Trading Institutions in Experimental Asset Markets: Theory and Evidence

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Abstract

We report the results of an experiment that examines the impact of centralized trading institutions on 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 parsimonious model with heterogeneous agents with different levels of sophistication, featuring fundamental and myopic-noise traders. The model matches untargeted data moments and produces larger bubbles under Double Auction, consistent with the experimental data. This is because multiple trades occur within a period under this institution, amplifying the impact of myopic traders with a 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. Even the most brilliant minds are not immune to the detrimental effects of financial bubbles. As an example, Isaac Newton is said to have lost a considerable amount of money in the South Sea bubble and is quoted as saying "*I can calculate the motions of heavenly bodies, but not the madness of people.*" More recent examples include the real estate bubble crash of 2008, the 2018 Bitcoin and other crypto-currencies crashes.

The main goal of this paper is to leverage experimental methods to investigate the extent to which the design of centralized trading institutions can play a role in mitigating bubbles and the impact of the "madness of people."[1] As price bubbles represent a phenomenon difficult to predict and with substantive economic implications, they are widely studied in finance and economics. Experimental methods are a valuable tool in the study of bubbles as they provide unique insights into the formation of bubbles. They allow researchers to control for and manipulate factors that are difficult to isolate in field markets, such as the fundamental value process, trading mechanisms, and traders' information. For instance, with respect to trading institutions, which is the main subject of this paper, different institutions are employed in different countries and for different asset classes, limiting the range of controlled comparisons feasible with field data (for an exception see Holden et al. [2021]).

Smith et al. [1988] were the first to observe price bubbles in long-lived finite horizon experimental asset markets. Many studies have followed their pioneering work in order to test the robustness

[1] As a first step, we are interested in studying price bubbles. Additional interesting questions include the impact of trading institutions on the aggregation of information, mispricing, and efficiency more generally, which, as we mention in our concluding remarks, we leave for future research.

of the price bubble phenomenon.[2] Thus, as a first step in our research agenda, we focus on this canonical framework (more on this below).

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 interaction effects between trading institutions, expectations' heterogeneity, and the influence of unsophisticated traders on mispricing are understudied. The purpose of this paper is to study such interactions to deepen our understanding of the underlying mechanisms of bubble formation. Further impetus to study such interactions arises from the fact that i) electronic trading platforms are becoming increasingly accessible to (unsophisticated) traders, and ii) while policymakers have little control over the sophistication level of traders, they can regulate trading institutions.

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 centralized trading institutions: Double Auction (DA), Call Market (CM) and Tâtonnement (TT).[3] While the first two institutions have been widely used in long-lived asset markets, the introduction of Tâtonnement (TT) to asset markets is new. 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, thus also potentially protecting less sophisticated traders. Gode and 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.

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

[3] These are all-to-all markets but employ different price formation mechanisms. For a more detailed description of how they work, see Section 3.2. Call markets may also be referred to as clearinghouse mechanisms in the literature (see Friedman [1993] or Limit Order Books).

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 are driven 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] or Carle et al. [2019]).

Our emphasis on DA, CM and TT institutions is driven by a number of considerations. First, variants of DA and CM have been widely used in both field and experimental asset markets. We introduce the TT to experimental asset markets because it is a trading institution of historical and contemporary relevance. Indeed, TT is one of the earliest classical theories that 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]). Second, while they all capture centralized markets, there are significant differences between these institutions that can affect price formation. 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 non-binding 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, amplify the impact of noise 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, game-theoretic model is available to capture the main patterns of the data. Therefore, we use a computational approach to provide insights into the determinants of market behavior across institutions (see also [Duffy and Ünver, 2006, Haruvy and Noussair, 2006]). Specifically, building on the existing literature and guided by the experimental evidence, we provide a heterogeneous-agents model with myopic and fundamental traders, and use the experimental data to calibrate its parameters.

Relative to Haruvy and Noussair [2006] and Duffy and Ünver [2006], whose focus is on a single institution, we study the impact of DA, CM, and TT on bubbles' formation within a unified framework.[4] 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 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 the structural parameters of the model using experimental

[4] 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.

data from the TT and CM institutions.[5] 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, the estimate of the myopic traders' valuation bias is 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. Compared to other institutions we consider, DA allows for multiple transaction prices within a period. This allows myopic traders to update their valuation and price expectations within a period, thus amplifying the impact of positive bias on transaction prices and yielding larger price bubbles relative to other mechanisms.

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, which is an untargeted variable of the calibration process.[6] 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 (capturing sophistication) 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, bubble formation, and distributional effects of mispricing. Our paper suggests that, in the context of *asset markets*, the design of trading institutions plays an important role in determining whether limited intelligence traders have an impact on aggregate outcomes and bubble formation, and thus on markets' intelligence. Furthermore, it provides suggestive evidence that uniform-price institutions, unlike DA, protect less sophisticated traders.

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

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

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.[7] 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." In other words, the selection of trading institutions may be endogenous in the field, making an analysis of their causal impact on economic outcomes challenging. 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. The laboratory environment allows us to address these limitations by varying 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. Cheung and Palan [2012] compare the behavior of individuals and teams (of two) in experimental asset markets. They find smaller price bubbles in markets populated by teams, regardless of whether trading occurred under DA or CM. Cheung and Palan [2012] do not directly compare DA with CM. However, we took segments of

[7]For an experimental study of different pre-opening mechanisms on price discovery see Biais et al. [2014].

the data closest to ours (e.g., from markets populated by individual and inexperienced traders) and conducted non-parametric tests on them. Some bubble measures are larger in DA than in CM, so the data provided in their study is consistent with our model results.[8] 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 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 and by studying DA.

Deck et al. [2020] complements the research conducted here as it also studies the impact of institutions on bubble mitigation. Their study is exploratory, examining novel institutions motivated by performance in previous laboratory commodity market studies. More specifically, they compare two uniform price institutions (Double Dutch and English Dutch) to the traditional continuous double auction. They find differing performances across these institutions. The English Dutch auction suppresses bubble formation, but the Double Dutch auction presents significant bubbles with mispricing similar to that of the double auction. While this result provides insights into the relative performance of two novel uniform price institutions to the discriminatory auction, we study the main workhorse trading institutions in the literature that also more closely capture features of trading institutions employed in field financial markets. Importantly, we additionally provide a model that we estimate using the experimental data to provide a deeper understanding of the mechanisms by which trading institutions may influence bubble formation.

[8] Turnover and Normalized Deviation are significantly higher under Double Auction. Other bubble measures were not significantly different.

While here we compare institutions capturing centralized trade, Ding et al. [2022] compare a decentralized market institution with a centralized market one and find that bubbles are greatly reduced in an Over-the-Counter market relative to DA markets. Lu and Zhan [2022] provide models of bilateral trade with multiple prices featuring near-zero intelligence traders, specifically focusing on OTC (Over-The-Counter) markets with and without dealers as well as DA markets. 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 double auctions in the experiments and on a TT setting with heterogeneous agents in the model.[9] 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. Relative to Lu and Zhan [2022] we focus on different trading institutions implementing centralized trade, contrast *uniform price institutions* (CM and TT) with DA, and provide a richer theoretical framework. Importantly, we provide a unified parsimonious model that uncovers possible mechanisms behind the experimental results and we 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 different cognitive reflection skills are associated with higher earnings inequality under DA than TT or CM.

[9] The authors describe the following Tâtonnement-like procedure for the determination of simulated prices: "Prices are determined by setting net demand equal to 0, that is equating demand and supply. When net demand is positive, the price is increased, and when it is negative, the price is decreased. The price is adjusted until the net excess demand equals 0" (see p. 1143-1144).

3 Experimental Design, Procedures and Data

3.1 Procedures

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.[10] 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 recruitment system (Greiner [2015]). 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 (Fischbacher [2007]). 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.[11] 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

[10] We conducted 5 markets (session) in each institution. Double Auction and Call Market sessions were conducted at Indiana University, while Tâtonnement sessions took place at the University of Canterbury. Previous literature has shown that asset markets perform similarly between participants at the University of Canterbury and Indiana University. More specifically, Ding et al. [2022] find no significant difference in bubble measures between Double Auction markets (without purchasing constraints) conducted at both institutions. Additionally, care was taken to ensure that procedures were the same in both locations.

[11] The double auction and call market sessions lasted 90 minutes on average. Tâtonnement sessions lasted on average 120 minutes. The additional 30 minutes on average is attributed to the iterative process of price discovery within the Tâtonnement market mechanism. All durations include instructional period and subject payments.

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 (the cash-to-asset ratio is 2.78).[12] In each trading period, traders were allowed to buy and/or sell units of the asset according to the following constraints. A trader must have sufficient cash to purchase the asset or sufficient units of assets in their inventory to make the sale. Each market prohibited trading with oneself and imposed a purchase restriction of 10 assets in each period. This restriction is motivated by the price adjustment process under the Tâtonnement. [13] The restriction is also imposed on the DA and CM to avoid confounding effects. Lastly, 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.[14]

At the beginning of each session, a cognitive reflection test (CRT) was conducted [Frederick, 2005].[15] The average number of correct CRT answers has been shown to be correlated with mis-

[12]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, Tucker and Xu, 2024b, 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., 2014, Ding et al., 2018, Noussair and Xu, 2015, Deck et al., 2020, Tucker and Xu, 2024a, among others]. Since our focus is on the impact of trading institutions in abating bubbles, it is logical to opt for a parameterization that is prone to bubble formation.

[13]Note, without a restriction on purchases, there could be substantial asymmetries in the price adjustment process under the Tâtonnement given the proportional price-adjustment rule (price is adjusted proportionally upward or downward given the extent of excess demand or excess supply respectively). The impact of a subject on aggregate supply is limited by his asset endowment, which, on average, is 10. In contrast, the potential 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.

[14]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.

[15]The test consists of the following three questions: i) 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?; ii) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?; and iii) In a lake, there is a patch of lily pads. Every day, the

pricing and traders' performance (e.g., see [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 fundamental values. Additionally, subjects with lower (higher) average CRT scores are more (less) prone to engage in unprofitable transactions. Since CRT measures a subject's ability to reflect, we interpret the CRT scores as a measure of a subject's level of sophistication.[16] 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.[17] Then, 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: DA, CM, or TT.

3.2 Institutions: 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 time at a specified price

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.

[16]CRT scores have been shown to be correlated with SAT scores and performance in IQ tests (see Frederick [2005]. Further, some research indicates that subjects with lower CRT scores may be more susceptible to behavioral biases (e.g., Oechssler et al. [2009], Hoppe and Kusterer [2011]).

[17]Instructions for each treatment are included as supplementary material.

(multiple units can be bought or sold within a period).[18] 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. If subjects did not wish to buy or sell, they could enter a zero quantity. Once all offers to buy/sell are submitted, the computer aggregates them into demand and supply schedules, and the uniform market price is calculated as the lowest price that clears the market. Traders who submit buy (sell) orders above (below) the market price make purchases (sales). Ties for the last unit bought/sold are resolved randomly. To prohibit self-trades, the market requires the offered buy price to be less than the offered sell price.

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). We chose to use the median forecasted price to reduce the impact of an individual forecast on the initial price. 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

[18] In this paper we focus on the most common version of double auction where, while traders can trade multiple units within a period they need to trade one unit at a time. Other implementation of DA where traders can submit orders with multiple units are left for future research.

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 two different rules depending upon the extent of excess supply or excess demand (see also Joyce [1984, 1998]). The first rule applies to excess supply/demand greater than 1. In this case, the price adjusts proportionally according to the following rule:

$$p_t = p_{t-1} + \theta_t(q_{d,t-1} - q_{s,t-1}),$$

where $\theta_t \in \{2, 1, 0.75, 0.5, 0.25, 0.05\}$ 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 $(q_{d,t-1} - q_{s,t-1})$. The second rule applies to levels of excess supply/demand less than 1, in which case the price adjustment rule is replaced by $p_t = p_{t-1} + 1 \quad \text{if} \quad 0 < \theta_t(q_{d,t-1} - q_{s,t-1}) < 1$, and $p_t = p_{t-1} - 1 \quad \text{if} \quad -1 < \theta_t(q_{d,t-1} - q_{s,t-1}) < 0$. The price adjustment process continues

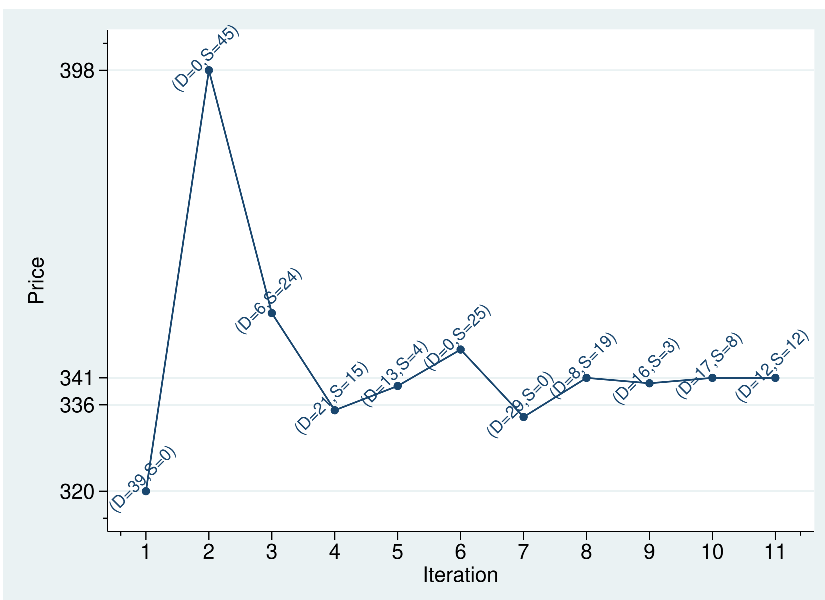


Figure 1: Tâtonnement Price Iterations in Period 2 of Session 1

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 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.

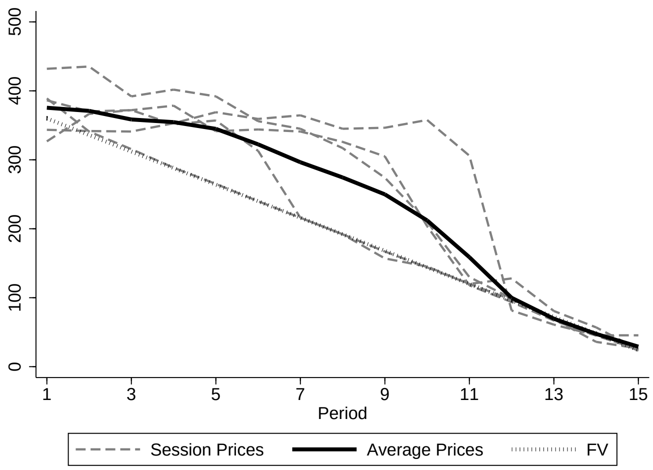
Figure 1 illustrates how the price adjustment rule works via the data collected in period 2 of session 1 of the Tâtonnement treatment. At the initial price of $p_1 = 320$, aggregate demand is $q_{d,1} = 39$ and aggregate supply is $q_{s,1} = 0$. In the next iteration, the price is $p_2 = 320 + 2(39 - 0) = 398$. 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.

3.3 Experimental Results

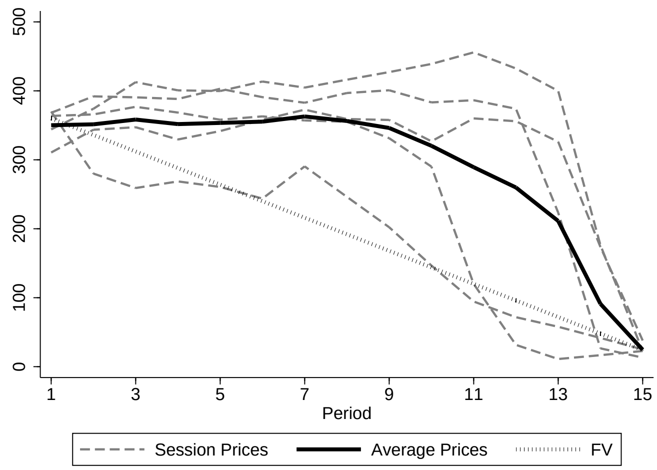
Figure 2 depicts the time series of prices and fundamental values in our experiment for each session and each trading institution. The horizontal axis represents periods, and the vertical axis represents market-clearing prices (for DA, prices reflect session average transaction prices). The last graph (panel d) compares the mean prices across trading institutions. We start by formally comparing the deviation of traded prices from the fundamental value (i.e., mispricing) between DA and uniform-price institutions.

Result 1. *Mispricing, calculated as proportional deviation of the transaction prices from fundamental value, is over 40% higher under Double Auction than under the uniform-price institutions, Call Market and Tâtonnement. The absolute value of this measure shows similar differences: between 40 and 51 percent.*

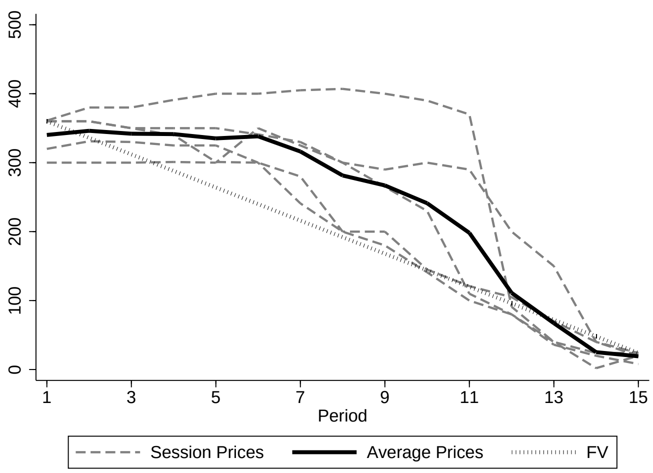
Support for Result 1: Panel (d) of Figure 2 shows that Double Auction average prices are



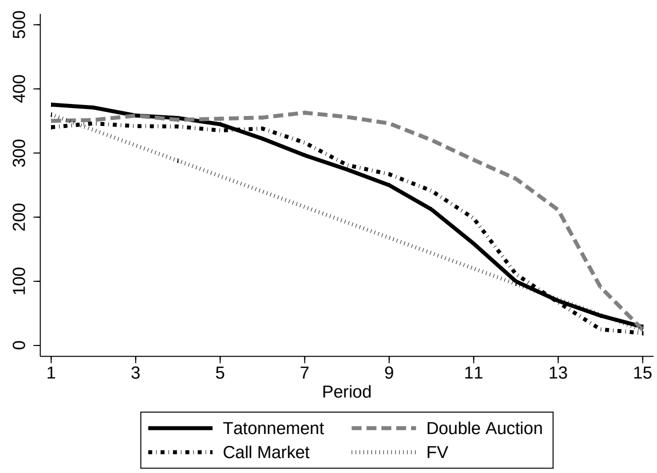
(a) Tâtonnement



(b) Double Auction (Average Transaction Prices)



(c) Call Market



(d) Average Prices (across Sessions) by Institution

Figure 2: Experimental Data on Prices Across Institutions

significantly above the average prices of the CM and TT. We complement these observations with formal regression analysis. Towards this goal, we consider two dependent variables: (i) the relative price deviation from the FV in a given period, $\frac{P_t - FV_t}{FV_t}$; and (ii) the absolute value of this deviation, $\frac{|P_t - FV_t|}{FV_t}$. The unit of observation is at the treatment-session-period level. The independent variables include period-specific fixed effects to control for potential dynamics of the bubble process and three dummy variables: DA, CM, and TT, where each dummy variable is equal to one for its treatment and zero otherwise. Table 1 reports on three different regressions per independent variable (six in total), which vary based on which of these dummy variables are included. They show statistically significant and positive DA coefficients regardless of the specification. Mispricing is always larger in DA, regardless of whether we compare it to each individual uniform-price institution (see cols 1 and 4 for comparisons against TT and cols 2 and 5 for comparisons against CM) or against both uniform-price trading institutions (cols 3 and 6). The magnitudes are also economically significant as they show that the extent of mispricing is up to 51% greater under DA than under uniform-price institutions. At the same time, the CM and TT coefficients are not statistically significant, indicating only minor differences in mispricing between the CM and TT. □

In order to further analyze differences in market performance across treatments, we calculated several bubble measures typically used in the literature.[19] The definitions of each measure, as well as their average values for each institution, are presented in Table 2. We calculated several bubble measures to provide a more accurate picture of the bubble's magnitude, as each measure captures a different aspect of a bubble. 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 the number of periods $T = 15$. It can be interpreted as an average per-period fraction of shares traded, out of all

[19]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), the 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, as it provides a more precise assessment of mispricing in each period.

Table 1: The Impact of Trading Institution on Mispricing

	Dependent Variable					
		$\frac{P_{mst}-FV_t}{FV_t}$			$\frac{\lvert P_{mst}-FV_t\rvert}{FV_t}$	
DA	0.41***	0.43***	0.42***	0.51***	0.40***	0.46***
	(0.11)	(0.11)	(0.09)	(0.09)	(0.09)	(0.08)
CM	-0.02			0.11		
	(0.11)			(0.09)		
TT		0.02			-0.11	
		(0.11)			(0.09)	
Adj-R2	0.15	0.15	0.15	0.22	0.22	0.22
No. Obs	225	225	225	225	225	225
Adj-R2	0.04	0.04	0.04	0.04	0.04	0.04
No. Obs	225	225	225	225	225	225

*N*otes: The unit of observation is at the treatment (m)-session (s)-period (t) level. The dependent variables are defined in the header of the table. DA, CM, and TT are independent dummy variables equal to one for its treatment and zero otherwise. All regressions include period-specific fixed effects. Standard errors in parentheses. *** denotes 1% significance level, **—5%, and *—10%.

shares. A high turnover indicates a high volume of trade, which can be an indication of a bubble. 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 indicates the presence of a negative bubble.

Table 2: 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

Table 3: 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.

Table 3 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.

Based on the estimation results from Table 3, we conclude that

Result 2. *Bubbles measures are significantly higher under Double Auction than under the uniform-price institutions, Call Market and Tâtonnement.*

This conclusion is also robust to the non-parametric pairwise comparisons of bubble measures across institutions, using the Mann-Whitney test with sessions as units of observation. The results of these comparisons are reported in Table 8 of Appendix D. While the results are overall consistent with the regression results provided in Table 3, the significance level of some pairwise comparisons is somewhat lower. This is not surprising as non-parametric tests tend to be more conservative than parametric tests.

Next, while Results 1 and 2 focus on the impact of trading institutions on aggregate outcomes, such as prices and volume of trade, Result 3 and Result 4 focus on individual traders' earnings. Result 3 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 3. *Double Auction results in higher inequality in traders' earnings than the uniform-price Call Market and Tâtonnement institutions.*

Table 4: 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

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

Support for Result 3: 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:[20]

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

where $DA_S = 1$ for DA sessions and zero otherwise. Table 4 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 4, these differences are significant at the 10% level for both measures of inequality. □

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

Result 4. *Subjects with High-CRT scores earned significantly higher payoffs than subjects with Low-CRT scores under Double Auction. However, there is no significant difference in earnings between subjects with High-CRT and Low-CRT under the uniform-price Call Market and Tâtonnement institutions.*

Table 5: 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 $CRT * DA$ (top row) and CRT (bottom row) from equation (2).

Support for Result 4: Table 5 reports the number of subjects (n) with low CRT (subjects whose CRT score was 0 or 1) and high CRT (subjects whose CRT score was 2 or 3) scores and the means

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

of their individual earnings, separately for double auction and for the uniform-price institutions (CM and TT).[21] 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 regression of individual earnings (IE):[22]

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

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).[23] □

Taken together, these results indicate that heterogeneity in traders' sophistication plays an important role for both 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 the experimental data, we also perform out-of-sample validation tests by showing in Section 4.3 that the model can match untargeted moments of the data.

4 Theoretical Model and Results

This section provides a parsimonious model that reproduces the main features of the data patterns we observed 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

[21] 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.

[22] 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.

[23] Note that average market CRT scores are not significantly different across treatments.

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.

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).[24]

Valuations: The valuation of the asset differs across individuals. We assume there are two types of individuals: myopic traders and fundamental traders.[25] This choice captures the heterogeneity in price forecasting among traders in the empirical data as presented in Result 5 in Section 4.3.3. We think of valuations as the future price expectation of a trader. The valuation for each type is

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

[25] While prior work in behavioral finance, including some conducted by some of us, assumes three types of agents, we opted for two types as it still provides interesting insights into heterogeneity and bubble formation while being more parsimonious. The model can be extended to incorporate more types, albeit at the expense of introducing additional parameters.

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. 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. 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.[26] 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 and finance.[27] On the other hand, fundamental trader's valuations are equal to the fundamental value of the asset.

We denote the fraction of myopic traders by δ_t, and assume it changes over time. Specifically, we assume that myopic traders are heterogenous in the degree of their foresight abilities, with some of them realizing that their valuations deviate from fundamental value sooner than others. That is, δ_t decreases over time and converges to zero by the end of the experiment, i.e., all myopic traders switch to fundamental traders by the end of the trading horizon. Thus, the parameter δ_t captures that myopic traders switch to fundamental traders at different points in time.[28] Potentially the process

[26] 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.

[27] 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]. Anchoring in our setting implies that subjects use previous prices as an anchor (see, e.g., Loomes et al. [2003] and Tufano [2010]).

[28] Another interpretation of δ_t is that types are fixed, and δ_t represents the fraction of traders expecting the future

driving δ_t can differ across institutions. However, in the interest of keeping the institutions directly comparable, we assume that this process is the same across all institutions. It is straightforward to extend the model to incorporate additional features.

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

Proposition 4.1. *The expected market-clearing price in Tâtonnement given the last period transaction price:*

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

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. □

Trading Price Expectations: We next describe how we model price expectations p_t^i in equation (3). We assume that p_t^i is the expected trading price within a period and it is also the price individuals submit as their bid/ask price. In TT, there is no price submission and 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 the trading price, which also will be their bid/ask price. We assume that, in CM and DA, the trading price expectation p_t^i is normally distributed around the expected market-clearing price of TT:

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

price, valuation, to return to fundamental value at time t whereas the rest expects it to follow a growing pattern.

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.[29][30]

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 moving average of the trading price in the previous period, adjusted for the dividend drop, and all the previous trading prices observed within the period. 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 are more opportunities for individuals to update this price. More specifically, we assume that $\tilde{p}_{t,j}^i$ is updated as follows:

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

where $p_{t,j}^*$ is the trading price in period t for the j^{th} transaction and $\alpha_{t,j}^i$ is an individual level shock drawn from a uniform distribution between 0 and 1. That is, in DA, α^* fraction of individuals

[29] 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.

[30] In period 1, price expectation depends on period 0 price, which is not defined. We estimate this price to match the first period observed price for all sessions.

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

With these assumptions 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.[31]

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 6 for the parameters' interpretation).[32] 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

[31] 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.

[32] Haruvy and Noussair [2006] and DeLong et al. [1990] both use a model with six parameters whereas Baghestanian et al. [2015] uses a model with eight parameters to study similar trading environments with bubbles.

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

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.

Table 6: 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
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	
α^*	Updating	0.09	
J	max number of transactions within period in DA	300	

a. 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 J are exogenously set and do not have a standard error to be reported.

Table 6 presents the results of the estimation (more details on the estimation can be found in

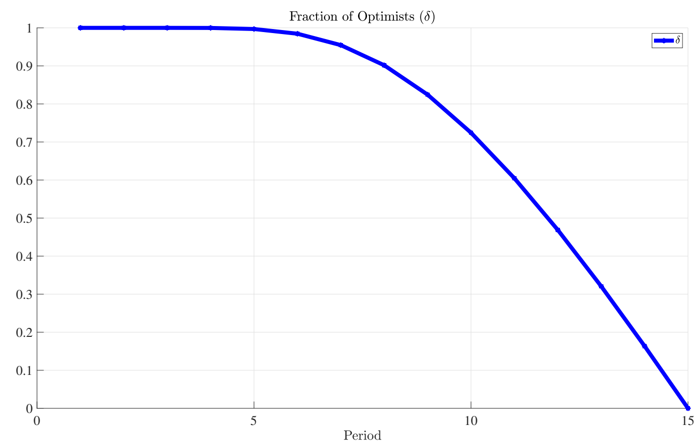


Figure 3: Estimated Share of Myopic Traders in Population

Appendix B). 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 traders in the population follows the pattern in Figure 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.[33]

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.[34]

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

[33]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 the price is equal to the fundamental value, $p_t^i = FV_t$.

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

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 DA 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, J, to 300 to match the average number of transactions per individual observed within a period in DA experiments.

4.3 Model Results

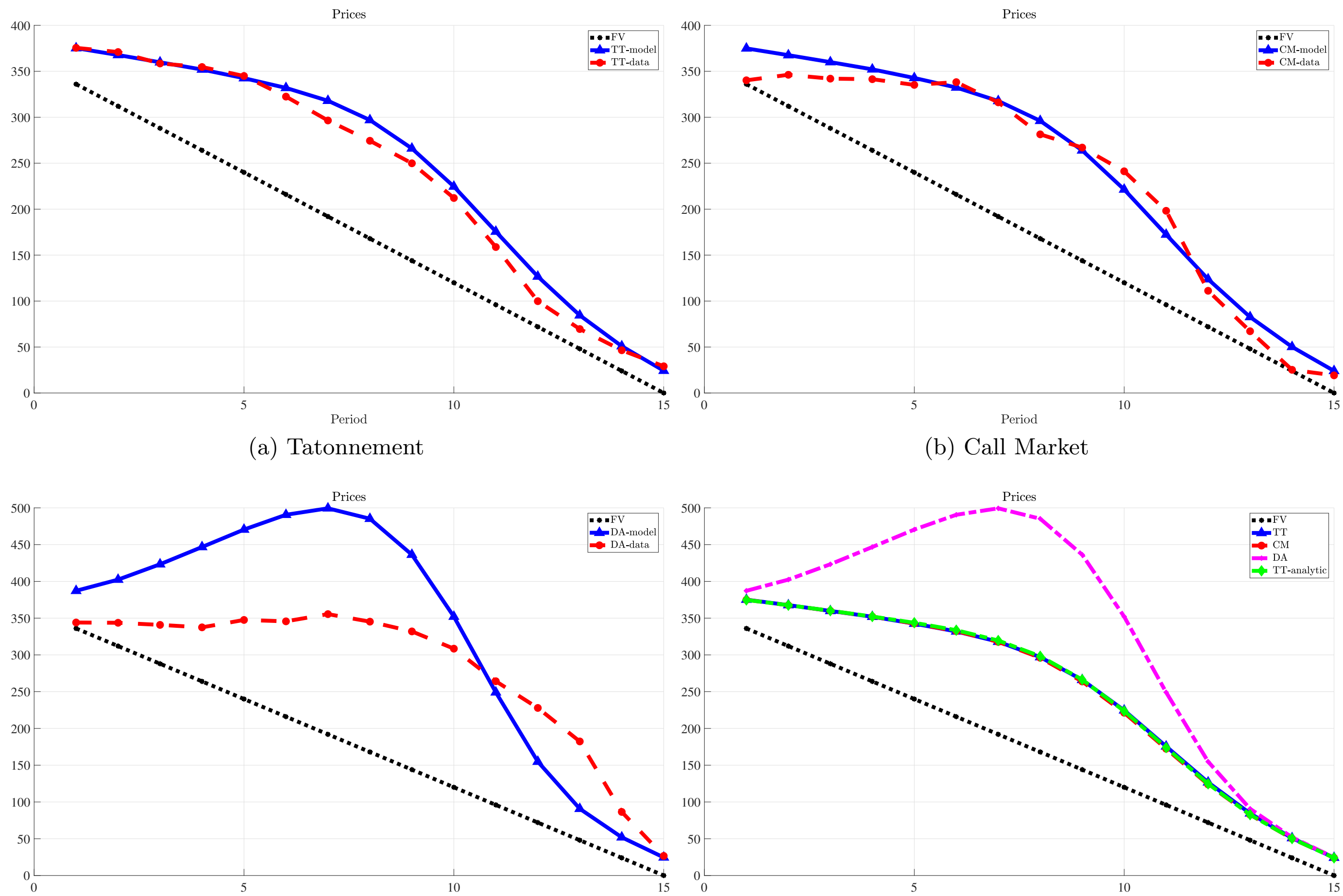
Given the estimated parameters, we use the theoretical model to simulate market-clearing prices for each institution. To isolate the impact of institutional differences on market-clearing prices and quantities, we keep the parameters of the model constant across institutions.[35] Note that we did not use the data from Double Auction markets to estimate the model's parameters. Appendix C provides details on how each institution is simulated.

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.[36] Figure 4d compares the model-generated prices across trading institutions. The model generates larger

[35] This is a crucial point. Allowing parameters to vary across institutions would provide an advantage to the model and hinder our ability to isolate the direct impact of trading institutions on pricing by introducing confounding factors. That is, differences in the simulated data generated by the model could arise from differences in the structural parameters of the model rather than from institutional differences, limiting our understanding of direct institutional mechanisms.

[36] The number of parameters in the model is 5. The number of data points to be matched is 140 data points for prices (14 periods and 5 sessions, in total 14*5=70 price data points for TT and CM each) and 1540 data points for quantities (630 quantity data points for TT (14 periods, 5 sessions and 9 individuals for each session: 14*5*9=630) and 910 quantity data points for CM. In CM individuals can submit both bid and ask, but not all individuals submitted both in every period.)



(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.

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 Results 1 and 2 and Figure 2(d) in Section 3.3). Notice that the parameters of the model are not chosen to match any data from DA. The 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: 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 updating structure, 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 increasing 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.

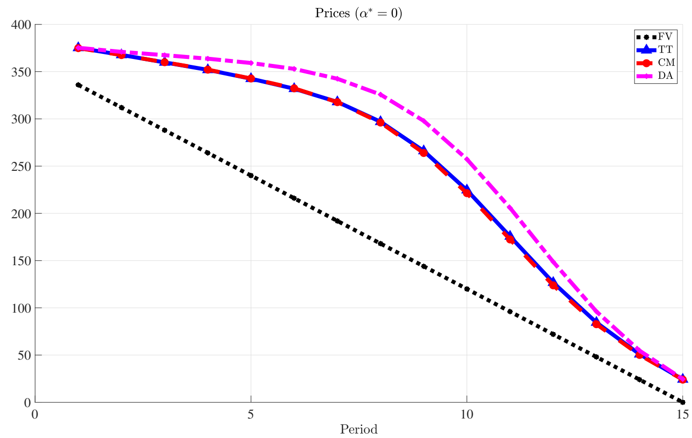
Figures 5a to 5d display the effect of updating on the formation of bubbles across different institutions. In these figures, we compare the model-generated prices with different assumptions about the intensity of updating. Notice that α^* represents the degree of updating, as it captures the fraction 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.[37] Figures 5a to 5d show that as updating becomes more prevalent, bubbles become larger in DA, while there is no impact on prices in TT and CM.

4.3.2 Within-Period Price Updating in DA

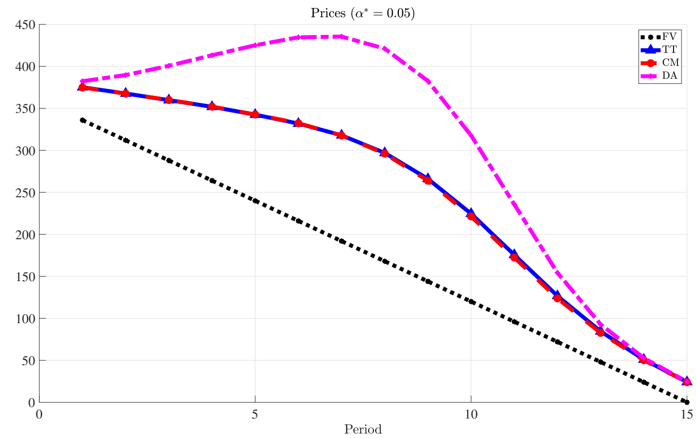
Our model predicts that the main difference in the bubble size between the DA and uniform-price institutions (CM and TT) is due to within-period updating in the DA (by design, there is only one transaction price in both CM and TT). This section investigates whether the predicted within-period updating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

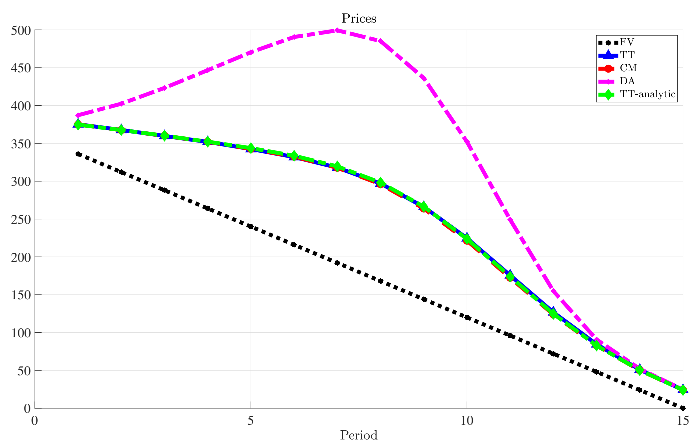
[37]When $\alpha^* = 0$, the model still generates a slightly higher bubble in DA compared to TT and CM. The main reason for this is the presence of the short-selling constraint. In DA, most of the transactions happen between individuals with extreme beliefs. In principle, the extreme positive and negative beliefs should cancel out, and we should observe a similar pattern 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.



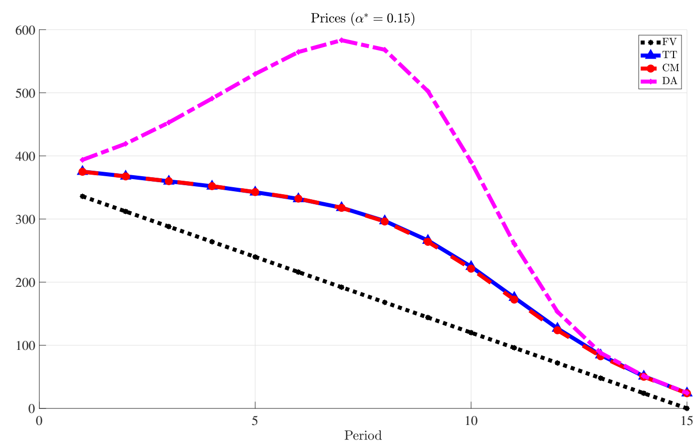
(a) $\alpha^* = 0$



(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.

stronger as the difference between transaction prices and the fundamental value converges from the peak to the fundamental value. Towards the end of the experiment, the magnitude of the 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 t, we regressed the individual transaction price (p_{jst}) on the within-period transaction counter (j=1,2,3,...). The estimated slope represents the within-period price growth per transaction. For each period t, 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.[38]

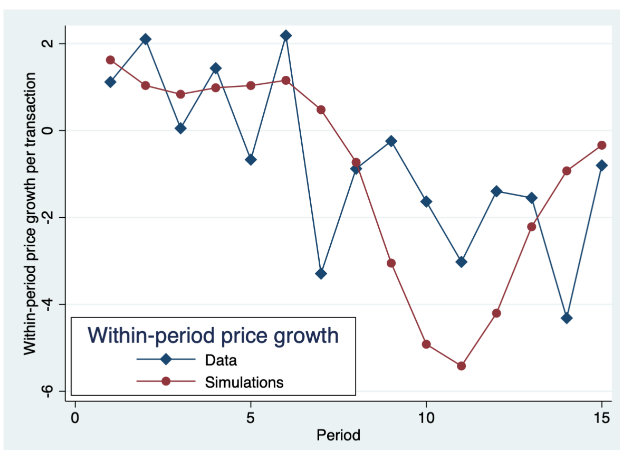


Figure 6: **Within-period price growth rates in DA: data and model simulations.**

Our model makes other predictions that could be tested in future experiments. For example,

[38]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.

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.

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 7, 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 3, both measures of inequality imply that DA results in higher inequality in trader earnings than uniform-price trading institutions.

Table 7: 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 11 periods of the experiment. Group 2 includes the remaining traders.[39] 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 11 periods, the vast majority of all simulated traders are myopic. That is, 11 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 12, 50% of traders switch to fundamental traders, and their share keeps increasing after that. Therefore, in periods 12-15, 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 11-period interval and for the last 4-period interval: $\widetilde{NV}_{s,1-11}$ and $\widetilde{NV}_{s,12-15}$, and regress them on the $\widetilde{CRT}$ dummy variable in two separate OLS regressions. Our estimation results are presented below:[40]

$$\begin{aligned} \widetilde{NV}_{s,1-11} &= \underset{(0.0)}{1.34} - \underset{(0.0)}{0.01}\widetilde{CRT}_s \\ \widetilde{NV}_{s,12-15} &= \underset{(0.0)}{1.97} - \underset{(0.0)}{0.49}\widetilde{CRT}_s. \end{aligned} \tag{10}$$

In line with our expectations, compared to Group 2 traders, Group 1 traders have only 1% lower valuations in periods 1-11, but 49% lower valuations in periods 12-15.

[39] 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. We set the time period to 11 so that across all institutions, around 50% of the traders belong to Group 1 and the rest belongs to Group 2 to replicate the empirical share of the sophisticated traders (high CRT) in the experiments.

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

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 11-period interval and for the last 4-period interval: $NF_{s,1-11}$ and $NF_{s,12-15}$, respectively. The OLS estimates of regressing the NF on the constant and CRT dummy with the standard errors clustered by session are presented below:[41]

$$\begin{aligned} NF_{s,1-11} &= \underset{(0.07)}{1.38} - \underset{(0.09)}{0.05} CRT_s \\ NF_{s,12-15} &= \underset{(0.55)}{2.42} - \underset{(0.55)}{0.79} CRT_s, \end{aligned} \tag{11}$$

where $CRT = 1$ for High-CRT subjects and $CRT = 0$ for Low-CRT subjects.[42]

The results indicate that (i) in periods 1-11, the difference in forecasts between the High-CRT and Low-CRT traders is not statistically significant, and (2) in periods 12-15, High-CRT traders have 79% lower forecasts than Low-CRT traders. Formally, we summarize this evidence in the following result.[43]

Result 5. *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 last 4-period interval 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 1.02. This ratio is 1.01 in CM. However, in DA, this ratio increases to 1.20. More

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

[42]Recall that the definitions and distributions of the High-CRT and Low-CRT are provided in Table 5.

[43]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.

formally, we run the same regression as in equation 2:

$$IE_s = \underset{(0.01)}{13.45} + \underset{(0.01)}{0.18} CRT_s - \underset{(0.01)}{1.23} DA_s + \underset{(0.02)}{2.31} CRT_s * DA_s. \tag{12}$$

Consistent with the empirical results summarized in Result 4, 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.

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. Since in this paper we primarily focus on bubble formation, as a first step, we have employed the canonical Smith et al. [1988] framework. Other intriguing questions are related to the aggregation of information in markets (e.g., see recent work by Corgnet et al. [2022], Corgnet et al. [forthcoming], Bosch-Rosa and Corgnet [2021] or Cipriani et al. [2020]). To investigate this question, we leave the study of different institutions within the context of Plott and Sunder [1982] and Plott and Sunder [1988] for future research (see also Pouget [2007]). Similarly, to study the impact on mispricing and efficiency more generally, we plan to investigate other environments, e.g., with short selling, different dividend processes (including stationary ones) or with private values and incentives to trade.

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Appendix 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:

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

To become a buyer, η^i needs to satisfy

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

So, the total demand from fundamental traders becomes:

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

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:

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

□

Appendix 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 $\gamma\sigma_\eta + \sigma_\epsilon$.

Appendix 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.[44] Initially each agent i is endowed with x_0^i units of cash and y_0^i units of the financial asset. At the end of every period the asset pays random dividends drawn with equal probability from a commonly known support $\{d_1, d_2, d_3, d_4\}$, with $d_i \geq 0$ 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.[45]

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.[46] 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

[44] In the experiments $N = 9$ and $T = 15$. In the simulations we set $N = 100$ and $T = 15$ to reduce the noise in the simulations due to a low number of agents.

[45] 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.

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

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

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:

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

where θ_t is the adjustment factor. We set θ_t as in the experimental design. Conditional on the new indicative prices, agents re-submit new quantities y_t^i. Iterations continue until $|z_t| < \xi$, where we set $\xi = 1$.

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.

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.[47] 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).[48] 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.[49] 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.

[47] 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.

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

[49] 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.

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 J 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 $p^a_{t,j}$, the identity of the individual who posted the ask price $i^a_{t,j}$, a bid price $p^b_{t,j}$ and the identity of the individual who posted the bid price $i^b_{t,j}$. The initial value for the ask price is set to a very high value, and the initial value for the bid price is set to a very low 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 $\left(p^i_t\right)$ is higher than the ask price $p^a_{t,j}$ and the individual's demand q^i_t given by equation (3) is greater than 1 at the current ask price $p_t = p^a_{t,j}$, 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 ($\left(p^i_t\right) < p^b_{t,j}$), and the demand of the individual at the expected price is less than -1 ($q^i_t \left(p_t = p^b_{t,j}\right) < -1$), 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 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^i_t is drawn from a normal distribution with mean 0 and variance σ^2_η at the beginning of each period and $p^j_t = p^*_{t-1} - d$. 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^j_t as the moving average price between the last period price, adjusted with dividend, and j^{th} transaction within a period as in equation 7. At the end of each period, p_t is computed as the average price across all transactions within a period.

Appendix D Comparison of Bubble Measures

Table 8: 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.