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. We employ three trading institutions: Call Market, Double Auction, and Tâtonnement. The results show that bubbles are significantly smaller in uniform-price institutions than in Double Auction. We reproduce this and other critical patterns of the data by calibrating a heterogeneous agent model with fundamental and myopic-noise traders. The model produces larger bubbles under Double Auction because multiple trades occur within a period, amplifying the impact of myopic traders with positive bias on transaction prices.

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 craftsman's annual income and then suddenly crashed to a fraction of its value. More recent examples include the real estate bubble crash of 2008, the 2018 Bitcoin and other crypto-currencies crashes.

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. They allow researchers to control for and manipulate factors that are difficult to do so 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.[1]

The leading behavioral explanations for the existence of price bubbles include heterogeneity in price expectations and levels of trader sophistication, e.g., [Smith et al., 1988, Lei et al., 2001, Cheung et al., 2014, Noussair et al., 2016].We believe that there are important and understudied interaction effects between trading institutions, expectations' heterogeneity and the impact of unsophisticated traders on mispricing. The purpose of this paper is to study such interactions.

We use experimental methods to study the effect of trading institutions on the formation of bubbles and crashes in the Smith et al. [1988] environment and focus on three trading institutions: Double Auction (DA), Call Market (CM) and Tâtonnement (TT).[2] We employ the Smith et al. [1988] paradigm for several reasons. First, the fundamental value of the asset is well-defined, allowing us to identify and measure bubbles. Second, our focus is on bubbles' taming, and bubbles are a robust finding of this environment. Third, noise and limited intelligence appear to play an important role in this context (e.g., Lei et al. [2001] and Hussam et al. [2008]), allowing us to study whether trading institutions play a role in decreasing the impact of noise and limited intelligence on price formation. Specifically, Gode and

[1]For reviews, see Plott and Smith [2008], Noussair and Tucker [2013], Palan [2013], Powell and Shestakova [2016].

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

Sunder [1993] show that double auctions tend to reach high levels of allocative efficiency in *goods* markets even when they are populated by zero-intelligence traders, who submit bids and asks randomly subject to minimal constraints. That is, goods markets can be smart, even though individual traders are not rational. Clearly, experimental evidence shows that this property of the double auction does not transfer to SSW *asset* markets, leaving the door open to explorations as to whether trading institutions other than the double auction may lead to more "intelligent" market outcomes. Fourth, this environment has been extensively studied in experimental economics, allowing us to compare our results to a large body of existing studies. Finally, bubbles in this environment appear to be generated also by heterogeneity in beliefs and trading strategies, which also play an essential role in the formation of bubbles in the field (see also Haruvy and Noussair [2006]).

We focus on these three institutions for several reasons. First, while DA and CM have been widely used in both the field and experimental asset markets, the TT is a trading institution of historical and contemporary relevance. Indeed, TT is one of the earliest classical theories, which is explicit about market price dynamics and adjustment to equilibrium (see Duffie and Sonnenschein [1989]). Furthermore, TT 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]). Second, these institutions differ substantively. In DA, 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 CM, bids and asks are accumulated, and the maximum possible number of transactions are simultaneously cleared at a uniform price per period. In TT, 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 until a market-clearing price is realized.

Based on these differences, CM and TT can be classified as uniform-price institutions with the price being the same for all trades within a given period, while DA is characterized by multiple transaction prices in each period. This multiplicity in transaction prices may potentially lead to more heterogeneous expectations about the value of an asset in DA compared to uniform-priced CM and TT and thus result in larger bubbles in discriminatory market institutions.

Our experimental findings support this conjecture: We find that price bubbles are mitigated in the uniform-price TT and CM institutions compared to DA. Due to the complexity of the trading environment, no micro founded model can be used to capture the main patterns of the data. Therefore, we use a computational approach to provide insights to the determinants of market behavior across institutions [see also Duffy and Ünver, 2006, Haruvy and Noussair, 2006]. Specifically, building on the existing literature, we provide a heterogeneous-agents model with myopic and fundamental traders.

Relative to Haruvy and Noussair [2006] and Duffy and Ünver [2006], we study the impact of DA, CM, and TT on bubbles' formation within a unified framework.[3] 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 is 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 that 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 assumption 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 TT and CM institutions.[4] Then, using the same set of parameters, we simulate the model under all three trading institutions. This method ensures 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 model's parameters. 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 larger in DA, whereas TT and CM generate similar size bubbles. The two main reasons for the occurrence of the bubble-crash pattern across all institutions are the following. First, myopic traders' valuation bias is estimated to be positive. Second, the share of individuals acting as myopic traders decreases over time, while the share of individuals acting as fundamental traders increases over time. However, these features are not enough to generate a larger bubble in DA. The key characteristic of DA

[3] Duffy and Ünver [2006] focuses on double auctions in both experiments and model, while Haruvy and Noussair [2006] focus on experimental double auctions and a Tâtonnement setting for the model.

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

leading to larger bubbles is that multiple trades occur within a period. This characteristic allows myopic traders to update their valuation and price expectation within a period, thus amplifying the impact of positive bias on transaction prices.

We also report results from out-of-sample exercises to further validate the mechanism of the model. We show that the model produces similar dynamics for within-period price growth in the DA.[5] Importantly, our paper is the first to study the effect of trading institutions on distributional outcomes. Specifically, both in the data and in the model, we show that DA results in higher inequality in trader earnings than uniform-price institutions, CM and TT. Furthermore, subjects with higher cognitive-reflection skills earned more than those with lower skills in DA but not in CM and TT.

Overall, 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 the markets' intelligence. Furthermore, it provides suggestive evidence that uniform-price institutions, unlike DA, protect against the adverse effects of limited intelligence traders.

2 Related Literature

The effect of trading institutions on the formation of bubbles, price discovery, efficiency levels, and excess volatility have been investigated by various authors with mixed results. In field studies, 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 (CM and TT) trading institutions, whereas the actual trading prices are determined via price formation mechanisms similar to DA. 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

[5]Recall that we did not use any data from the DA to estimate the parameters of the model.

effects difficult. Also, different trading institutions are typically used for different assets, so it is difficult to infer whether differences in the price function arise from the trading institution or the asset class. On the other hand, our laboratory environment allows us to vary trading institutions exogenously, enabling us to make causal statements. We next limit our discussion to laboratory studies most closely related to ours and refer the reader to Noussair and Tucker [2013], Palan [2013], Powell and Shestakova [2016] or Bosch-Rosa and Corgnet [2021] for more comprehensive reviews of laboratory research on asset markets.

Van Boening et al. [1993] show that bubbles arise in both CM and DA with inexperienced subjects. However, the limited number of observations (2 per institution) did not allow them to make statistical comparisons of bubbles across institutions. Friedman [1993] compares DA to CM experimentally in an environment where order flow information available to traders changes across treatments. He reports that double auctions increase trading volume, but the informational efficiency across trading institutions is similar. Furthermore, the allocative efficiency in CM tends to be higher than in DA under limited order flow information.

Pouget [2007] studies the performance, in terms of information aggregation, of a Walrasian TT and CM trading institutions in a laboratory environment with common values and asymmetric information as in Plott and Sunder [1982]. While prices are fully revealing in both TT and CM, gains from trade are higher in TT since TT fosters learning, which mitigates the impact of bounded rationality and strategic uncertainty on trading outcomes. We complement this work by focusing on bubble formation.

More recently, Deck et al. [2020] find that the English Dutch auction performs better than a Double Dutch Auction and DA in an SSW setting. Ding et al. [2020] find that bubbles are greatly reduced in an Over-the-Counter market relative to DA markets. We complement these studies by introducing the TT institution and providing a model that we estimate using the experimental data. Duffy and Ünver [2006] focus on DA in both experiments and model where traders are assumed to be near-Zero Intelligent. Haruvy and Noussair [2006] focus on experimental double auctions and on a TT setting with heterogeneous agents for the model. Relative to Duffy and Ünver [2006] and Haruvy and Noussair [2006], we conduct experiments to compare the impact of *three* distinct institutions on bubbles' formation. Importantly, we also provide a unified parsimonious model that uncovers possible mechanisms behind the experimental results and conduct out-of-sample exercises to provide support for the proposed mechanisms.

Breaban and Noussair [2015] and Corgnet et al. [2015] find a positive correlation between traders' cognitive reflection scores and earnings (see also Bosch-Rosa and Corgnet [2021] for a literature review on the role that cognitive skills play in financial markets). We add to this evidence by uncovering interactions between traders' characteristics and trading institutions, e.g., we find that cognitive reflection skills generate higher earnings inequality under DA than TT or CM.

3 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 132 participants. Participants were undergraduate students at each respective university recruited using the ORSEE subject recruitment and management program.[6] 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.[7] 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 the treatment.[8] We set the parameters in all sessions 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 asset's fundamental value 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.[9] In each trading period,

[6]See Greiner [2015] for a discussion of the ORSEE recruitment program.

[7]See Fischbacher [2007] for a discussion of the z-Tree software package.

[8]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.

[9]Relatively high cash to asset ratios have been shown to bring about greater mispricing [Caginalp et al., 1998, 2001, Haruvy and Noussair, 2006, Noussair and Tucker, 2006, 2016, Kopanyi-Peuker and Weber, 2021, among others]. Similar endowments, and thus cash to asset ratios, to those used in our study are common in the literature when bubble prone markets are a key component of the research question [Lei et al., 2001, Lei and Vesely, 2009, Lugovskyy et al., 2011, **?**,

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 market 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 large endowment 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, a cognitive reflection test (CRT) was conducted [Frederick, 2005]. The test consists of the following three questions:

1. A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

CRT allows for the distinction between system 1 and system 2 cognitive processes [Stanovich and West, 2000, Kahneman and Frederick, 2002]. System 1 processes are conducted reflexively and involve minimal mental reflection. A subject employing system 1 will provide the intuitive but incorrect answers to these questions, i.e., 10, 100, and 24, respectively. The correct answers of 5, 5, and 47 require conscious mental effort and depth of thinking associated with system 2 processes. The average number of correct CRT answers has been shown to be correlated with mispricing [Corgnet et al., 2015, Charness and Neugebauer, 2019, Bosch-Rosa et al., 2018, Noussair and Tucker, 2016, Noussair et al., 2016]. More specifically, markets exhibiting higher average CRT scores are associated with smaller deviations between prices and

among others] (Lei et al. 2001, Lei and Vesely 2009, Lugovskyy et al. 2014, Noussair and Xu 2015, Ding et al. 2018, Deck et al. 2020, among others).

[10]Note that the impact of a subject on aggregate supply is limited by his asset endowment, which, on average, is 10. In contrast, his impact on aggregate demand is typically much greater than 10, as his cash holdings and prices determine it. For instance, if the asset is priced at fundamental value in period 1, each subject can afford 27 shares. In period 15, a subject with the initial cash endowment of 10,000 francs can afford at least 416 shares priced at fundamental value. 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 the 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.

fundamental values. Additionally, subjects with lower (higher) average CRT scores are more (less) prone to engage in unprofitable transactions, i.e., purchases at prices above fundamental value and/or sales at prices below fundamental values. Since CRT measures a subject's willingness to think deeply/logically, we can interpret the CRT scores as a measure of a subject's level of sophistication.

For participating in the CRT, 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.[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: DA, CM, and TT.

3.1 Experimental Procedures: Double Auction, Call Market, and Tâtonnement

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 a 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, in each period, traders simultaneously submit their offers to buy and sell units of the asset. 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 they want to purchase and the maximum price they are willing to pay for each unit. Similarly, an offer to sell consists of the maximum quantity they want to sell and the minimum per-unit price 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

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

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.

Under the Tâtonnement, in each period, subjects are allowed either to buy or to sell units of the asset as long as they have 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 is determined by the median forecasted price (recall that subjects provided price forecasts at the beginning of each period). Then, each subject decides how many units of the asset they want to buy or sell at this price by placing bids or asks respectively. The computer aggregates individual decisions and compares the market quantity demanded (Q_D) to the market quantity supplied (Q_S). If the market clears ($Q_D = Q_S$), then the process stops, and transactions are completed. If the market does not clear at the initial price, then the price adjusts in the appropriate direction. Specifically, we employ 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 with the aggregate demand and supply of stocks in every iteration of every period. We did not implement an improvement rule: Players were free to submit new bids and asks without any constraints on their behavior from prior iterations after

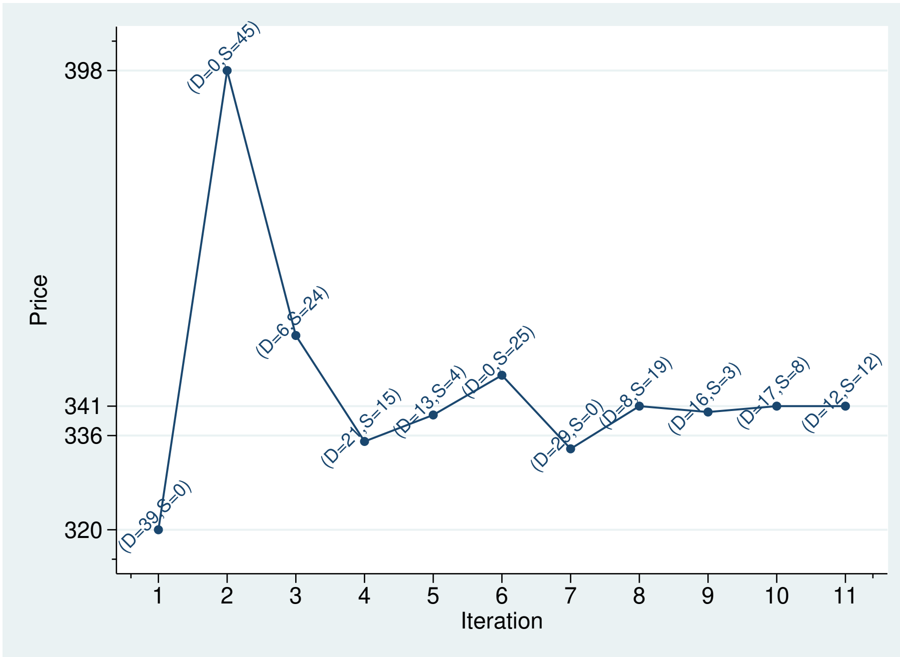


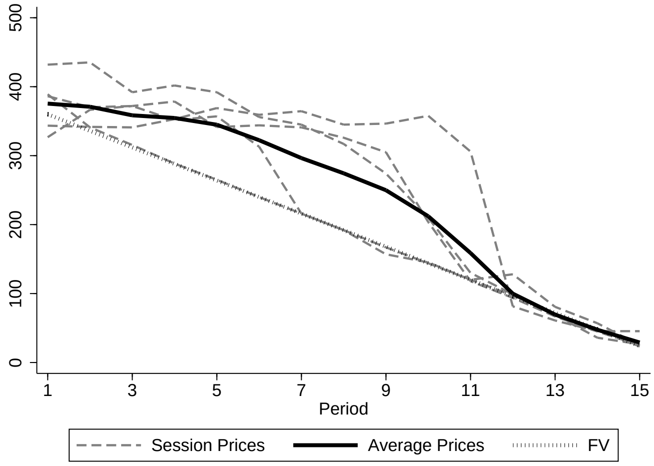
Figure 1: Tâtonnement Price Iterations in Period 2 of Session 1

each price announcement. 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.

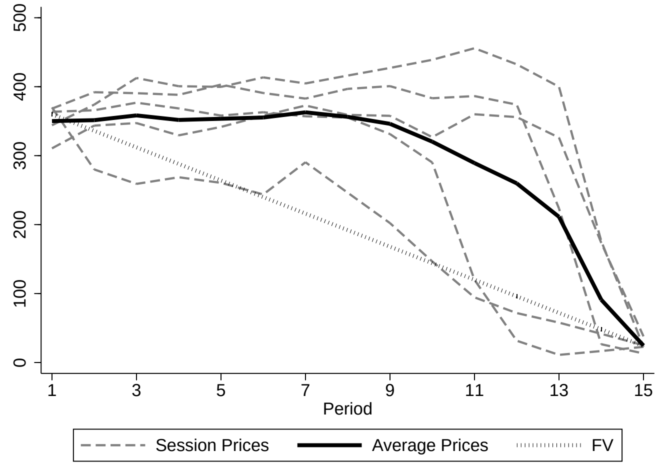
Figure 1 illustrates how the price adjustment rule works via the data collected in period 2 of session 1 of Tâtonnement treatment. At the initial price of $P_1 = 320$, aggregate demand is $Q_{D,1} = 39$ and aggregate supply is $Q_{S,1} = 0$. In the next iteration, the price is $P_2 = 320 + 2(39 - 0)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

3.2 Experimental Results

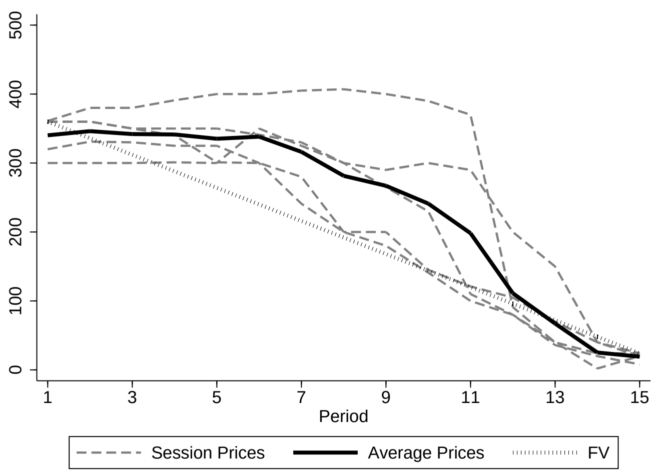
Figure 2 depicts the time series of prices and fundamental values in our experiment for each session and each trading institution. The horizontal axis represents periods, and the vertical axis represents market-clearing prices (for DA, prices reflect session average transaction prices). The last graph (panel d) compares the mean prices across trading institutions. Figure 2 shows that Double Auction average prices are significantly above the average prices of the CM and TT.



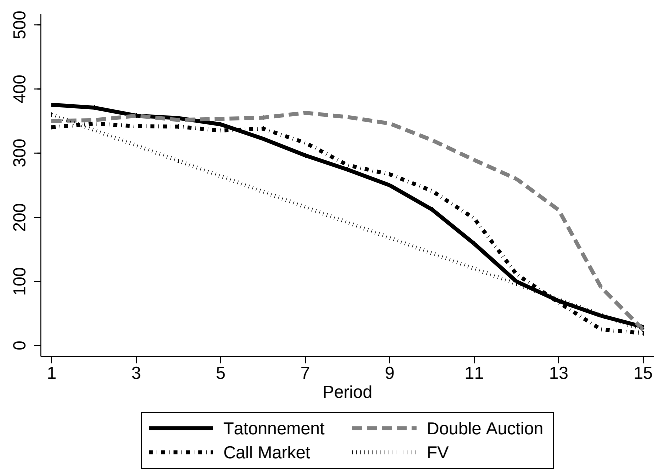
(a) Tâtonnement



(b) Double Auction (Average Transaction Prices)



(c) Call Market



(d) Average Prices (across Sessions) by Institution

Figure 2: Experimental Data on Prices Across Institutions

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 the bubble's magnitude, as each measure captures a different aspect of a bubble. For example,

[13]See Haruvy and Noussair [2006], Haruvy et al. [2007], Kirchler et al. [2010]. We updated the definitions of some of the measures by normalizing them by either the total number of shares (TSU), number of periods, or the combination of the two. The goal was to make them universal for any TSU or number of periods and to enable an intuitive interpretation of these measures. For example, with our current definition of Turnover, the magnitude of 0.27 has the following interpretation: in each period, subjects trade, on average, 27% of the TSU. In RPAD and RPD, we normalize price deviations in each period by the fundamental value of that period rather than the overall fundamental value.

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) and number of periods $T = 15$. It can be interpreted as an average per-period fraction of all shares. A high turnover indicates a high volume of trade, which can be an indication of a bubble.

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= $\frac{1}{TSU}\frac{1}{15}\sum_{t=1}^{15} q_t$	0.27	0.08	0.11	0.10
ND= $\frac{1}{TSU}\frac{1}{15}\sum_{t=1}^{15} q_t \lvert P_t - FV_t \rvert$	23.89	4.11	6.66	5.38
RND= $\frac{1}{TSU}\frac{1}{15}\sum_{t=1}^{15} q_t \frac{\lvert P_t - FV_t \rvert}{FV_t}$	0.2	0.03	0.03	0.03
RPAD= $\frac{1}{15}\sum_{t=1}^{15} \frac{\lvert P_t - FV_t \rvert}{FV_t}$	0.82	0.35	0.28	0.30
RPD= $\frac{1}{15}\sum_{t=1}^{15} \frac{P_t - FV_t}{FV_t}$	0.74	0.11	0.24	0.18

Normalized Deviation (ND) is defined as the weighted 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 and number of periods. A high ND indicates that prices depart from fundamental value and that trade volume at these prices is relatively high. In the Relative Normalized Deviation (RND), these period differences are further normalized by the respective fundamental value. For example, $RND = 0.2$ indicates that the average absolute deviation of price from the FV was 20%. The Relative Proportional Absolute Deviation (RPAD) differs from the RND in that it is not weighted by the quantity. A greater value in all of the above measures is indicative of a greater bubble. Finally, the Relative Proportional Deviation (RPD) differs from the RPAD in that it takes into account the difference between period price and period fundamental value rather than the absolute difference. That is, the RPD also indicates the direction of the bubble. Specifically, a positive RPD indicates that prices tend to be above fundamental value, while a negative RPD s the presence of a negative bubble.

Result 1. *Most bubbles measures are significantly higher under Double Auction than under the uniform-price institutions, Call Market and Tâtonnement.*

Table 2: Pairwise Comparison of Bubble Measures for DA, Tâtonnement and CM: Coefficient k of the OLS regression: $Measure = Const + k * TreatmentDummy$

Measure	DA vs. TT k*DA	CM vs. TT k*CM	DA vs. CM k*DA	DA vs. (CM & TT) k*DA
Turnover	0.151^{**} (0.045)	-0.026 (0.017)	0.177^{***} (0.045)	0.164^{***} (0.032)
ND	22.783^{**} (8.90)	-0.538 (2.23)	23.321^{**} (8.89)	23.052^{***} (6.14)
RND	0.184^{**} (0.067)	0.005 (0.013)	0.180^{**} (0.067)	0.182^{***} (0.046)
RPAD	0.513^{*} (0.236)	0.134 (0.111)	0.402 (0.240)	0.457^{**} (0.176)
RPD	0.409 (0.267)	0.017 (0.143)	0.425 (0.281)	0.417^{*} (0.198)

***1%, **5%, *10% significance levels.

Support for Result 1: Table 2 reports the results from OLS regressions where the dependent variable is given by the bubble measure of reference and the independent variable is given by the treatment dummy variable of interest. The treatment and omitted dummy variables determine the comparison of interest. For example, column (1), DA vs. TT, shows that bubble measures, except for RPD, are higher in DA than in TT. Similar results hold for DA vs. CM and DA vs. pooled CM and TT. The unit of observation is at the session level. Therefore, the number of observations in the first 3 columns is 10, and in the last column 15. □

While Result 1 focuses on the impact of trading institutions on aggregate outcomes, such as prices and volume of trade, Result 2 and Result 3 focus on individual traders' earnings. Result 2 provides evidence that trading institutions matter for the distribution of earnings across traders and that earnings' inequality is higher in the DA trading institution.

Result 2. *Double Auction results in higher inequality in traders' earnings than the uniform-price Call Market and Tâtonnement institutions.*

Table 3: Within-Session Inequality in Earnings

	Call Market & Tâtonnement		Double Auction
Coefficient of Variation	0.098	< (0.08)	0.164
Gini Coefficient	0.048	< (0.07)	0.083

In parenthesis, we report p-values of the coefficients for the DA variable from equation (1), with robust standard errors.

Support for Result 2: To evaluate the differences in earnings inequality, we calculated the coefficient of variation and Gini coefficient for each session based on the final earnings of subjects. We then regressed each of them on the Double Auction indicator variable, DA_S:[14]

$$\begin{aligned} \text{CoefVariation}_S &= \underset{(0.016)}{0.098} + \underset{(0.035)}{0.065} DA_S \\ \text{GiniCoef}_S &= \underset{(0.008)}{0.049} + \underset{(0.017)}{0.035} DA_S, \end{aligned} \tag{1}$$

where $DA_S = 1$ for DA sessions and zero otherwise. Table 3 reports the means for the uniform-price trading institutions and for the DA, and the p-values of the DA dummy variable from regressions specifications provided in equation (1). The unit of observation is at the session level and the number of observations in both regressions is 15. As reported in Table 3, these differences are statistically and economically significant for both measures of inequality. □

Our next result shows that trading institutions interact with individual cognitive reflection scores in determining individual traders' earnings.

Result 3. *Subjects with High-CRT scores earned significantly higher payoffs than subjects with low-CRT scores under Double Auction, but not under the uniform-price Call Market and Tâtonnement institutions.*

Table 4: Final Individual Earnings, by CRT Types and Trading Institution

	Low CRT (0,1)		High CRT (2,3)
Double Auction	13.04 n=22	$<$ (0.04)	14.43 n=20
Call Market & Tâtonnement	13.84 n=38	$>$ (0.33)	13.48 n=43

Earnings are reported in thousands of experimental franks; n denotes the number of subjects. In parenthesis, we report p-values of the coefficients for the CRT (first row) and $CRT * DA$ (bottom row) from equation (2).

Support for Result 3: Table 4 reports the number of subjects (n) with low CRT (CRT=0,1) and high CRT (CRT=2,3) scores and the means of their individual earnings, separately for double auction and for the uniform-price institutions (CM and TT).[15] Under DA, High-CRT subjects earned, on average, 10.7% more than Low-CRT subjects. This difference is also statistically significant based on the following OLS

[14] The number of observations in each regression is 15; robust standard errors.

[15] The CRT consists of 3 questions. We classified as Low-CRT subjects who answered either 0 or 1 question correctly and as High-CRT subjects who answered 2 or 3 questions correctly.

regression of individual earnings (IE):[16]

$$IE_s = \underset{(0.28)}{13.84} - \underset{(0.36)}{0.35} CRT_s - \underset{(0.54)}{0.80} DA_s + \underset{(0.84)}{1.73} CRT_s * DA_s, \tag{2}$$

where index s denotes subject; $CRT \in \{0, 1\}$ is a CRT-type dummy variable set to 0 for low CRT types (with either 0 or 1 correct answers) and to 1 for high-CRT types (with either 2 or 3 correct answers); and $DA \in \{0, 1\}$ is the trading institution dummy variable set to 1 for DA and to 0 for uniform-price institutions (CM and TT). □

Taken together, these results indicate that heterogeneity in traders' sophistication plays an important role both for aggregate and individual outcomes. We next provide a model featuring such heterogeneous agents that can reproduce the above data patterns at the aggregate and individual levels. In addition to estimating the model using some of the experimental data, we also perform out-of-sample validation tests in Section 4.3.

4 Theoretical Model and Results

This section provides 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, present the theoretical model results, 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 those 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. We also provide additional out-of-sample evidence in support of the model in Section 4.3.3.

4.1 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. Appendix C provides further details on how each institution is modeled.

[16] IE_s is defined as final earnings of subject s in thousands of experimental francs. Robust standard errors are reported in parentheses. The number of observations is 123.

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

$$q_t^i = \gamma \left(\frac{V_t^i - p_t^i}{FV_t} \right) + \epsilon_t^i, \tag{3}$$

where ϵ_t^i is a noise term normally distributed with mean 0 and standard deviation σ_ϵ, and γ is a parameter to be estimated. Note that 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).[17]

Valuations The valuation of the asset differs across individuals. We assume there are two types of individuals: myopic traders and fundamental traders. This choice captures the heterogeneity in price forecasting among traders in the empirical data as presented in Result 4 in Section 4.3.3. We think of valuations as the future price expectation of a trader. The valuation for each type is given by

$$V_t^i = \begin{cases} \tilde{p}_t^i (1+\beta) & \text{if} \quad \text{myopic trader} \\ FV_t & \text{if} \quad \text{fundamental trader} \end{cases}, \tag{4}$$

where $\tilde{p}_t^i$ is the anchoring price, and β is a parameter to be estimated.[18] 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 exhibits a bias if β is not equal to zero.[19] 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 documented in behavioral economics.[20] On the other hand, fundamental trader's valuations are equal to the fundamental value of the asset.

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

[18] In TT and CM, we assume this price equals 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.

[19] 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.

[20] The anchoring-and-adjustment heuristic was first introduced by Tversky and Kahneman [1974]. Following this work, many studies documented the presence of anchoring effects in decision making processes. Some examples include Ariely et al. [2003] and Critcher and Gilovich [2008], who documented anchoring effects in valuations/purchasing decisions and in forecasting tasks, respectively. For a literature review, see Furnham and Boo [2011]. According to anchoring, investors use pre-existing information or the first information they find to estimate the value of a financial instrument.

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. Thus, the parameter δ_t captures that myopic traders switch to fundamental traders at different points in time. Potentially the process driving δ_t can differ across institutions. However, in the interest of keeping the institutions comparable, we assume that this process is the same across all institutions.

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

$$p_t^* = (1+\beta)\,\delta_t\left(p_{t-1}^* - d\right) + (1-\delta_t)\,FV_t. \tag{5}$$

Proof. The expected market-clearing TT price in equation (5) is obtained by plugging valuations of myopic and fundamental traders from equation (4) into equation (3), 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 (5) also in CM. The proof for the expected market-clearing price under CM is more involved, and we provide it in Appendix A.[21]

Price Expectations We next describe how we model price expectations p_t^i in equation (3). 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

[21]We cannot derive the 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:

$$p_t^i = (1+\beta)\,\delta_t \tilde{p}_t^i + \left(1 - \delta_t + \eta_t^i\right) FV_t, \tag{6}$$

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.[22]

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 affects the price expectation of all individuals in the current period and 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, affecting only 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 happen 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:

$$\tilde{p}_{t,s}^i = \begin{cases} p_{t-1}^* - d & \text{if} \quad s = 1 \\ \frac{\sum_{\tau=1}^{\tau=s-1} p_{t,\tau}^* + p_{t-1}^* - d}{s} & \text{if} \quad s > 1 \;\&\; \alpha_{t,s}^i < \alpha^* \\ \tilde{p}_{t,s-1} & \text{else} \end{cases}, \tag{7}$$

where $p_{t,s}^*$ is the trading price in period t for the s^{th} transaction and $\alpha_{t,s}^i$ is an individual level shock drawn from a uniform distribution between 0 and 1. That is, in DA, α^* fraction of individuals update their anchoring price as the average of all the prices observed within that period plus the previous average period transaction price. We also set the maximum number of transactions within an period to be S in

[22] 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.

DA to replicate the time limit set within a period in DA experiments.

4.2 Model 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:

$$\delta_t^* = 1 - e^{-\delta\left(\frac{15-t}{t-1}\right)}. \tag{8}$$

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 5 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 (5). We normalize equation (6) by the corresponding fundamental value, which gives us

$$\frac{p_t^i}{FV_t} = \frac{(1+\beta)\,\delta_t\left(p_{t-1}^* - d\right)}{FV_t} + \left(1 - \delta_t + \eta_t^i\right). \tag{9}$$

We estimate β and δ by minimizing the squared 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 5 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

Table 5: Parameters Estimation

Parameter	Definition	Value	Standard Deviation[a]
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	st. dev. of the noise in the demand function	1.0	
σ_η	st. dev. of the noise in the market-clearing price	0.26	
S	max number of transactions within period in DA	300	

The standard errors for the parameters β and δ are computed using the standard error formulas for the GMM estimation. The standard error for the parameter γ is computed using the Fisher information matrix from the MLE estimation. The parameters σ_ϵ and σ_η are the standard errors of the residuals from the estimation, and they do not have standard errors to be reported. The parameters α^* and S are exogenously set and does not have a standard error to be reported.

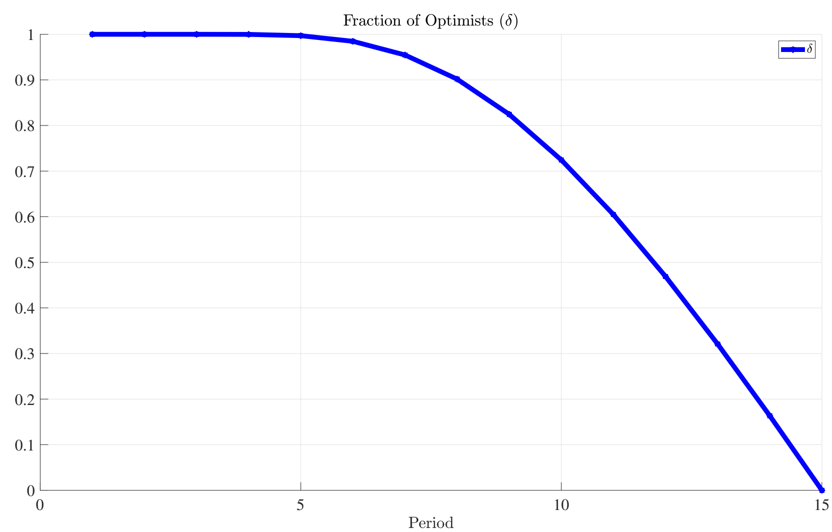


Figure 3: Estimated Share of Myopic Optimists in Population

3. The value of the demand parameter γ, equal to 1.93, can be interpreted as follows. If the price equals the fundamental value, the valuation should be 1.26 times greater than the price to generate at least one unit of expected demand.[23]

Next, we can interpret the estimated value of $\sigma_\epsilon = 1$ as follows. In the simulation, we round the quantity demanded to the nearest integer. So, any $\epsilon \geq 0.5$ results in a positive demand of one unit with probability $1 - F(0.5)$, where F is normally distributed with mean 0 and standard deviation σ_ϵ. For an individual with a valuation equal to the current price, there is a 31% probability of buying one unit or more and a 31% probability of selling one unit or more. Similarly, the estimated value of $\sigma_\eta = 0.26$ implies that for 35% of traders, their price expectation will exceed the trading price by 10% of the FV.[24]

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 do not use data from the Double Auction to estimate the model's parameters, the model does a good job at reproducing patterns of the data. We also conduct a robustness analysis with respect to the α^* parameter. Lastly, we set the maximum number of transactions allowed within a period in DA, S, to 300 to match the average number of transactions per individual observed within a period in DA experiments.

4.3 Model Results

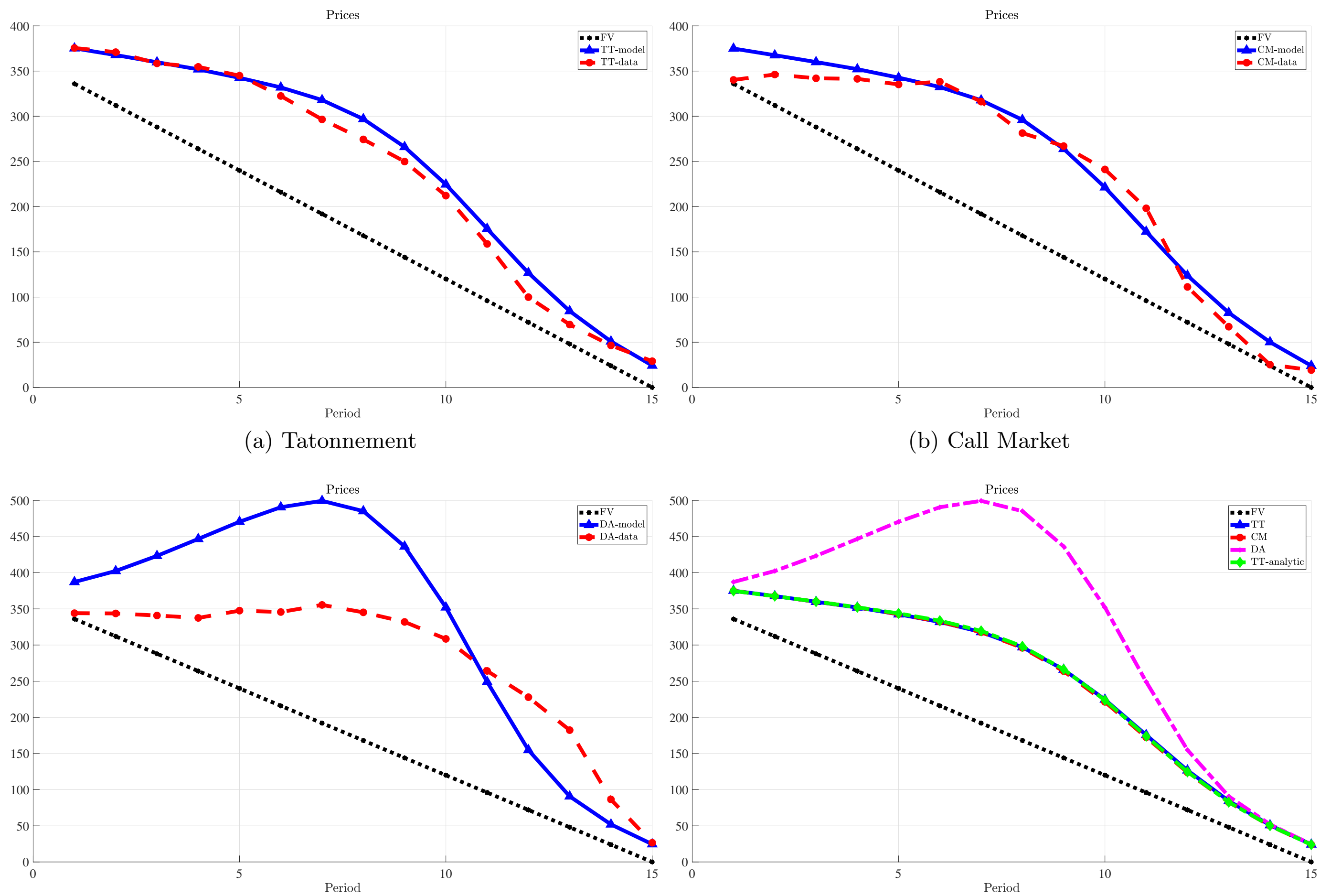
Given the estimated parameters, we use the theoretical model to simulate market-clearing prices for each institution. To isolate the impact of institutional differences on market-clearing prices and quantities, we keep the parameters of the model constant across institutions. Note that we did not use the data from Double Auction markets to estimate the model's parameters. We provide details on how each institution is simulated in Appendix C.

[23]Non-integer quantity demanded is rounded to the nearest integer. From equation 3, to get at least one unit of demand, we need $q_t^i \geq 0.5$, which gives us $V_t^i \geq 1 + \frac{0.5}{\gamma} = 1.26$ when price is equal to the fundamental value, $p_t^i = FV_t$.

[24]Here, $1 - G(0.1) = 0.35$, where G is normally distributed with mean 0 and standard deviation $\sigma_\eta = 0.26$.

4.3.1 Price Comparison Across Institutions

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-crash pattern of asset prices observed in the data for all institutions, even though we used a limited set of parameters.[25]



(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.

Figure 4d compares the model-generated prices across trading institutions. The model generates larger bubbles in DA than in TT and CM. This 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 in Section 3.2). Notice that the parameters of the model are not chosen to match any data from DA. The

[25] The number of 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 TT and CM) and 1540 data points for quantities.

model parameters are all chosen to match the price and quantity realizations in TT and CM. Thus, the result that DA generates a larger bubble than uniform-price institutions is not a targeted outcome of the model.

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 DA 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. For example, using equation (5), when all traders are myopic ($\delta_t = 1$), we have $p^*_t = (1+\beta)\left(p^*_{t-1} - d\right)$, which results in an explosive path for prices. Instead, when all traders are fundamental traders ($\delta_t = 0$), price converges to fundamental value: $p^*_t = FV_t$. More generally, the price path expressed as the difference between current and last period prices is given by:

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

This path implies that when δ_t is close to 1, the price change 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.

Our model also ranks institutions according to the magnitudes of bubbles. Importantly, this ranking is in line with the ranking observed in the experimental data: Tâtonnement and Call Markets generate similar bubbles, whereas Double Auction generates a significantly larger bubble. Next, we explain what generates this ranking in the model. The main difference between DA and other institutions is the decentralized nature of trades in the former. That is, in DA, unlike in TT and CM, 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.

Given the structure of updating we consider, in TT and CM, individuals only update their price expectations across periods, and price expectations coincide with the evolution of the theoretical price.

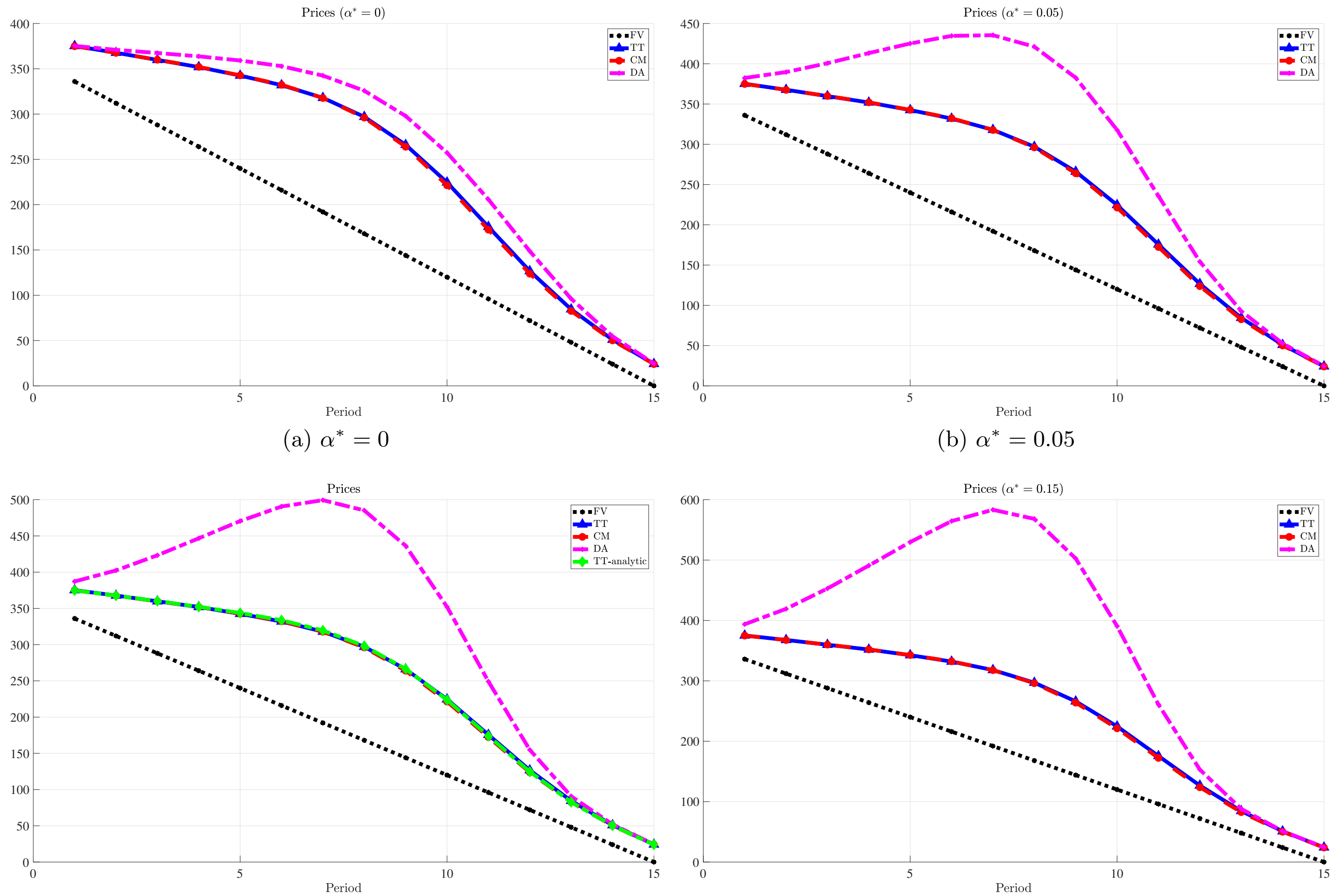
Since in TT and CM, the market-clearing price is identical to the theoretical price, updating contributes nothing to individuals' information set. Therefore, even if we introduce updating in the TT based on provisional prices within a period, market-clearing prices are not significantly affected. Unlike in DA, the positive bias does not amplify price departures from the FV in the TT. This happens because of two reasons. First, in the TT, updating affects only asset valuations. It does not affect price expectations since price expectations play no role in the TT. Secondly, the updating mechanism of the provisional price plays an anchoring role in the asset valuation. When the asset valuation is high, and there is excess demand in the market, the next iteration provisional price is updated upward to clear the market. This results in upward updating of the asset valuation in the next iteration. Similarly, when the asset valuation is low and there is excess supply, the provisional price is updated downward, decreasing the asset valuation in the next iteration. Thus, the provisional price plays the role of anchoring the asset valuation towards the theoretical market clearing price in the presence of within period updating. Hence, updating does not affect prices in TT.

In contrast, in DA, 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 TT and CM, 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 early periods, δ_t is close to 1, resulting in an exploding price path since $\beta > 0$. This model feature results in a larger bubble in DA as long as 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 price expectations based on observed prices increases.[26] Figures 5a to 5d show that as updating becomes more prevalent, bubbles become larger in

[26] When $\alpha^* = 0$, the model still generates a 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

DA, while there is no impact on prices in TT and CM.



(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 a 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.

4.3.2 Within-Period Price Updating in DA

Our model predicts that the main difference in the bubble size between the DA and uniform-price institutions (CM and TT) is due to within-period updating in the DA (by design, there is only one transaction price in both CM and TT). This section investigates whether the predicted within-period updating pattern

as in TT and CM. However, because of the short-selling constraint, sellers with extreme beliefs have a limited effect on transaction prices, and buyers with extreme beliefs have a stronger impact on transaction prices. This mechanism generates a slightly 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 the short-selling constraint.

in the DA model-simulated data matches that in the experimental data. This exercise can be considered 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 to construct 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 bubble's peak. The negative trend first becomes stronger as the difference between transaction prices and the fundamental value converges from the peak to the fundamental value. 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 five 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 price 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 price growth.* Figure 6 compares the evolution of within-period price growths across periods. It illustrates that the price 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 uniform-price institutions is due to the within-period price updating and growth in DA.[27]

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

[27]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.

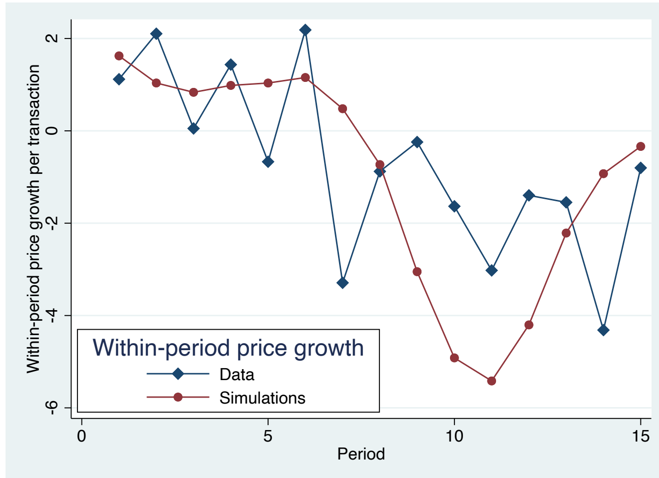


Figure 6: **Within-period price growth rates in DA: data and model simulations.**

4.3.3 Distributional Effects and Forecasts

We compare the distributional effects of institutions on terminal period cash holdings generated by our model simulations. As shown in Table 6, we find that while uniform-price institutions (CM and TT) yield similar measures of inequality, DA generates substantially higher inequality among traders. Specifically, the coefficient of variation of cash holdings in CM and TT is around 0.07, whereas, in DA, this statistic increases to 0.28. The Gini coefficient of cash holdings in CM and TT is around 0.04. This number increases to 0.15 in DA. That is, consistent with the empirical results summarized in Result 2, both measures of inequality imply that DA results in higher inequality in trader earnings than uniform-price trading institutions.

Table 6: Distributional Effects

	Tâtonnement	Call Market	Double Auction
Coefficient of Variation	0.07	0.07	0.28
Gini Coefficient	0.04	0.04	0.15

The Table shows various measures of inequality for the terminal period cash holdings among all traders across all the model simulations. Coefficient of variation is measured as the ratio of the standard deviation to the average.

To better understand who the winners and losers are in each institution, we classified traders into two groups in the model simulations. Group 1 includes traders who switch from myopic-noise to fundamental trader in the first half of the experiment. Group 2 includes the remaining traders.[28] We think of this classification as the theoretical counterpart of the empirical classification into high CRT and low CRT groups. Therefore, we define a dummy variable $\widetilde{CRT}$ to be equal to 1 for Group 1 individuals and $\widetilde{CRT} = 0$ for Group 2 individuals.

According to Figure 3, during the first 7 periods, the vast majority of all simulated traders are myopic. That is, 7 periods are insufficient for the majority of Group 1 individuals to switch from myopic to fundamental traders. Therefore, we expect that, on average, Group 1 traders have only slightly lower valuations than Group 2 traders. However, by period 8, 10% of traders switch to fundamental traders, and their share keeps increasing after that. Therefore, in periods 8-15, we expect to see a pronounced difference in asset valuations between Group 1 and Group 2 traders. Specifically, Group 1 traders should have lower valuations than Group 2 traders. To test these conjectures with the simulated data, we first normalize all individual forecasts by the corresponding fundamental value: $\widetilde{NV}_{st} \equiv V_t^s/FV_t$., where V_t^s is defined as in equation 4. Then, for each trader, we calculate the mean Normalized Valuation (NV) for the first 7-period interval and for the last 8-period interval: $\widetilde{NV}_{s,1-7}$ and $\widetilde{NV}_{s,8-15}$, and regress them on the $\widetilde{CRT}$ dummy variable in two separate OLS regressions. Our estimation results are presented below:[29]

$$\begin{aligned} \widetilde{NV}_{s,1-7} &= \underset{(0.0)}{1.34} - \underset{(0.0)}{0.06}\widetilde{CRT}_s \\ \widetilde{NV}_{s,8-15} &= \underset{(0.0)}{1.77} - \underset{(0.0)}{0.62}\widetilde{CRT}_s. \end{aligned} \tag{10}$$

The results indicate that, in line with our expectations, compared to Group 2 traders, Group 1 traders have only 6% lower valuations in periods 1-7, but 62% lower valuations in periods 8-15.

Next, we check whether a similar pattern is observed in the experimental data. We use the observed data on forecasts provided by each subject before each period begins. As in the case of the simulated data, we normalize individual forecasts by the corresponding fundamental value, $NF_{st} \equiv Forecast_{st}/FV_t$, and calculate mean net forecasts for each subject for the first 7-period interval and for the last 8-period interval: $NF_{s,1-7}$ and $NF_{s,8-15}$, respectively. The OLS estimates of regressing the NF on the constant

[28] The idea behind this classification is that Group 1 traders can be thought of as sophisticated traders who predict the crash of the bubble in advance, whereas the traders in the second group are the somewhat less sophisticated ones. Across all institutions, 10% of the traders belong to Group 1 and the rest belongs to Group 2.

[29] The number of observations in each regression is 10,000.

and CRT dummy with the standard errors clustered by session are presented below:[30]

$$\begin{aligned} NF_{s,1-7} &= \underset{(0.05)}{1.09} + \underset{(0.07)}{0.02} CRT_s \\ NF_{s,8-15} &= \underset{(0.31)}{2.15} - \underset{(0.10)}{0.49} CRT_s, \end{aligned} \tag{11}$$

where $CRT = 1$ for High-CRT subjects and $CRT = 0$ for Low-CRT subjects.[31]

The results indicate that (i) in periods 1-7, the difference in forecasts between the High-CRT and Low-CRT traders is not statistically significant, and (2) in periods 8-15, High-CRT traders have 49% lower forecasts than Low-CRT traders. Formally, we summarize this evidence in the following result.[32]

Result 4. *High-CRT and Low-CRT subjects make similar forecasts in the first half of the experiment. High-CRT subjects make significantly lower forecasts than Low-CRT subjects in the second half of the experiment.*

Next, given the overlap of the CRT group classifications in the model and the data, we compare the earnings of the two groups across the institutions. We find that in all three institutions, terminal period cash holdings of the first group are always larger than the ones of the second group. However, this difference is much larger in DA. In TT, the ratio of Group 1 to Group 2 traders' average final earnings is 1.04. This ratio is 1.02 in CM. However, in DA, this ratio increases to 1.21. More formally, we run the same regression as in equation 2:

$$IE_s = \underset{(0.01)}{13.51} + \underset{(0.02)}{0.35} CRT_s - \underset{(0.01)}{0.25} DA_s + \underset{(0.03)}{2.49} CRT_s * DA_s. \tag{12}$$

Consistent with the empirical results summarized in Result 3, the simulated model also implies that Group 1 individuals (corresponding to high-CRT subjects in the data) have significantly higher earnings than Group 2 individuals (corresponding to low CRT subjects in the data) in the DA. In contrast, this difference is much smaller in the uniform-price institutions. These results suggest that more sophisticated traders (as captured by higher CRT scores) are more likely to take advantage of less sophisticated traders (with lower CRT scores) in DA than in uniform-price institutions such as TT and CM.

[30]The number of observations in each regression is 123, which corresponds to the number of all subjects with recorded CRT.

[31]Recall that the definitions and distributions of the High-CRT and Low-CRT are provided in Table 4.

[32]We do not provide a comparison of forecasts across institutions due to potential endogeneity problem. Namely, treatments with greater bubbles are more likely to have less accurate forecasts.

5 Conclusions

This paper explores the role that different trading institutions play in 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 uniform price institutions, Tâtonnement and Call Market, than in Double Auction, suggesting that the trading institution and the associated price formation mechanism play a crucial role in the formation of bubbles. We build on the approach of Duffy and Ünver [2006], Haruvy and Noussair [2006], Baghestanian et al. [2015], by providing a heterogeneous-agent model with myopic and fundamental-value traders to better understand the experimental results within a unified framework for the three institutions.

We use data only from the Tâtonnement and Call Market experiments to estimate the model. The model reproduces important data patterns, 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 unique key characteristics of the Double Auction trading institution. Namely that multiple transaction prices take place within a period, and those are public information. As a result, myopic traders update their price expectations within a period in the Double Auction, based on within-period transaction prices, and have amplifying effects on price departures from fundamental value.

In the model and the data, we find that trading institutions also play an essential role in the earnings distribution. Specifically, there is higher inequality in traders' earnings in Double Auction. Furthermore, sophisticated traders earn higher payoffs than unsophisticated traders only under Double Auction. These results suggest essential interaction effects between behavioral biases and trading institutions. 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 $q_t^{i,o} \leq 0$, that means the individual will sell $q_t^{i,o}$ quantities as long as the price is such that $p_t^* \geq p_t^{i,o}$. So, the condition to become a seller is:

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

which can be written as

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

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

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

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:

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

To become a buyer, η^i needs to satisfy

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

So, the total demand from fundamental traders becomes:

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

Then, aggregate demand becomes:

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

The equation above simplifies to

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

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 $(1-\delta_t)\,\omega_t^* + h\left(p_t^*\right) = 0$. 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 6, 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 3 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.[33] 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

[33] 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 $FV_t = \bar{d}(T - t + 1)$ for $t = 1, ..., T$. As in the experiment, we impose no-borrowing, no short-selling and no maximum trading quantity constraints.[34]

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 (3), where ϵ_t^i is drawn from a normal distribution with mean 0 and variance σ_ϵ^2 at the beginning of each period.[35] 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

$$z_t = \sum_i y_t^i. \tag{13}$$

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:

$$p_{j+1,t} = p_{j,t} + \theta z_{j,t}, \tag{14}$$

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 $\xi = 1$.[36] [37]

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.

[34] 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.

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

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

[37] Notice that the demand function (3) 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.[38] These bids are determined by equations (3) for quantities and (6) 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 (6) and q_t^i is determined by equation (3).[39] 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.[40] 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 (3) 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

[38] 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.

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

[40] 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 6 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.

D Additional Results

D.1 Bubble measures

Table 7 reports pairwise comparisons of bubble measures across institutions, using the Mann-Whitney test with sessions as units of observation. While the results are overall consistent with the regression results provided in Table 2 (and thus Result 1), the significance level of some pairwise comparisons is lower. This is not surprising as non-parametric tests tend to be more conservative that parametric tests.

Table 7: Pairwise Comparison of Bubble Measures for DA, Tâtonnement and CM:
z-statistics and significance levels of the Mann-Whitney Test.

Measure	DA vs. TT	CM vs. TT	DA vs. CM	DA vs. (CM & Tât)
Turnover	2.19**	−1.15	2.61***	2.82***
ND	1.78*	−0.10	1.98**	2.20**
RND	1.98**	0.10	1.98**	2.33**
RPAD	1.78*	0.73	1.36	1.84*
RPD	0.74	−0.31	1.36	1.35

***1%, **5%, *10% significance levels.