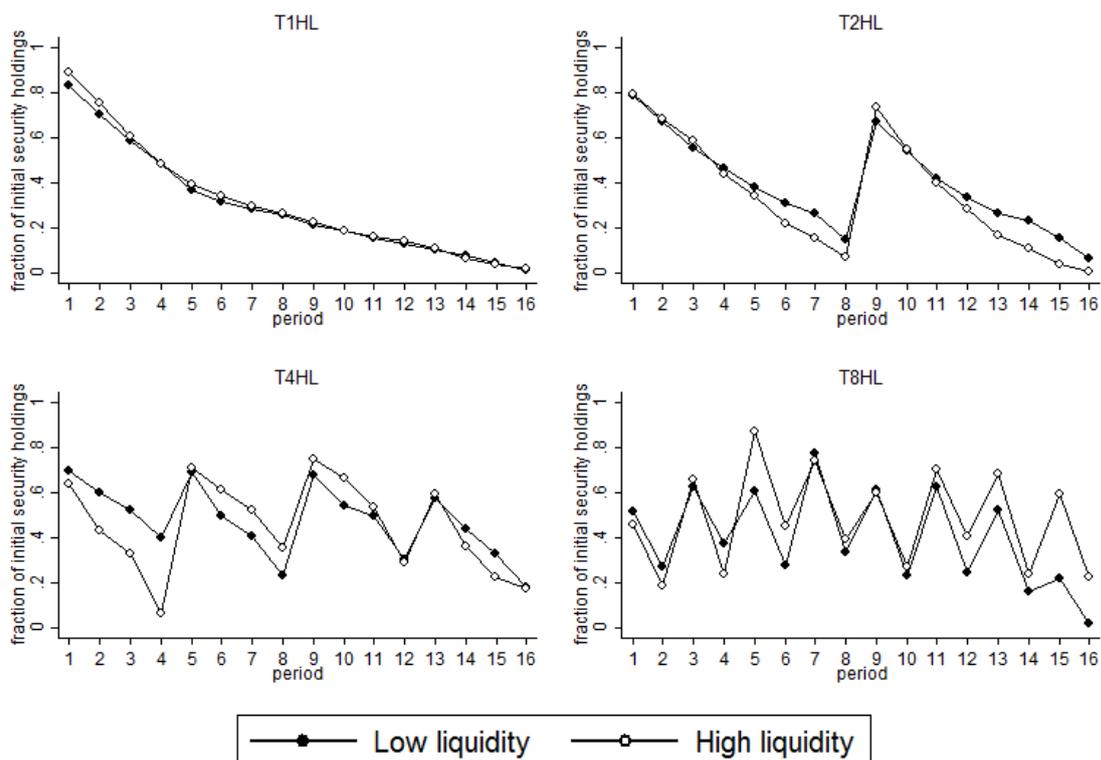
Appendix D: Additional Analyses

In Appendix D we present additional analyses on the forfeiture rates of assets across generations (section D.1.), the concentration of stock holdings among traders (section D.2.), and the accuracy of price predictions (section D.3.).

D.1. Forfeiture rates of securities

In designing the experiment, we decided that unsold securities in the hands of the exiting generation were to be forfeited (become worthless), and allocated randomly at no cost to the entering traders. To measure the share of the forfeited securities for each exiting generation of each treatment we provide two calculations and sets of figures: first, we calculate the exiting generation's share of initial security holdings which is a measure comparable across treatments with different parameters. If the exiting generation ends up with zero securities (as in REE) this measure would take a value of zero.

Figure D1: Exiting generations' share of initial security holdings by period



In Figure D1, we plot our measure conditional on period for each treatment and split into high and low liquidity markets. With each newly entering generation the measure returns to a value close to one and then falls as generations trade securities.⁵³ There is no marked difference between H and L treatments, and we also see, that usually final values are lower the longer generations have time to trade.

Table D1 provides numbers and significance tests whether the numbers are higher when speculating investors are leaving the market compared to dividend collecting investors. There is mixed evidence, as one test is significant on the 1% level, three are significant on the 10% level and two tests are not significant.

Table D1: Forfeiture rates (fractions of all securities not sold by exiting generation to entering generation) across treatments

Period	LOW LIQUIDITY				HIGH LIQUIDITY			
	T1	T2	T4	T8	T1	T2	T4	T8
2				0.27				0.18
4			0.40	0.37			0.06	0.24
6				0.27				0.45
8		0.15	0.23	0.33		0.07	0.35	0.39
10				0.23				0.27
12			0.30	0.24			0.29	0.41
14				0.16				0.24
16	0.01	0.06	0.18	0.02	0.02	0.01	0.18	0.23
mean all	0.01	0.11	0.28	0.24	0.02	0.04	0.22	0.30
mean spec.	--	0.15	0.31	0.27	--	0.07	0.23	0.31
mean non spec.	0.01	0.06	0.18	0.02	0.02	0.01	0.18	0.23
significance		n.s.	10%	1%		10%	10%	n.s.
obs.		6/6	18/6	42/6		6/6	18/6	42/6

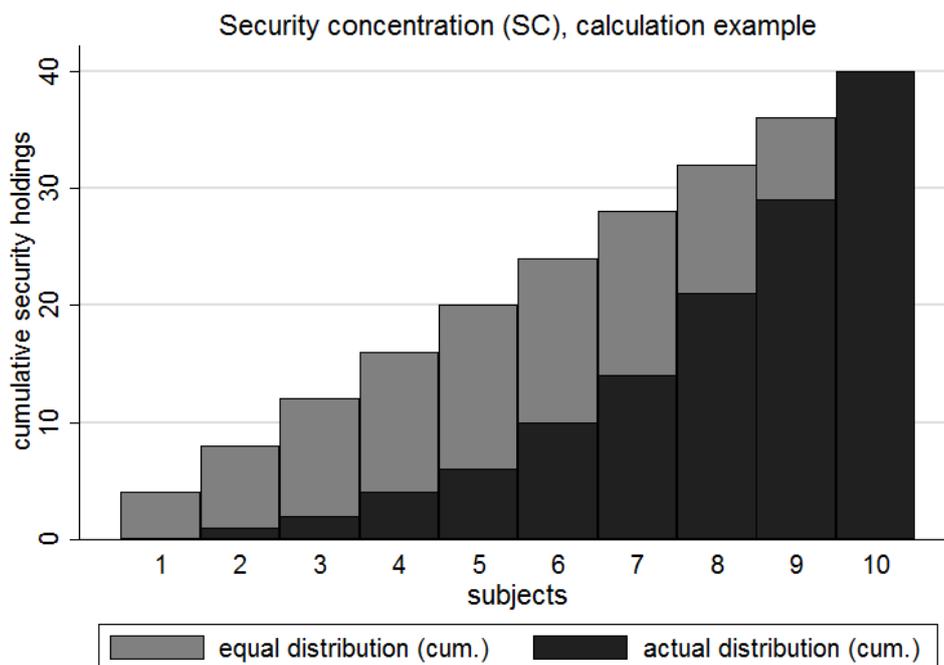
Significance is determined by Mann-Whitney U-tests. n.s. = not significant.

⁵³ Note that the values presented in the figure are end-of-period values, which explains the consistent deviation from one when new generations enter.

D.2. Concentration of security holdings among traders

We explore the concentration of security holdings among traders by period in each treatment (comparable to a Gini coefficient for shares across sessions) to see whether it is typically one or two subjects purchasing the security, or whether holdings are more evenly spread. To answer this question we calculate a measure of security allocation across subjects for each period. The calculation procedure follows the central idea of a Gini coefficient but we decided to use a different term – security concentration (SC). Figure D2, serves as an illustrative example for calculating SC.

Figure D2: Security concentration (SC), calculation example.



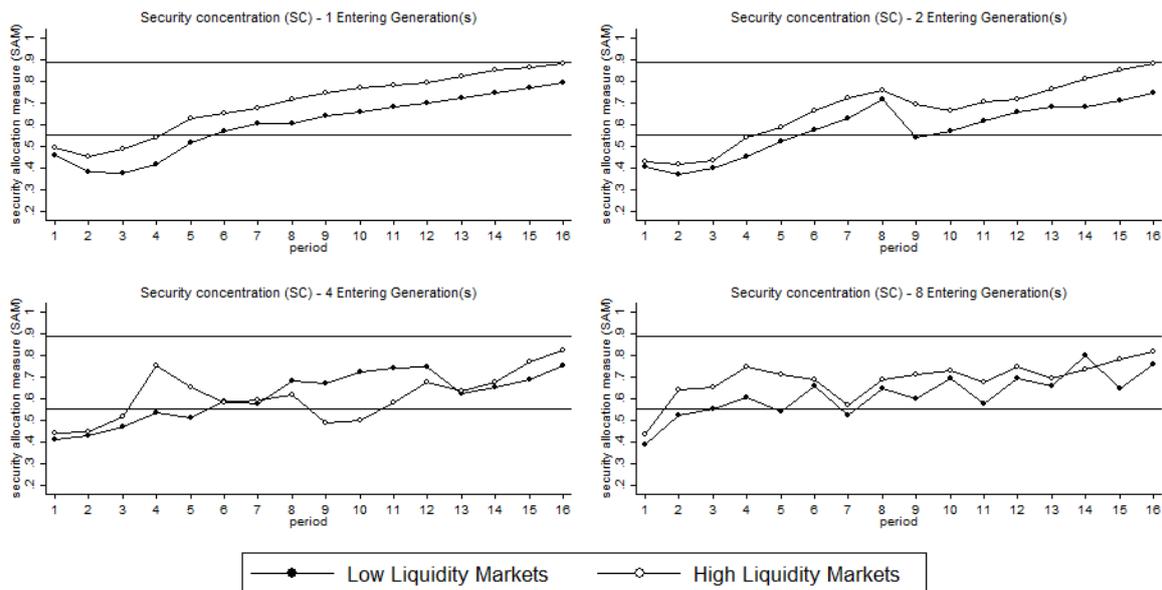
Notes: Data for the example is taken from market 6 (period 4) of a four generation session with low liquidity. Grey bars show the cumulative distribution of security holdings assuming that shares are equally spread among the 10 subjects in the market. Black bars show the actual cumulative distribution of security holdings among the 10 subjects in that period. The sum of cumulative security holding for equal (actual) distribution equals 220 (127) and SC equals $(220-127)/220 = 0.42$.

The benchmark level of SC constitutes the case when all shares are equally distributed among subjects. In Figure D2 this situation is illustrated by the grey bars which show the accumulated distribution of security holdings assuming that shares are equally spread among the ten subjects in the market. Summing up all individual bars yields our benchmark level for SC (in the example this value equals 220). In a second step this benchmark level is compared to the sum of accumulated security holdings actually realized at the end of the respective period (shown as black bars in Figure D2). For the example this value equals 127. SC is now calculated as the difference between the benchmark level and the actual realization, relative to the benchmark level. Note that SC is comparable across treatments despite the different parameter sets used. There are three extreme point realizations of SC. In the case of a perfectly uniform distribution of securities among subjects, SC takes a value of 0. At the initial securities distribution (G0) SC takes a value of 0.55. This value serves as a benchmark to evaluate subjects' purchasing behavior when entering the market. If all subjects of a given generation trade equally, we should expect a value close to 0.55. Higher values indicate uneven distribution of trading by individual members of a generation. For the case that one subject holds all available securities in the market, SC reaches its upper bound taking a value of 0.82. In a final step, we normalize values by this upper bound so that all values range between 0 and 1 and become percentages of the maximum.

To provide an overview, we initially report some summary statistics for SC. In low liquidity markets, the average SC equals 0.60 (384 observations, min = 0.23, max = 0.94, s.d.= 0.15) whereas in high liquidity markets the average SC is 0.67 (384 observations, min = 0.22, max=1, s.d.=0.17). Hence, high liquidity markets are characterized by a more uneven distribution of security holdings compared to the low liquidity markets. The difference is statistically significant at the 1%-level (t -test, $t = -5.3314$, $df = 766$, $p = 0.0000$).

To see whether it is typically one or two subjects purchasing most of the securities, or whether holdings are more evenly spread, we plot the development of SC conditional on period for high and low liquidity markets for each of the four generations in Figure D3.

Figure D3: Security concentration (SC) over time in the four treatments



SC is on average higher in high liquidity markets, especially in T1 and T2. In Table D2, we see that liquidity and number of security transfers in a treatment influenced the average period-SC. Specifically, in three out of four treatment comparisons, SC is significantly higher in the H sessions than in the L sessions, probably because the traders most willing to buy can do so more easily. Moreover, SC increases over the course of the experiment, indicating a stronger concentration of securities in the hands of few subjects. The lower horizontal black line in Figure D3 indicates the level of SC if securities are distributed evenly among the five subjects (initial endowment) of the generation. For most periods, SC is above that measure. SC approaches a level corresponding to even distribution between just two traders

(shown as the upper benchmark in the figure) in period 16 in each of the treatments, especially in high liquidity markets.

Table D2: The number of security transfers and average period-SC by treatment

Treatment	T1***	T2***	T4	T8***
High-liquidity session (H)	0.697 (96)	0.666 (96)	0.610 (96)	0.690 (96)
Low-liquidity session (L)	0.603 (96)	0.580 (96)	0.613 (96)	0.617 (96)

Notes: Sample size is in parentheses. *, **, *** indicate that the difference is statistically significant at 10%, 5%, or 1% level by two-sided t-test, respectively.

We also use SC to shed more light on our research questions: Table D3 compares the average Period-SC across all periods with dividend-collecting investors (0.725 in H and 0.633 in L) with periods populated only by speculating investors (0.613 in H and 0.577 in L). The respective difference (-0.112 in H and -0.055 in L) is large in absolute terms and statistically significant at the 1% level for each of the two liquidity treatments (two-sided t-test). These results indicate that in periods with dividend-collecting investors present the allocation of securities among subjects is more concentrated. With dividends being paid out to these investors the value of the securities is probably more salient and they are thus more eager to buy (as long as price is less than 50).

Table D3: Comparison of Average Period-SC between Periods with Dividend-collecting Investors and Periods with only Speculating Investors

	(1) Periods with dividend-collecting investors	(2) Periods with only speculating investors	Difference (2)-(1)
High liquidity Session (Treatment H)	0.725 (180)	0.613 (204)	-0.112***
Low liquidity Session (Treatment L)	0.633 (180)	0.577 (204)	-0.055***

Notes: Sample size is in parentheses. *** indicates that the difference is statistically significant at 1% level by two-sided t-test.

In a final step in this section we calculate how much of the buying is done for resale by speculating and dividend-collecting generations, respectively. We contrast the number of transactions (volume) with the sum of absolute changes in security holdings in each period (figures are double counts in this analysis). The net change in security holdings of each trader is calculated as the difference between her purchases and her sales. From this data we calculate a measure, called SPEC, by taking the difference between trading volume and the absolute sum of changes in securities holdings relating it to trading volume. A value of zero, the lower bound for SPEC, indicates that the volume in that period did not exceed the absolute sum of changes in securities holdings and the speculating activity equals zero. Higher values indicate trading activity exceeding the net change in securities holdings. Table D4 compares the average Period-SPEC across all periods with dividend-collecting investors (0.289 in H and 0.232 in L) with periods populated only by speculating investors (0.301 in H and 0.322 in L). The respective difference (0.091 in L) is large in absolute terms and statistically significant at the 1% level in the low liquidity treatment (two-sided t-test). Hence, in treatment L many (most) of the transactions happened for re-sale and can thus be classified as speculative – with the share significantly higher when only speculating investors present.

Table D4: Comparison of average period-SPEC between periods with dividend-collecting investors and periods with only speculating investors

	(1) Periods with dividend-collecting investors	(2) Periods with only speculating investors	Difference (2)-(1)
High liquidity sessions (Treatment H)	0.289 (178)	0.301 (204)	0.012
Low liquidity sessions (Treatment L)	0.232 (178)	0.322 (203)	0.091***

Note: Sample size is in parentheses. *** indicates that the difference is statistically significant at 1% level by two-sided *t*-test.

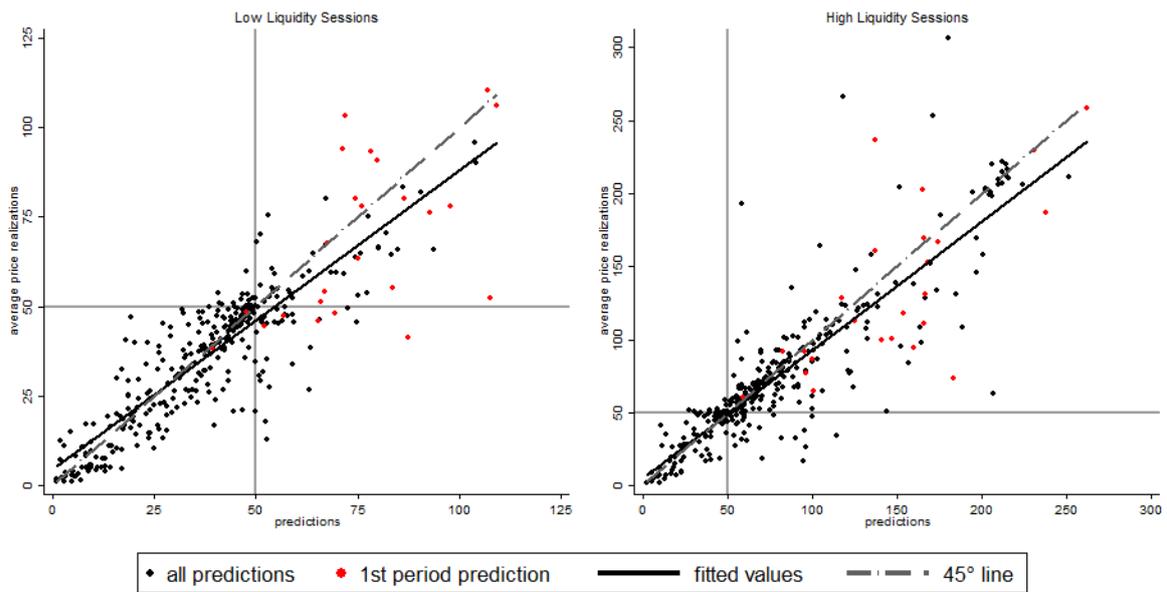
D.3. The accuracy of price predictions

In a final set of analyses we turn to the price predictions submitted by the predictors. The five (in T1) or eight (in all other treatments) predictor subjects were not active in the market in the periods they made predictions for. We first chart and calculate how price predictions relate to observed prices. The two panels of figure D4 show the relation between price predictions and the average price realizations for H (left panel) and L (right panel) treatments. We see that there is clearly a strong relationship in both treatments and the correlation coefficient is 0.87 in each treatment. The average absolute deviation between price predictions and realized prices is 5.2 or 11.4 percent of the average price, which we consider fairly accurate.

The most difficult prediction is arguably the one in the first period, as no price history is available at that time. We already saw in Figure 2 that prices in the first period were usually above 50, with an average around 140 in H and 70 in L. Remarkable, these levels were also predicted: in high liquidity treatments first period prices (P_1) are above 50 in all (24) sessions. The predicted first-period prices are also above 50 in all (24) sessions. Similarly, in low liquidity sessions first-period prices were above 50 in 17 of 24 sessions. Predictions for all 17 of these markets were also above 50 (of the remaining seven sessions with $P_1 < 50$ pre-

dictions are > 50 in five and < 50 in two sessions). These results show that subjects correctly predict $P_1 > 50$ irrespective of the liquidity level.

Figure D4: Average period price predictions and average period price realizations.



Notes: Average period price predictions and average period price realizations in low (left panel) and high (right panel) liquidity sessions. Solid grey lines indicate the fundamental value (50); black dots show predictions vs. average price realizations; red dots show predictions vs. average price realizations for period 1; the solid black line indicates the fitted values of a simple linear regression (with or without a constant?); the dash-dotted grey line is the 45° line.

In Table 8, we saw that price predictions are less accurate in periods with only speculating investors than periods with dividend-collecting investors. To explore whether prices are easier or harder to predict when the number of future generations increases, we regress the measure of prediction error ($\text{abs}(EP-P)/P$) on the “Number of entering generations left”. The resulting coefficients of “Number of entering generations left” are always positive (see Table D5), showing that predictions are less accurate (and prices thus harder to predict) with a higher number of generations left. Furthermore, the regression results on “Number of peri-

ods left” show that the coefficients are always positive, which means that prices are harder to predict at the beginning of the session compared to later periods.

Table D5: Prediction Accuracy (regression analysis)

Panel A: High Liquidity Sessions

dependent variables	<i>Abs(EP-P)/P</i>		<i>Abs(EP-P)/50</i>	
<i>Intercept</i>	0.250 *** (0.048)	0.197 ** (0.011)	0.230 *** (0.037)	0.130 ** (0.051)
<i>Number of Entering generations Left</i>	0.016 (0.018)		0.046 * (0.026)	
<i>Number of Periods Left</i>		0.010 (0.007)		0.021 *** (0.005)
R ²	0.004	0.008	0.038	0.050
N	381	381	381	381

Panel B: Low Liquidity Sessions

dependent variables	<i>Abs(EP-P)/P</i>		<i>Abs(EP-P)/50</i>	
<i>Intercept</i>	0.224 *** (0.045)	0.184 *** (0.051)	0.106 *** (0.015)	0.060 *** (0.014)
<i>Number of Entering generations Left</i>	0.041 ** (0.017)		0.020 *** (0.006)	
<i>Number of Periods Left</i>		0.013 * (0.006)		0.010 *** (0.002)
R ²	0.028	0.017	0.060	0.084
N	381	381	381	381

Notes: Standard errors clustered by session in parenthesis. Significance levels: * (10%), ** (5%) and *** (1%).

Finally, we analyze whether subjects correctly predict that prices will drop in high-liquidity treatments when the 3rd-to-last generation is trading with the penultimate generation. In high liquidity treatments, of 78 periods when the 3rd-to-last generation is trading with the penultimate generation, 58 periods experienced a price drop (compared to the period before). Of the 58 periods with price drops in 39 periods (67.2% of cases) subjects correctly expected a price drop. In low liquidity treatments, in 43 (74.1%) of 58 periods that experienced a price drop, the subjects correctly expected the price drop. We thus conclude that subjects are mostly able to predict the price drop once the penultimate generation enters the market.