Department of Economics
Seminar Series

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“Trading Institutions in Experimental Asset Markets: Theory and Evidence”

Friday,
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3:30 pm.
212 Middlebush
We report the results of an experiment designed to study the role of institutional structure in the 
formation of bubbles and crashes in laboratory asset markets. In this study, in addition to Call Market 
and Double Auction, we employ the Tâtonnement trading institution, which has not been previously 
explored in laboratory asset markets, despite its historical and contemporary relevance. The results 
show that bubbles are significantly smaller in Tâtonnement than in Double Auction, suggesting that 
the trading institution plays a crucial role in the formation of bubbles.

We provide a heterogeneous agent model with speculators, fundamental and noise traders to better 
understand these results. For each trading institution, we provide structural estimates of the para-
meters of the model using experimental data. The model allows us to identify the different types 
of traders empirically. We find that speculation is more prominent in Double Auction than in other 
trading institutions. Furthermore, Tâtonnement produces more accurate and less dispersed (among 
traders) price forecasts towards the end of the experiment, which indicates that Tâtonnement favors 
more homogenous expectations.

Keywords: Experimental Asset Markets, Bubbles, Traders’ Heterogeneity, Trading In-
stitutions

JEL Classifications: C90, C91, D03, G02, G12
1 Introduction

Price bubbles are not a rare phenomenon. Indeed, there are many historical examples of commodity or financial asset markets that have experienced a period of sharp rising prices followed by an abrupt crash. One of the earliest recorded and most famous examples is the Tulip mania (Holland, 1637) in which prices reached a peak of over ten times greater than a skilled craftsman’s annual income and then suddenly crashed to a fraction of its value. More recently, the real estate bubble of 2007 plagued many of the major economies of the world from which most are still reeling today (see Akerlof and Shiller [2009]).

As price bubbles represent a phenomenon with substantive economic implications, they are widely studied in finance and economics. Smith et al. [1988] were the first to observe price bubbles in long-lived finite horizon experimental asset markets. Many studies have followed the pioneering work of Smith et al. in order to test the robustness of the price bubble phenomenon. To date, the only treatment variable that appears to consistently eliminate the existence of the price bubble is experience of all or some of markets participants via participation in previous asset market sessions with identical environments (Smith et al. [1988], Boening et al. [1993], Dufwenberg et al. [2005], Haruvy et al. [2007]).

Asset market experience addresses what we believe to be two leading explanations for the existence of price bubbles. The first is the lack of common expectations due to the rationality of subjects not being common knowledge (Smith et al., 1988; Smith, 1994). Even though the experimenter can make every effort to explain the dividend process to all subjects, they may still be skeptical about the rationality of other traders. That is, some subjects may believe that other traders may be willing to make a purchase at a price greater than the fundamental value, and thus provide opportunities for capital gains via speculation. This speculative demand can build upon itself, and thus endogenously push the prices higher and higher above the fundamental value creating a price bubble. The second explanation, as argued by Lei, Noussair, and Plott (2002) and Lei and Vesely (2009), is that the difficulty in assessing the dynamic asset valuation may generate confusion and decision errors leading to bubble formation. More specifically, subjects may struggle with backward induction in order to correctly calculate the fundamental value, and thus a rational price, in a given period. Accumulating experience by participating in multiple asset markets allows subjects to gain confidence in the rationality of other traders as well as to learn the

\[1\] NOTE to Steve: We need to mention other factors that are now also well known to contribute to bubble formation, i.e. particularly those listed by the AER referees. CA ratio is going to be listed here as well. Possibly add brief argument that we’ve created a bubble prone environment.
dynamic asset valuation process, and thus eliminate confusion and decision errors.

In this paper, we study the effect of trading institutions on the formation of bubbles and crashes and introduce the Tâtonnement trading institution to be investigated along with the double auction and call market institutions\(^2\) that are typically used in experimental asset markets. We are interested in the Tâtonnement for two reasons. Firstly, we believe that it addresses both of the driving forces for bubble formation described above, and thus conjecture that price bubbles will be significantly reduced by the Tâtonnements implementation relative to the call market or double auction institutions. Furthermore, the Tâtonnement is a trading institution of historical and contemporary relevance. Indeed, the Tâtonnement is one of the earliest classical theories, which is explicit about market price dynamics and adjustment to equilibrium (see Duffie and Sonnenschein [1989]). Furthermore, the Tâtonnement is not just an abstract theoretical construct as it has been employed in some actual markets, e.g., the Tokyo grain exchange (Eaves and Williams [2007]) or the pre-opening trading period on the Paris-Bourse (see Biais et al. [1999]).

A characteristic of the double auction institution is that buyers and sellers tender bids/asks publicly. Typically the highest bid to buy and the lowest ask to sell are displayed and open to acceptance, and price quotes progress to reduce the bid ask spread. Trading is open for a limited period of time and occurs bilaterally and sequentially at different prices within a period. In the call market, on the other hand, bids and asks are accumulated and the maximum possible number of transactions are simultaneously cleared at a single price per period. How does the Tâtonnement differ from these institutions? In our implementation of Tâtonnement institution, subjects submit quantities to buy or sell at a given price. If aggregate demand is equal to aggregate supply, the market clears. Otherwise, the market proceeds with price adjustment iterations. More specifically, the provisional price moves upward if there is excess demand and downward if there is excess supply. Subjects submit their desired quantity to buy or sell at the new provisional price, and the process continues until the market clears. Thus, there may be several non-binding iterations within each period that are publicly observable and reflect the formation of aggregate demand, aggregate supply, and market-clearing price.

We believe that these non-binding price adjustment iterations in each period take into account both leading conjectures of bubble formation that are addressed by experience, and thus the Tâtonnement may significantly reduce price bubbles even with inexperienced subjects. That is, the Tâtonnement may

\(^2\)Call markets may also be referred to as clearinghouse mechanisms in the literature (see Friedman [1993]).
allow subjects to learn from each other in each period thereby establishing common expectations and reducing decision errors and confusion. Indeed, subjects now have the ability to learn demand, supply, and market-clearing price without actual trading. This is in contrast with the double auction institution where trades occur in continuous time, and thus extreme behavior associated with confusion or decision errors may more easily influence the market into a price bubble scenario. In other words, in order for trade to occur under the Tâtonnement, subjects need to come to a collective agreement (as market clears only if excess demand/supply is equal to zero) while in the double auction or call market institutions that is not the case. Under Tâtonnement, the sequence of non-binding price adjustment within a period itself reveals information, allowing subjects to have a more accurate belief about market-clearing price, and gain experience within a period rather than across periods as is the case under the double auction and call market institutions. Thus, there is a mechanism embodied in the Tâtonnement institution that allows inexperienced traders to acquire important market information, and thereby reduce confusion and decision errors.

The effect of trading institutions on the formation of bubbles, efficiency levels and excess volatility has been investigated by various authors with mixed results. Boening et al. [1993] provide an experimental comparison between Call Market- and Double Auction environments, for single long lived assets. They observe similar bubble crash patterns across trading institutions for inexperienced subjects. Friedman [1993] also compares double auctions to call markets experimentally. He reports that double auctions increase trading volume but the informational efficiency across trading institutions is similar. Furthermore, the allocational efficiency in call markets tends to be higher than in double auctions under limited order flow information. Amihud and Mendelson [1987] and Stoll and Whaley [1990] compare pre-opening prices to actual trading prices on the New York Stock Exchange (NYSE). The pre-opening period on the NYSE uses a trading institution similar to both standard clearinghouses and Tâtonnement trading institutions, whereas the actual trading prices are determined via double auctions. Both, Amihud and Mendelson [1987] and Stoll and Whaley [1990] find that the pre-opening prices are significantly more

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3In a sense, the Tâtonnement price adjustment process protects the market from extreme bids that (particularly in early periods) may lead to speculative bubbles under a double auction institution.

4Under the Tâtonnement, the magnitude of excess supply/excess demand within the price adjustment process signals to subjects the general consensus regarding the market-clearing price and where their decision lies in relation to that consensus. Informally, suppose that the total number of shares is 120 units. If the excess supply is only 5 shares and I am a buyer, I should not be that concerned about doing something wrong. However, if excess supply is 100, and I am trying to buy, I might start thinking about why the vast majority of subjects have very different beliefs about the market-clearing price than me.
volatile than the actual trading prices. However, as Friedman [1993] notes: “neither paper considers the interpretation that the clearinghouse institution was chosen to reduce volatility, which might otherwise be even higher”.

We find that under the Tâtonnement institution, price bubbles are mitigated compared to double auction, according to most bubble measures employed in the literature. We provide a heterogeneous agent model with speculators, fundamental- and noise traders to better understand these results.

Independently of the underlying trading institution, we modeled heterogeneity via different behavioral rules and heterogeneous expectation formation processes. Noise traders submit bids and asks, which are convex combinations of a noise and a previous-price-anchoring-component (Duffy and Ünver [2006]). Speculators are modeled in the spirit of level-1 agents (Nagel [1995], Stahl and Wilson [1994, 1995], Crawford et al. [2013] etc.), i.e., they form price-forecasts conditional on facing a population of noise traders but also take the fundamental value of the asset partially into account. Fundamental traders form adaptive expectations and focus in their buy and sales decision only on the fundamental value. The mechanics of the bubble-crash pattern in our model is as follows. The behavioral rules of noise- and fundamental traders generate an initial momentum, leading to upward trending trading prices. Prices eventually exceed the fundamental value of the asset and the positive trend generates further purchases of anchoring noise traders. With prices above the fundamental value, fundamental traders start liquidating their positions, whereas speculators and noise traders continue to purchase the asset at increasing prices (bubble). Speculators buy assets assuming that they can sell them to a noise trader in future periods. More specifically, since we consider a finite horizon and decreasing fundamental value framework to be consistent with the majority of the previous literature, speculators eventually start selling to noise traders upon predicting the peak of the bubble. The sell-orders of speculators together with the behavior of anchoring noise traders generates downward trending prices (crash). The model provides another example of destabilizing speculation (Hart and Kreps [1986], DeLong et al. [1990], Cutler et al. [1990], Hirshleifer [2001], Abreu and Brunnermeier [2003], Brunnermeier and Pedersen [2005]) under the presence of noise traders and incorporates Black [1986]: “Noise makes financial markets possible, but it also makes them imperfect. If there is no noise trading, there will be very little trading in individual assets.” 

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5 For an overview over computational, heterogeneous agent models used in the economics and finance literature see Hommes [2006].
6 See ? for evidence on adaptive expectation formation processes.
7 The model assumes that speculative traders only condition their behavior on noise traders.
For each trading institution, we provide structural estimates of the parameters of the model using experimental data. Therefore, we can estimate the underlying trader type distributions for each market and thus classify market participants individually into the different trader types. We find that speculative traders are more prominent in double auctions than in other trading institutions. Furthermore, Tatonnement generates more accurate, less dispersed, and therefore more homogeneous, price forecasts among trader types. Hence, the results extend the findings of Hommes et al. [2005, 2008], Hommes [2010], Hülsler et al. [2013] and suggest that convergence of expectations, and thus propensity of bubble formation, is sensitive to the underlying trading institution.

Overall, both our experimental and computational results indicate that trading institutions play an important role in price discovery and bubble formation.

2 Experimental Design and Data

The experiment consists of 15 markets conducted between October 2011 and March 2013 at Indiana University in Bloomington, USA and at the University of Canterbury in Christchurch, New Zealand. There were 9 traders in 12 markets, and 8 traders in 3 markets resulting in a total of 135 participants. Participants were undergraduate students at each of the respective universities recruited using the ORSEE subject recruitment and management program. Some of the subjects had participated in previous economics experiments, but all subjects were inexperienced with asset markets and only participated in a single market of this study. The experiments were computerized and programmed with the z-Tree software package. All trade took place via the experimental currency francs and final cash holdings were paid out in NZ (US) dollars according to a predetermined and publicly known exchange rate. Each session lasted approximately 90 – 120 minutes depending upon treatment. The parameters in all sessions were set to generate average earnings of $18 per hour.

The markets consisted of 15 periods in which participants had an opportunity to trade an asset with a stochastic dividend process. The dividends each period were independently and randomly drawn with equal probability from a 4-point distribution of 0, 8, 28, or 60 francs (e.g., Smith et al. 1988, King et al.).

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8See Greiner [2004] for a discussion of the ORSEE recruitment program.
9See Fischbacher [2007] for a discussion of the z-Tree software package.
10Tatonnement sessions lasted on average 120 minutes while double auction and call market sessions lasted 90 minutes on average. All durations include instructional period and subject payments.
Therefore, the average dividend per unit equaled 24 francs in each period. The asset had no terminal buyout value, and thus, assuming risk neutrality, the fundamental value of the asset at any time equaled 24 francs times the number of periods remaining. More specifically, the fundamental value declined from 360 francs in period 1 to 24 francs in period 15.

Traders were initially endowed with 10 units of the asset and 10,000 francs. In each trading period, traders were allowed to buy and/or sell units of the asset according to the following constraints. A trader must have sufficient cash to purchase the asset or sufficient units of assets in their inventory to make the sale. Each of the markets prohibited trading with oneself and imposed a purchase restriction of 10 assets in each period. There were no trading fees and no interest paid on cash holdings.

At the beginning of each period traders also made forecasts of the transaction price for that period. In particular, they made predictions of the average transaction price in the double auction treatment and uniform market-clearing price in the other treatments. They were paid for the accuracy of their forecasts.\footnote{\textsuperscript{11}They were paid 50 francs for the forecast within 10%, 20 francs for within 25%, and 10 francs for within 50% of actual price. We followed \citet{Haruvy et al. 2007} for the forecast rewards structure. All earnings from forecasting accumulated in a separate account from the traders’ cash on hand, and thus these payments did not affect the market capital asset ratio.}

At the beginning of each session, subjects completed a three-question cognitive reflection test \citep{Frederick 2005}. Subjects earned $2 for each correct answer. No payment information was provided until they received their overall earnings at the end of the session. Upon completion of the test, subjects were given the market instructions and provided 15 minutes to read through them on their own.\footnote{\textsuperscript{12}Instructions for each treatment are available upon request.} After 15 minutes, the experimenter summarized the market, explained the interface of the bidding screen, and provided answers to the market quiz questions. The experimenter answered any questions and then started the market. The subjects were paid privately at the end of the experiment.

The only treatment variable in the study is the trading institution. We focused on three different trading institutions: Double Auction (DA), closed-book Call Market (CM), and Tâtonnement (TT).

\subsection*{2.1 Experimental Procedures: Double Auction and Call Market}

The Double Auction and Call Market trading institutions are widely used in experimental asset market studies, thus in what follows we only briefly summarize the main features. The baseline treatment uses
a continuous double auction with an open order book (e.g., see Smith [1962] or Plott and Gray [1990]).

Under the continuous double auction rules, the market is open for 3 minutes, during which the buyer/seller can submit orders to buy/sell one unit at a specified price. A trader’s acceptance of an offer to buy/sell concludes a trade at the price specified by the offer. Therefore, all transactions in a double auction typically trade at different prices within a period.

The trading institution in the second treatment is a closed-book call market (e.g. Smith et al. [2000], Friedman [1993], Cason and Friedman [1997]). Under the call market rules, traders submit their offers to buy/sell units of the asset for the period simultaneously. They have the opportunity to submit one offer to buy and one offer to sell each period. An offer to buy consists of the maximum quantity that they want to purchase and the maximum price that they are willing to pay for each unit. Similarly, an offer to sell consists of the maximum quantity that they want to sell and the minimum per unit price that they are willing to sell each of those units. Once all offers to buy/sell are submitted, the computer aggregates them into demand and supply schedules and the uniform market price is calculated as the lowest price that clears the market. Traders who submit buy (sell) orders above (below) the market price make purchases (sales). Ties for the last unit bought/sold are resolved randomly. To prohibit self-trades, the market requires the offered buy price to be less than the offered sell price.

2.2 Experimental Procedures: Tâtonnement

Under the Tâtonnement, in each period subjects were allowed either to buy or to sell units of the asset as long as they had sufficient cash on hand to cover the purchase or sufficient inventory of assets to make the sale. At the beginning of each period, the initial price was determined by the median forecasted price (recall that subjects provided price forecasts at the beginning of each period). Each subject decided how many units of the asset they wanted to buy or sell at this price by placing bids or asks respectively. The computer aggregated individual decisions and compared the market quantity demanded \((Q_D)\) to the market quantity supplied \((Q_S)\). If the market cleared \((Q_D = Q_S)\), then the process stopped and transactions were completed. If the market did not clear at the initial price, then the price would adjust in the appropriate direction. Specifically, we employed a proportional adjustment rule, which can be thought of as proceeding in two stages (see also Joyce [1984, 1998]).
In the first stage, the price adjusts proportionally according to the following rule:

\[ P_t = P_{t-1} + \gamma_t(Q_{D,t-1} - Q_{S,t-1}) \]

where \( \gamma_t \in \{2, 1, 0.75, 0.5, 0.25, 0.05\} \) is the adjustment factor and subscript \( t \) is the iteration of adjustment. The initial adjustment factor is 2 and it decreases to the next lower value unless we observe either an excess supply or an excess demand twice in a row, i.e., unless \( (Q_{D,t} - Q_{S,t}) \) is of the same sign as \( (Q_{D,t-1} - Q_{S,t-1}) \). For small levels of excess supply/demand (or in the second stage), the price adjustment rule is replaced by

\[ P_t = P_{t-1} + 1 \text{ if } 0 < \gamma_t(Q_{D,t-1} - Q_{S,t-1}) < 1, \]

and

\[ P_t = P_{t-1} - 1 \text{ if } -1 < \gamma_t(Q_{D,t-1} - Q_{S,t-1}) < 0. \]

The price adjustment process continues until a market-clearing price is attained upon which all units are transacted at the uniform price. Subjects had access to flow information so they could see the aggregate demand and supply of stocks in every iteration of every period. We did not implement an improvement rule. That is, following each price announcement, players were free to submit new bids and asks, without
any constraints on their behavior from prior iterations. As a result, it is possible with the price adjustment process to get oscillating prices, and thus we implemented two ending rules for a period. In particular, a period was concluded if (1) the difference between excess supply and excess demand was two units or less; and (2) the price remained strictly within a three franc region for three price adjustment iterations in a row.

Figure 1 illustrates how the price adjustment rule works via the data collected in period 2 of session 1 of Tâtonnement treatment. At the initial price of $P_1 = 320$, aggregate demand is $Q_{D,1} = 39$ and aggregate supply is $Q_{S,1} = 0$. In the next iteration, the price is $P_2 = 320 + 2(39 - 0) = 398$. At $P_2 = 398$, aggregate demand is $Q_{D,2} = 0$ and aggregate supply is $Q_{S,2} = 45$, which implies that the adjustment factor used in the iteration will be 1, so that $P_3 = 353$. The same process continues for all other prices in the iteration sequence of the period.

2.3 Experimental Results

Figure 2 depicts the time series of prices and fundamental values in our experiment for each session and for each trading institution. Each period of the experiment is provided on the horizontal axis and market clearing prices are indicated on the vertical axis. The last graph (panel d) compares the mean prices across trading institutions. Figure 2 shows that Double Auction mean prices are significantly above the mean prices of the Call Market and Tâtonnement.

For each session we calculated several bubble measures typically used in the literature. The definitions of the measures as well as their average values for each institution are presented in Table 1. Then we compared bubble measures across institutions using the Mann-Whitney test (with sessions as units of observation). The results are presented in Table 2.

Table 1 indicates that bubbles are the lowest under Tâtonnement and the highest under Double Auction. Indeed the Mann-Whitney test confirms that bubbles are significantly lower under Tâtonnement than under Double Auction. Bubbles under Call Market tend to be higher than under Tâtonnement, but lower than under Double Auction. However, these differences are not statistically significant. Note that even though Turnover and Normalized Deviation are significantly lower under Call Market than under Double Auction, it is not surprising, since both of these measures depend on the volume of trade and

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13 For Double Auction, prices reflect session average transaction prices.
14 See Haruvy and Noussair [2006], Haruvy et al. [2007], Kirchler et al. [2010].
Figure 2: Experimental Data on Prices Across Institutions
Table 1: Bubble Measures for DA, CM, and Tâtonnement, Averaged over All Sessions

<table>
<thead>
<tr>
<th>Measure</th>
<th>Double Auction</th>
<th>Tâtonnement</th>
<th>Call Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turnover</td>
<td>$\sum_{t=1}^{15} q_t / T SU$</td>
<td>4.05</td>
<td>1.49</td>
</tr>
<tr>
<td>Amplitude</td>
<td>$\max_t \left{ \frac{(P_t-FV_t)}{FV_t} \right} - \min_t \left{ \frac{(P_t-FV_t)}{FV_t} \right}$</td>
<td>0.65</td>
<td>0.29</td>
</tr>
<tr>
<td>Norm. Dev.</td>
<td>$\frac{1}{TSU} \sum_{t=1}^{15} q_t</td>
<td>P_t - FV_t</td>
<td>$</td>
</tr>
<tr>
<td>APD</td>
<td>$\frac{1}{TSU} \sum_{t=1}^{15}</td>
<td>P_t - FV_t</td>
<td>$</td>
</tr>
<tr>
<td>RAD</td>
<td>$\frac{1}{15} \sum_{t=1}^{15} \frac{</td>
<td>P_t - FV_t</td>
<td>}{\text{mean}(FV)}$</td>
</tr>
<tr>
<td>RD</td>
<td>$\frac{1}{15} \sum_{t=1}^{15} \frac{(P_t-FV_t)}{\text{mean}(FV)}$</td>
<td>0.36</td>
<td>0.14</td>
</tr>
<tr>
<td>RPAD</td>
<td>$\frac{1}{15} \sum_{t=1}^{15} \frac{</td>
<td>P_t - FV_t</td>
<td>}{FV_t}$</td>
</tr>
<tr>
<td>Haessel</td>
<td>$R^2$ of OLS regression $P_t = \alpha + \beta FV_t + \epsilon_t$</td>
<td>0.46</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Table 2: Pairwise Comparison of Bubble Measures for DA, Tâtonnement and CM: p-values of the Mann-Whitney Test.

<table>
<thead>
<tr>
<th>Measure</th>
<th>TT vs. DA</th>
<th>TT vs. CM</th>
<th>DA vs. CM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turnover</td>
<td>0.02, &lt;</td>
<td>0.75</td>
<td>0.01, &gt;</td>
</tr>
<tr>
<td>Amplitude</td>
<td>0.05, &lt;</td>
<td>0.35</td>
<td>0.17,</td>
</tr>
<tr>
<td>Norm. Dev.</td>
<td>0.05, &lt;</td>
<td>0.60</td>
<td>0.05, &gt;</td>
</tr>
<tr>
<td>APD</td>
<td>0.03, &lt;</td>
<td>0.46</td>
<td>0.12,</td>
</tr>
<tr>
<td>RAD</td>
<td>0.07, &lt;</td>
<td>0.46</td>
<td>0.17,</td>
</tr>
<tr>
<td>RD</td>
<td>0.46,</td>
<td>0.60</td>
<td>0.35</td>
</tr>
<tr>
<td>RPAD</td>
<td>0.05, &lt;</td>
<td>0.25</td>
<td>0.17,</td>
</tr>
<tr>
<td>Haessel</td>
<td>0.03, &gt;</td>
<td>0.17</td>
<td>0.12,</td>
</tr>
</tbody>
</table>

3 Model: Simulated Market Environments

In this section, we provide a heterogeneous agent model which generates price and volume patterns that are similar to the observed data. Our model builds on [Duffy and Unver 2006] and [Haruvy and Noussair 2006]. The model captures important features of the data described in Section 2. In each market environment, $N$ agents interact in $T$ periods and trade a single financial asset. Initially each agent $i$ is endowed with $x_0^i$ units of cash and $y_0^i$ units of the financial asset. At the end of every period the asset pays random dividends drawn with equal probability from a commonly known support $\{d_1, d_2, d_3, d_4\}$, with each unit can be only traded once under CM and TT and multiple times under DA.
\( d_i \geq 0 \) and \( d_1 < d_2 < d_3 < d_4 \). The expected dividend is denoted as \( \bar{d} = \frac{1}{4} \sum_{i=1}^{4} d_i \). Since our model is supposed to fit the laboratory environment, the dividend support is \{0, 8, 28, 60\}. In general, the support does not necessarily have to be restricted to four values or to an i.i.d. dividend process. The fundamental value of the asset in every period is common knowledge and given by \( FV_t = \bar{d}(T - t + 1) \) for \( t = 1, \ldots, T \). As in the experiment, no short selling is allowed. Under rational expectations and risk neutrality, prices should equal the fundamental value.

Next we provide a more detailed description of each market environment.

### 3.1 Call Markets

In every trading period \( t = 1, \ldots, T \) traders may either buy or sell units of the financial asset (or remain inactive). During the experiments, traders are allowed to submit both bids and asks simultaneously, potentially for multiple units. To capture this feature in the simulations, we subdivide each trading period into \( S \) submission rounds. In each of the \( s = 1, \ldots, S \) submission rounds a trader is either a seller or a buyer (the decision or probability to be buyer or seller is described below). Trader \( i \) in submission round \( s \) and trading period \( t \) can submit an ask price, \( a_{i,s,t} \), for one unit of the asset if she is a seller and can submit a bid, \( b_{i,s,t} \), if she is a buyer. This feature of the model allows us to track the volume of the traded asset during the experiments more accurately. As in the experiment, no short selling is allowed.

In every submission round in trading period \( t \) all the bids and ask prices are aggregated to obtain the price and quantity traded\(^{15}\). That is, as in the experiments, the trading institution used to determine market clearing prices is a closed book call market\(^{16}\)

In each round, any buyer who submits a bid above the market-clearing price \( p_{s,t}^b \) buys one unit of the asset at \( p_{s,t}^b \). Thus, the updated cash and unit holdings of a buyer are

\[
\begin{align*}
    x_{s,t}^i &= x_{s-1,t}^i - p_{s,t}^b \mathbbm{1}_{(b_{i,s,t} > p_{s,t}^b)} \\
    y_{s,t}^i &= y_{s-1,t}^i + 1 \mathbbm{1}_{(b_{i,s,t} > p_{s,t}^b)}
\end{align*}
\]

for each submission round \( s \) of trading period \( t \). The symbol \( \mathbbm{1}_C \) is an indicator function, taking the value

\(^{15}\)Bids are ordered from highest to lowest to obtain the inverse demand schedule, while asks are ordered from lowest to highest to obtain the inverse supply schedule. The trading price is determined as the intersection of the inverse demand and supply schedules. Note that we can have multiple market clearing prices within a period. The number of rounds fitting the data best is given below. Further, the average simulated difference across submission prices within a period is negligibly small.

\(^{16}\)In closed book call markets traders observe only the market clearing price (on their screens) but are not informed about the identities of the traders who sell or buy units of the asset. Typically they also do not observe the trading volume in this market environment.
1 if condition $C$ is satisfied and 0 otherwise. The assumptions on the behavior of traders will imply that prices across submission periods $p_{s1}^t$ and $p_{s2}^t$ with $s_1 \neq s_2$ will not vary systematically. This particular structure was chosen to account for the possibility of trading multiple units in a period and to fit the simulated trading volume to the data.

In each round, any seller who submits an ask below the market-clearing price $p_{s,t}^t$ sells one unit at $p_{s,t}^t$. The updated cash and unit holdings of a seller are

$$x_{s,t}^i = x_{s-1,t}^i + p_{s,t}^t \mathbb{1}_{(a_{s,t}^i < p_{s,t}^t)}$$
$$y_{s,t}^i = y_{s-1,t}^i - 1_{(a_{s,t}^i < p_{s,t}^t)}$$

for each submission round $s$ of trading period $t$. The market-clearing price is the lowest price at which the number of buyers equals the number of sellers. If the entire demand schedule is below the supply schedule, the highest bid price serves as a proxy for the market-clearing price. No trades are executed at this price during the simulations\textsuperscript{17}

After the $S$th (last) submission round in trading period $t$, the random dividend $D_t$ is realized and traders update their cash holdings according to: $x_{1,t+1}^i = x_{S,t}^i + D_t y_{S,t}^i$. The period market-clearing price is given by the average market-clearing price across $S$ rounds, i.e., $p_t = \frac{1}{S} \sum_s p_{s,t}^t$\textsuperscript{18}

### 3.2 Double Auction

A characteristic of the double auction market mechanism is that buyers and sellers tender bids/asks publicly. Typically the highest bid to buy and the lowest ask to sell are displayed and open to acceptance, and price quotes progress to reduce the bid-ask spread. Trading is open for a limited period of time and occurs bilaterally and sequentially at different prices within a period. Thus, unlike the call market institution, potentially different transaction prices are observed during the period. Similar to the call market environment, we subdivide each trading period into $S$ submission rounds in the simulations.

In each of the $s = 1,...,S$ submission rounds a trader is either a seller or a buyer (the decision or probability to be buyer or seller is described below). Trader $i$ in submission round $s$ and trading period $t$ can submit an ask price, $a_{s,t}^i$, for one unit of the asset if she is a seller or a bid, $b_{s,t}^i$, if she is a buyer.

\textsuperscript{17}In the model, the case in which identical bids or asks are submitted occurs with probability zero. In this hypothetical case, buyers and/or sellers are determined randomly among agents with identical bids or asks.

\textsuperscript{18}Like in Baghestanian et al. [2012] there are no systematic differences across round market-clearing prices within a period.
In every period bids and asks are collected in the “order book”. The highest bid in the order book, $B_t$, is called the best current bid and the lowest ask, $A_t$, is called the best current ask. During the experiments the best bid and ask are highlighted on the computer screens of the participants. A subject can trade by accepting the best bid/ask, in which case the second highest (lowest) bid (ask) in the order book becomes the best current bid (ask). Alternatively, a subject can submit a bid or ask and wait for it to be accepted.

In our simulations we compare agent $i$’s bid, $b_{i,s,t}$, to the best current ask, $A_t$. If

$$b_{i,s,t}^i \geq A_t,$$

(1)

it indicates that agent $i$ is willing to buy the asset at a price, which exceeds the best current ask and trade takes place at transaction price $A_t$. Similarly, we compare agent $i$’s ask $a_{s,t}^i$ to the best current bid, $B_t$. If

$$a_{s,t}^i \leq B_t,$$

(2)

it indicates that agent $i$ is willing to sell the asset at a price, which is below the best current bid and trade takes place at transaction price $B_t$. Units as well as cash holdings are updated accordingly. The second lowest (highest) ask (bid) in the order book becomes the best current ask (bid) $A_t$ ($B_t$). If there is no corresponding second lowest (highest) ask (bid) in the order book the next ask (bid) submitted by some trader becomes either $A_t$ or $B_t$.

On the other hand, if neither of these conditions are satisfied, agent $i$ does not immediately trade, and her bid/ask is stored in the order book and is highlighted only if it becomes the best current bid/ask.

Let $vol_t$ denote the total number of asset units traded in period $t$ and $p_j$ denote each individual transaction price (in period $t$), then the average trading price in period $t$ under a double auction trading institution is

$$p_t = \frac{1}{vol_t} \sum_{j=1}^{vol_t} p_j.$$

At the end of every trading period (after $S$ trading rounds) the order book is cleared.
3.3 Tâtonnement

Similar to call markets and unlike double auctions, tâtonnement markets are uniform-price trading environments. In every trading period \( t = 1, ..., T \) traders may either buy or sell units of the financial asset (or remain inactive). In tâtonnement auctions every trading period starts at some initial price \( p_{0,t} \). Conditional on this “indicative” price, a trader may submit either an ask quantity (supply), \( y^i_{a,t} \) if she is a seller or a bid quantity (demand), \( y^i_{b,t} \), if she is a buyer. Based on those submitted demand and supply quantities, the auctioneer/experimenter computes the aggregate excess demand, \( z_t \), where

\[
z_t = \sum_i y^i_{b,t} - \sum_i y^i_{a,t}.
\] (3)

If \( z_t = 0 \) at the initial price, markets clear immediately at prices \( p_{0,t} \), trades are executed and cash and unit holdings are updated accordingly. If \( z_t > 0 \), there is excess demand at the indicative price \( p_{0,t} \), while, if \( z_t < 0 \), there is excess supply at the indicative price \( p_{0,t} \). Prices are updated following a proportional rule:

\[
p_{j+1,t} = p_{j,t} + \beta_j z_{j,t},
\] (4)

where \( \beta_j \in \{ r_1, r_2, r_3, ..., r_K \} \) is the adjustment factor and subscript \( j \) is the iteration of adjustment with \( r_1 > r_2 > r_3, ... > r_K \). The initial adjustment factor is \( r_1 \) and it decreases to the next lower value unless we observe either an excess supply or an excess demand twice in a row, i.e., unless \( z_{j,t} \) is of the same sign as \( z_{j-1,t} \). For low levels of excess supply/demand, the price adjustment rule is replaced by

\[
p_{j+1,t} = p_{j,t} + 1 \quad \text{if } 0 < \beta_j z_t < 1,
\] (5)

\[
p_{j+1,t} = p_{j,t} - 1 \quad \text{if } -1 < \beta_j z_t < 0.
\] (6)

Conditional on the new indicative prices, agents may re-submit new quantities for \( y^i_{a,t} \) or \( y^i_{b,t} \).

Iterations should continue until \( z_t = 0 \). However, as described in the experimental design, to facilitate convergence and coordination of demand and supply, two stopping rules were introduced. The first stopping rule was implemented when the excess demand/supply was low. Namely, whenever \( 0 < |z_t| \leq 2 \), subjects who wished to buy had the opportunity to either increase (if they had enough cash) or to reduce their demands one unit at a time. Subjects who wished to sell had the option (whenever possible) to
increase or decrease their supply in step sizes of one single unit. During this process prices remained unchanged. This stopping-rule process was based on a first-come first-served basis and continued until markets cleared perfectly \( z_t = 0 \). This feature was captured in the simulations by randomly increasing or decreasing individual demand/supply quantities of randomly selected agents. The second stopping rule was implemented whenever three consecutive indicative prices oscillated within a range of three cash units. For example, if the price went from 100, to 101, to 100 then back to 102. Whenever this happened the tâtonnement procedure was stopped and subjects were asked to increase or decrease their demand/supply at the last observed price until the market cleared perfectly. This feature was captured in the simulations by randomly increasing or decreasing individual demand/supply quantities of randomly selected agents. In every period the simulated indicative price at which \( z_t = 0 \) is the market clearing price \( p_t \).

4 Model: Traders’ Behavior

As suggested by previous theoretical and experimental studies, traders heterogeneity can help to understand bubble dynamics. As in [DeLong et al. 1990] and [Haruvy and Nousair 2006], we consider a model with three types of traders: noise, fundamental and speculative traders. We assume that there are \( k_1 \) fundamental traders, \( k_2 \) speculators and \( (N - k_1 - k_2) \) noise traders in the market with \( k_1, k_2 \in \{0, 1, ..., N\} \) and \( k_1 + k_2 \leq N \). We start by describing trader types in call markets and double auctions.

4.1 Noise Traders in Call Markets and Double Auctions

At the beginning of every submission round \( s \) in every period \( t \), a noise trader is a buyer with probability \( \pi_t \) and a seller with probability \( 1 - \pi_t \). We assume that \( \pi_t = \pi = 0.5 \). We depart from [Duffy and Ünver 2006] who assume that \( \pi_t = \max\{0.5 - \phi t, 0\} \) with \( \phi \in [0, \frac{0.5}{T}] \), i.e., the probability of being a noise-buyer is decreasing over time and initially equal to 0.5. [Duffy and Ünver 2006] refer to this as ‘weak foresight’ assumption. This assumption implies that as \( t \) increases, the excess supply increases and generates a downturn of prices. [Duffy and Ünver 2006] need this assumption to generate the crash pattern, given that their model consists of only noise traders. We do not impose the ‘weak foresight’ assumption since in our model the crash is generated by the interplay of different types of traders.
If a noise trader is a buyer in trading round $t$ and submission period $s$, she submits a bid subject to cash availability. Her bid is of the form

$$b_{n,i}^{s,t} = \min \left\{ (1 - \alpha)\epsilon_t + \alpha p_{t-1}, x_{i,s,t} \right\}$$

where $\alpha \in (0,1)$, $\epsilon_t \sim U[0,\kappa FV_t]$, $\kappa \geq 0$, and $x_{i,s,t}$ denotes the current cash holdings of agent $i$. In call markets $p_{t-1}$ is the market-clearing price in period $t-1$, while in double auctions $p_{t-1}$ denotes the average transaction price in period $t-1$. Further, in the presence of demand restrictions we limit the number of units that an agent can demand in each period.

Similarly, if a noise trader is a seller in trading round $t$ and submission period $s$, she submits an ask subject to her unit holdings. Her ask is of the form

$$a_{n,i}^{s,t} = (1 - \alpha)\epsilon_t + \alpha p_{t-1},$$

where $\alpha \in (0,1)$ and $\epsilon_t \sim U[0,\kappa FV_t]$.

To summarize, noise traders submit bids and asks based on the previous period price and a noise term. The parameter $\alpha \in (0,1)$ captures anchoring effects of the market clearing price in the previous period.

### 4.2 Fundamental Traders in Call Markets and Double Auctions

We model fundamental traders by modifying the adaptive agents considered by Cason [1992] and the passive investors considered by Haruvy and Noussair [2006]. A fundamental trader computes in every period the bound

$$l_t = \alpha^f (l_{t-1} - \bar{d}) + (1 - \alpha^f)\tilde{p}_t,$$

where $l_0 = FV_1 + \bar{d}$. For call markets $\tilde{p}_t$ is the market clearing price in period $t-1$ ($p_{t-1}$). For double auctions $\tilde{p}_t$ is the average period $t$ transaction price, observed by a fundamental trader before she submits her bid/ask. If no transaction occurred in period $t$ we let $\tilde{p}_t$ be the average transaction price from period $t-1$.

The bound $l_t$ serves as a proxy for the expected market-clearing price in period $t$, since the market-
clearing price is not known at the stage of the bid/ask submission. We subtract \( \bar{d} \) to control for the decreasing fundamental value. The functional form of \( l_t \) suggests that price expectations are formed adaptively (empirical evidence for adaptive expectation formation, used by subjects during asset market experiments, is provided by Haruvy et al. [2007], Smith et al. [1988] and Williams [1987]). Notice that for call markets \( l_t \) does not depend on the submission round \( s \), i.e., we do not allow fundamental traders to update \( l_t \) within a period, which is in line with the experimental design. On the other hand, in double auctions \( \tilde{p}_t \) is updated within a period after each transaction to reflect the feature that traders observe transaction prices within a period.

While noise traders are randomly determined to be buyers or sellers, a fundamental trader decides whether to be a buyer or a seller. If the bound is below the fundamental value, \( l_t \leq FV_t \), and her cash holdings are positive, \( x_{s,t} > 0 \), then she chooses to be a buyer and submits a bid as follows:

\[
\begin{align*}
    b_{s,t}^{f,i} &= \min \{ B_{s,t}^i, x_{s,t} \} \\
    B_{s,t}^i &\sim U[l_t, FV_t]. 
\end{align*}
\] (9)

That is, if the trader believes that the transaction price will be below the fundamental value, she submits a bid \( b_{s,t}^{f,i} \in [l_t, FV_t] \) subject to cash constraint. If the bound is above the fundamental value, \( l_t > FV_t \), and her asset holdings are positive, \( y_{s,t} > 0 \), then she chooses to be a seller and submits an ask from the interval between the fundamental value and the bound:

\[
\begin{align*}
    a_{s,t}^{f,i} &\sim U[FV_t, l_t]. 
\end{align*}
\] (10)

Bids and asks are uniformly distributed in the intervals \( U[l_t, FV_t] \) and \( U[FV_t, l_t] \) respectively, to allow for some decision errors.

### 4.3 Speculators in Call Markets and Double Auctions

Speculator \( i \) decides whether to buy or sell assets based on her expectations about transaction prices in period \( t \) and period \( t+1 \). If

\[
E_t^i(p_{t+1}) + \bar{d} > E_t^i(p_t),
\]

speculator \( i \) decides to submit a bid order expecting to make capital gains by selling in the following period. We use a level-\( k \) modeling approach to compute speculators’ expectations \( E_t^i(p_t) \) (e.g., Stahl and
Wilson [1994, 1995], Crawford et al. [2013], Crawford and Iriberri [2007]). Specifically we assume that speculators are level-1 traders, best responding against a benchmark population of level-0 noise traders. The average market-clearing price process in a population consisting solely of noise traders takes the form:

\[ E^i_t(p_t) = \alpha \tilde{p}_t + (1 - \alpha) \frac{\kappa}{2} FV_t. \]

The assumption that speculators know the actual values of \( \alpha \) and \( \kappa \) is too strong, especially in a closed book call market. We therefore assume that speculator \( j \) forms expectations in the following way:

\[ E^i_t(p_t) = \gamma_1 \tilde{p}_t + \gamma_2 FV_t, \tag{11} \]

with \( \gamma_1 \in [0, 1] \) and \( \gamma_2 \geq 0 \). For call markets \( \tilde{p}_t \) is the market clearing price in period \( t - 1 \) (\( p_{t-1} \)). For double auctions \( \tilde{p}_t \) is the average period \( t \) transaction price, observed by a fundamental trader before she submits her bid/ask. If no transaction occurred in period \( t \), we let \( \tilde{p}_t \) be the average transaction price from period \( t - 1 \). Iterating (11) one period forward we obtain \( E^i_t(p_{t+1}) \) as a function of publicly observed variables, namely, \( FV_t, FV_{t+1} \) and \( \tilde{p}_t \).

Speculators expect to make profits by placing bids in the interval \([E^i_t(p_t), E^i_t(p_{t+1}) + \bar{d}] \). Thus we assume that speculators submit bids as follows:

\[ b^{sp, i}_{s, t} = \min \{ B^{i}_{s, t}, x_{s, t} \}, \tag{12} \]

where \( B^{i}_{s, t} \sim U[E^i_t(p_{t+1}) + \bar{d}, E^i_t(p_t)] \) to allow for potential decision errors.

Similarly, if

\[ E^i_t(p_{t+1}) + \bar{d} \leq E^i_t(p_t) \]

speculator \( i \) decides to sell and submits an ask order of the form:

\[ a^{sp, i}_{s, t} \sim U[E^i_t(p_{t+1}) + \bar{d}, E^i_t(p_t)], \tag{13} \]

subject to asset holdings constraints.
4.4 Trader’s behavior under tâtonnement

In the experiment the initial indicative price in each trading period was determined by the median forecasted price in period \( t \). In the model, the price forecasts are determined as follows.

Noise traders form noisy forecasts:

\[
E_{t-1}^n p_t = (1 - \alpha) \varepsilon_t + \alpha p_{t-1}
\]

where \( \alpha \in [0, 1] \), \( \varepsilon_t \sim U[0, \kappa FV_t] \), \( \kappa \geq 0 \) is a parameter and \( p_{t-1} \) is the transaction price in period \( t - 1 \).

Fundamental traders form adaptive forecasts:

\[
E_{t-1}^f p_t = \alpha^f (l_t - \bar{d}) + (1 - \alpha^f) p_{t-1}
\]

where \( l_0 = FV_1 + \bar{d}, \alpha^f \in [0, 1] \) and \( p_{t-1} \) is the transaction price in period \( t - 1 \).

Speculators form the following forecasts:

\[
E_{t-1}^{sp} p_t = \gamma_1 p_{t-1} + \gamma_2 FV_t
\]

where \( \gamma_1 \in [0, 1] \) and \( \gamma_2 \geq 0 \), \( p_{t-1} \) is the transaction price in period \( t - 1 \).\(^{20}\)

Let \( p_{jt} \) denote the indicative price in iteration \( j \) of period \( t \). The median forecast yields the initial indicative price for the tâtonnement process, \( p_{0,t} \). Next we describe each trader’s type behavior.

4.4.1 Noise traders in tâtonnement auctions

For every given indicative price \( p_{jt} \), a noise trader is a buyer or a seller with equal probability. As a buyer, in trading period \( t \) and iteration \( j \), noise trader \( i \) bids for a random quantity demanded subject to cash availability:

\[
y_{b,j,t}^i = \min \{ B_{b,j,t}^i, Y \}, \quad B_{b,j,t}^i \sim \bar{U}[0, \lfloor x_i t / p_{jt} \rfloor]
\]

where \( \bar{U} \) denotes the discrete uniform distribution since the assets are indivisible, \( x_i t \) denotes the cash holdings of agent \( i \) in period \( t \), and \( \lfloor x \rfloor \) denotes the largest integer not greater than \( x \). \( Y \) denotes an upper bound on the quantity demanded.

\(^{20}\)We let \( p_0 = 0 \).
As a seller, in trading period $t$ and iteration $j$, noise trader $i$ submits an ask for a random quantity supplied subject to asset holdings availability:

$$y_{a,j,t}^i \sim \bar{U}[0, y_{i,t}]$$  \hspace{1cm} (15)

where $\bar{U}$ denotes the discrete uniform distribution and $y_{i,t}$ denotes the unit holdings of agent $i$ in period $t$.

4.4.2 Fundamental traders in tâtonnement auctions

While noise traders are randomly determined to be buyers or sellers, a fundamental trader decides whether to be a buyer or a seller. If the indicative price in iteration $j$ of period $t$ is below the fundamental value, i.e., $p_{j,t} \leq FV_t$, then she chooses to be a buyer and submits a demand quantity as follows:

$$y_{b,t}^i = \min \{ B_{b,j,t}^i, Y \} ,$$  \hspace{1cm} (16)

where $B_{b,j,t}^i \sim \bar{U}[0, \lfloor x_{t}^i/p_{j,t} \rfloor]$ to allow for some decision errors. If the indicative price is above the fundamental value, i.e., $p_{j,t} \geq FV_t$, then she chooses to be a seller and submits a supply quantity as follows (allowing for decision errors):

$$y_{a,j,t}^i \sim \bar{U}[0, y_{i,t}] .$$  \hspace{1cm} (17)

4.4.3 Speculators in tâtonnement auctions

Speculator $i$ decides whether to buy or sell assets based on her expectations about transaction prices in period $t+1$ and given indicative price $p_{j,t}$ in iteration $j$ of period $t$. If

$$E^i(p_{t+1}) + \tilde{d} > p_{j,t}$$

speculator $i$ decides to submit a demand order of the form

$$y_{b,j,t}^i = \min \{ B_{b,j,t}^i, Y \} \hspace{1cm} B_{b,j,t}^i \sim U[0, \lfloor x_{t}/p_{j,t} \rfloor] ,$$

(18)
where $Y$ denotes an upper-bound on individual demand. If there is no restriction on the individual demands $Y = \infty$.

If, on the other hand,
\[ E^i(p_{t+1} + \bar{d}) \leq p_{j,t} \]
speculator $i$ decides to sell and submits an ask order (subject to the holding constraint) of the form:
\[ y_{a,t}^i \sim U[0, y_{i,t}] \]  
(19)

Similar to other trading institutions, we assume that speculator $i$ forms expectations in the following way:
\[ E^i(p_{t+1}) = \gamma_1 p_{j,t} + \gamma_2 FV_{t+1} \]  
(20)
with $\gamma_1 \in [0,1]$ and $\gamma_2 \geq 0$. Note, that in the tâtonnement speculators update expectations in each iteration of a given period.

4.5 Simulations steps for all institutions

Call markets

We next summarize the simulations steps within a period $t$ for call markets:

1. At the beginning of submission round $s \in \{1, ..., S\}$ each of the $(N-k_1-k_2)$ noise traders is selected to be either a buyer or a seller with probability $\pi = 0.5$. Noise buyers submit bids and noise sellers submit asks according to the rules specified in (7) and (8).

2. Simultaneously, each of the $k_1$ fundamental traders computes $l_t$ and decides to be either a buyer (if $l_t \leq FV_t$) or a seller (if $l_t > FV_t$). Depending on this decision, a fundamental trader submits either a bid or an ask according to the rules stated in (9) and (10).

3. Simultaneously, each of the $k_2$ speculators computes $E^i_{t-1}(p_t)$ and $E^i_{t-1}(p_{t+1})$ based on (11) and decides to be either a buyer (if $E^i_{t-1}(p_{t+1}) + \bar{d} > E^i_{t-1}(p_t)$) or a seller (if $E^i_{t-1}(p_{t+1}) + \bar{d} \leq E^i_{t-1}(p_t)$). Depending on this decision, a speculator submits either a bid or an ask according to the rules stated in (12) and (13).
4. After all the bids and asks are submitted, the market-clearing price is computed. The market-clearing price is then reported (no additional information is revealed to the traders) and trades are executed. Traders’ cash and unit holdings are updated accordingly.

5. The process above is repeated for the $S$ submission rounds. After trades in the $S^{th}$ submission round are executed, the asset pays its random dividends and cash holdings are updated accordingly.

For a given set of parameters $(S, \alpha, \kappa, \alpha^f, k_1, k_2, \gamma_1, \gamma_2)$ and experimental characteristics, $N, T$ and endowments $(\{x_0^i\}_{i=1}^N, \{y_0^i\}_{i=1}^N)$, each simulation run $m = 1, 2, ..., M$ of the model will generate a price sequence $(p_1^m, p_2^m, ..., p_T^m)$, an $N \times T$ matrix of cash holdings and an $N \times T$ matrix of asset holdings. The results can be interpreted as the simulation-equivalent of one experimental closed book call market session.

**Double auctions**

We next summarize the simulations steps within a period $t$ for double auctions. Without loss of generality, we let the first $1$ to $N - k_1 - k_2$ traders be noise traders, the following $N - k_1 - k_2 + 1$ to $N - k_2$ traders be fundamental traders and the last $N - k_2 + 1$ to $N$ traders be speculators.

1. At the beginning of submission round $s \in \{1, ..., S\}$ a sequence of $N$ natural random numbers (without replacement) is generated. This sequence determines the order in which every trader submits either a bid or an ask to the order book in submission round $s$ of trading period $t$.

2. Each of the $(N - k_1 - k_2)$ noise traders is selected to be either a buyer or a seller with probability $\pi = 0.5$. Noise buyers submit bids and noise sellers submit asks according to the rules specified in (7) and (8). If a noise trader is selected to be a buyer then her actions are described by step 5a below. If a noise trader is selected to be a seller then her actions are described by step 5b below.

3. Each of the $k_1$ fundamental traders in submission round $s$ computes $l_t$ and decides to be either a buyer (if $l_t \leq FV_t$) or a seller (if $l_t > FV_t$). Depending on this decision, a fundamental trader submits either a bid or an ask according to the rules stated in (9) and (10). In contrast to noise traders, fundamental traders exploit the information generated within a period to form price expectations. If a fundamental trader is a buyer then her actions are described by step 5a below. If a fundamental trader is a seller then her actions are described by step 5b below.
4. Each of the \( k_2 \) speculators in submission round \( s \) computes \( E^i(p_t) \) and \( E^i(p_{t+1}) \) based on (11) and decides to be either a buyer (if \( E^i(p_{t+1}) + \bar{d} > E^i(p_t) \)) or a seller (if \( E^i(p_{t+1}) + \bar{d} \leq E^i(p_t) \)). Depending on this decision, a speculator submits either a bid or an ask according to the rules stated in (12) and (13). If a speculator is a buyer (seller), her behavior is described by (5a) (5b) below.

5. **Auction-step:** In contrast to call markets the price is not determined by the intersection of aggregate demand and supply. Instead, after the submission of every individual bid or ask, the following process starts:

   (a) If a trader’s bid is greater than the current best ask \( A_t \), then the trade is executed at \( A_t \). Cash and unit constraints of the buying and selling traders are updated appropriately and the second lowest ask price in the order book becomes the new best ask. If there is no second lowest ask price in the order book, the next submitted ask price to the order book becomes the best current ask. If, on the other hand, a trader’s bid is below the best ask or if there is no best ask, the agent’s bid is stored in the order book.

   (b) If a trader’s ask is below the current best bid \( B_t \), then a trade is executed at \( B_t \). Cash and unit constraints are updated appropriately and the second highest bid price in the order book becomes the best bid. If there is no second highest bid in the order book the next submitted bid becomes the best current bid. If a submitted ask is above the current best bid or if there is no best bid, the agent’s ask is stored in the order book.

6. The process above is repeated for the \( S \) submission rounds. After the submission of the last bid or ask in the \( S^{th} \) submission round, the asset pays its random dividends and cash holdings are updated accordingly.

For a given set of parameters \((S, \alpha, \kappa, \alpha^f, k_1, k_2, \gamma_1, \gamma_2)\) and experimental characteristics, \(N, T\) and endowments \((\{x_i^0\}_{i=1}^{N}, \{y_i^0\}_{i=1}^{N})\), each simulation run \( m = 1, 2, ..., M \) of the model will generate a price sequence \((p_1^m, p_2^m, ..., p_T^m)\), an \( N \times T \) matrix of cash holdings and an \( N \times T \) matrix of asset holdings. The results can be interpreted as the simulation-equivalent of one experimental double auction asset market session.

**Tâtonnement**

We next summarize the simulations steps within a period \( t \) for tâtonnement markets:
1. At the beginning of every trading period all trader types submit their period $t$ trading price expectations as described in Section 4.4. This step determines the initial indicative price $p_{0,t}$.

2. For every indicative price the $(N - k_1 - k_2)$ noise traders are selected to be either buyers or sellers with probability $\pi = 0.5$. Noise buyers submit bid-quantities and noise sellers submit ask-quantities according to (14) and (15).

3. Each of the $k_1$ fundamental traders decides to be either a buyer (if $p_{i,t} \leq FV_t$) or a seller (if $p_{i,t} > FV_t$) and submits either a bid-quantity or an ask-quantity according to (16) and (17).

4. Each of the $k_2$ speculators decides to be either a buyer (if $E^i(p_{t+1}) + \bar{d} > p_{i,t}$) or a seller (if $E^i(p_{t+1}) + \bar{d} \leq p_{i,t}$) and submits either a bid-quantity or an ask-quantity according to (18) and (19).

5. After all the individual demands and supplies are submitted, the net excess demand $z_t$ is computed. If $|z_t| > \Lambda = 2$ and prices’ oscillations are large enough, the indicative tâtonnement price is adjusted proportionally as described in section 3.3. Based on the new indicative price steps 2-5 are repeated. If at some indicative price $z_t = 0$, the market clears perfectly, trades are executed and cash as well as unit constraints are updated. If $0 < |z_t| < 2$ or three consecutive prices oscillate by one frank, one of the stopping rules becomes effective. If the market does not clear perfectly, random buyers whose cash-constraints are not binding and random sellers whose unit constraints are not binding are selected. Depending on the sign of $z_t$ the buyer’s demand is increased or decreased by one unit and (if necessary) the seller’s supply is either decreased or increased by one unit. This unit-updating process continues until $z_t = 0$. Prices are not changed during this process. Hence whenever $|z_t| \leq \Lambda = 2$ or prices oscillate (see section 3.3), trades are executed at indicative price $p_{j,t}$ and cash as well as unit constraints are updated.

6. After trades in period $t$ are executed, the asset pays its random dividends and cash holdings are updated accordingly.

For a given set of parameters $(\alpha, \kappa, \alpha^f, k_1, k_2, \gamma_1, \gamma_2)$ and experimental characteristics, $N, T$ and endowments $(\{x^i_0\}_{i=1}^N, \{y^i_0\}_{i=1}^N)$, each simulation run $m = 1, 2, \ldots, M$ of the model will generate a price sequence $(p^m_1, p^m_2, \ldots, p^m_T)$, an $N \times T$ matrix of cash holdings and an $N \times T$ matrix of asset holdings. The results can be interpreted as the simulation-equivalent of one experimental tâtonnement market session.
We next show how to estimate the parameters of the model using our experimental data.

5 Results

In this section, we estimate the structural parameters of the model for each market environment, using aggregate prices and quantities. We use these estimates to characterize the individual asset-holding strategies used by speculators, fundamental and noise traders. Then we use these results to identify the different types of traders in the data.

Given the initial cash and asset-holdings endowment from the experimental design (10000 francs and 10 units), the upper bound on individual demand $Y$, the number of traders $N$, and the number of trading periods $T$, the model consists of eight free parameters: the number of submission rounds $S$, the anchoring parameter of the noise traders $\alpha$, the noise-support parameter $\kappa$ of the noise traders, the learning speed parameter of the fundamental traders $\alpha^f$, the expectations parameters for speculators $\gamma_1$ and $\gamma_2$, the number of fundamental traders $k_1$ and the number of speculators $k_2$. We impose the restriction that $\alpha^f = \alpha$ to reduce the dimensionality of the parameters. In order to obtain parameter estimates, we specify a grid of parameters

\[
S \in \{1, 2, 3, 4, 5, \ldots, 100\}, \alpha \in \{0.05, 0.1, \ldots, 0.95\}, \kappa \in \{0.1, 0.6, \ldots, 10\}, \gamma_1 \in \{0.01, 0.1, \ldots, 0.99\}, \gamma_2 \in \{0.1, 0.6, \ldots, 10\}, k_1, k_2 \in \{1, 2, 3, \ldots, 9\}.
\]

We then compute the best fit according to the SSE-objective function within this grid. This gives an initial estimate for each parameter. We then fix the integer parameters $S$, $k_1$, and $k_2$ from this procedure and construct for each parameter an individual $\epsilon$ interval around the initial value ($\text{parameter} \pm \epsilon_{\text{parameter}}$). The value of $\epsilon$ for each parameter varied and was taken to be 20% of the initial guess. Within the new boundary points in the $\epsilon$ interval of every parameter, 30 new equally spaced grid points were chosen. The minimization procedure for the fixed $k_1$, $k_2$ and $S$ within the new grid space was then repeated to obtain the final parameter estimates.
Table 3: Estimation Results

<table>
<thead>
<tr>
<th></th>
<th>Noise Traders</th>
<th>Fundamental Traders ($k_1$)</th>
<th>Speculators ($k_2$)</th>
<th>$\alpha$</th>
<th>$\kappa$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Double Auction</td>
<td>22.22%</td>
<td>11.11%</td>
<td>66.67%</td>
<td>0.718</td>
<td>3.26</td>
<td>0.01</td>
<td>1.207</td>
<td>48</td>
</tr>
<tr>
<td>Call Market</td>
<td>22.22%</td>
<td>55.56%</td>
<td>22.22%</td>
<td>0.604</td>
<td>4.512</td>
<td>0.148</td>
<td>0.293</td>
<td>7</td>
</tr>
<tr>
<td>Tâtonnement</td>
<td>11.11%</td>
<td>66.67%</td>
<td>22.22%</td>
<td>0.94</td>
<td>0.81</td>
<td>0.277</td>
<td>1.032</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3 provides the best fit parameter combination for every trading institution. The main difference across institutions is that in double auction there are more speculators and fewer fundamental traders than in other institutions. This suggests that the distribution of types is endogenous with respect to the trading institution.

The fitted and actual aggregate variables (prices and quantities) are displayed in Figure 3. The fit is very accurate for prices under all institutions and for volume under tâtonnement. The volume fit under call market and double auction is not as good, because trading volume in the data is quite noisy.

Table 4 provides several average bubble measures (for definitions see Table 1) computed using the data and the model. A quick look at the simulated bubble measures reveals that they are indeed close to the actual data measures, indicating that the model captures important features of the data.

Table 4: Bubble Measures: Simulations vs. Data (Averages)

<table>
<thead>
<tr>
<th>Measure</th>
<th>DA</th>
<th>Simulation</th>
<th>Tâtonnement</th>
<th>Simulation</th>
<th>Call Market</th>
<th>Actual</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turnover</td>
<td>3.91</td>
<td>3.36</td>
<td>1.44</td>
<td>1.71</td>
<td>1.25</td>
<td>1.05</td>
<td></td>
</tr>
<tr>
<td>Amplitude</td>
<td>0.69</td>
<td>0.51</td>
<td>0.30</td>
<td>0.26</td>
<td>0.47</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>Norm. Dev.</td>
<td>423.43</td>
<td>321.75</td>
<td>61.1</td>
<td>82.92</td>
<td>73.63</td>
<td>51.77</td>
<td></td>
</tr>
<tr>
<td>Tot. Disp.</td>
<td>155.40</td>
<td>137.53</td>
<td>111.15</td>
<td>104.69</td>
<td>122.6</td>
<td>114.05</td>
<td></td>
</tr>
<tr>
<td>Av. Bias</td>
<td>140.88</td>
<td>130.81</td>
<td>55.30</td>
<td>73.49</td>
<td>84</td>
<td>93.54</td>
<td></td>
</tr>
<tr>
<td>APD</td>
<td>18.20</td>
<td>16.51</td>
<td>6.3</td>
<td>9.12</td>
<td>9.724</td>
<td>8.89</td>
<td></td>
</tr>
<tr>
<td>PD</td>
<td>15.33</td>
<td>13.91</td>
<td>5.96</td>
<td>9.12</td>
<td>7.667</td>
<td>8.03</td>
<td></td>
</tr>
<tr>
<td>RAD</td>
<td>0.537</td>
<td>0.52</td>
<td>0.20</td>
<td>0.29</td>
<td>0.304</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>RD</td>
<td>0.454</td>
<td>0.44</td>
<td>0.19</td>
<td>0.24</td>
<td>0.240</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>RPAD</td>
<td>0.77</td>
<td>0.714</td>
<td>0.21</td>
<td>0.33</td>
<td>0.370</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>Haessel</td>
<td>0.547</td>
<td>0.503</td>
<td>0.90</td>
<td>0.98</td>
<td>0.786</td>
<td>0.87</td>
<td></td>
</tr>
<tr>
<td>Boom</td>
<td>10.4</td>
<td>13</td>
<td>7.60</td>
<td>15</td>
<td>9.600</td>
<td>14</td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>7.8</td>
<td>9</td>
<td>3.4</td>
<td>3</td>
<td>5.600</td>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>
Figure 3: Simulated Prices and Volumes.

(a) Tâtonnement; Prices

(b) Tâtonnement; Volume

(c) Double Auction; Prices

(d) Double Auction; Volume

(e) Call Market; Prices

(f) Call Market; Volume
5.1 Individual Behavior: Results

As in Baghestanian et al. [2012], we use the simulated trading strategies to identify trader types at the micro-level using individual asset holdings data. For each trader $i$ in session $s$ we let $u_{i,t}^s$ be trader $i$'s stock of assets in period $t$. We denote with $\bar{u}_t^S$ the average period $t$ asset holdings of simulated speculators and with $\bar{u}_t^F$ the average asset holdings of simulated fundamental traders. To classify traders into types for every trader we run two OLS regressions (controlling for heteroscedasticity):

$$u_{i,t}^s = b_k^i + \beta_k^i \bar{u}_t^k + \epsilon_{i,t}^s \quad k \in \{S, F\}.$$  (22)

That is, we regress the actual traders’ asset holdings on the simulated asset holdings. If $\beta_F^i$ is greater than zero at a 5% significance level, then we classify trader $i$ as a fundamental trader, and, similarly, if $\beta_S^i > 0$, we classify trader $i$ as a speculator. We never encountered a case in which both $\beta_F^i$ and $\beta_S^i$ were greater than zero. If neither $\beta_F^i$ nor $\beta_S^i$ are greater than zero, we classify subject $i$ as a noise trader.

Table 5 shows the number of identified speculators, fundamental and noise traders for every session.

<table>
<thead>
<tr>
<th>Table 5: Individual Trader Types</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Double Auction</strong></td>
</tr>
<tr>
<td>Session 1</td>
</tr>
<tr>
<td>Fundamental Traders</td>
</tr>
<tr>
<td>0 %</td>
</tr>
<tr>
<td>Speculators</td>
</tr>
<tr>
<td>75%</td>
</tr>
<tr>
<td>Noise Traders</td>
</tr>
<tr>
<td>25%</td>
</tr>
<tr>
<td>N (Subjects)</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>Session 2</td>
</tr>
<tr>
<td>25%</td>
</tr>
<tr>
<td>37.5%</td>
</tr>
<tr>
<td>37.5%</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>Session 3</td>
</tr>
<tr>
<td>12.5%</td>
</tr>
<tr>
<td>62.5%</td>
</tr>
<tr>
<td>25%</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>Session 4</td>
</tr>
<tr>
<td>56%</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 5</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>45%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Average</td>
</tr>
<tr>
<td>23%</td>
</tr>
<tr>
<td>46%</td>
</tr>
<tr>
<td>31%</td>
</tr>
<tr>
<td>42</td>
</tr>
<tr>
<td><strong>Call Market</strong></td>
</tr>
<tr>
<td>Session 1</td>
</tr>
<tr>
<td>67 %</td>
</tr>
<tr>
<td>0%</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 2</td>
</tr>
<tr>
<td>45%</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 3</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>45%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 4</td>
</tr>
<tr>
<td>56%</td>
</tr>
<tr>
<td>0%</td>
</tr>
<tr>
<td>44%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 5</td>
</tr>
<tr>
<td>44%</td>
</tr>
<tr>
<td>0%</td>
</tr>
<tr>
<td>56%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Average</td>
</tr>
<tr>
<td>47%</td>
</tr>
<tr>
<td>11%</td>
</tr>
<tr>
<td>42%</td>
</tr>
<tr>
<td>45</td>
</tr>
<tr>
<td><strong>Tâtonnement</strong></td>
</tr>
<tr>
<td>Session 1</td>
</tr>
<tr>
<td>45 %</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 2</td>
</tr>
<tr>
<td>45 %</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 3</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>33%</td>
</tr>
<tr>
<td>45%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 4</td>
</tr>
<tr>
<td>67%</td>
</tr>
<tr>
<td>11%</td>
</tr>
<tr>
<td>22%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Session 5</td>
</tr>
<tr>
<td>33.3%</td>
</tr>
<tr>
<td>33.3%</td>
</tr>
<tr>
<td>33.3%</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>Average</td>
</tr>
<tr>
<td>42%</td>
</tr>
<tr>
<td>29%</td>
</tr>
<tr>
<td>29%</td>
</tr>
<tr>
<td>45</td>
</tr>
</tbody>
</table>

Note that in the previous section we used aggregate prices and quantities to estimate the parameters of the model and we did not directly fit individual behavior of simulated agents to the observed behavior of experimental subjects.
These results are qualitatively consistent with the estimated distribution of types, as there are more speculators and fewer fundamental traders under double auction.

5.1.1 Expectation Accuracy

Next, we analyze the forecast accuracy conditional on trader types. As in Baghestanian et al. [2012], we compute for every trader $i$, who participated in session $s$ an individual accuracy measure:

$$Acc^s_i = \frac{E^s_i(p_t|F_{t-1}) - p_t}{p_t},$$

where $E^s_i(p_t|F_{t-1})$ denotes the expectation of trader $i$ in session $s$ about the market clearing price in period $t$ at the beginning of period $t$ (i.e.: conditional on information generated until period $t - 1$: $F_{t-1}$) and $p_t$ denotes the actual realized market clearing price (or average transaction price for double auctions).

Note that the accuracy was rewarded as described in the experimental design section. After computing the accuracy measures we grouped them according to the trader type classes. The results are presented in Figure 4.

Across trading institutions, we observe that expectations start out heterogeneously and then tend to converge (to non-rational expectations) during positive price trends. After price-peaks on the other hand, coordination of expectations weakens and heterogeneity tends to increase. After the peak and as heterogeneity increases prices tend to converge to the fundamental value of the asset. These observations are perfectly consistent with the results in Hommes [2010]. Our model allows us to gain additional insights into the accuracy patterns of different trader types across trading institutions:

In double auctions, in period one, fundamental traders have more accurate price forecasts than other trader types (MW $p-value < 0.05$). Similarly fundamental traders and speculators have jointly more accurate price forecasts than noise traders in period one under a double auction trading institution (MW $p-value < 0.1$). Like in Baghestanian et al. [2012] noise traders and speculators underpredict prices in period one.

A similar result holds for Tâtonnement markets: Fundamental traders and speculators have more accurate price forecasts than noise traders in period one (MW $p-value < 0.01$ and $p-value < 0.1$).

The relationship between trader type and accuracy is less pronounced in call markets: Fundamental

---

23In Tâtonnement and call markets subjects were asked to provide estimates about market clearing prices. In double auctions subjects were asked to provide expectations about average transaction prices in period $t$. 

traders and speculators have jointly slightly more accurate than noise traders (MW $p\text{-value} = 0.13$).

Finally we compare the average accuracy ($Acc^d_t$) across trading institutions (without grouping traders into trader types) to the simulation analogue. To derive the simulation analogue we compute

$$E(p_t|F_{t-1}) = \frac{N - k_1 - k_2}{N} E^N(p_t|F_{t-1}) + \frac{k_1}{N} E^{FV}(p_t|F_{t-1}) + \frac{k_2}{N} E^S(p_t|F_{t-1})$$

(23)

where\(^{24}\)

$$E^N(p_t|F_{t-1}) = (1 - \alpha)\frac{k}{2} FV_t + \alpha p_{t-1},$$

\(^{24}\)Recall $p_0 = 0$, $l_0 = FV_1 + d$. 

Figure 4: Deviations of price forecasts from actual prices across trading institutions.
Figure 5: Average Forecasts Errors, Data and Simulations

\[ E^{FV}(p_t|F_{t-1}) = \alpha f(l_{t-1} - \bar{d}) + (1 - \alpha f) p_{t-1}, \]

and

\[ E^S(p_t|F_{t-1}) = \gamma_1 p_{t-1} + \gamma_2 FV_t. \]

We use the estimates from Table 3 to compute for every trading institution the average expectation in (23) and compute the corresponding average expectation-accuracy. We then compare the observed average expectation accuracy to the simulation-analogue in Figure (5).

Note that we used aggregate actual prices and quantities to estimate the model, and we did not use the price forecast data in the estimation. Despite this fact, when comparing the simulated and actual average price forecasts, we observe a fairly good fit across trading institutions.
5.1.2 Accuracy of Expectations Across Institutions

In this section we look at the dispersion and accuracies of price forecasts at the beginning and at the end of each session across different institutions to analyze the impact of trading institutions on price discovery.

Figures 4 and 6 indicate that the accuracy of price forecasts in the last periods is less dispersed and significantly better under tâtonnement trading rules than under other trading institutions. This indicates that the tâtonnement facilitates more homogeneous and accurate price forecasts. Under the double auction, on the other hand, the price forecasts in later periods are more dispersed and less accurate than under the call market and Tâtonnement.

Table 6: Expectation Accuracy and Price Discovery across Trading Institutions

<table>
<thead>
<tr>
<th>Tâtonnement</th>
<th>Call Market</th>
<th>Double Auction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy comparison: Period 1 vs Period 15, Within Institutions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medians Period 1 &amp; 15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.23</td>
<td>0.17</td>
<td>0.33</td>
</tr>
<tr>
<td>0.08</td>
<td>0.25</td>
<td>0.66</td>
</tr>
<tr>
<td>$W = 1334$</td>
<td>$W = 599$</td>
<td>$W = 486$</td>
</tr>
<tr>
<td>$p-value = 0.01$</td>
<td>$p-value = 0.58$</td>
<td>$p-value &lt; 0.01$</td>
</tr>
</tbody>
</table>

| Across Market Comparison Period 1 | | |
| Tâ. vs CM: $W = 708$, $p-value = 0.33$; Tâ. vs DA: $W = 976$, $p-value = 0.79$; | CM vs DA: $W = 646$, $p-value = 0.27$ | |
| CM vs DA: $W = 486$, $p-value = 0.66$ | | |

| Across Market Comparison Period 15 | | |
| Tâ. vs CM: $W = 959$, $p-value = 0.16$; Tâ. vs DA: $W = 1583.5$, $p-value < 0.01$ | CM vs DA: $W = 1108$, $p-value < 0.01$ | |
The comparison of the median accuracy of price forecasts in periods 1 and 15, indicates that, over time, the forecasts improve under Tâtonnement, remain the same under CM, and worsen under DA (see Table 6). Moreover, while the median prediction error is not significantly different across trading institutions in period 1, in period 15 it is significantly lower under Tâtonnement and CM than under DA.

5.2 Robustness

The predicted differences across institutions might be potentially explained by the differences in the estimated parameters, such as, for example, the distribution of trader types. To rule out that the differences across institutions stem from different estimated parameters, we use the Call Market estimation results from Table 3 for all trading institutions. This will allow us to provide a better comparison of the effect of trading institutions on bubble formation. Table 7 provides the simulated bubble measures associated with this exercise.

Table 7: Simulated bubble measures using call market estimated parameters for all institutions.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Double Auction</th>
<th>Tâtonnement</th>
<th>Call Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turnover</td>
<td>1.46</td>
<td>2.45</td>
<td>1.05</td>
</tr>
<tr>
<td>Amplitude</td>
<td>0.43</td>
<td>1.96</td>
<td>0.62</td>
</tr>
<tr>
<td>Norm. Dev.</td>
<td>82.27</td>
<td>25.55</td>
<td>51.77</td>
</tr>
<tr>
<td>APD</td>
<td>10.41</td>
<td>1.74</td>
<td>8.89</td>
</tr>
<tr>
<td>RAD</td>
<td>0.33</td>
<td>0.05</td>
<td>0.28</td>
</tr>
<tr>
<td>RD</td>
<td>0.33</td>
<td>0.05</td>
<td>0.25</td>
</tr>
<tr>
<td>RPAD</td>
<td>0.38</td>
<td>0.22</td>
<td>0.34</td>
</tr>
<tr>
<td>Haessel</td>
<td>0.92</td>
<td>0.99</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Relative to Call Markets, under Double Auction all bubble measures indicate a larger bubble except for Amplitude, Trend and Haessl $R^2$. Under Tâtonnement, on the other hand, all bubble measures indicate a smaller bubble except for Turnover, Trend and Amplitude.

Given the parameters estimated using the CM data, the model predicts Tâtonnement to mitigate bubbles compared to other trading institutions. The Double Auction, on the other hand, is expected to produce larger bubbles. These results can be attributed to the differences in the within-period expectation formation. Under Call Market, expectations are formed only once, in the beginning of the trading period. Under Double Auction, expectations are updated after each transaction, i.e. multiple times within a period. In particular, speculators and fundamental traders recalculate the average period price after each transaction, and then update their expectations based on this price. As a result expectations are
sensitive to every transaction price, which gives rise to higher volatility of prices within the period as well as across periods. Finally, under Tâtonnement, expectations are updated after each iteration. However, speculators and fundamental traders take into account only the last available indicative price and the previous period trading price, when they update their expectations.

It is important to point out that Double Auction is the only trading institution which allows for within-period speculation. To illustrate the impact of within-period speculation on prices we construct new DA prices which control for within-period speculation. To this end, we define a subject to be a net-buyer in period $t$ if he buys more units than he sells within period $t$. Then we record only the first transaction price at which a net-buyer purchased his first unit. Using a similar procedure, we record only the first transaction price at which a net-seller sells his first unit. We ignore all other prices, including all the prices of zero-balance within-period traders, and calculate the average price in $t$ using only the recorded prices. We chose to use only the first prices, since they are the least affected by the within-period dynamics, which makes them closer to the CM in which the price expectations are formed only once (in the beginning of the period).

Figure 7 displays DA actual and newly constructed prices. It shows that the within-period speculation has a strong positive effect on prices in the first half of the experiment.
6 Conclusions

This paper explores the role that different trading institutions play on bubbles’ formation in laboratory asset markets. In this study, in addition to Call Market and Double Auction, we employ the Tâtonnement trading institution, which has not been previously explored in laboratory asset markets, despite its historical and contemporary relevance. The results show that bubbles are significantly smaller in Tâtonnement than in Double Auction, suggesting that the trading institution plays a crucial role in the formation of bubbles. We build on Duffy (2006), Haruvy and Noussair (2006) and Baghestanian, Lugovskyy and Puzzello (2014) and provide a heterogeneous agent model with speculators, fundamental and noise traders to better understand these results. For each trading institution, we provide structural estimates of the parameters of the model using experimental data. The model allows us to identify the different types of traders in the experimental data. We find that speculation is more prominent in Double Auction than in other trading institutions, providing some support for the conjecture that traders’ types are in part endogenous to the trading institution. Furthermore, Tâtonnement produces more accurate and less dispersed (among traders) price forecasts towards the end of the experiment, which indicates that Tâtonnement favors more homogenous expectations.
References


