Trading Institutions in Experimental Asset Markets: Theory and Evidence

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Abstract

We report the results of an experiment designed to study the role of trading institutions 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 either Tâtonnement or Tâtonnement and Call Market combined than in Double Auction, suggesting that trading institutions play an important role in the formation of bubbles.

We provide a heterogeneous agent model with fundamental and myopic-noise traders to better understand these results. We calibrate the parameters of the model using experimental data from the Tâtonnement and Call Market trading institutions. The model captures some critical patterns of the data, as we find that bubbles are more prominent in Double Auctions than in other trading institutions.

Keywords: Experimental Asset Markets, Bubbles, Traders' Heterogeneity, Trading Institutions

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

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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 craftsmans 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. Experimental methods are a valuable tool in the study of bubbles as they allow researchers to control for factors that are difficult to control for in field markets, such as the fundamental value process, trading rules and traders' information. 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, a 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]).[1]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

[1]If the environment is not stationary, Hussam et al. (2008) show that bubbles can be rekindled.

asset markets allows subjects to gain confidence in the rationality of other traders as well as to learn specific dynamic asset valuation processes, and thus reduce confusion and decision errors.

In this paper, we study the effect of trading institutions on the formation of bubbles and crashes in the Smith et al. [1988] environment, and introduce the Tâtonnement trading institution to be investigated along with the double auction and call market institutions that are typically used in experimental asset markets. We chose to study the impact of different trading institutions in the environment proposed by Smith et al. [1988] for several reasons. First, the fundamental value of the asset is well-defined allowing us to identify and measure bubbles. Further, our focus is on bubbles' taming institutions and bubbles are a robust finding of this environment. Confusion, noise and limited intelligence appear to play an important role in this context, allowing us to study whether trading institutions play a role in decreasing the impact of confusion on price formation, and in protecting confused traders (e.g., Lei et al. [2001] and Hussam et al. [2008]). Another advantage is that this environment has been extensively studied in experimental economics allowing us to compare our results with existing studies. Importantly, bubbles in this environment appear to be generated by heterogeneity in beliefs and trading strategies, that also play an important role in the formation of bubbles in the field (see also Haruvy and Noussair [2006]). [2]

We are interested in the Tâtonnement for two reasons. Firstly, we believe that it mitigates both of the driving forces for bubble formation described above, and thus conjecture that price bubbles will be significantly reduced by the Tâtonnement 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]). To understand why we conjecture that the Tâtonnement may help to limit the impact of confused traders on prices and thus, help reduce bubbles, especially as related to double auction, we next briefly describe how prices are formed under the three trading institutions we consider in this paper.

A characteristic of the double auction institution is that buyers and sellers tender bids/asks publicly.

[2] Call markets may also be referred to as clearinghouse mechanisms in the literature (see Friedman [1993] or Limit Order Books).

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. Importantly, no trades take place at these non-binding iterations.

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 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 partially observe demand, supply, and the 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.[3] 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.[4]

Thus, there is a mechanism embodied in the Tâtonement institution that allows inexperienced traders

[3]In 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.

[4]Under 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.

to acquire important market information, and thereby reduce confusion and decision errors. In the Call Market, subjects post bids and asks, and those are aggregated to obtain step demand and supply functions. The transaction price is determined as the lowest price that clears the market, and subjects succeed to trade if their bid (ask) is above (below) the market-clearing price. The Call Market is similar to the Tâtonement in that there is a single market-clearing price, but it differs from the Tâtonement in that there are no provisional prices and no iterations within a period.

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 (Call Markets) 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 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". Put differently, the choice of trading institutions could be endogenous in the field, making an analysis of their effects difficult. Also, typically, different trading institutions are used for different assets, so it is difficult to infer whether differences in the price function arise from the trading institution or from the asset class. Our laboratory environment, on the other hand, allows us to vary trading institutions exogenously, enabling us to make causal statements. More recently, Deck et al. [2020] find that the English Dutch auction performs better than a Double Dutch Auction and Double Auction. Ding et al. [2020] find that bubbles are greatly reduced in an Over-the-Counter market relative to Double Auction markets. We complement these studies by introducing the Tâtonnement institution, and by providing a model which we estimate using the experimental data.

We find that under the Tâtonnement institution, price bubbles are mitigated compared to Double

Auction, according to most bubble measures employed in the literature. The Call Market performs somewhere (not significantly) in between with smaller bubbles than Double Auction but larger bubbles than Tâtonnement. Due to the complexity of the trading environment, there is no micro founded model that can be used to capture the main patterns of the data. Therefore, the literature has up to date followed a computational approach (e.g., Duffy and Ünver [2006] and Haruvy and Noussair [2006]). Duffy and Ünver [2006] focuses on double auctions in both experiments and model, while Haruvy and Noussair [2006] focus on experimental double auctions and on a Tâtonnement setting for the model. We build on the existing literature by providing a heterogeneous-agents model with myopic and fundamental traders to better understand the experimental results.

Relative to Haruvy and Noussair [2006] and Duffy and Ünver [2006], we study the impact of three distinct institutions on bubbles' formation within a unified framework. The functional form of the demand function is the same across all institutions, namely the quantity demanded is proportional to the difference between how much an agent values the asset and his price expectation. However, traders' valuation of the asset are different between fundamental value traders and myopic traders. Fundamental value traders' valuations are equal to the fundamental value of the asset. On the other hand, myopic traders anchor their valuation to the previous period's price, with a bias, capturing the existence of anchoring biases which have been documented in behavioral finance. We assume that all traders are myopic at the beginning of the economy, and they switch to fundamental value traders, as the economy unfolds over time. This captures the idea that traders may exhibit different degrees of foresight, i.e., some traders may realize that prices will eventually converge to the fundamental value earlier, while it may take longer to come to this realization for other traders.

We estimate structural parameters of the model using experimental data from the Tâtonnement and Call Market institutions.[5] Then, using the same set of the parameters, we simulate the model under all three trading institutions. This way we make sure that the differences across simulated data are only due to institutional differences across the three trading mechanisms, and not simply due to the changes in the parameters of the model. The model generates price patterns very similar to the experimental data. We observe a bubble and crash pattern across all institutions. More importantly, consistent with the experimental data the size of the bubble is much higher in Double Auction, whereas Tâtonnement and Call Markets generate similar size bubbles. The main reason for the occurrence of the bubble across all

[5] We use these institutions to estimate the parameters since we have a closed form solution for the market-clearing price.

institutions is (i) myopic traders' valuation bias is estimated to be positive, and (ii) the share of individuals acting as myopic traders is declining over time and the share of individuals acting as fundamental traders is increasing over time. However, these assumptions are not enough to generate a larger bubble in Double Auction. Why does the model generate higher bubbles in Double Auction? The key characteristic of double auction that contributes to generate larger bubbles is that multiple trades occur within a period. This allows myopic traders to update their valuation within a period, thus amplifying the impact of positive bias on transaction prices.

We also reports results from an out-of-sample exercise, to further validate the mechanism of the model. We show that the model produces similar dynamics for within-period price growth in the Double Auction.[6] Overall, both our experimental and computational results indicate that trading institutions play an important role in price discovery and bubble formation. Gode and Sunder [1993, 1997] show that goods markets can be intelligent, even if traders have zero intelligence. Our paper suggests that, in the context of *asset markets*, trading institutions play an important role in determining whether limited intelligence traders have an impact on aggregate outcomes and bubble formation, and thus on markets' intelligence. Section 2 reports the experimental design, procedures and results. Section 3 describes the model environment, results and the out-of-sample exercise.

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.[7] 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.[8] 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

[6] Recall that we did not use any data from the double auction to estimate the parameters of the model.
[7] See Greiner [2004] for a discussion of the ORSEE recruitment program.
[8] See Fischbacher [2007] for a discussion of the z-Tree software package.

session lasted approximately 90 – 120 minutes depending upon treatment.[9] 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. [1993], Caginalp et al. [2000], Lei et al. [2001], Haruvy and Noussair [2006], Noussair and Tucker [2006], Hussam et al. [2008]). 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. This restriction is motivated by the very large cash endowment (the cash-to-asset ratio is 2.78). This could cause substantial asymmetries in the price adjustment process under the tâtonnement given the proportional price-adjustment rule.[10] 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.[11]

At the beginning of each session, subjects completed a three-question cognitive reflection test (Frederick, 2005). Subjects earned $2 for each correct answer. No payment information was provided until they

[9] Tâtonnement 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.

[10] Note that the impact of a subject on aggregate supply is limited by his asset endowment which, on average, is 10, while his impact on aggregate demand is determined by his cash holdings and prices, which is typically much greater than 10. For instance, if the asset is priced at fundamental value in period 1, each subject can afford 27 shares, whereas in period 15 a subject can afford on average at least 416 shares priced at fundamental value – even if all dividend realizations are zeros. For more details on the adjustment rule please see the next section.

[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 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.

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.[12] 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).

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.

[12] Instructions for each treatment are available upon request.

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

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

and

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

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,

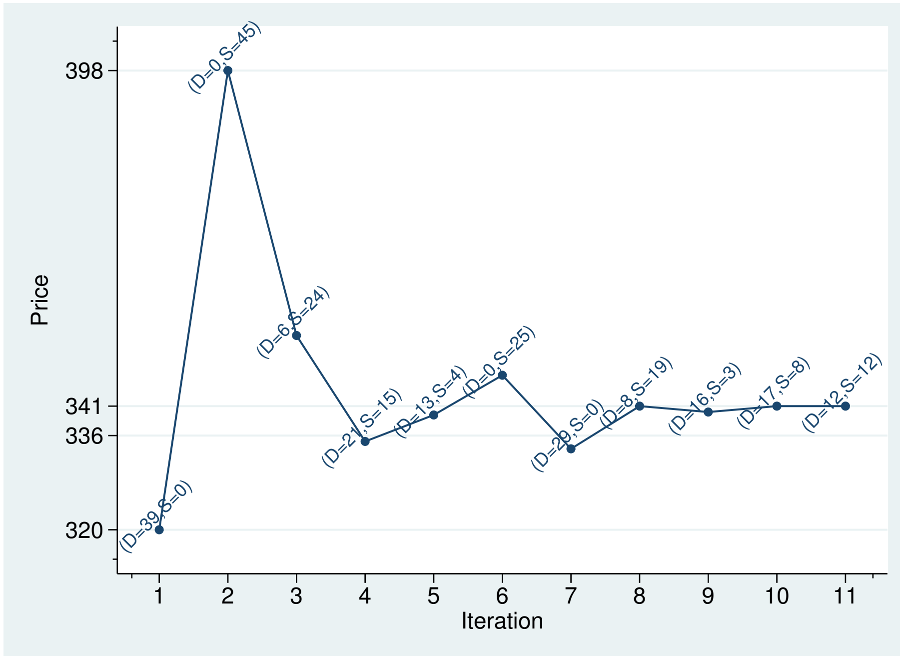


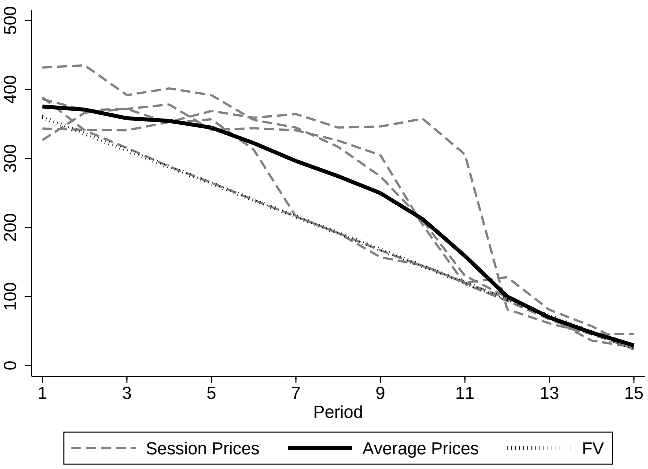
Figure 1: Tâtonnement Price Iterations in Period 2 of Session 1

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.

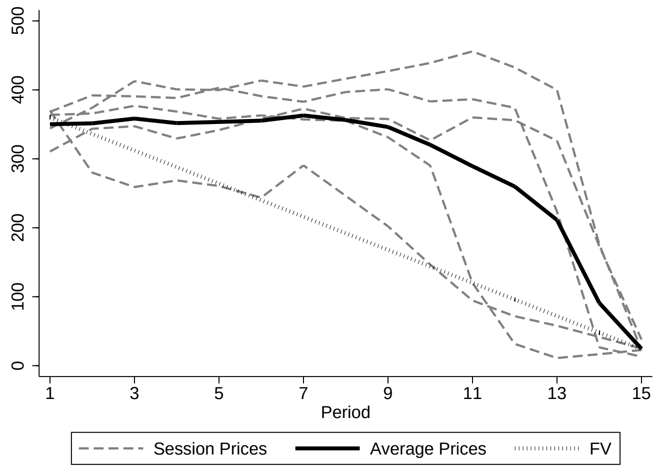
Figure 1 illustrates how the price adjustment rule works via the data collected in period 2 of session 1 of Tâtonnement treatment. At the initial price of $P_1 = 320$, aggregate demand is $Q_{D,1} = 39$ and aggregate supply is $Q_{S,1} = 0$. In the next iteration, the price is $P_2 = 320 + 2(39 - 0) = 398$. 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 second iteration is 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

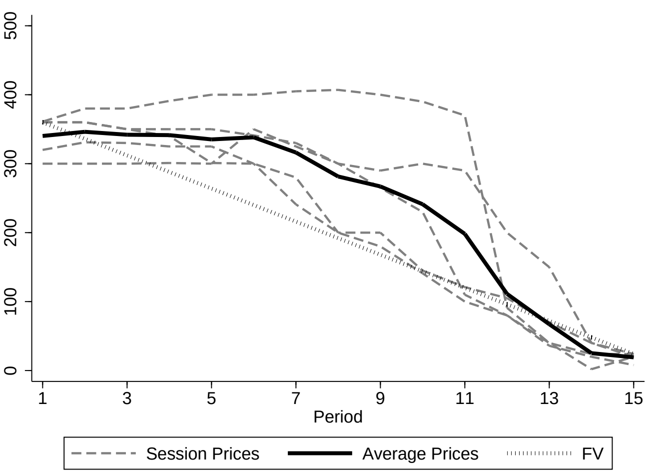
Figure 2 depicts the time series of prices and fundamental values in our experiment for each session and for each trading institution. Each period of the experiment is provided on the horizontal axis and market clearing prices are indicated on the vertical axis (for Double Auction, prices reflect session average transaction prices). 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



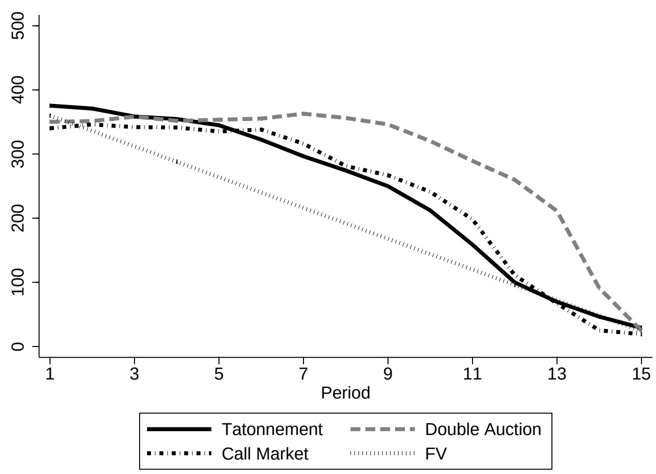
(a) Tâtonnement



(b) Double Auction (Average Transaction Prices)



(c) Call Market



(d) Average Prices (across Sessions) by Institution

Figure 2: Experimental Data on Prices Across Institutions

Tâtonnement.

Table 1: Bubble Measures for DA, CM, and Tâtonnement, Medians over All Sessions by Treatment

Bubble Measure	Double Auction	Call Market	Tâtonnement	Tât. & CM combined
Turnover= $\sum_{t=1}^{15} q_t/TSU$	4.05	1.18	1.58	1.51
Amplitude= $\max_t\left\{\frac{P_t-FV_t}{FV_1}\right\}-\min_t\left\{\frac{P_t-FV_t}{FV_1}\right\}$	0.65	0.44	0.39	0.42
Norm. Dev.= $\frac{1}{TSU}\sum_{t=1}^{15} q_t\|P_t-FV_t\|$	358.32	61.59	99.89	80.74
APD= $\frac{1}{TSU}\sum_{t=1}^{15}\|P_t-FV_t\|$	15.64	9.16	9.61	9.38
RAD= $\frac{1}{15}\sum_{t=1}^{15}\frac{\|P_t-FV_t\|}{mean(FV)}$	0.49	0.29	0.30	0.29
RD= $\frac{1}{15}\sum_{t=1}^{15}\frac{(P_t-FV_t)}{mean(FV)}$	0.36	0.21	0.27	0.24
RPAD= $\frac{1}{15}\sum_{t=1}^{15}\frac{\|P_t-FV_t\|}{FV_t}$	0.82	0.35	0.28	0.30
Haessel= R^2 of OLS regression $P_t=\alpha+\beta FV_t+\epsilon_t$	0.46	0.87	0.94	0.90

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

Measure	DA vs. TT	TT vs. CM	DA vs. CM	DA vs. (CM & Tât)
Turnover	0.03, $>$	0.25	0.01, $>$	0.00, $>$
Amplitude	0.08, $>$	0.75	0.17	0.04, $>$
Norm. Dev.	0.08, $>$	0.92	0.05, $>$	0.03, $>$
APD	0.05, $>$	0.92	0.12	0.08, $>$
RAD	0.12,	0.92	0.17	0.09, $>$
RD	0.47,	0.92	0.35	0.33
RPAD	0.08, $>$	0.47	0.17	0.07, $>$
Haessel	0.05, $<$	0.47	0.12	0.04, $<$

In order to further analyze these differences, for each session we calculated several bubble measures typically used in the literature.[13] The definitions of the measures as well as their average values for each institution are presented in Table 1. We calculated several bubbles measures to provide a more accurate picture of bubbles magnitude, as each measure captures a different aspect of a bubble. For example, Turnover is given by the total sum of the number of shares traded in each period (q_t) normalized by the total number of shares (TSU). A high turnover indicates high volume of trade, which can be an

[13] See Haruvy and Noussair [2006], Haruvy et al. [2007], Kirchler et al. [2010].

indication of a bubble. Absolute Price Deviation (APD) is defined as the sum, over all 15 periods, of the absolute deviation of period price (average period price for double auction), P_t, from period fundamental value, FV_t, normalized by the total number of shares. A high APD indicates that prices depart from fundamental value. In the Normalized Deviation, these period differences are weighted by the number of units traded, while in the Relative Absolute Deviation (RAD) they are normalized by the average fundamental value (in the Relative Proportional Absolute Deviation period differences are normalized by the period fundamental values). A high Normalized Deviation indicates a considerable volume of trade at prices that depart from the fundamental value. The Relative Deviation (RD) differs from the RAD in that it takes the difference between period price and period fundamental value rather than the absolute difference. Thus a high RAD indicates departures of prices from fundamentals, while RD indicates also the direction (a positive RD indicates that prices tend to be above fundamental value while a negative RD may indicate the presence of negative bubbles). Haessel is a measure of correlation of prices with fundamental value, thus a low Haessel indicates that prices do not track the fundamental value. Table 1 indicates that bubbles are the lowest under Tâtonnement and the highest under Double Auction.

Result 1. *Bubbles are significantly lower under under Tâtonnement than under Double Auction.*

Support for Result 1: We compared bubble measures across institutions using a two-sided Mann-Whitney test (with sessions as units of observation). The results are presented in Table 2. 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 each unit can be only traded once under CM and TT and multiple times under DA. □

Table 1 indicates that bubbles are lower when we pool the data from Call Market and Tâtonnement than under Double Auction. Bubble measures are of similar magnitudes between Call Market and Tâtonnement.

2.4 Within-period Price Trend in Double Auction

In this section, we focus on within-period transaction price trends under Double Auction. We will revisit this finding when we test the out-of-sample performance of our model in Section 3.4. Both Tâtonnement and Call Market are single-price institutions: in a given period, all traders face the same transaction price. Under Double Auction, however, in each period, there are multiple trades and potentially multiple prices. Is there a within-period trend in prices in the first period? The reason we focus on the first period is because it is crucial in determining the price path of the whole experiment.

Result 2. *Under Double Auction, within-period transaction prices in the first period exhibit a positive trend.*

Support for this finding is given by the following regression:

$$p_\tau^S = a^S + b\tau + \epsilon_{S\tau}, \tag{1}$$

where p_τ^S is the price of the τ's transaction in period one, session S; a^S is the session fixed effect; and τ is the transaction's number. The positive and statistically significant coefficient $b = 2.02^{***}(se = 0.69)$ indicates that, on average, price increases by 2.02 francs with each next transaction. Since the (across-sessions) median number of transactions is 39 in the first period, the corresponding total within-period increase in price is roughly 79 francs, or 22% of the fundamental value. That is, the within-period trend is not only statistically significant, but also highly economically significant.[14]

3 Theoretical Model and Results

In this section, we provide a parsimonious model that reproduces the main features of the data patterns we observe in the experiments. We discuss the calibration of the model parameters, and lastly we present the results of the theoretical model and compare them to the experimental data. Finally, we show that the model predicts within-period dynamics for transaction prices in the double-auction institution that are similar to the ones observed in the data. Since data from the double auction institution was not used to calibrate the model, this evidence provides validation for the model.

[14]The results are robust to using a log-log specification and other forms of non-linear specification. The trend coefficient is not statistically significant in periods 2 and 3 and is statistically significant, although of a smaller magnitude (1.22) in period 4.

3.1 Outline of the Model

Our modeling of price formation closely follows the experimental design used to implement each institution. In what follows, we introduce the main parts of the model. For details on how each institution is modeled, please see Appendix C.

Demand Function The economy consists of individuals with heterogeneous beliefs about the value of the asset and the expected trading price. The demand function for each individual is assumed to be proportional to the difference between her asset valuation and (expected) transaction price, normalized by the fundamental value:

$$q_t^i = \gamma \left(\frac{V_t^i - p_t^i}{FV_t} \right) + \epsilon_t^i, \tag{2}$$

where q_t^i is the quantity demanded by individual i at time t, V_t^i is the per-unit valuation of the asset for individual i at time t, p_t^i is the price of the asset at time t in TT and the expected price in CM and DA (more on this below), FV_t is the fundamental value of the asset at time t, and ϵ_t^i is the noise term normally distributed with mean 0 and standard deviation σ_ϵ.[15] The parameter γ is to be estimated.

Valuations The valuation of the asset differs across individuals. We assume there are two types of individuals: myopic traders and fundamental traders. The valuation for each type is given by

$$V_t^i = \begin{cases} \tilde{p}_t^i (1+\beta) & \text{if} \quad \text{myopic trader} \\ FV_t & \text{if} \quad \text{fundamental trader} \end{cases}, \tag{3}$$

where $\tilde{p}_t^i$ is the anchoring price and β is a parameter to be estimated.[16] That is, the valuation of myopic traders in a period, is anchored to the previous period's price adjusted for the period expected dividend, and it may exhibit a bias if β is not equal to zero.[17] For example, if $\beta > 0$ ($\beta < 0$), myopic traders exhibit an upward bias (downward bias). The assumption that agents anchor their valuation to the previous period price is designed to capture anchoring as a behavioral bias which has been documented

[15] We include superscript i for the price noting that in Double Auction the price could be individual-specific.

[16] In TT and CM, we assume this price is equal to the market-clearing price in the last period adjusted by the average dividend. However, this price is different in DA since transaction prices are observed both within and across periods. We assume that $\tilde{p}_t$ is equal to the average price in the previous period adjusted by the average dividend across periods at the beginning of the period, whereas it is equal to the average of transaction prices within a period.

[17] For example, if the price in period $t-1$ is equal to the fundamental value in period $t-1$ and $\beta > 0$, then the myopic trader's valuation in period t is higher than the fundamental value of the asset in period t.

in behavioral finance.[18] On the other hand, fundamental trader's valuations are equal to the fundamental value of the asset.

We denote the fraction of myopic traders by δ_t, and assume it changes over time. Specifically, we assume that myopic traders are heterogenous in the degree of their foresight abilities with some of them realizing that their valuations deviate from fundamental value sooner than others. That is, δ_t decreases over time and converges to zero by the end of the experiment, i.e., all myopic traders switch to fundamental traders by the end of the trading horizon. The parameter δ_t captures that myopic traders switch to fundamental traders at different points in time.

Market Clearing Price in TT and CM The parsimonious structure of the model allows us to have a closed-form solution for the expected market-clearing price in Tâtonnement:

Proposition 3.1. *The expected market-clearing price in Tâtonnement is given by:*

$$p_t^* = (1+\beta)\,\delta_t\left(p_{t-1}^* - d\right) + (1-\delta_t)\,FV_t. \tag{4}$$

Proof. The expected market-clearing TT price in equation (4) is obtained by plugging valuations of myopic and fundamental traders from equation (3) into equation (2), weighting the quantity demanded/supplied by myopic and fundamental traders by δ_t and $1-\delta_t$, respectively, and setting aggregate demand equal to zero. □

If we assume that expectations are normally distributed around the expected TT market-clearing price, we can show that the expected market clearing price is equal to equation (4) also in the Call Market trading institution. The proof for the expected market-clearing price under Call Market is more involved and we provide it in the Appendix.[19]

Price Expectations We next describe how we model price expectations p_t^i in equation (2). In TT, p_t^i is the provisional price within each period. In CM and DA there is no provisional price and thus individuals need to form expectations about it. In CM and DA, we assume that the price expectation p_t^i

[18] According to anchoring investors use pre-existing information or the first information they find to estimate the value of a financial instrument.

[19] We cannot derive analytical expression for the equilibrium price in DA, however, in the simulations we verify that when there is no updating within a period and when individuals are not subject to short-sale and cash constraints, the equilibrium price in DA coincides with the market clearing price in TT and CM.

is normally distributed around the expected market-clearing price of TT:

$$p_t^i = (1+\beta)\,\delta_t \tilde{p}_t^i + \left(1 - \delta_t + \eta_t^i\right) FV_t, \tag{5}$$

where η_t^i is drawn from a common knowledge normal distribution with mean 0 and standard deviation σ_η, capturing heterogeneity in beliefs about the expected price.[20]

Expectations' Updating We assume in all institutions individuals are not fully rational, i.e., they are of limited intelligence. They form their expectation about the price and the asset valuation through the price $\tilde{p}_t^i$. In TT and CM institutions, we assume this price is equal to the market-clearing price in the previous period adjusted by the mean dividend across periods: $\tilde{p}_t^i = p_{t-1}^* - d$, where p_{t-1}^* is the market clearing price in the previous period. In DA, this price is equal to the average of the trading prices in the previous period, adjusted for the dividend drop. This price not only affects the price expectation of all individuals in the current period, but it also affects the asset valuation of myopic traders. The key difference across institutions is the frequency with which agents update their price expectations.

Specifically, in TT, this price is updated only across periods and it only affects the asset valuation of myopic traders because price expectations do not play any role within a period. In CM, this price is again only updated across periods since there is a unique market-clearing price within a period. However, this price, in CM, affects the price expectation of all traders in addition to the asset valuation of myopic traders. In DA, since multiple trades happens within a period, there is more opportunity for individuals to update this price. More specifically, we assume that $\tilde{p}_{t,s}^i$ is updated as follows:

$$\tilde{p}_{t,s}^i = \begin{cases} p_{t-1}^* - d & \text{if} \quad s = 1 \\ \frac{\sum_{\tau=1}^{\tau=s-1} p_{t,\tau}^* + p_{t-1}^* - d}{s} & \text{if} \quad s > 1 \;\&\; \alpha_{t,s}^i < \alpha^* \\ \tilde{p}_{t,s-1} & \text{else} \end{cases}, \tag{6}$$

where $p_{t,s}^*$ is the trading price in period t for the s^{th} transaction. That is, in DA, α^* fraction of individuals update their anchoring price as the average of all the prices observed within that period including the average of the previous period transaction prices.

[20] We assume the noise term to be proportional to the fundamental value so that the effect of the noise term on the demand function has no trend.

3.2 Estimation

We next use the experimental data to estimate the model. To this end, we assume that the fraction of myopic traders decreases over time following the process:

$$\delta_t^* = 1 - e^{-\delta\left(\frac{15-t}{t-1}\right)}. \tag{7}$$

This functional form implies that $\delta_t^* \in [0,1]$. Specifically, it is decreasing from $\delta_1^* = 1$ to $\delta_{15}^* = 0$. The parameter δ captures the speed of convergence of δ_t^* to 0. Given this assumption, we need to estimate five parameters: $\gamma, \beta, \delta, \sigma_\epsilon, \sigma_\eta$ (see Table 3 for the parameters' interpretation). We estimate these parameters in two stages using the data from experiments with the Tâtonnement and Call Market institutions as we have closed-form solutions for the market-clearing prices in these institutions.

Specifically, in the first stage, we estimate β and δ using the market-clearing price data from the Tâtonnement and Call Market experiments. Our model implies an analytical solution for the market-clearing price in these institutions as a function of β and δ as shown in equation (4). We normalize equation (5) by the corresponding fundamental value, which gives us

$$\frac{p_t^i}{FV_t} = \frac{(1+\beta)\,\delta_t\left(p_{t-1}^* - d\right)}{FV_t} + \left(1 - \delta_t + \eta_t^i\right). \tag{8}$$

We estimate β and δ by minimizing the square of the distance between the theoretical market-clearing prices and the transaction prices observed in the data (both normalized by the fundamental values). The standard deviation of the error term from this estimation gives us the estimate of σ_η.

In the second stage, we use the data on the quantity traded to estimate γ. We do this again by minimizing the sum of the squared distance between model implied quantity predictions and their data counterparts. The standard deviation of the error term from this estimation gives us the estimate for σ_ϵ.

The details of the estimation can be found in Appendix B. Table 3 presents the results of the estimation. We estimate that there is an upward bias: β is equal to 4.8%. The estimated speed of convergence, $\delta = 2.32$, implies that the evolution of the share of myopic in the population follows the pattern in Figure 3. The value of the estimated demand parameter γ equal to 1.93 and can be interpreted as follows. If the price is equal to the fundamental value, the valuation should be 1.52 times greater than the price to generate a positive expected demand of one unit. Alternatively, if the price exceeds the fundamental value by 20%, the valuation should be 1.43 times greater than the price to generate a positive expected demand of one unit.

We can interpret the obtained value of σ_ϵ as follows. For an individual having a valuation equal to the current price, there is a 31% probability that he will buy one unit or more and a 31% probability that he will sell one unit or more.[21] The estimated value of $\sigma_\eta = 0.25$ implies that the fraction of individuals with a price expectation that is 10% of the fundamental value higher than the trading price will be 34%.

In the experiments, we have 9 individuals on average. However, simulations have 100 individuals. To match the same number of price updates within after each transaction in DA, we set alpha=9/100=0.09. This corresponds to updating after each transaction in experiments. This is the external way of calibrating alpha. This way we can claim that the model doesn't target the price movements in DA, but still does a decent job.

Finally, to determine the fraction of myopic traders who update their price expectation within a period, we set $\alpha^* = 0.09$ to account for the fact that we have 100 individuals in the simulation, whereas there are 9 traders in the experimental economies. This choice implies that individuals have approximately the same number of opportunities to update their subjective price beliefs within a period, both in the model and the data. In the next section, we show that even if we do not target price movements in the Double Auction and we do not use data from the Double Auction to estimate the parameters of the model, the model does a good job at reproducing patterns of the data. We also conduct a robustness analysis with respect to the α^* parameter.

3.3 Results

Given the estimated parameters, we use the theoretical model to simulate market-clearing prices for each institution. In order to isolate the impact of institutional differences on market-clearing prices and quantities, we keep the parameters of the model constant across institutions.[22] Please also note that we

[21] The demand function is defined over real numbers. In the simulation, we round the demand to the nearest integer. So, any $\epsilon >= 0.5$ will result in a one unit of positive demand, which happens with probability $1 - F(0.5)$ where F is normally distributed with mean 0 and standard deviation σ_ϵ.

[22] Recall that in Tâtonnement markets, current period price is defined as the within period off-equilibrium (provisional) price computed as in the experiments. In Call Market and Double Auction, on the other hand, there is no provisional price, and agents form expectations about the market-clearing price as defined in equation (5).

Table 3: Parameters Estimation

Parameter	Definition	Value	Standard Deviation
β	myopic traders' upward bias	0.048	0.008
δ	speed of convergence of the share of myopic traders	2.32	0.08
γ	demand parameter	1.93	0.25
α^*	Updating	0.09	
σ_ϵ	variance of the noise in the demand function	1.0	
σ_η	variance of the noise in the market-clearing price	0.26	

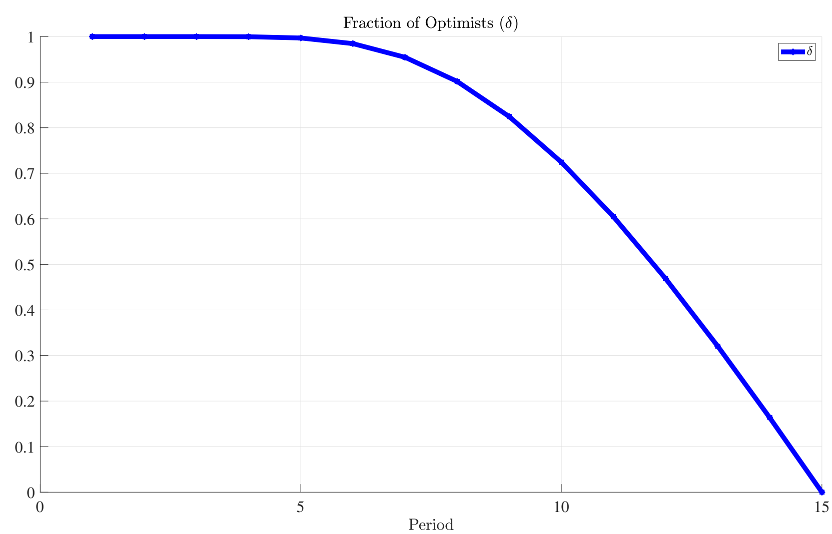


Figure 3: Estimated Share of myopic optimists in Population

did not use the data from Double Auction markets to estimate the parameters of the model. We provide details on how each institution is simulated in Appendix C.

Figures 4a-4c compare the model-generated and actual transaction prices from the data for the three institutions. The model does a fairly good job in capturing the bubble and crash of the asset prices as observed in the data for all institutions, even though we used a limited set of parameters.[23]

Figure 4d compares the model-generated prices across trading institutions and allows us to formulate the following result.

Result 3. *The model generates larger bubbles in Double Auction than in Tâtonnement and Call Market.*

This estimation result indicates that the model succeeds in reproducing important patterns observed in the experimental data (see Result 1, Figure 2(d), and Tables 1 and 2). Next, we provide more intuition on the mechanism of the model. What features of the model generate bubbles and crashes? Why are bubbles more prominent in Double Auction than in uniform-price TT and CM, as observed in the data?

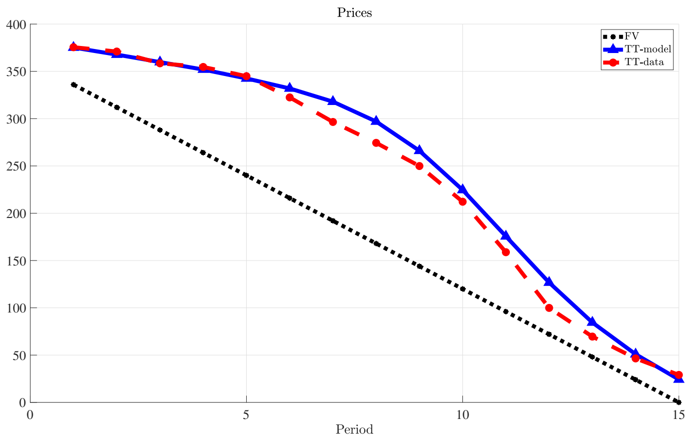
The main driving force behind the formation of bubbles and crashes is the presence of myopic traders who exhibit a positive bias. As can be seen from the theoretical price in TT, as long as $p^*_{t-1} > FV_{t-1}$, $\beta > 0$ (the bias is positive) and $\delta_t > 0$ (there are myopic traders), the model generates a price path that is higher than the fundamental value (see equation (4)). Turning to the price path, the difference between current and last period prices is given by:

$$p^*_t - p^*_{t-1} = \beta\delta_t p^*_{t-1} - (1+\beta)\delta_t d + (1-\delta_t)(FV_t - p^*_{t-1}),$$

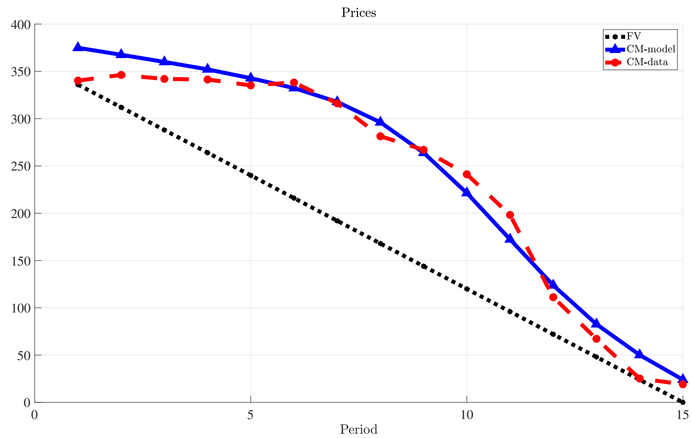
which implies that when δ_t is close to 1, the change in price is greater than $-d$, and can even be positive producing an increasing price path. However, as δ_t approaches zero, the change in price becomes smaller than $-d$ since $FV_t - p_{t-1} = FV_{t-1} - d - p_{t-1} < -d$. Therefore, the decline in δ_t over time leads to a crash. That is, as δ_t approaches zero, all traders become fundamental value traders and the impact of the positive bias becomes smaller.

Importantly, our model also ranks institutions according to the magnitudes of bubbles and this ranking is in line with the ranking observed in the experimental data: Tâtonnement and Call Markets generate

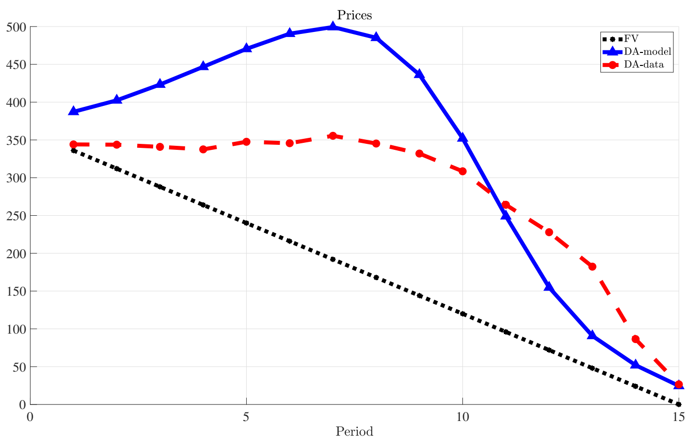
[23] Notice that the number of the parameters in the model is 5 whereas the number of data points to be matched is 140 data points for prices (70 price data points for each TT and CM) and 1540 data points for quantities.



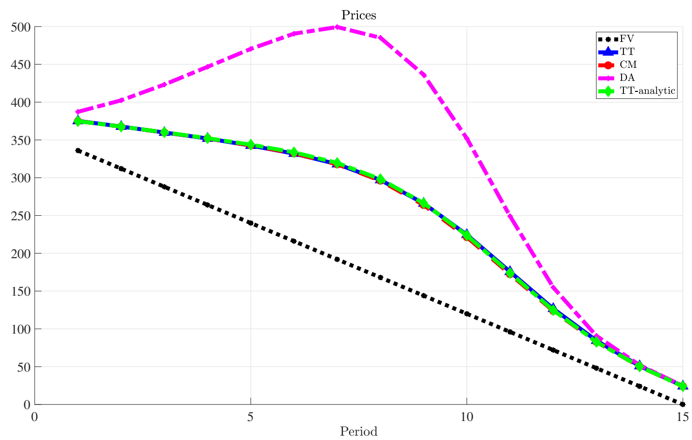
(a) Tatonnement



(b) Call Market



(c) Double Auction



(d) Model

Figure 4: **Prices across Institutions** Figures 4a-4c compare the model-generated and actual transaction prices from the data for each institution. Figure 4d shows the model simulated prices across the three institutions.

similar bubbles whereas Double Auction generates a significantly larger bubble. Next we explain what generates this ranking in the model. The main difference between Double Auction and other institutions is the decentralized nature of trades in the former. That is, in Double Auction, multiple trades take place within a period and traders update their price expectations within a period. This process enables expectations' updating also within a period, in addition to across periods.

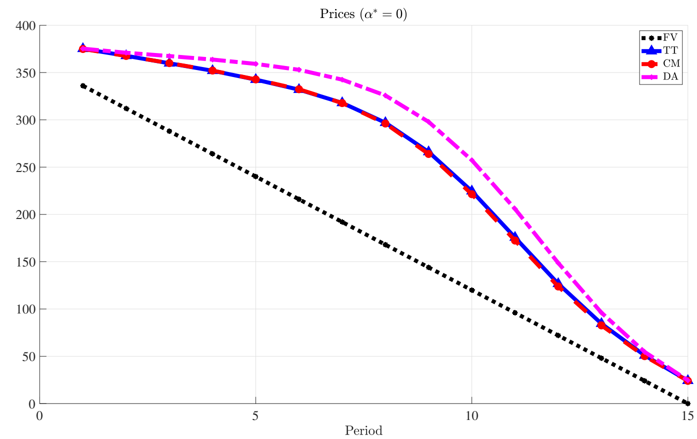
Notice that given the structure of updating we consider, updating has no effect on market-clearing prices in Tâtonnement and Call Markets. To see this, notice that individuals only update their price expectations across periods and price expectations coincide with the evolution of the theoretical price. Since in Tâtonnement and Call Market, the market-clearing price is identical to the theoretical price, updating contributes nothing to individuals information set. Even if we introducing updating in the Tâtonnement based on provisional prices within a period, market-clearing prices are not affected much. That is, unlike in Double Auction, the positive bias does not amplify price departures from the FV in the Tâtonnement.

However, in Double Auction, there is more room for updating since more information is revealed within a period through decentralized transactions. If these observations are used in updating price expectations within a period, they have amplifying effects on bubble formation. To see this, notice that given the functional form for price expectations, which is derived from the theoretical market-clearing price in Tâtonnement and Call Markets, individuals assign weight $(1 + \beta)\delta_t$ to the observation of last period price and weight $(1 - \delta_t)$ to the fundamental value. Since δ_t converges to 0 over time, price expectations converge to the fundamental value over time. However, in the early periods, δ_t is close to 1 and $\beta > 0$ resulting in an exploding price path. This feature of the model results in a larger bubble in Double Auction as long as some of the individuals are allowed to update their prices within a period.

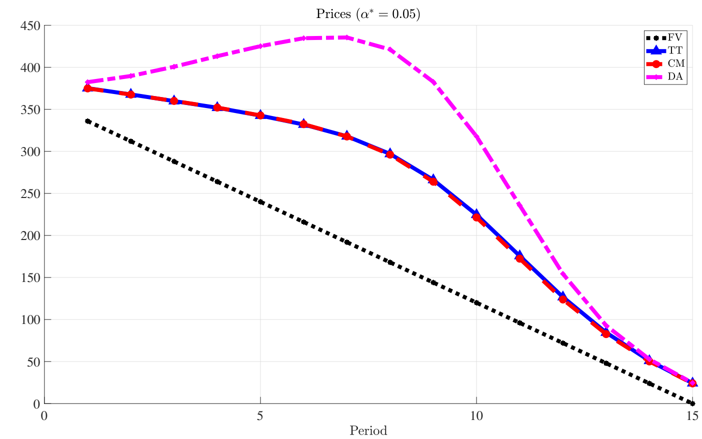
Figures 5a to 5d display the effect of updating on the formation of bubbles across different institutions. In these figures, we compare the model generated prices with different assumptions about the intensity of updating. Notice that α^* represents the degree of updating, as it captures the fraction of myopic traders who update their expectations within a period. When $\alpha^* = 0$, there is no updating, while as α^* increases , the fraction of individuals who update their expectations based on observed prices increases.[24] As can

[24] When $\alpha^* = 0$, the model still generates slightly higher bubble in DA compared to TT and CM. The main reason for this is the presence of the short selling constraint. In DA, most of the transactions happen between individuals with extreme beliefs. In principle, the extreme positive and negative beliefs should cancel out and we should observe a similar pattern as in TT and CM. However, because of the short-selling constraint, sellers with extreme beliefs have limited effect on transaction prices and buyers with extreme beliefs have a stronger impact on transaction prices. This mechanism generates a slightly

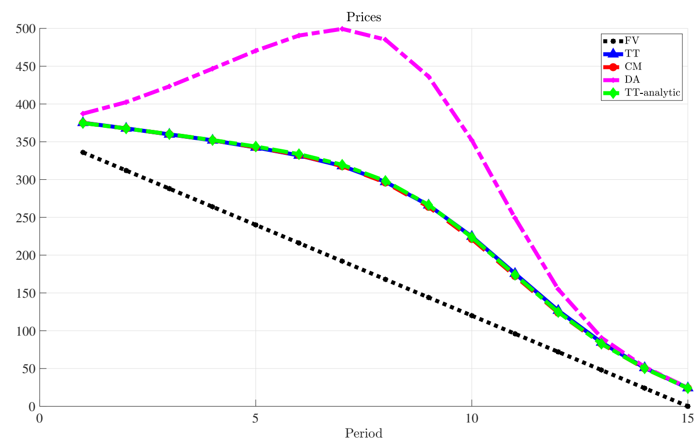
be seen from Figures 5a to 5d, as updating becomes more prevalent, bubbles become larger in Double Auction, while there is no impact on prices in Tâtonnement and Call Markets.



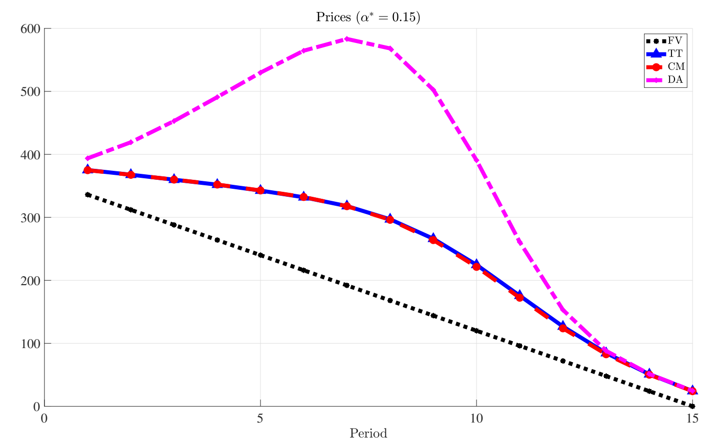
(a) $\alpha = 0$



(b) $\alpha = 0.05$



(c) $\alpha = 0.09$



(d) $\alpha = 0.15$

Figure 5: **Price Comparison:** The figures plot model generated prices under different parametrizations for the fraction of individuals updating their price expectations within a period in DA. In all institutions all individuals update their price expectations across every period. However, in DA within each period α fraction of individuals update their prices given the average price observed within that period.

3.4 Out of Sample

Our model predicts that the main difference in the bubble size between the DA and single-price institutions (CM and TT) is due to the within-period updating in the DA (by design, there is only one transaction price in both CM and TT). In this section we investigate wether the predicted within-period updating pattern

higher bubble in DA compared to TT and CM. This mechanism weakens as we increase the number of individuals simulated and disappears if we relax short selling constraint.

in the model-simulated data matches that in the experimental data. This exercise can be considered as an out-of-sample test of our model since neither the disaggregated transaction-level DA prices nor the aggregated period-level DA prices were used in constructing the simulated data.

According to the model, the within-period price trends are positive in initial periods and then switch to a negative trend in periods that follow the peak of the bubble. The negative trend first becomes stronger as the difference between transaction prices and the fundamental value converge from the peak to the fundamental value but, towards the very end of the experiment the magnitude of the negative trend decreases. To test this prediction, we constructed the average within-period price trends for the simulated and the experimental data as we describe next.

In the experimental data, we have 5 DA sessions, each consisting of 15 periods. For each session s and period p, we regressed the individual transaction price (P_{pst}) on the within-period transaction counter (t=1,2,3,...). The estimated slope represents the within-period price growth per transaction. For each period p, we then calculated the average slope and labeled it as the *data within-period growth.* For the simulated data, we performed the same exercise for each period of 1000 simulated sessions and labeled the corresponding average slope as the *simulated within-period growth.* Figure 6 compares the evolution of within-period price growths across periods. It illustrates that the growth patterns are very similar both in terms of the magnitude and dynamics across periods, which validates the theoretical mechanism that the difference between the DA and single-price institutions is due to the within-period price updating and growth in DA.[25]

Our model makes other predictions that could be tested in future experiments. The model predicts that bubbles are smaller if we limit the opportunities for updating within a period under Double Auction. This can be accomplished, e.g., if subjects have access to bids and asks but do not explicitly see all transaction prices in Double Auction but only see their own transaction prices. Additional evidence that provides support for the mechanism of the model is also provided by Ding et al. [2020], who compare an Over-the-Counter trading institution to the Double Auction. Unlike the Double Auction, in the Over-the-Counter markets, bids and asks are not publicly available: subjects need to contact counterparties to be able to trade. Ding et al. [2020] show that this feature decreases the number of transactions within a period, and eliminates bubbles.

[25] Note that the peaks, both in the experimental and simulated data do not always occur in the same period, which makes the exact match between the simulated and experimental average within-period trends highly unlikely.

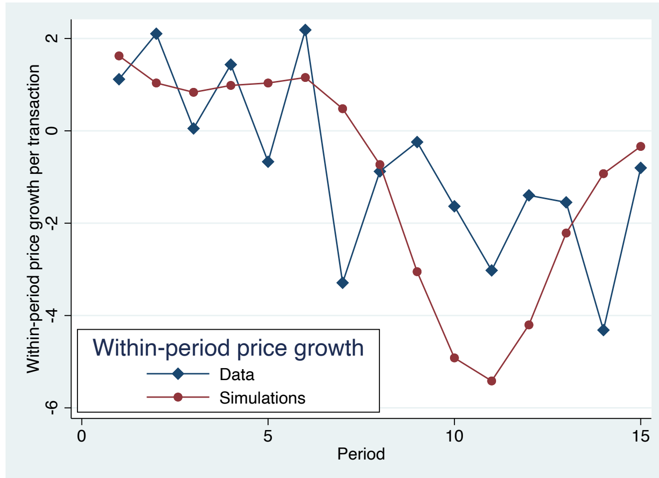


Figure 6: **Within-period price growth rates in DA: data and simulations.**

4 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 and Ünver [2006], Haruvy and Noussair (2006) and Baghestanian, Lugovskyy and Puzzello (2014) and provide a heterogeneous-agent model with myopic and fundamental-value traders to better understand these results within a unified framework for the three institutions. We use data from the Tâtonnement and Call Market experiments to estimate the model. The model reproduces important patterns of the data, including that bubbles are larger in Double Auction than in the other two trading institutions. This result is due to the presence of myopic traders with a positive bias and is linked to two key characteristics of the Double Auction trading institution, namely that multiple transaction prices take place within a period and those are public information. Specifically, myopic traders update their price expectations within a period in the Double Auction, based on within-period transaction prices, and have an amplifying effects on price departures from fundamental value. These results suggest that there are important interaction effects between behavioral biases and trading institutions, and that trading institutions play an important role in determining the degree of market intelligence when limited intelligence traders are present.

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A Proofs

Proof. In TT, the market-clearing price is given by $\sum_i q_t^i\left(p_{t,TT}^*\right) = 0$ which results:

$$p_{t,TT}^* = (1+\beta)\,\delta_t\left(p_{t-1}^* - d\right) + (1-\delta_t)\,FV_t$$

To find the market-clearing price in CM, we need to find out the price which clears the market, i.e. equalizing the aggregate demand to 0. We will study the total demand of myopic and fundamental traders separately.

Myopic Traders Myopic traders submit the quote $\left(p_t^{i,o}, q_t^{i,o}\right)$ where $p_t^{i,o} = (1+\beta)\,\delta_t\left(p_{t-1}^* - d\right) + \left(1-\delta_t+\eta^i\right)FV_t$ and $q_t^{i,o} = \gamma\left(\frac{(1+\beta)\left(p_{t-1}^*-d\right)-p_t^{i,o}}{FV_t}\right) + \epsilon_t^i = \gamma\,(1-\delta_t)\left((1+\beta)\left(\frac{p_{t-1}^*-d}{FV_t}\right)-1\right) - \gamma\eta^i + \epsilon_t^i$. These quotes determine whether they will be buyers or sellers. If $q_t^{i,o} \le 0$, that means the individual will sell $q_t^{i,o}$ quantities as long as the price is such that $p_t^* \ge p_t^{i,o}$. So, the condition to become a seller is:

$$\begin{aligned}
\gamma\,(1-\delta_t)\left((1+\beta)\left(\frac{p_{t-1}^*-d}{FV_t}\right)-1\right) - \gamma\eta^i + \epsilon_t^i \le 0 \\
p_t^* - (1+\beta)\,\delta_t\left(p_{t-1}^*-d\right) - \left(1-\delta_t+\eta^i\right)FV_t \ge 0
\end{aligned}$$

which can be written as

$$\begin{aligned}
\eta^i &\le (1-\delta_t)\,\omega_t^* + h\left(p_t^*\right) \\
\epsilon_t^i &\le -\gamma\,(1-\delta_t)\,\omega_t^* + \gamma\eta^i
\end{aligned}$$

where $\omega_t^* = (1+\beta)\left(\frac{p_{t-1}^*-d}{FV_t}\right) - 1$ and $h\left(p_t^*\right) = \frac{p_t^*-(1+\beta)\left(p_{t-1}^*-d\right)}{FV_t}$. In this interval of η, the individual becomes a seller and demands $q_t^{i,o} = \gamma\,(1-\delta_t)\,\omega_t^* - \gamma\eta^i + \epsilon_t^i$.

Similarly, if $q_t^{i,o} \ge 0$, that means the individual will buy $q_t^{i,o}$ quantities as long as the price is such that $p_t^* \le p_t^{i,o}$. This implies that the condition to become a buyer is:

$$\begin{aligned}
\eta^i &\ge (1-\delta_t)\,\omega_t^* + h\left(p_t^*\right) \\
\epsilon_t^i &\ge -\gamma\,(1-\delta_t)\,\omega_t^* + \gamma\eta^i.
\end{aligned}$$

Thus, the total demand of myopic traders becomes:

$$\begin{aligned}
Q_t^o\left(p_t^*\right) = \delta_t \int_{-\infty}^{(1-\delta_t)\omega_t^*+h(p_t^*)} \int_{-\infty}^{-\gamma(1-\delta_t)\omega_t^*+\gamma\eta} \left(\gamma\,(1-\delta_t)\,\omega_t^* - \gamma\eta + \epsilon\right) dF_\epsilon(\epsilon)\, dF_\eta(\eta) + \\
\delta_t \int_{(1-\delta_t)\omega_t^*+h(p_t^*)}^{\infty} \int_{-\gamma(1-\delta_t)\omega_t^*+\gamma\eta}^{\infty} \left(\gamma\,(1-\delta_t)\,\omega_t^* - \gamma\eta + \epsilon\right) dF_\epsilon(\epsilon)\, dF_\eta(\eta)\,.
\end{aligned}$$

Fundamental Traders Fundamental traders submit $\left(p_t^{i,f}, q_t^{i,f}\right)$ where $p_t^{i,f} = (1+\beta)\,\delta_t\left(p_{t-1}^*-d\right) + \left(1-\delta_t+\eta^i\right)FV_t$ and $q_t^{i,f} = \gamma\left(\frac{FV_t-p_t^{i,f}}{FV_t}\right) + \epsilon_t^i = \gamma\delta_t\left(1-(1+\beta)\left(\frac{p_{t-1}^*-d}{FV_t}\right)\right) - \gamma\eta^i + \epsilon_t^i$. Given these quotes, we can determine the conditions to become a seller or a buyer for fundamental traders. To become a seller, η^i needs to satisfy:

$$\eta^i \leq (1-\delta_t)\,\omega_t^* + h\,(p_t^*)$$
$$\epsilon_t^i \leq \gamma\delta_t\omega_t^* + \gamma\eta^i.$$

To become a buyer, η^i needs to satisfy

$$\eta^i \geq (1-\delta_t)\,\omega_t^* + h\,(p_t^*)$$
$$\epsilon_t^i \geq \gamma\delta_t\omega_t^* + \gamma\eta^i.$$

So, the total demand from fundamental traders becomes:

$$Q_t^f\,(p_t^*) = (1-\delta_t)\int_{-\infty}^{(1-\delta_t)\omega_t^*+h(p_t^*)}\int_{-\infty}^{\gamma\delta_t\omega_t^*+\gamma\eta}\left(-\gamma\delta_t\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon)\,dF_\eta\,(\eta) +$$
$$(1-\delta_t)\int_{(1-\delta_t)\omega_t^*+h(p_t^*)}^{\infty}\int_{\gamma\delta_t\omega_t^*+\gamma\eta}^{\infty}\left(-\gamma\delta_t\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon)\,dF_\eta\,(\eta)\,.$$

Then, aggregate demand becomes:

$$\begin{aligned} Q_t\,(p_t^*) &= Q_t^o\,(p_t^*) + Q_t^f\,(p_t^*) \\ &= \int_{-\infty}^{(1-\delta_t)\omega_t^*+h(p_t^*)}\left[\begin{array}{c} \delta_t\int_{-\infty}^{\gamma\delta_t\omega_t^*+\gamma\eta-\gamma\omega_t^*}\left(\gamma\,(1-\delta_t)\,\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) + \\ (1-\delta_t)\int_{-\infty}^{\gamma\delta_t\omega_t^*+\gamma\eta}\left(-\gamma\delta_t\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) \end{array}\right]dF_\eta\,(\eta) + \\ &\int_{(1-\delta_t)\omega_t^*+h(p_t^*)}^{\infty}\left[\begin{array}{c} \delta_t\int_{\gamma\delta_t\omega_t^*+\gamma\eta-\gamma\omega_t^*}^{\infty}\left(\gamma\,(1-\delta_t)\,\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) + \\ (1-\delta_t)\int_{\gamma\delta_t\omega_t^*+\gamma\eta}^{\infty}\left(-\gamma\delta_t\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) \end{array}\right]dF_\eta\,(\eta)\,. \end{aligned}$$

The equation above simplifies to

$$\begin{aligned} Q_t\,(p_t^*) = &\int_{-\infty}^{(1-\delta_t)\omega_t^*+h(p_t^*)}\left[\begin{array}{c} \int_{-\infty}^{\gamma\delta_t\omega_t^*+\gamma\eta-\gamma\omega_t^*}\left(-\gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) + \\ (1-\delta_t)\int_{\gamma\delta_t\omega_t^*+\gamma\eta-\gamma\omega_t^*}^{\gamma\delta_t\omega_t^*+\gamma\eta}\left(-\gamma\delta_t\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) \end{array}\right]dF_\eta\,(\eta) + \\ &\int_{(1-\delta_t)\omega_t^*+h(p_t^*)}^{\infty}\left[\begin{array}{c} \int_{\gamma\delta_t\omega_t^*+\gamma\eta-\gamma\omega_t^*}^{\infty}\left(-\gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) + \\ (1-\delta_t)\int_{\gamma\delta_t\omega_t^*+\gamma\eta}^{\gamma\delta_t\omega_t^*+\gamma\eta-\gamma\omega_t^*}\left(-\gamma\delta_t\omega_t^* - \gamma\eta + \epsilon\right)dF_\epsilon\,(\epsilon) \end{array}\right]dF_\eta\,(\eta)\,. \end{aligned}$$

Since the terms in the bracket are symmetric around 0 for any η, and η is drawn from a Normal distribution with mean 0, the equation above is equal to 0, if $(1-\delta_t)\,\omega_t^* + h\,(p_t^*) = 0$. Thus, the market-clearing price in CM also becomes:

$$p_{t,CM}^* = (1+\beta)\,\delta_t\left(p_{t-1}^* - d\right) + (1-\delta_t)\,FV_t.$$

□

B Estimation

The calibration is conducted in two stages. In the first stage, using the analytical price equation in TT and CM, we estimate β and δ by minimizing the square of the distance between the theoretical price in TT and the equilibrium trading price in the experiments for TT and CM. This gives us 140 observations (70 for each institution) since we have 5 sessions for each institution conducted and each of them consists of15 periods. However, we drop the first observation in each experiment since theoretical price depends on the market-clearing trading price in the previous period, which is not observed for the first period. Instead, we use the first period market-clearing price to pin down the initial belief about the price in period 0. Specifically, we solve the following minimization problem:

$$\min_{\beta,\delta} \sum_{i=1}^{2} \sum_{s=1}^{5} \sum_{t=2}^{15} \left(\frac{p_t^{s,i} - (1+\beta)\,\delta_t \left(p_{t-1}^{s,i} - d\right) - (1-\delta_t)\,FV_t}{FV_t} \right)^2$$

where $p_t^{s,i}$ is the observed price in institution $i \in \{TT, CM\}$, session s, and period t and FV_t is the fundamental value in period t. Notice that using equation 5, this minimization problem can also be written as

$$\min_{\beta,\delta} \sum_{i=1}^{2} \sum_{s=1}^{5} \sum_{t=2}^{15} \left(\eta_t^{s,i}\right)^2$$

which allows us to obtain an estimate for σ_η.

Then, in the second stage, we use the demand function in equation 2 to estimate the parameters γ and σ_ϵ, given the parameter estimates for β and δ from the first stage. We again estimate these parameters by minimizing the sum of the squared distance between the model implied quantity prediction and the data from the TT and CM experiments. Since traders' valuations include prices in the previous period, the demand function for traders in a given period will also include prices in the previous period. Therefore, we only use quantity data starting from period 2 for each individual. This gives us 14 observations for each individual. We have 9 individuals in each of the five sessions in TT, which gives us 45 individuals. So, we have 45*14=630 observations from the TT experiment. In CM, individuals can post both bid and ask prices. We dropped all the observations with 0 quantities. This results in 910 quantity observations in CM experiment. In total, we have 1540 data points for quantities.

The demand function becomes:

$$q_t^{s,i} = \begin{cases} \gamma\left(\frac{\left(p_{t-1}^{s,j}-d\right)(1+\beta)-p_t^{s,j}}{FV_t}\right) + \epsilon_t^{s,i} & \text{with prob} \quad \delta_t \\ \gamma\left(1 - \frac{p_t^{s,j}}{FV_t}\right) + \epsilon_t^{s,j,i} & \text{with prob} \quad 1-\delta_t \end{cases}$$

where i denotes the individual, s denotes the session, and j denotes the institution.

Then, γ solve

$$\min_{\gamma} \sum_{j=1}^{2} \sum_{s=1}^{5} \sum_{i=1}^{N_s^j} \sum_{t=2}^{15} \left(\tilde{q}_t^{s,j,i} - q_t^{s,j,i}\right)^2$$

where $\tilde{q}_t^{s,j,i}$ is the quantity for individual i in period t session s and institution j. Notice that $\tilde{q}_t^{s,j,i} - q_t^{s,j,i} = -\gamma\eta_t^i + \epsilon_t^i$, i.e., the standard deviation of the error in the estimation will serve as an estimate for $\gamma\sigma_\eta + \sigma_\epsilon$.

C Simulation

In this appendix we provide a detailed description of each simulated market environment. Similar to the experimental setting, in each market, N agents interact in T periods and trade a single financial asset.[26] 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

[26]In the experiments $N = 9$ and $T = 16$. In the simulations we set $N = 100$ and $T = 16$ to reduce the noise in the simulations due to a low number of agents.

known support $\{d_1, d_2, d_3, d_4\}$, with $d_i \geq 0$ and $d_1 < d_2 < d_3 < d_4$. The expected dividend is denoted as $\bar{d} = \frac{1}{4}\sum_{i=1}^{4} d_i$. To fit the laboratory environment, we set the dividend support to $\{0, 8, 28, 60\}$, but 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 $FV_t = \bar{d}(T - t + 1) \quad \text{for} \quad t = 1, ..., T$. As in the experiment, we impose no-borrowing, no short-selling and no maximum trading quantity constraints.[27]

At the beginning of the experiment a random number from a uniform distribution is drawn for each individual to determine their types; myopic or fundamental traders. This random number for each individual is fixed over time and across all institutions in the simulations. If this random number is smaller than δ_t, the individual is assigned to be a myopic trader, otherwise she becomes a fundamental trader.

C.1 Tâtonnement

In tâtonnement auctions every trading period starts at some initial price $p_{0,t}$. Conditional on this "indicative" price, a trader submits his/her quantity following equation (2), where ϵ_t^i is drawn from a normal distribution with mean 0 and variance σ_ϵ^2 at the beginning of each period.[28] Notice that if the quantity submitted is positive, the trader is on the demand side, and if it is negative the trader is on the supply side of the market. Based on those submitted demand and supply quantities, the auctioneer/experimenter computes the aggregate excess demand, z_t, where

$$z_t = \sum_i y_t^i. \tag{9}$$

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:

$$p_{j+1,t} = p_{j,t} + \theta z_{j,t}, \tag{10}$$

where θ is the adjustment factor. We set θ to a sufficiently low number to ensure the convergence on market clearing price. Conditional on the new indicative prices, agents re-submit new quantities y_t^i. Iterations continue until $|z_t| < \xi$, where we set $\xi = 1$.[29] [30]

Once the market-clearing price is determined, trade occurs according to the submitted quantities at the market-clearing price. We update the total cash and aggregate quantities each individual hold, and draw a random number to determine the realization of the dividend payments. Given the dividend payment, we update the cash holdings for each individual, and move to the next period.

[27] When individuals buy the asset, they are constrained with their cash holdings, they cannot borrow to buy an asset (borrowing constraint). If the borrowing constraint is violated, the quantity is determined by dividing the total cash holding to the price. When they sell the asset, they are constrained with the amount they hold (short-selling constraint). If the short-selling constraint is violated, the quantity submitted becomes the total amount of asset holding individual has. We also restrict individuals to trade at most 10 quantities of asset in each period as in the experiments.

[28] We fix these draws across all institutions to avoid any potential bias due to random numbers.

[29] Lowering this number does not change the result. For $N = 1000$, average number of trades occurring within a period is around 300.

[30] Notice that the demand function (2) allows for non-integer quantities to be submitted. We allow such quantities to be submitted during the simulation in tâtonnement auctions. Restricting the quantities submitted to only integers does not change the qualitative conclusions of the paper.

C.2 Call Markets

As in the experiments, in the Call-Market auctions, individuals submit their price and quantity bids simultaneously. Unlike in the experiments, we only allow agents to submit one offer either to buy or sell the asset.[31] These bids are determined by equations (2) for quantities and (**??**) for prices. As in TT, ϵ_t^i is drawn from a normal distribution with mean 0 and variance σ_ϵ^2, and η_t^i is drawn from a normal distribution with mean 0 and variance σ_η^2 at the beginning of each period. Then, an offer in the call market can be expressed by a pair $\left(p_t^i, q_t^i\right)$, where p_t^i is determined by equation (**??**) and q_t^i is determined by equation (2).[32] Notice that q_t^i can be positive or negative. When $q_t^i > 0$, p_t^i is the maximum price at which the agent is willing to buy q_t^i units of the asset. When $q_t^i < 0$, p_t^i is the minimum price at which the agent is willing to sell q_t^i units of the asset.

Given the bids and asks, we construct the demand and supply schedules by aggregating all these offers, and assign the lowest price that clears the market as the market-clearing price. Given the market-clearing price, we conduct the trade as suggested by the offers.[33] Once trades are completed, the quantity and cash holdings for each individual are updated. We, then, draw a random number to determine dividend payments, and update their cash holdings given these dividend payments, and move to the next period.

C.3 Double Auction

In the experiments with double auction, within each period trade has to occur in a specified time frame. To mimic this feature of the experiments, in the simulations, we divide a period into S subperiods. In each subperiod, we draw a random number for each individual $i \in 1, 2, ..., N$, and rank these individuals according to this random number. Each subperiod starts with an ask price $p_{t,s}^a$, the identity of the individual who posted the ask price $i_{t,s}^a$, a bid price $p_{t,s}^b$ and the identity of the individual who posted the bid price $i_{t,s}^b$. The initial value for the ask price is set to a very low value, and the initial value for the bid price is set to a very high value, such that each individual finds it optimal to update the ask/bid prices when it is their turn.

Within each period, starting from the highest ranked individual, we ask the individual whether s/he wants to trade at the current bid or ask price. If the expected price of the individual $\left(E_{t-1}p_t^i\right)$ is higher than the ask price $p_{t,s}^a$ and the individual's demand q_t^i given by equation (2) is greater than 1 at the current ask price $p_t = p_{t,s}^a$, trade occurs, and the individual buys the unit from the other party who posts the ask price. Once the quantity and cash holdings of both individuals are updated, we move to the next subperiod.

Otherwise, if the expected price of the individual is lower than the bid price ($\left(E_{t-1}p_t^i\right) < p_{t,s}^b$), and the demand of the individual at the expected price is less than -1 ($q_t^i\left(p_t = p_{t,s}^b\right) < -1$), again trade occurs by the individual selling the unit to the individual who submitted the bid price. Once the quantity and cash holdings of both individuals are updated, we move to the next subperiod.

If the individual does not want to trade at the current ask/bid prices, the individual is able to update the current ask/bid prices. This is determined by comparing the expected price of the individual to the current ask/bid prices. If the expected price of the individual is lower than the current ask price, and if the individual wants to sell at least a unit at his/her expected price, the ask price and the identity of the submitter of the ask price are updated. If the expected price of the individual is higher than the current

[31] In the data, more than 70% of the time, individuals submit one active offer. In these cases, the other offer has no effect on equilibrium prices and quantities.

[32] As in the tâtonement auction, these offers are also subject to no borrowing and no short-selling constraints.

[33] At this stage, it is possible to have excess demand or supply given the equilibrium price since offers indicate the maximum amount of quantities to be traded at the indicated prices. We conduct the trade by ranking the individuals according to their willingness to buy and sell indicated by their price bids. This process allocates the asset to the ones who value it the most.

bid price and the individual is willing to buy at least a unit at his/her expected price, then the current bid price and the identity of the submitter of the bid price are updated.

If trade doesn't occur with individual i, we move to the next individual according to their ranks. We continue this procedure until trade occurs within a subperiod. Once trade occurs, we update the cash and quantity holdings of each party in the trade, and move to the next subperiod. We continue this procedure for all subperiods within a period.

At the end of each period, price expectations are updated according to equation **??** where η_t^i is drawn from a normal distribution with mean 0 and variance σ_η^2 at the beginning of each period and $p_t^s = p_{t-1}^* - d$. Within each period and after each transaction, another random number from a uniform distribution is drawn for each individual and if this random number is smaller than α, the individual updates her price expectation setting p_t^s as the average price between the first and s^{th} transaction within a period: $p_t^s = \sum_{j=1}^s p_t^j$. At the end of each period, p_t is computed as the average price across all transactions within a period.